

**A Data-driven Analysis to Attest Regional Interlinkages
between Economics and Environment:**

Utilization of SDG Indicators for Spatio-temporal Analysis

Dissertation

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To my parents

Preface

This dissertation is submitted for the degree of Doctor of Philosophy from Graduate School of Economics, Hiroshima University of Economics. The main objective of this dissertation is to employ a research to unravel interlinkages among indicators for sustainable development goals (SDG indicators) across space and time. The SDG indicators provide a feasible framework to comprehend and analyze socio-economics and environment in harmony.

There is no doubt that one of the major causes of the present environmental changes should be attributed to humans, especially economic activities. There are not so many precedent researches which combine socio-economic and environmental factors, especially that try to utilize satellite data, without the usage of hypothetical assumptions. This dissertation becomes the quantitative pioneering guidance to combine both of the datasets for the application in the regional analysis.

More and more data are being accumulated not only from satellites but also from socio-economic dataset. The methodology deployed in this dissertation will provide a workable tool to comprehend and analyze the integrated sustainable development goals in regional data to provide reasonable regional policies.

Hiroshima, August 2020
Gigih Fitrianto

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بِسْمِ اللَّهِ الرَّحْمَنِ الرَّحِيمِ

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Contents

Preface.....	i
Acknowledgments.....	ii
Contents	iii
List of Figures	v
List of Tables	vii
Summary of Chapters	viii
Chapter 1. Frameworking Data-driven Analysis with the Usage of SDG Indicators	1
1.1. Introduction	2
1.2. Industrial Structure Review in Sumatra Island and Variable Setup for Analysis.....	5
1.3. Profile of Palm Oil and Mining Industry in Sumatra Island, Indonesia	8
1.3.1. Palm Oil Industry.....	8
1.3.2. Mining Industry	9
1.4. Literature Review.....	10
1.4.1. Breakpoint Analysis for Structural Change.....	10
1.4.2. Spatio-temporal Analysis for Extracting Interlinkages	11
1.5. Methodology for Data Incorporation	14
References	16
Chapter 2. Utilization of SDG Indicators to Analyze Economic Structural Change and Regional Resilience with Respect to Neighbor Municipal Bodies	21
2.1. Introduction	22
2.2. Methodology	23
2.2.1. Data and Target Variable	23
2.2.2. Empirical Model	24
2.3. The Result	27
2.3.1. The Stationary Test	27
2.3.2. Breakpoint Analysis of US Regional Data	27
2.3.3. Breakpoint Analysis of Japanese Regional Data	32
2.4. Discussion and Conclusion.....	36
References	37
Chapter 3. Generic Methodology for Variable Selection in Spatial Regression Analysis to Attest Regional Interlinkages among SDG Indicators: A Study Case of Sumatra Island, Indonesia	41
3.1. Introduction	42
3.2. Various Spatial Regression Models	42
3.3. Estimation Methods in Spatial Regression Models and the Difficulty	43
3.4. Variable Selection and Interlinkages	45

3.5. Methodology	46
3.5.1. Variable Selection in Spatial Regression Method (VSSR).....	46
3.6. Data and Variables	47
3.6.1. List of Variables	47
3.6.2. Source of Data	48
3.6.3. Descriptive Statistics	48
3.7. Model Specification	52
3.8. Interim Result	52
3.9. Additional Variables and The Effect to Attest Interlinkages.....	55
3.9.1. Inclusion of Environmental Variable	56
3.9.1.1. Data Limitation for Forest Cover Data	56
3.9.1.2. The Inclusion of Altitude Data	59
3.9.2. New Model Specification.....	64
3.9.3. Results after Addition of A New Variable	66
3.10. Concluding Remarks	67
3.11. Future Works	68
References	69
Chapter 4. Formulation of Huge Lattice Spatial Adjacency Matrices With Non-rectangular Shape of Socio-economic Grid-Cell Data for the Analysis of Sustainable Economy With High Computational Efficiency	75
4.1. Introduction	76
4.2. Weighted Neighbor Relation Matrices	80
4.2.1. Rectangular Lattice.....	80
4.2.2. Non-rectangular Lattice	82
4.3. Formulation of W Matrices	83
4.3.1. Kronecker Product.....	83
4.3.2. Polygon and Cell Based on <i>spdep</i> R Package.....	85
4.3.3. Kronecker Product for Non-rectangular Case.....	86
4.4. Computational Efficiency Comparison: A Simulation	87
4.5. Kronecker Product Method Performance for Very Large W Matrices	90
4.6. Concluding Remarks	90
4.7. Future Works	91
References	91
Appendix 1. List of Global Indicator Framework for the Sustainable Goals and Targets	95
Appendix 2. Breakpoint Test Results for The US Data	125
Appendix 3. Example of Oil Palm Mills Owned by the Same Parent Company	135
Appendix 4. List of Satellite Data Product	143
Appendix 5. Prior Research in Constructing Spatial W Matrices.....	161

List of Figures

Figure 1.1.	Analytical framework following SDG goals and target	4
Figure 1.2.	Detailed Map of Sumatra Islands, Indonesia	5
Figure 1.3.	Industrial Contribution Toward GRP for Riau, Sumatra Utara, and Sumatra Selatan in 2017	7
Figure 1.4.	Sumatra Regional Plots based on 2016 data for: (i) population growth, (ii) crude palm oil production per labor, (iii) mining output per labor, and (iv) wholesale and retail trade output per labor	8
Figure 1.5.	Map of Oil Palm Plantation in Sumatra 1990 and 2009 (Gunarso et al. 2013).....	9
Figure 1.6.	Generic Methodology of Incorporated Analysis.....	15
Figure 1.7.	Incorporated Data Process for Regular Lattice structure	15
Figure 1.8.	Incorporated Data Process for Non-lattice structure	15
Figure 2.1.	Growth of the US National GDP by Quarterly Change, 2004-2007 (BEA, 2008)	22
Figure 2.2.	Japan national growth rate of GDP by quarterly change (2007:Q1 – 2010Q4)	24
Figure 2.3.	Regional Economic Growth Rate in U.S: Before and After Crisis	24
Figure 2.4.	Regional Economic Growth for all states in the US: Before-After Crisis	28
Figure 2.5.	The regional trend comparison before (left) and after (right) breakpoint in US	31
Figure 2.6.	The F-test (left) and Wald Test (right) for Spatially-Independent model	31
Figure 2.7.	The spatial correlation before (left) and after (right) breakpoint in US	32
Figure 2.8.	The F-test (left) and Wald Test (right) for Spatially-Dependent model.....	32
Figure 2.9.	Regional Economic Growth Rate in Japan: Before and After Crisis.....	32
Figure 2.10.	Regional Economic Growth for all Prefectures in Japan: Before-After Crisis	33
Figure 2.11.	The regional economic trend comparison before (left) and after (right) breakpoint in Japan	35
Figure 2.12.	The spatial correlation before (left) and after (right) breakpoint in Japan	36
Figure 3.1.	Generic Flow Chart of VSSR Process	47
Figure 3.2.	Parameter estimation of λ with respect to AIC for full and VSSR models....	53
Figure 3.3.	Total forest cover and oil palm area in Sumatra Island based on MoFE	57
Figure 3.4.	Map agreement and disagreement for forest and non-forest classes of the Ministry of Forestry and Class set based on Margono et al. (2014).....	58
Figure 3.5.	Forest Cover for each Province in Sumatra Island based on MoFE	

Publications	58
Figure 3.6. Global Altitude Map from GTOPO30 Dataset (USGS, 2001).....	59
Figure 3.7a. Riau polygon object and rectangular extent.....	60
Figure 3.7b. Cropping GTOPO30 image to obtain Riau Rectangular Image.....	61
Figure 3.7c. Obtain Riau Provincial Raster Image for Altitude Data	62
Figure 3.7d. Obtain Standard Deviation of Altitude for Riau Province	62
Figure 3.8. Flow Chart of Incorporated Process GTOPO data into the Analysis	63
Figure 3.9. Provincial Raster Image based on GTOPO30 Dataset	64
Figure 3.10. Parameter estimation of λ with respect to AIC for full and VSSR models ...	66
Figure 4.1. General shapefile handling process for spatial analysis.....	78
Figure 4.2. Comparison of formulation of w for the neighborhood of eastern area of Lake Apopka, Florida.....	79
Figure 4.3. Nearest Neighbors Grid System of $s(x_i, y_i)$	81
Figure 4.4a. Neighbor Cell Construction of $1N$	81
Figure 4.4b. Neighbor Cell Construction of $2N$	82
Figure 4.4c. Neighbor Cell Construction of total neighbor.....	82
Figure 4.5. Nonrectangular Lattice $D_{3 \times 3}$	83
Figure 4.6. Neighborhood Examples for cell (1,1), (2,2), and (3,2) on $D_{3 \times 3}$	83
Figure 4.7. Kronecker Product Method by using Shift Matrix.....	84
Figure 4.8a. Illustration of ‘poly2nb’ Process	85
Figure 4.8b. Illustration of ‘cell2nb’ Process	85
Figure 4.9. Comparison of elapsed time between Script 4.1 and <i>spdep</i> method.....	89
Figure 4.10. Object size comparison between Script 4.1 and <i>spdep</i> method	90

List of Tables

Table 1.1.	Sustainable Development Goals (SDGs) Global Framework.....	2
Table 1.2.	Sector contribution to gross regional product (GRP) for each province in Sumatra Island, 2017	6
Table 2.1.	A Yearly Accumulation of Japan Growth Rate of GDP, 2007 – 2010	22
Table 3.1.	Spatial Configuration and Maximum Combination Required for Variable Selection Process to Attest Interlinkages.....	43
Table 3.2.	Summary of Estimation Methods in Spatial Models	44
Table 3.3.	Descriptive Statistics after Riau Islands Removal (datasize = 63).	48
Table 3.4.	Estimation Result.....	54
Table 3.5.	Analysis-ready Dataset for Forest Area	56
Table 3.6.	Descriptive Statistics for Altitude Variable by Province	65
Table 3.7.	New Estimation Result	66
Table 4.1.	Examples of related sustainable goals and targets for incorporated analysis ...	76
Table 4.2.	Examples of grid-cell data source for socio-economic variables	77
Table 4.3.	Construction $\mathbf{W}_{9 \times 9}$ Spatial Weighted Neighborhood Matrix	84
Table 4.4.	Construction $\mathbf{W}_{9 \times 9}$ Weighted Neighborhood Matrix for $1N_i$	84
Table 4.5.	Computational environments for simulations.....	87
Table 4.6.	Total elapsed time comparison for all methods	88
Table 4.7.	Actual object memory size comparison between all methods* (in MB).....	89
Table 4.8.	Kronecker product method performances for larger \mathbf{W} Matrices.....	90

Summary of Chapters

This dissertation conducted to unravel interlinkages among indicators for sustainable development goals (SDG indicators) across space and time for comprehensive regional analysis. To accomplish this, data availability for spatial and temporal data length is important. Chapter 1 depicts the generic framework between socio-economic and environmental factors through spatio-temporal analysis. This dissertation tries to deploy a data-driven analytical approach under datasize limitation targeting for Indonesia data by considering temporal and spatial factors in statistical models.

Chapter 2 focused on how to utilize the time series analysis in conjunction with spatial dependency information to detect the resilience against Lehman's shock in the regional spectrum. Because Lehman's shock is selected as a study case, Indonesian gross regional product (GRP) with 2010 base year data that only begin from 2010 could not be used. This condition forced the study to use Japanese data instead of the Indonesian in comparison with the US data of larger datasize.

In the US, it was indicated that the negative impact of crisis clustered in West Coast, Southeastern, and Great Lake region. Those regions had good manufacturing, construction, insurance, and finance as the main contributor for their GRP. On the other hand, states that relied on agriculture, forestry, fishing, hunting, and mining sectors had resilience. In contrast, Japan showed that negative impacts spread-out across all the regions.

Chapter 3 focused on spatial factor in regional analysis to unravel interlinkages among SDG indicators across region. To select the best variables to attest regional interlinkages variable selection process in spatial regression is used. By using Sumatra data, the results showed that palm oil industry gave strongly positive effect to income, but statistically no evidence found for child labor contribution.

The inclusion of standard deviation value for altitude as an additional variable into the analysis provide a better model to explain the data. The result showed a negative and significant of altitude variable, which indicated that highly produced oil palm plantation occurred only in several provinces that have vast areas and flat topography profiles that are more suitable for this industry.

Chapter 4 provided theoretical and practical ways to construct spatial neighbor matrix of lattice structure for incorporated gridded socio-economic and satellite data. The advantage of using grid-cell data for socio-economic analysis should be the feasibility to incorporate satellite data with high affinity to observe the relationship between socio-economics and nature.

Chapter 1

**Frameworking Data-driven Analysis with the Usage of
SDG Indicators**

1.1 Introduction

Establishment of sustainable development goals (SDGs) and the targets by United Nations General Assembly on 25 September 2015 have encouraged every nation to achieve social and economic development issues including poverty, hunger, health, education, global warming, gender equality, water, sanitation, energy, urbanization, environment and social justice (UNDP, 2015). UNDP then established the strategic plan (2018-2021) in the UN agenda 2030 that designed to be focused on an integrated response to broad development context: eradicating poverty, structural transformations, and building resilience.

Under this agreement, UNDP setup a list of SDG indicators to study the development for each country achievement of SDGs. The global indicators were developed and agreed at the 48th session of the United Nations Statistical Commission. These 232 indicators arrange to focus on each SDG components and relevance by income, sex, age, race, ethnicity, migratory status, or disability and geographic locations (UNDP, 2015). **Table 1.1** shows all 17 sustainable development goals with 169 associated target (details in **Appendix 1**) that are integrated into a comprehensive global framework to encourage social justice in harmony with environmental protection by 2030.

Table 1.1 Sustainable Development Goals (SDGs) Global Framework.

Goal 1 End poverty in all its forms everywhere	Goal 2 End hunger, achieve food security and improved nutrition and promote sustainable agriculture
Goal 3 Ensure healthy lives and promote well-being for all at all ages	Goal 4 Ensure inclusive and equitable quality education and promote lifelong learning opportunities
Goal 5 Achieve gender equality and empower all women and girls	Goal 6 Ensure availability and sustainable management of water and sanitation
Goal 7 Ensure access to affordable, reliable, sustainable and modern energy	Goal 8 Promote sustained, inclusive and sustainable economic growth, full and productive employment and decent work
Goal 9 Build resilient infrastructure, promote inclusive and sustainable industrialization and foster innovation	Goal 10 Reduce inequality within and among countries
Goal 11 Make cities and human settlements inclusive, safe, resilient and sustainable	Goal 12 Ensure sustainable consumption and production patterns
Goal 13 Take urgent action to combat climate change and its impacts	Goal 14 Conserve and sustainably use the oceans, seas and marine resources for sustainable development

<p>Goal 15</p> <p>Protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss</p>	<p>Goal 16</p> <p>Promote peaceful and inclusive societies for sustainable development, provide access to justice for all and build effective, accountable and inclusive institutions at all levels</p>
<p>Goal 17</p> <p>Strengthen the means of implementation and revitalize the Global Partnership for Sustainable Development</p>	

International Council for Science (2016) shows some interconnections between goals. For example, to end the poverty cannot be achieved without ensuring the sustainability of food and nutrition for all. Achieving food security by easy access to sufficient quantity and quality if food will ensure health and well-being. This condition driven from increasing agricultural production and productivity that produced from a better soil and water quality.

The other example for the connection between goals represented by ensuring access to affordable, sustainable, reliable, and modern energy service supports to end the poverty for all. Improvement of the access for the poor and/or isolated region will ensure children with poverty may improve their educational quality that will drive a better future.

A better energy support supports food production, where agricultural sector can play important role in producing biofuels energy. An increase in renewables and energy efficiency will support to avoid a climate change. A better environment that support to avoid a climate change is already having impacts on health. Maintain a better health condition for all people in the region will increase their productivity on doing the social and economic activities. The better environment also can be achieved from responsible economic activities from industrial sector to avoid negative environmental impacts, such as waste disposal policy or illegal logging that caused forest cover loss.

To achieve those integrated goals and output, a comprehensive research and policies should be designed. Understanding the interactions among SDGs will unravel an integrated analysis or policies at the local, regional, national, and global levels (International Council for Science, 2016).

This dissertation constructed more comprehensive and deepened regional analysis by using SDG indicators. **Figure 1.1** shows the relationship between regional income inequality (**Goals 10, Target 10.1**) in Sumatra Islands and socio-economic variables that measured by per capita economic growth (**Goals 8, Target 8.1**) and educational quality (**Goals 4, Target 4.3**) as human capital factor of production (Goldin, 2016). The negative effect that occurred in palm oil industry, such as environmental destruction (**Goals 15, Target 15.1**) and child labor participation (**Goals 8, Target 8.7**) are observed in the framework in **Figure 1.1**.

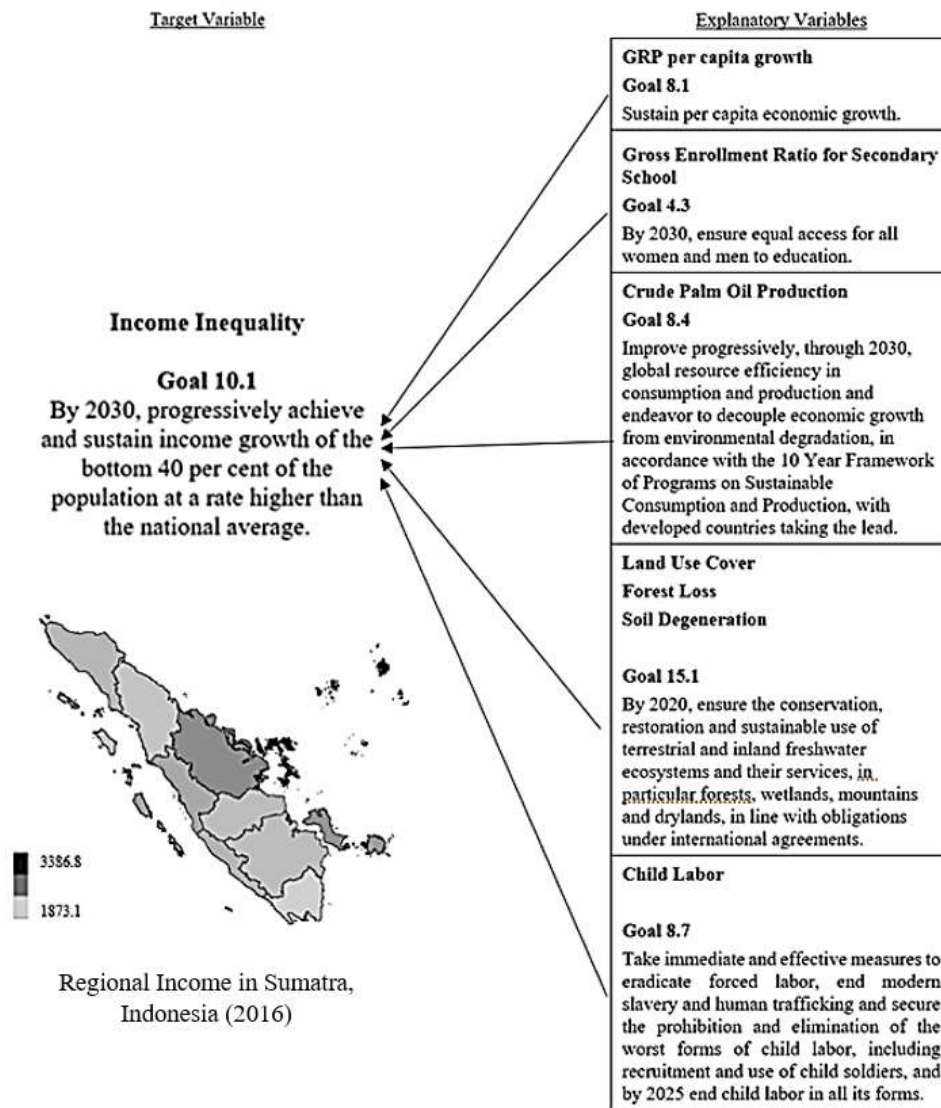


Figure 1.1. Analytical framework following SDG goals and target.

The main goals as mentioned in SDG framework are focusing on reducing poverty and income inequality. The main objective of this study is to observe the role of sustainable regional economic growth towards to regional poverty. Adams (2003) found that growth represents important meaning towards reducing poverty in the developing countries. Economic growth tends to increase income for all members of society, including the poor. Ravallion and Chen (1997) and Lopez and Serven (2006) also observe the relationship between poverty reduction and faster economic growth.

In accordance with the SDG goals and target relation in **Figure 1.1**, Mincer (1974), Fields (1980), and Tilak (2003) showed the negative correlation between educational quality and poverty rate. This implies the increase of educational factor may decrease the poverty rate. The increase of human capital (educational quality) also becomes a driving factor of economic growth (Topel, 1999; Krueger & Lindahl, 2001; and Hanushek & Wößmann, 2007). Nakabashi and Salvato (2007), Olejnik (2008), and Cravo, Becker, and Gourlay (2015) also found that people are seeking for a better living and educational quality causes the mobility to the richer region.

To show the application of this framework, this dissertation used data of all ten provinces in Sumatra Island (geographical detail shows in **Figure 1.2**) for regional analysis between palm oil industry and regional income. **Section 1.2** shows the industrial review in Sumatra which related to variable setup. **Section 1.3** describes more detail about palm oil and mining industries in Sumatra.

1.2 Industrial Structure Review in Sumatra Island and Variable Setup for Analysis

To demonstrate the incorporated analysis, Sumatra Island in Indonesia as regional study is selected. This selection based on the fact that the economy of Sumatra that mostly depend on natural resource had negative impact to the environment condition, such as fire emission, deforestation, and biodiversity loss (Nawir, Murniati, & Rumboko, 2007; Wicke et al., 2011; Abood et al., 2014; Marlier et al, 2015; and Vijay, et al., 2016). Besides, the social problem that arise due to the utilization of child labor in palm oil industry (Pye, Daud, Manurung, & Siagan, 2016; UNICEF, 2016; Schleicher, 2019; and ILO, n.d). This subsection reviews Sumatra's general industrial structure to give brief picture of economic activities in Sumatra Island that are essential for variable selection in **Chapter 3**.

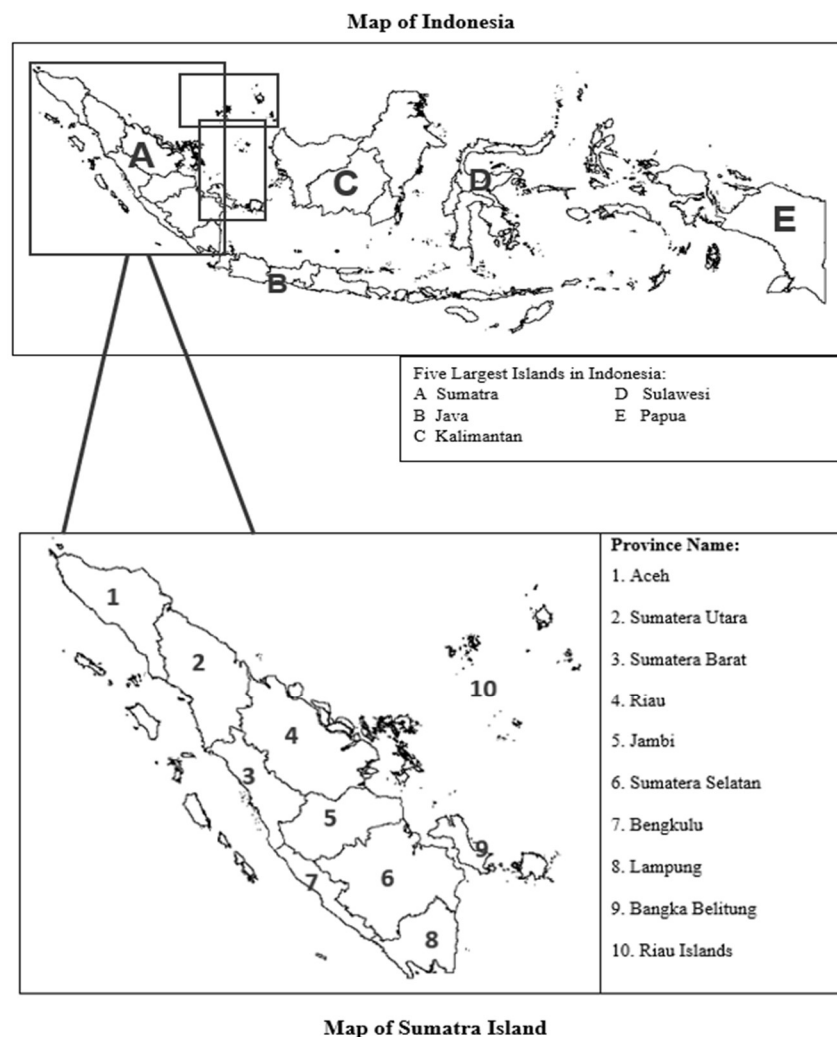


Figure 1.2. Detailed Map of Sumatra Islands, Indonesia.

Table 1.2. Sector contribution to gross regional product (GRP) for each province in Sumatra Island, 2017.

Industrial Origin	Contribution to GRP in %									
	Aceh	Sumatra Utara	Sumatra Barat	Riau	Jambi	Sumatra Selatan	Bengkulu	Lampung	Bangka Belitung Islands	Riau Islands
Agriculture, Forestry and Fishing	28.08	24.88	22.69	25.32	26.97	17.72	28.35	30.05	18.18	3.58
Mining and Quarrying	7.08	1.32	4.06	20.66	23.57	21.31	3.52	6.08	13.27	15.45
Manufacturing	4.87	19.03	10.60	29.68	10.76	18.92	6.24	17.96	22.70	37.60
Electricity and Gas	0.15	0.14	0.11	0.06	0.05	0.10	0.09	0.17	0.09	0.98
Water supply, Sewerage, Waste Management and Remediation Activities	0.03	0.10	0.10	0.01	0.13	0.11	0.22	0.10	0.02	0.13
Construction	9.61	12.55	9.02	8.13	7.19	11.94	4.49	9.54	8.50	17.48
Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles	15.63	17.53	15.57	9.19	9.61	10.19	15.44	11.98	14.51	8.23
Transportation and Storage	7.69	4.71	12.03	0.86	3.28	1.98	7.89	5.11	3.79	2.80
Accommodation and Food Service Activities	1.27	2.31	1.09	0.46	1.11	1.28	1.63	1.38	2.27	2.13
Information and Communication	3.56	2.65	6.93	0.87	3.61	3.30	4.46	4.67	2.01	2.25
Financial and Insurance Activities	1.70	2.99	2.96	0.93	2.35	2.60	3.33	2.12	1.76	2.69
Real Estate Activities	4.01	4.23	1.94	0.90	1.44	3.04	4.49	3.09	3.15	1.53
Business Activities	0.63	0.90	0.44	0.01	1.05	0.11	2.26	0.14	0.25	0.01
Public Administration and Defence; Compulsory Social Security	8.91	3.17	5.55	1.76	3.42	3.24	8.80	3.05	5.21	2.26
Education	2.48	2.01	3.82	0.48	3.26	2.71	6.37	2.73	2.37	1.46
Human Health and Social Work Activities	2.90	0.96	1.38	0.19	1.15	0.65	1.62	0.96	1.21	0.97
Other Services Activities	1.38	0.51	1.71	0.49	1.03	0.78	0.79	0.89	0.71	0.46
TOTAL GRP (in trillion Rupiahs)	121.26	487.53	155.98	470.98	136.50	281.57	42.07	220.63	49.99	166.08

Table 1.2 shows that there are four main industries that contribute to all province economies in Sumatra based on 2017 gross regional product (GRP) by industrial sectors. Those industries are: 1) agriculture, forestry, and fishing; 2) mining and quarrying; 3) manufacturing; and 4) wholesale and retail trade industry. Agriculture sector becomes the most contributor for each province in Sumatra with more than 17%, except the Kepulauan Riau province that has only 3.58% of their GRP. The mining industry also become main sectors in Riau, Jambi, and Sumatra Selatan. This industry contributed more than 20% for their GRP.

For example, there are three provinces that become top three producers of palm oil in Sumatra Island: Riau, Sumatra Utara, and Sumatra Selatan (BPS, 2017). **Figure 1.3** shows the contribution of 17 sectors toward each provincial GRP in 2017.

In Riau, 29.7% of their economy comes from manufacturing industry, followed by agricultural sector with 25% and mining with 21%. In Sumatra Utara, 24.9% of their economy comes from agricultural sector, then followed by manufacturing industry with 19%, and wholesale and retail industry with 17.5%. Sumatra Selatan also has mining industry as leading contributor with 21% of total GRP. Manufacturing and agricultural sectors followed by 19% and 18% of total Sumatra Selatan GRP.

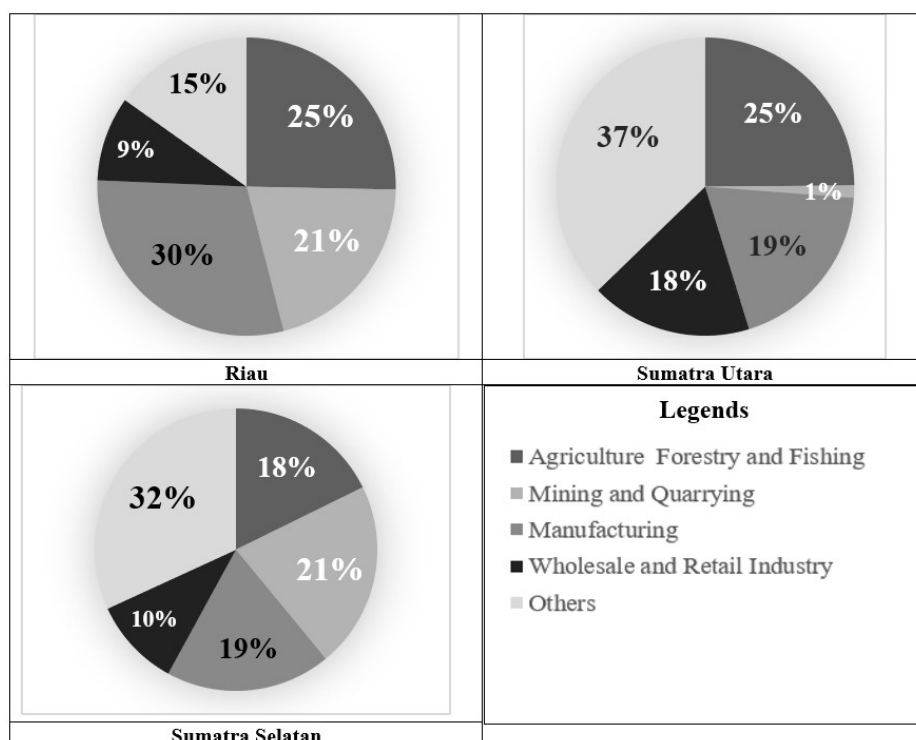


Figure 1.3. Industrial Contribution Toward GRP for Riau, Sumatra Utara, and Sumatra Selatan in 2017

On the other hand, wholesale and retail industry contributed between 8-17% of total GRP in each province. Riau Island become the exceptional province in Sumatra that does not depend on agriculture, forestry, and fishing sector. This is due to fact that this province consists of many small islands. Therefore, this province is not able to produce a lot of output from agricultural

sector compare to the others. In 2017 this sector only contributed 3.58% to their total GRP in 2017.

1.3 Profile of Palm Oil and Mining Industry in Sumatra Island, Indonesia

1.3.1 Palm Oil Industry

In Indonesian industrial classification, palm oil industry divided into two categories: 1) oil palm plantation in agricultural sector, and 2) crude palm oil in manufacturing industries. Based on 2017 Indonesian industrial classification code, oil palm plantation has code 01261 and crude palm oil production has code 1043¹.

This study interested in observing the role of palm oil production into income inequality in Sumatra Island. Sumatra Island selected as a study case due to the fact that provinces in Sumatra Islands contributed more than 68.2% from total 33 million ton of crude palm oil (CPO) production, followed by provinces in Kalimantan with 28% (BPS, 2017) in Indonesia. However, the percentage data of CPO production in manufacturing industry is difficult to obtain, but the ratio would be large in Sumatra. Food and beverages industry which includes CPO industry shows 74% contribution in Riau's manufacturing industry for 2017 data (BPS Riau, 2018).

Figure 1.4 shows the regional plot comparison between provinces in Sumatra Island with respect to their population growth, crude palm oil production, mining, and wholesale output per labor in 2016.

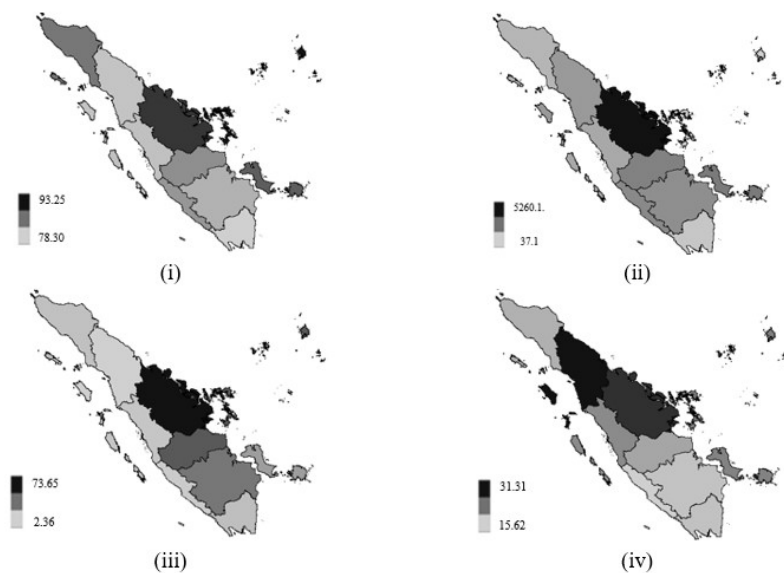


Figure 1.4. Sumatra Regional Plots based on 2016 data for: (i) population growth, (ii) crude palm oil production per labor, (iii) mining output per labor, and (iv) wholesale and retail trade output per labor.

¹ Detail information is available in <https://izin.co.id/KBLI-2017-terbaru.pdf> (in Bahasa Indonesia).

Those statistics shows the advancement of palm oil plantation in Sumatra island. Since it begun in 1910s the palm oil industry has become one of the main income sources of provinces in Sumatra, especially the east coast regions (Budidarsono, Susanti, & Zoomers, 2013).

Riau province becomes the largest area for oil palm plantation with 2,430 Kha, more than 20% compared to the total area in Indonesia. For all provinces in Sumatra Islands, they are contributed 7,191 Kha or 60.3% palm tree area. Kalimantan followed with 4.178 Kha in total or 35% of total in Indonesia. Besides, Riau also becomes the largest producer of crude palm oil (CPO) with more than 25.5% of total CPO production in Indonesia. Sumatra Utara and Sumatra Selatan become the second and third producer with 16% and 9% respectively.

Figure 1.5 shows the expansion of palm oil plantation in 1990-2009 from Riau and Sumatra Utara towards neighboring province, such as Jambi. The expansion conducted by large palm oil companies due to their limitation of land area to compete in this industry. This is also reflected that Sumatra Utara and Riau are the major producer of palm oil and become their industrial priorities.

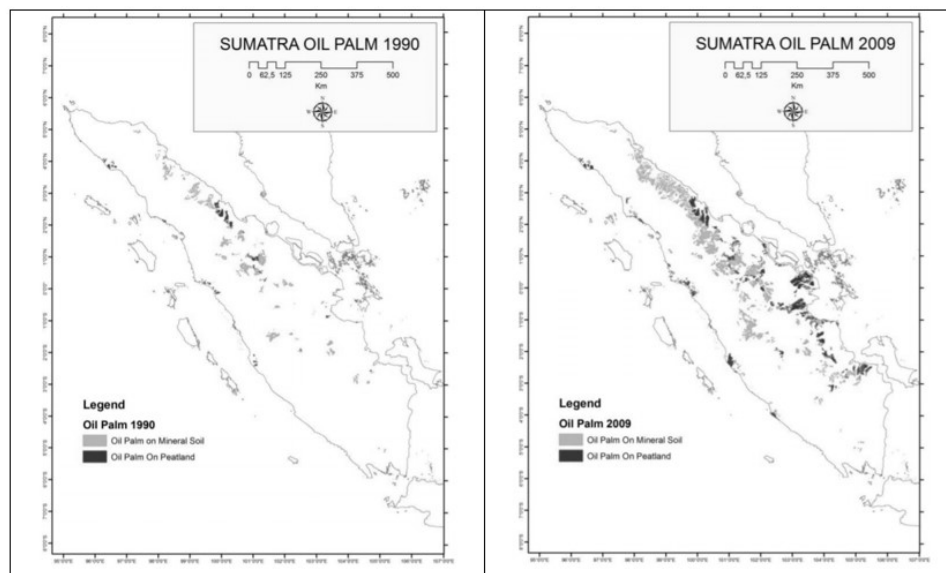


Figure 1.5. Map of Oil Palm Plantation in Sumatra 1990 and 2009 (Gunarso et al. 2013)

1.3.2 Mining Industry

There are several large mining and quarrying sites that located in Sumatra island, such as coal, oil, natural gas, and gold and silver. Based on 2017 data from Ministry of Energy and Mineral Resources of Indonesia, there are two main sites for natural gas deposits in Sumatra, there are Arun in Aceh and East Natuna in Kepulauan Riau. East Natuna has 32.23% of total deposit, become the largest site in Indonesia.

The other mining industry that locates in Sumatra is coal mining. Based on British Petroleum Statistical Review of World Energy (2017), Indonesia become the 9th coal mining deposit in the

world and one of the largest coal deposits located in Sumatra Selatan. There are also other mining sites located in Ombilin, Sumatra Barat and Muara Bungo, Jambi.

Even though the coal mining industry can generate income and economic activities, it is well-known the negative impact of environment, especially post exploration. For example, the post coal mining site in Muara Enim, Sumatra Selatan (Kodir *et al.*, 2017). Abood et al. (2014) found there are four industries that are contributed toward forest loss in Indonesia, especially in Sumatra, Kalimantan, Sulawesi, Maluku, and Papua. The deforestation impact in Sumatra become the largest in Indonesia, around 47% of national deforestation between 2011-2016 (Margono et al, 2014; Austin et al., 2019).

1.4 Literature Review

The essence of dynamic spatial panel model employed in this dissertation is to observe spatial relationship in cross-sectional and time to captures the effect of the previous information in the model. Elhorst (2014) described that this configuration should be able to deal with: 1) serial dependence between observations on each spatial unit over time; 2) spatial dependence among observations at each point in time; 3) unobservable spatial and/or time period specific time; and 4) endogeneity in space and/or time. To accomplish this analysis, data availability for spatial and temporal data length is important. On the other hand, the Indonesian data, especially for gross regional product (GRP) by industrial sector (as one of important variable in economic analysis), the time length data is limited.

This condition arose due to change in the data classification based on 2010 base year from 2000 base year. They change the number of industries from nine to seventeen industry classification that counts into GRP data. By using this new classification, the data availability from Bureau of Statistics Indonesia only begin from 2010². The time length is short (time = 9) to be used into the analysis that capture serial dependency from previous time data information.

Therefore, this dissertation considers temporal factor to observe structural change with time-series analysis in **Chapter 2** and spatial factor in the regression model in **Chapter 3**. The construction of integrated analysis between gridded of socio-economics and satellite data is in **Chapter 4**.

1.4.1. Breakpoint Analysis for Structural Change

There are precedent researches focused on how to analyze the structural change that occurred during a span temporal length data for economic variable, such as economic growth and output. Jouini and Boutahar (2005), Didier, Love, and Peria (2010), and Kaplan (2015) are several examples.

² The latest available data from Bureau of Statistics Indonesia is 2018.

Jouini and Boutahar (2005) showed the empirical illustration for breakpoint analysis using the monthly the US economic output during the period January 1956 to September 2002. They conducted the breakpoint for a single break and multiple break case. For the single breakpoint case, they are used F-test and Wald-test by selecting exogenous break time period 1933, during the US financial crisis. The results showed the existence of break point in 1933 time period which reflected the great depression that happened and made US economy slumped.

Didier, Love, and Peria (2010) showed the structural change analysis and investigated before and after Lehman's crisis impact toward stock market in the US. They exogenously selected September 2008 as the turning point period that lead into US crisis. Their main objective observed the relation between stock market return and variable that showed the closeness of 83 countries with the US, such as bilateral financial and trade value. They found that the main transmission for the crisis was financial linkages because countries with vulnerable banking and corporate sectors showed higher interactions with US market. On the other hand, this study could not find support for crisis transmission from trade channel.

Kaplan (2015) investigated the relation between oil prices, exchange rate, and economic growth in conjunction with several structural break points that reflected several economic crises that impacted Russian economic. By using quarterly data from 1995:q2-2014:q3 they identified several break points that correspond to Asia' economic crisis in 1997, Russia's economic crisis in 1998, global economic crisis in 2009, Syria's political crisis in 2011, and Ukraine's political crisis in 2014. The second finding showed that increase in oil prices and depreciation in domestic currencies towards dollar will impact Russia economic growth in the long run.

1.4.2. Spatio-temporal Analysis for Extracting Interlinkages

There are a lot of precedent researches that used the spatial analysis towards regional development. Rey and Montouri (1999), Ertur, LeGaallo, and Baumont (2006), Ertur and Koch (2007), Cravo, Becker, and Gourlay (2015) have shown the neighboring economic growth positively affected each regional growth. Day and Lewis (2013) using Indonesia's district level data from 2003-2008 and found that the demographics, human capital, infrastructure components, and GRP from neighboring region affected GRP per capita.

The other component affected to regional income and economic growth were found as such human capital, population growth and education, Olejnik (2008) shows that population growth variable as the endogenous factor of economic growth positively affected to the economic growth hence people tend to look for a better live and opportunities. Therefore, there exists a migration of people from poorer toward richer one. This implies a negative neighboring effect for population growth towards regional income.

The regional economic growth also driven by other factors such as business condition (Cravo, Becker, & Gourlay, 2015 and Pijnenburg & Kholodilin, 2014), innovation or technological spillover (Anselin, Vargas, and Arc, 1997; LeSage, Fischer, & Schernegell, 2007) research and development spillover (LeSage & Pace, 2009) knowledge spillover (Puškárová & Piribauer, 2016).

Rios (2016) used spatio-temporal analysis to observe the determinant factors of unemployment disparities in European regions during the period 2000-2011. The results suggested that before crisis period, unemployment disparities were driven by regional-level factors. Labor market institutions caused increasing of disparities after crisis. They also found a negative space-time diffusion that produce a bargaining power that reduced the capability of workers lowering their wages in each region. During after crisis period, the variability of spatial lag of neighboring information has higher percentage that explain disparities compared to space-time lag.

Rios, Pascual, and Cabases (2017) also used this model to analyze the determinant factors of local government spending in Spain. In general, they concluded that local government spending is explained by economic factors, but demographic and political factors are less relevant. The positive spatial interaction and negative space-time interactions showed that several fiscal policy coordination should be arranged to internalize decentralization and minimize inefficiencies.

Based on LeSage and Pace (2009) there are several well-known spatial econometric models: spatial autoregressive (SAR) model, spatial error terms (SEM) model, spatial autocorrelations (SAC) model³, spatial Durbin (SDM) model, and spatial Durbin error model (SDEM). On the other hand, very few precedent researches used the full spatial model of general nesting spatial (GNS) model. Elhorst (2014) argued that this mainly caused by the difficulty of estimation for GNS model and the parameters estimation result does not outperformed SDM and SDEM. This situation is problematic due to the fact that the research does not use the full information that may have explained the observations in the data-driven analysis.

LeSage and Pace (2009) also emphasized the missing information such that omitted the spatial dependence in the model may occur inaccurate interpretation of the explanatory variable coefficients. On the other hand, by omitting spatial error term will increase the loss of efficiency in the estimates and will become less of a problem relative to bias as sample is increased. By including the neighboring effect on independent variables then more information will be captured in the model.

SAR model includes the spatial neighboring effect of dependent variable. SEM includes the spatial lag of error terms in the model. SAC model includes both spatial configurations of SAR

³ This model is also referred as spatial autoregressive with additional autoregressive error structure (SARAR) (Kelejian & Prucha, 1998).

and SEM. SDM includes spatial neighboring effect not only for dependent variable but also independent variables. SDEM then includes the spatial neighboring effect independent variables, and error terms. GNS includes the spatial neighboring effect of dependent variables, independent variables, and error terms.

Even though GNS captured all information in the model, there is very few applications that implemented this model. Several literatures used SDM (e.g. Li & Xiong, 2017) and SDEM (e.g. Silva et al., 2017) after described the full GNS model in their methodology.

Palombi, Perman, and Tavera (2017) that examines the commuting effect towards real output growth and unemployment rate changes in Great Britain between 1985-2011. This study found the positive and significant estimated coefficient of endogenous and error term interactions. They described these relationships appeared due to the presence of regional dependence in labor markets from the linkages. The commuting flows caused the labor market outcomes affected by the labor-market or business conditions in the neighboring areas.

Kopczewska et al. (2017) examined several fiscal factors that affecting GDP between the years 2002–2015 in a number of European economies. This study found that increasing taxes reduces the GDP growth. The capital gains tax had a negative impact on economic performance. The labor tax was found to be significant in all considered models.

The tax rate has a negative sign which may be indicated of tax avoidance or outflow of capital and consumption to neighboring countries. Kopczewska et al. (2017) described this finding as an indirect evidence of the tax competition effect in neighboring countries. The insignificant neighboring effect of GDP described that interrelation between countries resulted from the market and economy conditions which determined economic growth, and not the economic growth itself. Saving rate had a negative and significant relationship with economic growth, which concluded that an increase in savings will affected a decrease in the economic growth because less money spent in the market.

Another example to extract the regional interlinkages by using spatial model was demonstrated by Cravo, Becker, and Gourlay (2015). They found that the human and capital movement across regions in Brazil, especially in small-medium enterprises (SME) sector affected the income dependency between regions. This condition implies the positive effect from neighboring regions' income.

The human migration to look for better education affect the positive relationship between neighboring education and regional income growth. The human and capital movement in SME sector then increase the competition between businesses and drove firm to increase their productivity to compete each other and generate positive regional growth in general. This finding also found in (Pijnenburg & Kholodilin, 2014).

The other example of the spatial neighboring effect, Erthur and Koch (2007), Olejnik (2008), and Cravo, Becker, and Gourlay (2015) found that the economic growth is affected not only by initial income level, population growth, educational quality, but also on those variables in

neighboring regions. Allers and Elhorst (2005) also found the neighboring effect of unobserved shock in disturbance term reflected to correct rent-seeking politicians for unanticipated fiscal policy changes.

Several precedent researches applied spatial regression model to provide the impact of interlinkages between regions for the analysis. Cole et al. (2013) applied the SDEM model to observe the determinant factor of each Japanese firms' carbon dioxide (CO₂) emission in manufacturing sector. They found that firms' CO₂ emissions are spatially correlated. They also found that there is significant error term interaction, which might be caused by the closeness of firms' location. The firm location then affected by unobserved factor, such as agglomeration effect.

Storm, Mittenzwei, and Heckelei (2014) also used this configuration to observe the farm survival between 1999-2009 in Norway as an impact of spatial competition among neighboring farms. The spatial autocorrelation in their study represent the interaction between neighboring farms are more complicated as there are other factors may affect firms' income outside the model. They described that cooperative network due to technology diffusion or among farming neighborhood is one of the reasons for the significant spatial autocorrelation coefficients.

The other example is Resende, Carvalho, and Sakowski (2013) applied the configuration to analyze the regional economic growth in Brazil between 1970 and 2000. The model is applied in several regional scales: micro-regions, meso-regions, and states level. For micro and meso-regions, they found negative and positive coefficients of endogenous and error term interaction respectively. On state level, both coefficients are positive. In the state level, the positive endogenous effect due to the investments in physical and human capital. This technological factor is unobserved in their regression model.

1.5 Methodology for Data Incorporation

Figure 1.6 shows the research flows for the generic methodology incorporated analysis of socio-economic and environmental factors from remote sensing data. The first two steps focus on frameworking process and the last two process focused on regression analysis. The first essential step is an alignment process of data structure. Both data, socio-economic variable and satellite output, should have the same data structure, either regular lattice or non-lattice structure.

For regular lattice data structure, there is called cell-to-cell matching process to combine both data. It is now become easier process due to the availability of grid-cell based data for socio-economic variable, such as gridded population of the world by Columbia University or LandScan data by Oak Ridge National Laboratory. The primary objectives of this process to align the grid-cell data with the same projection method and dimension, such as World Geodetic System 84 datum (WGS84) (LandScan, 2019). On the other hand, the second alignment process is used to non-lattice data structure or municipal based data which will be elucidated in **Chapter 3** in detail.

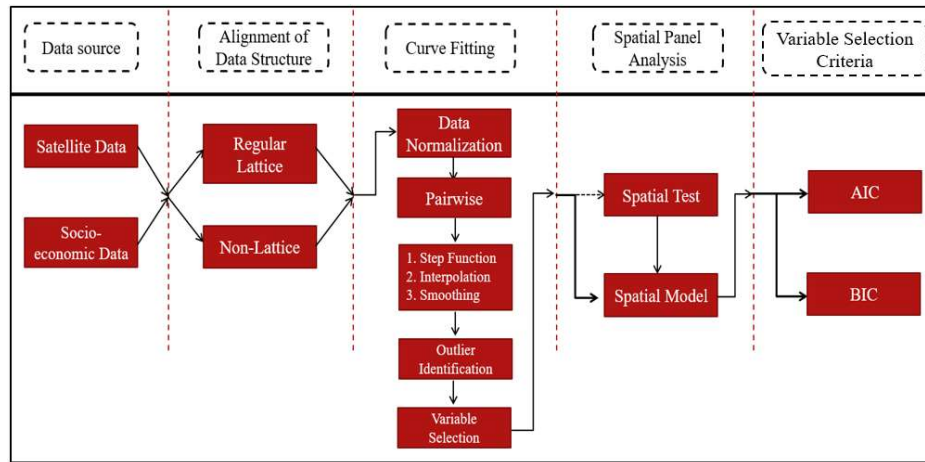


Figure 1.6. Generic Methodology of Incorporated Analysis.

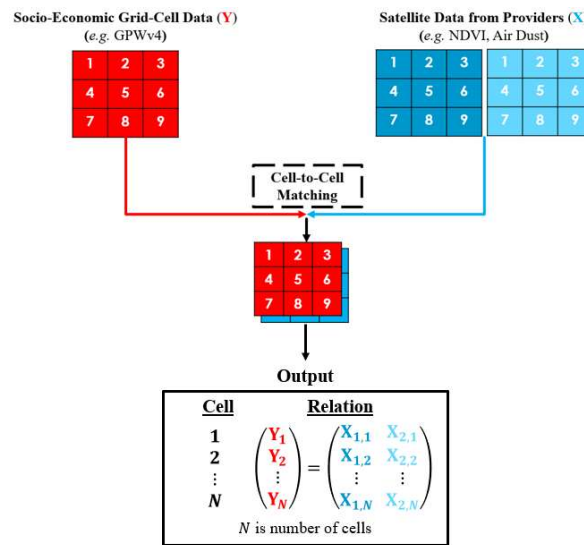


Figure 1.7. Incorporated Data Process for Regular Lattice Structure.

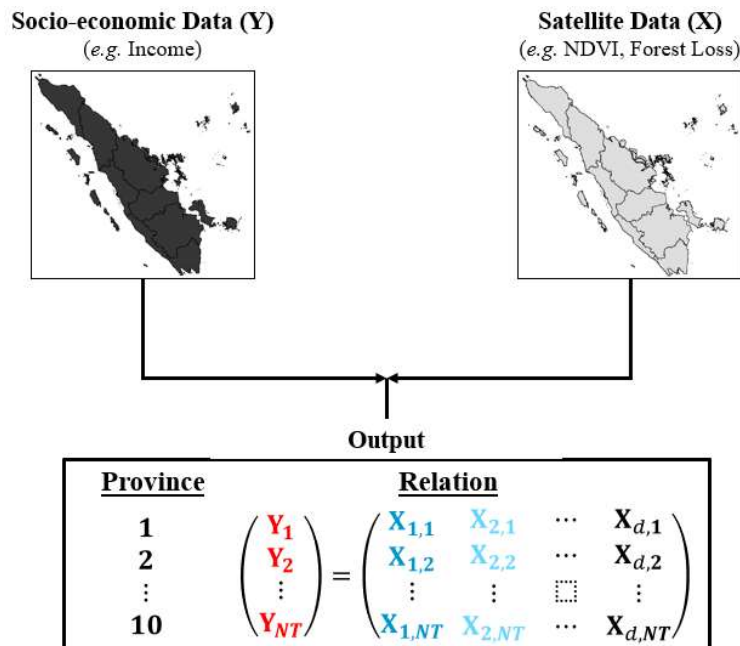


Figure 1.8. Incorporated Data Process for Non-lattice Structure.

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Chapter 2

**Utilization of SDG Indicators to Analyze Economic
Structural Change and Regional Resilience with Respect
to Neighbor Municipal Bodies**

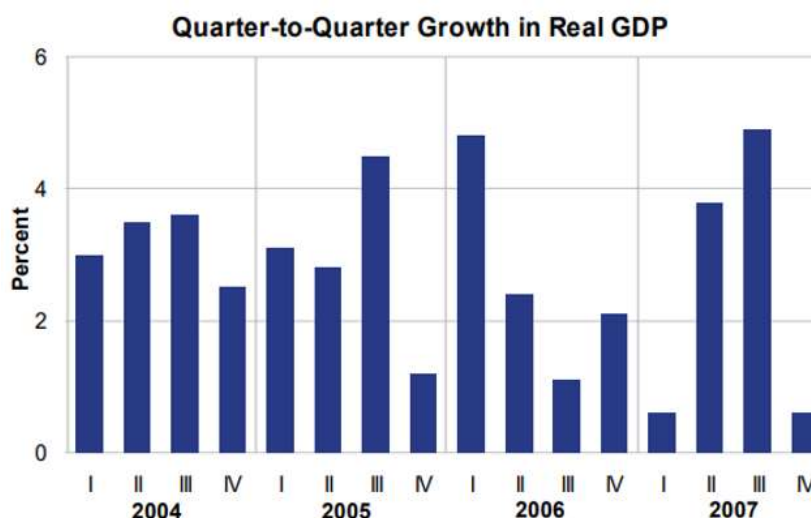
2.1. Introduction

This chapter focused on how to utilize the time series analysis of broken time-trend model (Greene, 2012) in conjunction with spatial dependency information to detect the resilience against economic shock in the regional spectrum and compare each regions' economic growth trend before and after shock. Lehman's shock selected as the case study.

Because Lehman's shock is used as a study case, this study could not use Indonesia data, due to the data limitation. Indonesia's GRP data that using 2010 base year only begin from 2010. The data range could not contain the economic shock that begin from 2007-2008. This condition forced the study to use Japanese data instead of the Indonesian in comparison with the US data of larger datasize.

One of the biggest economic crises, the Lehman's shock began the fall of US housing prices in 2007 which cause sub-prime crisis. These defaults spread-out to the financial sector (Reinhart & Rogoff, 2008) and interbank markets from August 2007 (BIS Report, 2009). The crisis was transmitted globally from two main channels: global financial interconnections (Longstaff, 2010; Aloui, Aissa, & Nguyen, 2011); and trade flows (Ahn, Amity, & Weinstein, 2011; Cetorelli & Goldberg, 2011).

The economic slowdown observed for the US real national gross domestic product (GDP) in the US. Based on Bureau of Economic Analysis (BEA) report (2008). **Figure 2.1** showed the growth of US national GDP decline from 4.9% in the third quarter of 2007 to 0.6 % in the fourth quarter of 2007.



Source: US Bureau of Economic Analysis (2008)

Figure 2.1 Growth of the US national GDP by quarterly change, 2004-2007 (BEA, 2008).

In Japan, the impact of Lehman's crisis heavily damaged the Japan economy from 2008. In 2008, Japan had a trade deficit and in 2009 the export values reported declined from -3.5% in 2008 to -33.1% in 2009 (MOF Press Release, 2012).

Kawai and Takagi (2009) have shown that this occurred by the increasing of Japan's export to GDP ratio and trade openness. Due to the declining of demand from US, then Japan had faced lower total export. This decline is also affected financial institutions' core profitability from trade credit and financing as the regional capital is not kept up the increasing off risk asset (BOJ Financial System Report, 2008). Demirer et al. (2017) also show that the Japanese banks have strong connection globally impacted the spread volatility across bank stocks, especially with US banks.

This chapter conducted further investigation for the impact of Lehman's shock towards US and Japan regional economic growth. By using this approach, a detailed illustration of how the shock transmitted within country is obtained.

2.2. Methodology

2.2.1. Data and Target Variable

Real gross regional product (GRP) based on production approach are used as the main dataset. The United States data were retrieved from regional statistics in Bureau Economic Analysis (BEA) and apply quarterly data from 1st Quarter of 2005 until 2nd Quarter of 2018 for 51 states (including District of Columbia). For Japan data used an annually GRP data from Economic and Social Research Institute, Cabinet Office for 47 prefectures from 2001 until 2014.

Based on Reinhart and Rogoff (2008) and Bank for International Settlement (BIS) Report (2009) the 1st quarter of 2008 as the breakpoint in the US is selected. On the other hand, following Filardo et al. (2009) and Kawai and Takagi (2009), 2008 is selected as the breakpoint for Japan regional data.

In this study, breakpoint time point was selected exogenously under assumption when the Lehman crisis begin in the US and Japan. For Japan data, there is problem occurred hence there is no quarterly data available for gross regional product (GRP). Only annual data available. To synchronize this condition and used condition that there was time lag of influence of Lehman crisis in Japan (in the US Lehman crisis begin in 2007), this study selected 2008 as the breakpoint. This selection justified by using quarterly growth of gross domestic product (GDP) for Japan in **Figure 2.2.**

Even though negative growth rate already observed since the first quarter of 2008, but the worst growth rate happened in the first quarter of 2009. To synchronize this graph with annual data, each year growth rate accumulation is needed.



Figure 2.2. Japan national growth rate of GDP by quarterly change (2007:Q1 – 2010Q4)

Table 2.1 shows that in the 2008 yearly accumulative growth is -14.8%, lower than 2009, which is -3.4%. This happened because in the second to fourth quarter of 2009, the growth of GDP shown positive trend. Therefore, 2008 is selected as breakpoint for Japan analysis.

Table 2.1. A Yearly Accumulation of Japan Growth Rate of GDP, 2007 - 2010

Quarterly Date	Growth of GDP	Yearly Accumulative
2007 Q1	3.0	3.4
2007 Q2	0.5	
2007 Q3	-2.0	
2007 Q4	1.9	
2008 Q1	1.0	-14.8**
2008 Q2	-1.5	
2008 Q3	-4.9	
2008 Q4	-9.4	
2009 Q1	-17.8*	-3.4
2009 Q2	8.6	
2009 Q3	0.2	
2009 Q4	5.6	

Note: *) The lowest growth of Japan national GDP by quarterly change.

**) The lowest yearly accumulative growth of Japan national GDP.

2.2.2. Empirical Model

Spatially-Independent Model

Focus of this chapter is to observe the behavior of regional economic growth fluctuation. This approach allowed us to identify before and after shock conditions and observed which area had a recovery. To observe this before-after condition, breakpoint test is commonly used for the analysis. Hansen (2001) summarized that there are two main methods for this analysis: 1) breakpoint

analysis with a known breaking date; or 2) estimates the breaking dates from the time series data. For this analysis, the first method is used by exogenously selected breaking date.

The usage of the first method to analyze structural change attributed to Chow (1960). Chow (1960) used the selected breakpoint and calculated based on the F statistic. Hansen (2001) pointed out that the usage of this method may lead to quite distinct conclusion based on different breakpoint candidate. Therefore, a clear and reasonable need for the selection process, such detailed in **Subsection 2.2.1**.

To observe the regional transitory, by analyzing the time-trend of regional economic growth before and after crisis by using least-square regression based on broken-trend model (Christiano, 1992; Fernandez, 1997; and Greene, 2012), which separates the time-series data based on a known breakpoint event as follows,

$$\ln\left(\frac{y_{i,t}}{y_{i,t-1}}\right) \equiv g_{i,t} = \mu_i + \tau_i t + (\mu_i^* + \tau_i^* t)I(t > t^*) + u_{i,t}, \quad u_{i,t} \sim iid N(0, \sigma_i^2) \text{ for } t \leq t^* \\ u_{i,t} \sim iid N(0, \sigma_i^{*2}) \text{ for } t > t^* \quad (2.1)$$

$y_{i,t}$ is GRP for states $i = 1, \dots, N$ at time period $t = 1, \dots, T$ and $\ln(y_{i,t}/y_{i,t-1})$ is regional economic growth, and t^* represents exogenously selected breakpoint. Here, μ_i are intercept and τ_i is time trend component before crisis. Similarly, $(\mu_i + \mu_i^*)$ and $(\tau_i + \tau_i^*)$ are defined after crisis.

Based on those models in (2.1), there are several methods for structural analysis: 1) F-test; and 2) Wald test. These methods use exogenously selected breakpoint, t^* . The F-test commonly used to analyze the structural change with known breakpoint date (Chow, 1960; Fisher, 1970; Gujarati, 1970; and Dufour, 1980). This test is calculated based on a simple regression model for time trend with known t^* . Gujarati (1970) explained the F-test procedure based on Chow (1960) as follows:

1. Compute the least square combination for all observations (before and after), obtain the parameter estimation, and calculate the sum of square residuals.
2. Compute separately for before and after crisis group to obtain each parameter estimation and calculate both sum of square residuals.
3. Apply the following F-test,

$$F = \frac{[S_1 - (S_2 + S_3)]/K}{(S_2 + S_3)/(n_1 + n_2 - 2K)} \quad (2.2)$$

n_1 is the number of observations from before crisis group ($t = 1, \dots, t^*$), n_2 is the number of observations for after crisis group ($t = t^* + 1, \dots, T$). S_1 is sum of square residual from combined data ($n_1 + n_2$), S_2 and S_3 are sum of squared residual from n_1 and n_2 respectively. K is the number of parameters.

The breakpoint test based on the F-test conducted under the null hypothesis that there is no breakpoint if $F\text{-test} < F\text{-critical}$. The alternative hypothesis there is a breakpoint when $F\text{-test} > F\text{-critical}$. The F-test value calculated based on equation (2.2) and the F.critical calculated based on 5% critical value following F-distribution with degree of freedom n_1 and n_2 . In this study, F.critical are 2.0376 and 4.9503 for the US and Japan analysis respectively.

To provide further evidence for structural change at breakpoint t^* , this study also adopted the Andrews (1993), Bai (1997), Jouini and Boutahar (2005), and Greene (2012) approach by applying the Wald test,

$$W = (\hat{\theta}_1 - \hat{\theta}_2)' (\hat{V}_1 + \hat{V}_2)^{-1} (\hat{\theta}_1 - \hat{\theta}_2) \sim \chi_2^2 \quad (2.3)$$

where $\theta_1 = (\mu_i, \tau_i)'$ and $\theta_2 = (\mu_i + \mu_i^*, \tau_i + \tau_i^*)'$ are used for spatially-independent model in (2.1). \hat{V}_1 and \hat{V}_2 are asymptotic covariance matrices under null hypothesis: $\theta_1 = \theta_2$ and alternative hypothesis: $\theta_1 \neq \theta_2$ respectively.

Spatially-Dependent Model

To include the neighboring relations as a factor for the analysis then equation (2.1) is extended into spatial autoregressive model as follows,

$$g_{i,t} = \mu_i + \tau_i t + \rho_i \sum_{j \neq i} w_{ij} g_{j,t} + (\mu_i^* + \tau_i^* t + \rho_i^* \sum_{j \neq i} w_{ij} g_{j,t}) I(t > t^*) + u_{i,t},$$

$$u_{i,t} \sim N(0, \sigma_i^2) \text{ for } t \leq t^*$$

$$u_{i,t} \sim N(0, \sigma_i^{*2}) \text{ for } t > t^* \quad (2.4)$$

where ρ_i and $\rho_i + \rho_i^*$ represents the spatial regression coefficients before and after crisis. The spatial relationship calculated by conditions $w_{ii} = 0$, and $w_{ij} = 1$ if region i and j shares a common border, otherwise $w_{ij} = 0$. Due to this condition, then Alaska, Hawaii, and Okinawa became to have no neighbor. Therefore, the datasize reduced into $N = 49$ and $N = 46$ for the US and Japan respectively.

Similar structural change test by using F-test and Wald test are conducted. Equation (2.4) include spatial factor ρ_i into Wald test analysis,

$$W = (\hat{\theta}_{1,s} - \hat{\theta}_{2,s})' (\hat{V}_{1,s} + \hat{V}_{2,s})^{-1} (\hat{\theta}_{1,s} - \hat{\theta}_{2,s}) \sim \chi_3^2 \quad (2.5)$$

where $\theta_{1,s} = (\mu_i, \tau_i, \rho_i)'$ and $\theta_{2,s} = (\mu_i + \mu_i^*, \tau_i + \tau_i^*, \rho_i + \rho_i^*)'$. $\hat{V}_{1,s}$ and $\hat{V}_{2,s}$ are asymptotic covariance matrices under equation (2.4).

The breakpoint test based on the Wald test conducted under the null hypothesis that there is no breakpoint if $\text{Wald.lower} < \text{Wald.value} < \text{Wald.upper}$ and the alternative hypothesis there is a breakpoint when $\text{Wald.value} < \text{Wald.lower}$ or $\text{Wald.value} > \text{Wald.upper}$.

The Wald.value calculated based on equation (2.3). Wald.lower and Wald.upper are the lower and upper critical values to reject null hypothesis. Those value based on 2.5% critical point for each tail following χ^2 -distribution with degree of freedom are the number of parameters. The values for Wald.lower and Wald upper are 0.0506 and 7.3778 for spatially-independent model. For spatially-dependent model, the value of lower and upper critical points are 0.2158 and 9.3484 respectively.

2.3. The Result

2.3.1. Stationarity Test

Stationarity test is an essential test in time series analysis to ensure that mean, variance, and covariance does not change across time (Greene, 2012). However, for a proper stationarity test a long time series data is required. This requirement due to the test have low power for short ranged time series data (Cochrane, 1991; De Jong *et al.*, 1992; and Jönsson, 2011). De Jong *et al.* (1992) show there are power and size problem for 100 time series data. In this study, there are only 54 quarterly data and 14 annual data for the US and Japan respectively which is too short to conduct stationarity test.

2.3.2. Breakpoint Analysis of US Regional Data

By Spatially-Independent Model

Based on the assumption that the Lehman's shock begun on the 1st Quarter of 2008 in the U.S. The data size before the crisis $n_1 = 12$, after the crisis $n_2 = 41$, respectively. **Figure 2.3** shows Virginia states had negative impact before crisis but recovered their economic growth after crisis. On the other hand, South Dakota show resilience by positive growth rates before and after crisis. Even though North Dakota have positive trend of regional economic growth before crisis, but it showed declines after crisis.

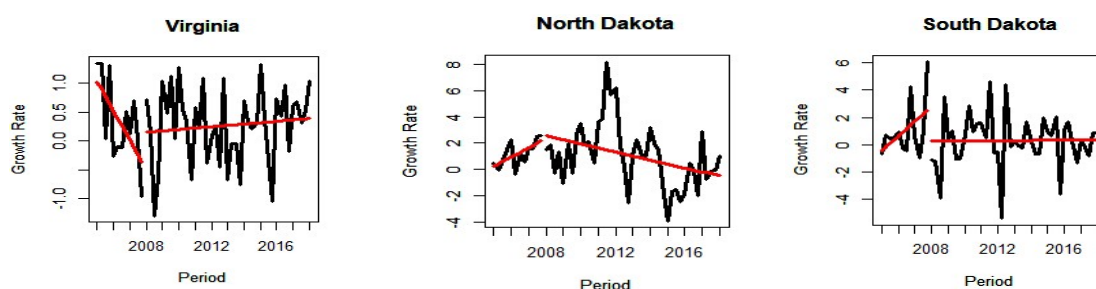


Figure 2.3. Regional Economic Growth Rate in U.S: Before and After Crisis

Virginia had a sharply declining trend before the Lehman's shock. This state was suffered due to the decline in nondurable goods manufacturing and housing market. **Figure 2.4** shows that a lot of state in the US has similar pattern with Virginia state, which had negative impact of crisis and then recovered their economic growth after crisis. For example, Arizona, California, Florida, Hawaii, Maine, Nevada, Utah, and Wisconsin.

Interestingly, only North Dakota states that has a declining of economic trend after crisis even though they had positive trend before crisis.

On the other, several states are resilience against crisis, where showed positive trend before and after crisis. Those state has similar pattern with South Dakota in **Figure 2.3**. Those resilient states are Colorado, Connecticut, Indiana, Massachusetts, Minnesota, Missouri, Mississippi, New Jersey, Ohio, and Pennsylvania.

Some states showed negative economic growth before and after crisis, such as Alaska, Nebraska, and Wyoming. Alaska also had negative economic condition due to the decline in petroleum extraction (BEA, 2009). Nebraska had the decline of household income and employment rate as an impact of crisis in the manufacturing and construction industries (Linares and Cogua-Lopez, 2016). The negative of economic growth in Wyoming mainly caused by the declining coal industries and natural gas prices after crisis (Goldby et al., 2015).

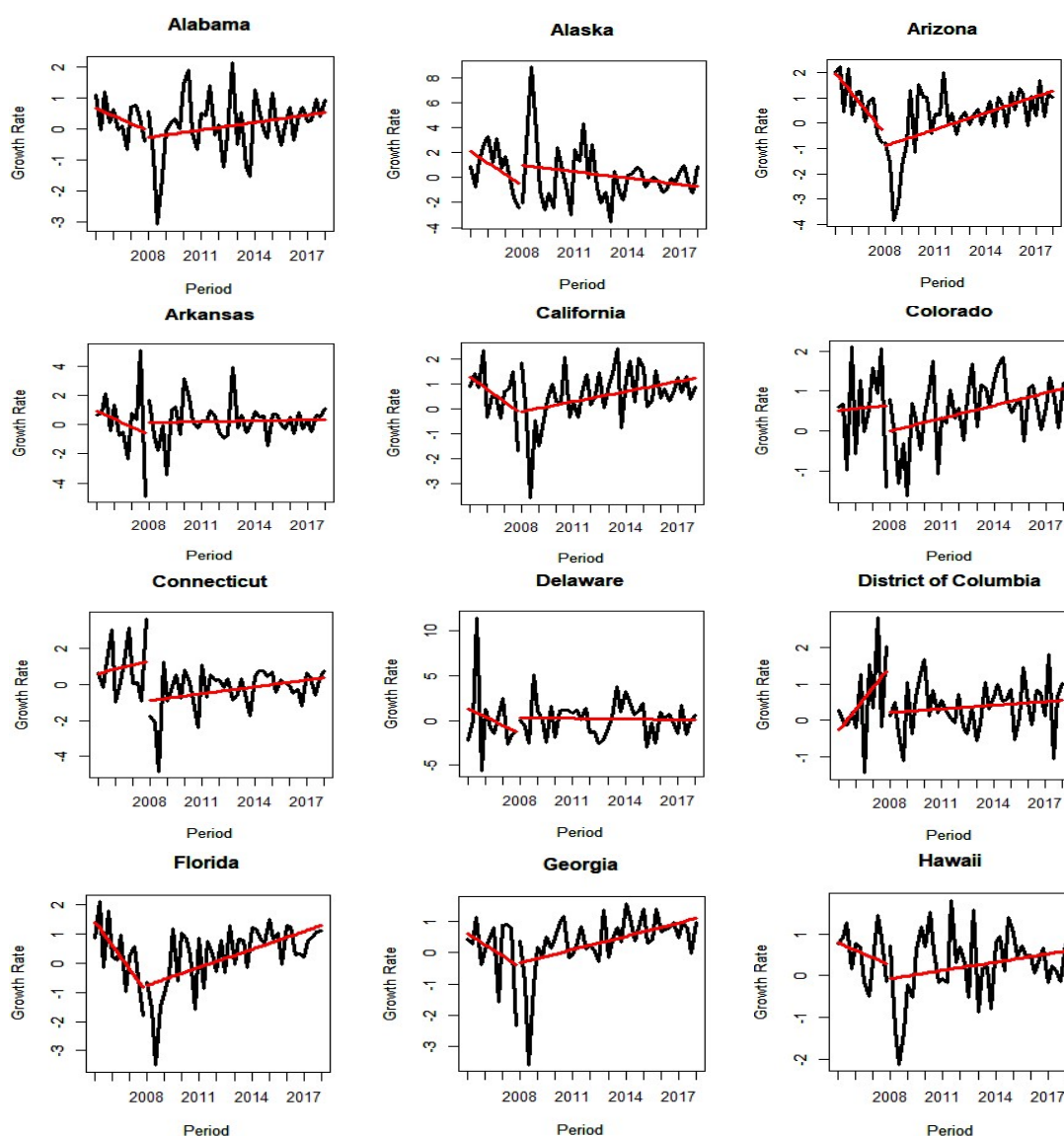


Figure 2.4. Regional Economic Growth for all states in the US: Before-After Crisis (*cont.*).

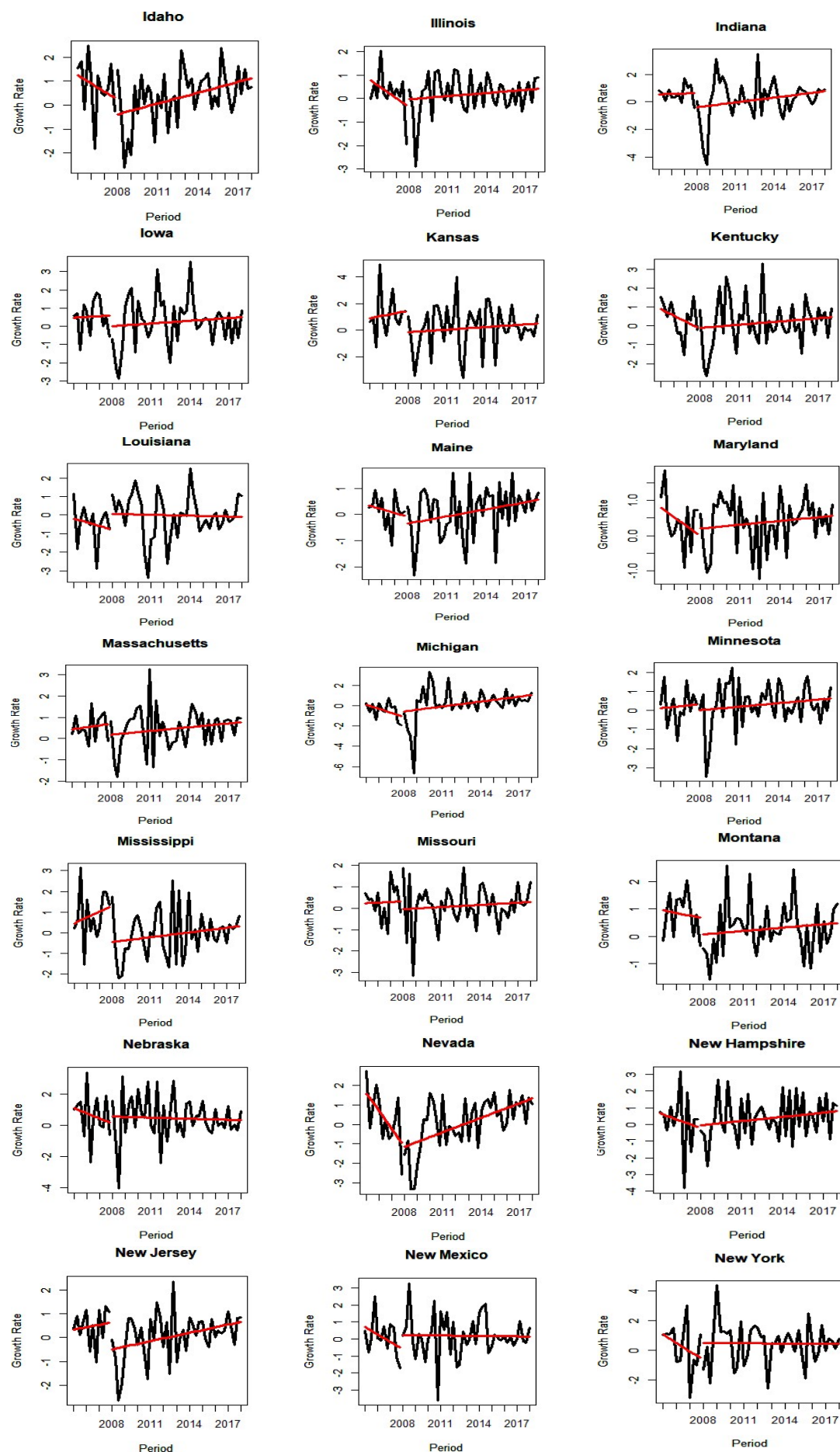


Figure 2.4. Regional Economic Growth for all states in the US: Before-After Crisis (*cont.*).

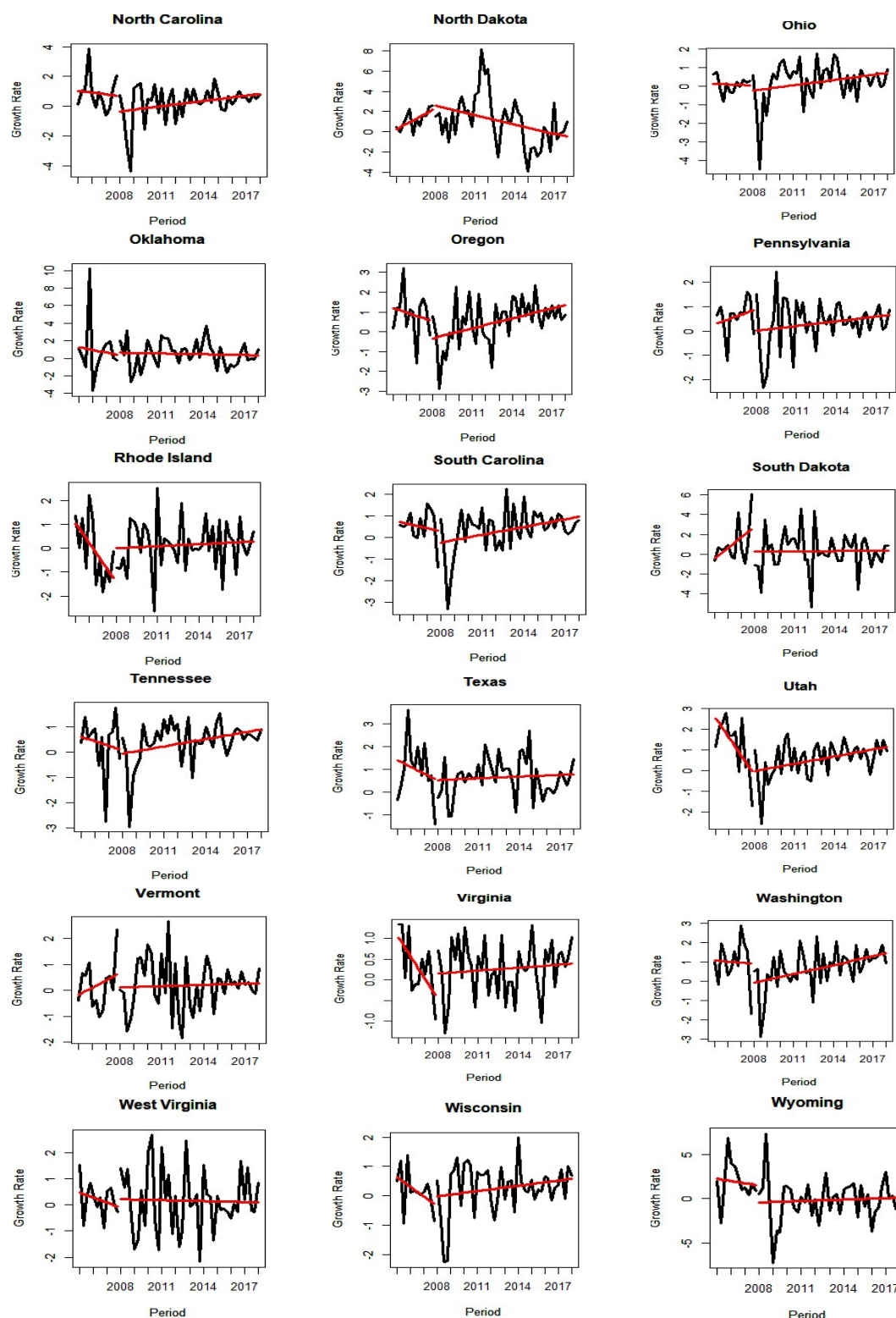


Figure 2.4. Regional Economic Growth for all states in the US: Before-After Crisis.

In **Figure 2.5**, the Southeastern, Great Lake, and West Coast region shows negative impact from the crisis. The main contributors to their GRP are goods manufacturing, construction, insurance, and finance (BEA Report, 2009).

On the other hand, BEA (2009) also reported that several states in Plains and Rocky Mountain regions such as Kansas, Colorado, Iowa, South Dakota, and Missouri show resilience. Those

states are mainly have agriculture, forestry, fishing, hunting, and mining sectors as the main contributor.

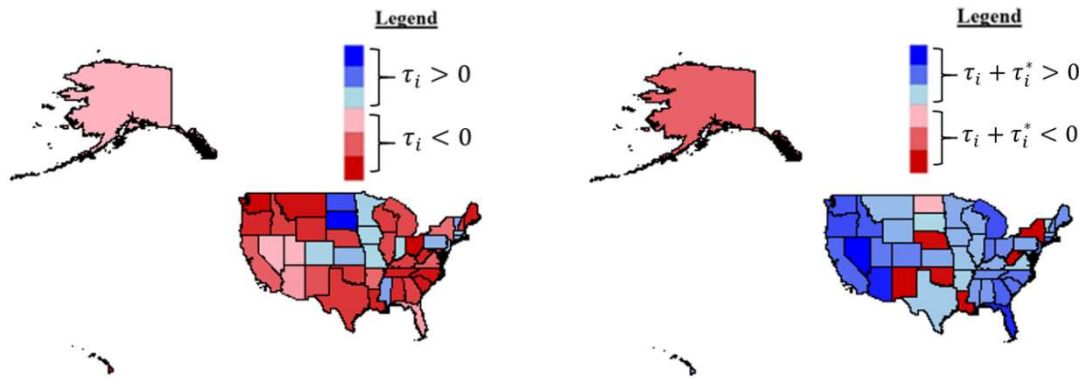


Figure 2.5. The regional trend comparison before (left) and after (right) breakpoint in US

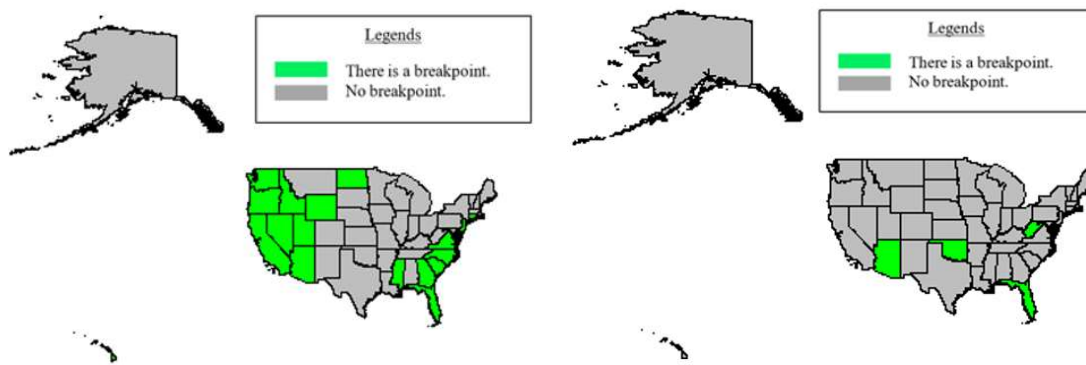


Figure 2.6. The F-test (left) and Wald Test (right) for Spatially-Independent model.

The F-test in **Figure 2.6** shows that mainly in the Southeastern and Far West region that observed the structural changes. Those states have good manufacturing, insurance, finance, and construction as their main contribution to their GRP. The detail of F-test and Wald test value for each state in **Appendix 2.1** and **2.2** respectively.

By Spatially-Dependent Model

Based on **Figures 2.7** and **2.8**, neighboring effects is clearly observed in the spread-out of Lehman's shock in US regional economic growth. The negative trend clustered in several regions, such as Far West, Southeastern, and Great Lake regions.

Figure 2.7 shows the positive $\hat{\rho}_i$ that indicates there is correspondence between spatial neighboring factor and the effects of Lehman's crisis in **Figure 2.5**. The positive $\hat{\rho}_i$ for states in Far West, Southeastern, and Great Lake indicates that the negative trend in the neighboring region affected the growth trend in those regions.

As the next finding, the positive spatial correlation after crisis is higher than before crisis (see in **Figure 2.7**). Connecticut, Florida, Michigan, Maine, and South Carolina are states that have high spatial correlation ($\hat{\rho}_i + \hat{\rho}_i^*$) after crisis which indicates the recoveries from neighboring states have effect toward those states' regional economic recoveries. Wyoming become the only state that has $(\hat{\rho}_i + \hat{\rho}_i^*) < 0$.

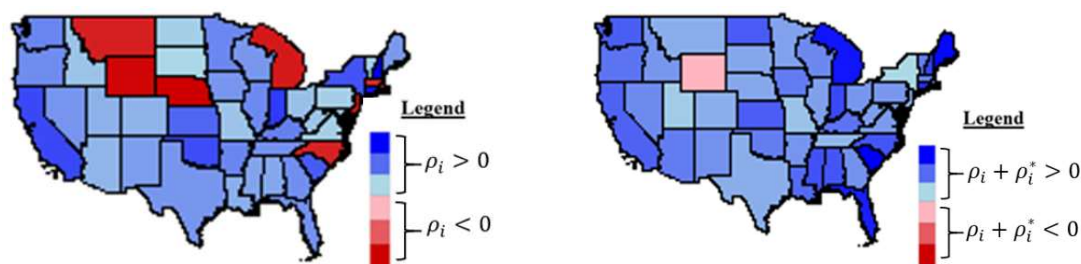


Figure 2.7. The spatial correlation before (left) and after (right) breakpoint in US

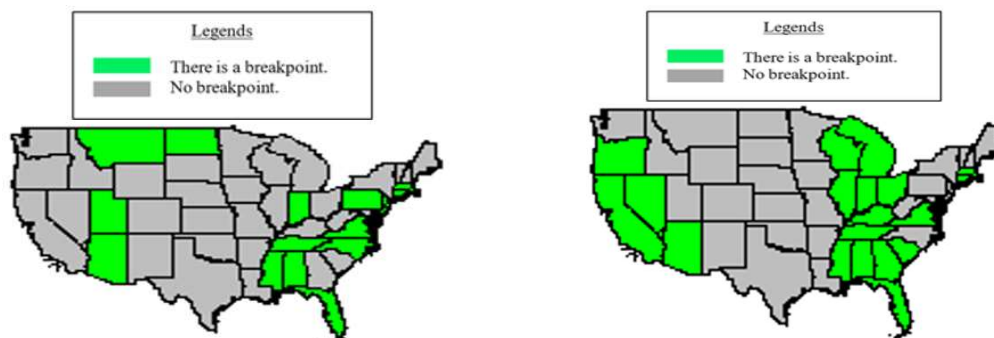


Figure 2.8. The F-test (left) and Wald Test (right) for Spatially-Dependent model.

Figure 2.8 shows the evidence that supports the structural break in US. The Wald test results shows more appropriate test compared to the F-test. The endogeneity (explanatory variable correlated with error term) in spatially-dependent model might imply the F-test become non-robust for autocorrelated disturbances (Krämer, 2003). On the other hand, the Wald test produce more appropriate results hence the test focus to evaluate the distance between the estimated parameters in constrained and unconstrained form (Greene, 2012). The detail of F-test and Wald test value for each state in **Appendix 2.3** and **2.4** respectively.

2.3.3. Breakpoint Analysis of Japanese Regional Data

By Spatially-Independent Model

By using 2008 as the breakpoint, only Kagawa and Ishikawa prefectures that shows positive trend before crisis occurred (see **Figures 2.9** and **2.10**). However, this exceptional case was occurred due to the impact of the massive increase in manufacturing production for Kagawa in 2007 based on Bank of Japan (BOJ) Report (2008).

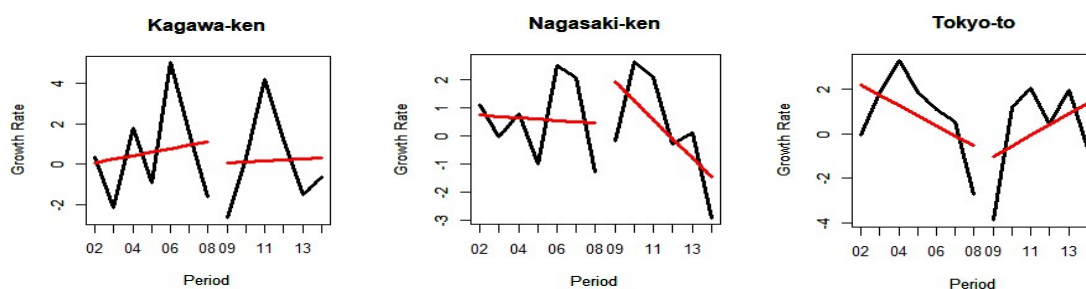


Figure 2.9. Regional Economic Growth Rate in Japan: Before and After Crisis

The other prefecture showed a negative trend before crisis, such as Tokyo prefecture. However, Tokyo shows a strong recovery for regional economic growth after crisis. The recovery also showed by other prefectures in **Figure 2.10**, such as Aichi, Chiba, Fukushima, Gifu, Hiroshima, Iwate, Kyoto, Miyagi, Okinawa, Osaka, Shiga, and Yamaguchi.

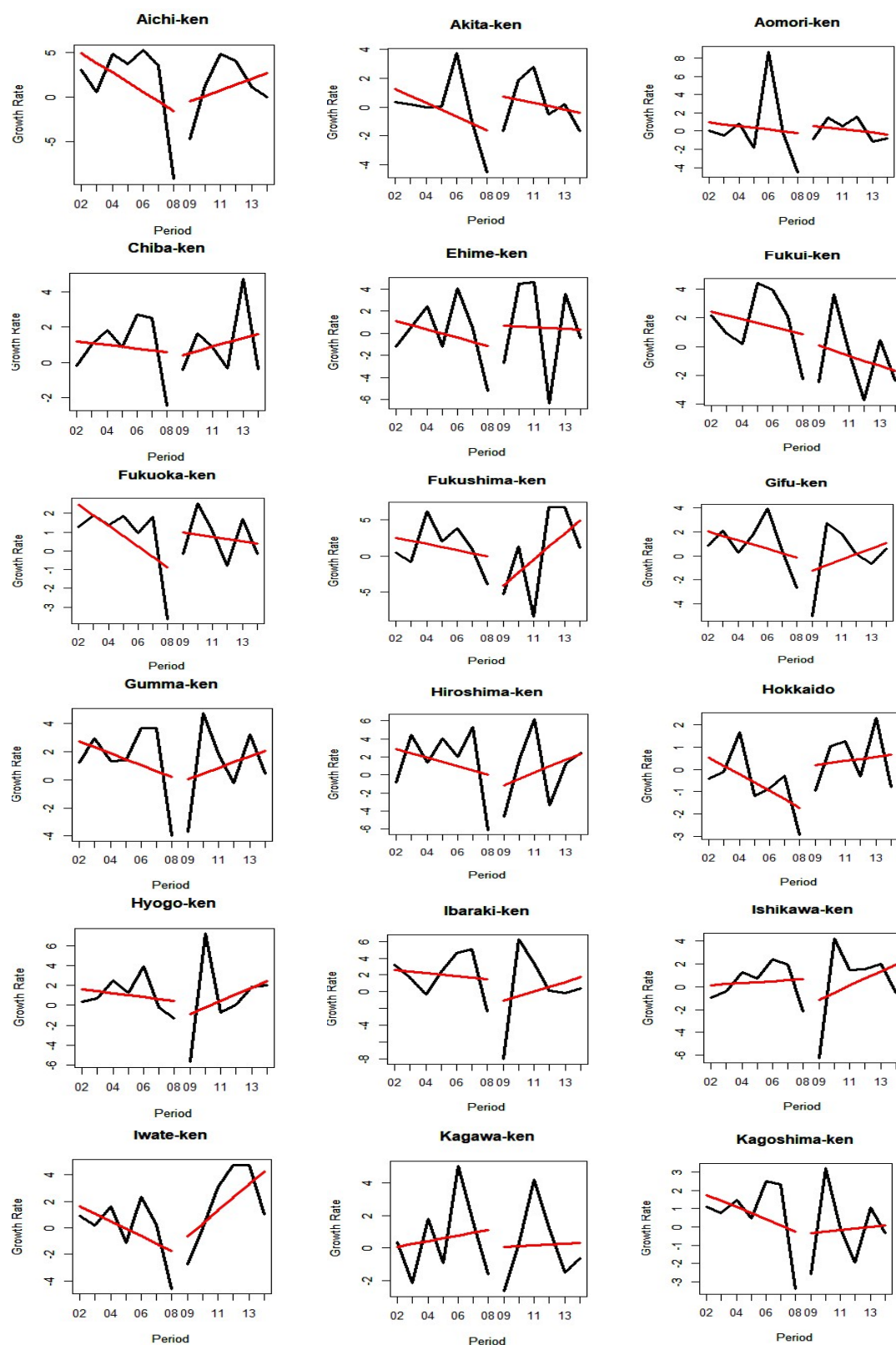


Figure 2.10. Regional Economic Growth for all Prefectures in Japan: Before-After Crisis (cont.).

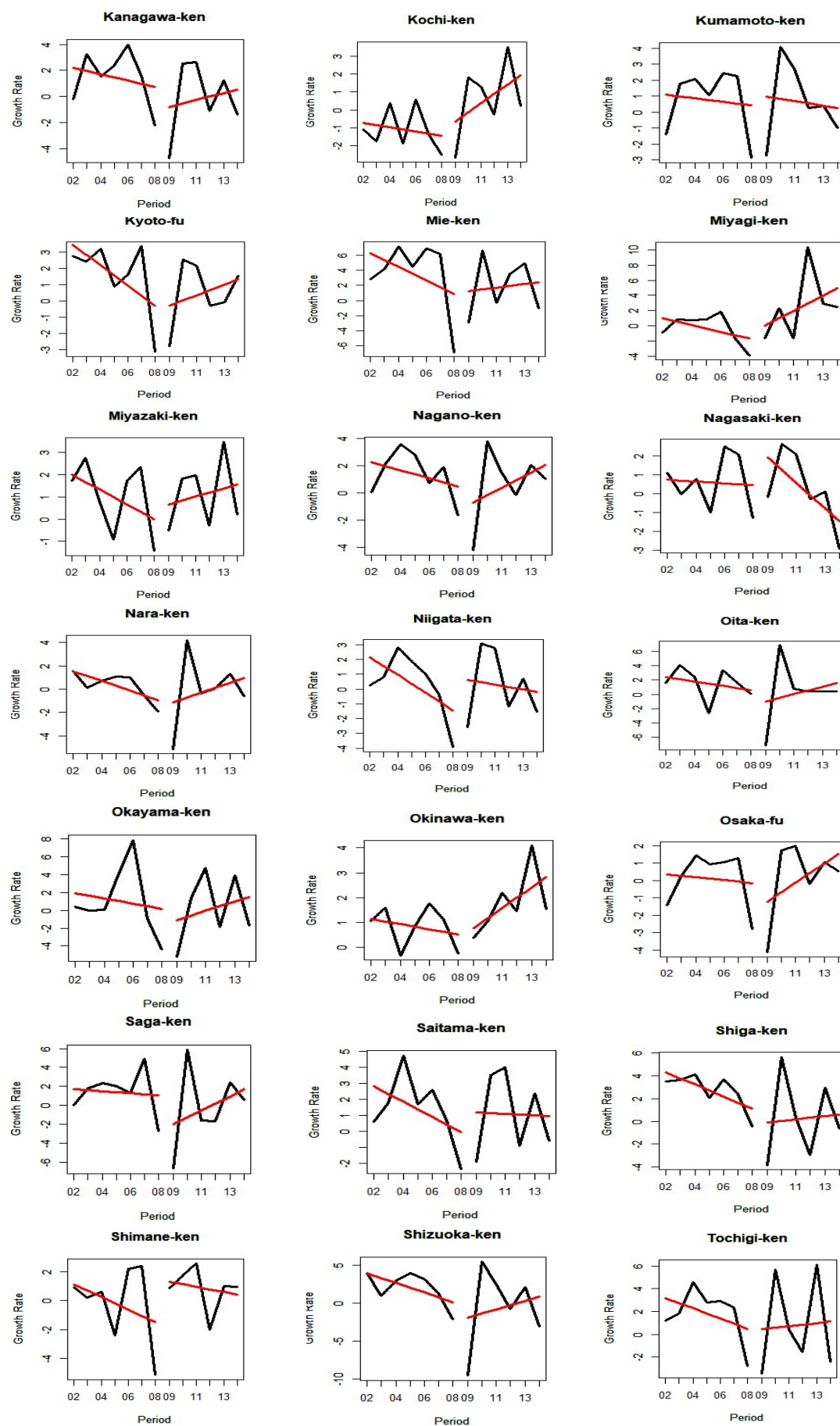


Figure 2.10. Regional Economic Growth for all Prefectures in Japan: Before-After Crisis
(*cont.*).

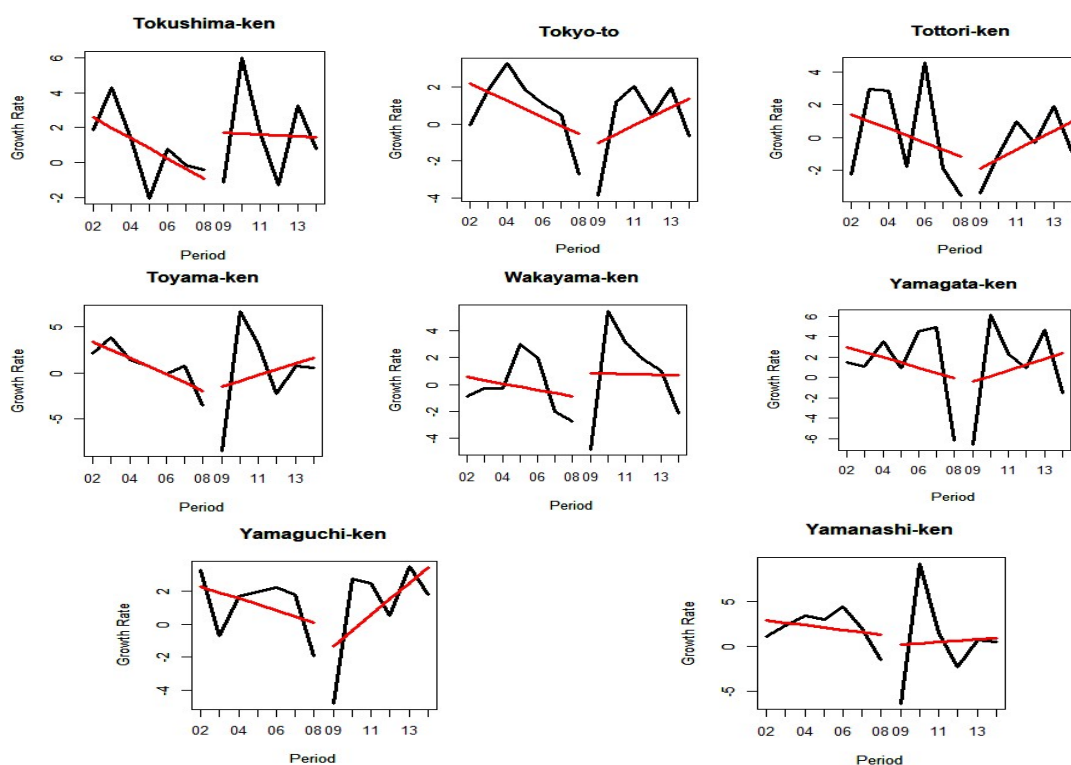


Figure 2.10. Regional Economic Growth for all Prefectures in Japan: Before-After Crisis.

The declining of economic growth that spread out Japan due to the declining in manufacturing production, business investment, and private consumption weakens regional economic growth. As the production and consumption declines, there was further declining impact of the crisis (BOJ, 2008).

Figure 2.11 shows recovery for most prefectures after the improvement in manufacturing production and business environment throughout Japan (BOJ Report, 2014). However, there are several prefectures that show negative trend, such as Fukui and Nagasaki prefectures. This trend in Nagasaki prefecture mainly affected by decline in the ship building industry, fisheries industry, and small enterprise (Miyao, 2014).

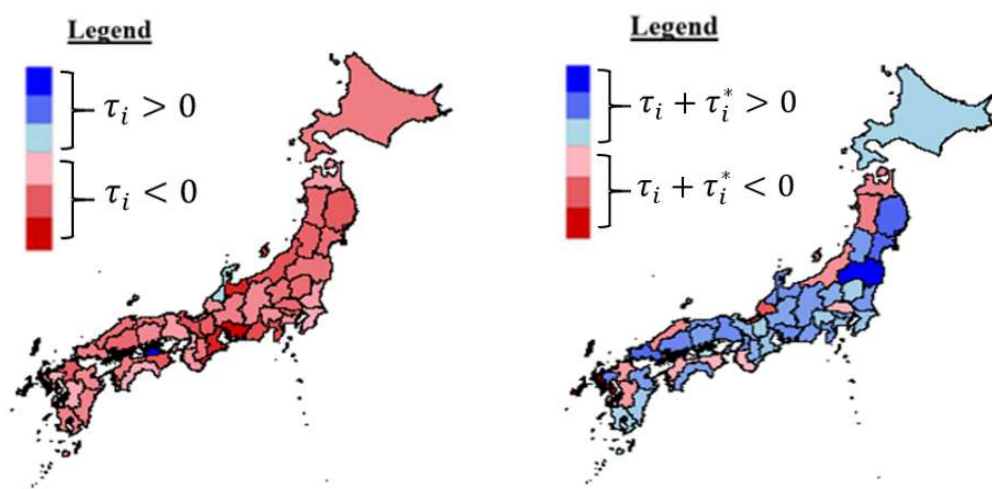


Figure 2.11. The regional economic trend comparison before (left) and after (right) breakpoint in Japan.

By Spatially-Dependent Model

Even though the structural change in Japan case based on F-test were not observed, but the widespread for the impact of Lehman's shock supported by the spatial correlation coefficients in **Figure 2.12**. The results indicate the growth rate in the neighboring prefectures induced each prefecture's economic growth in the same direction.

Wald test cannot be conducted in Japan data due to the small sample size (Greene, 2012). In this case, the sample size only $T = 13$ with $n_1 = 7$ and $n_2 = 6$, which is too small for the requirement.

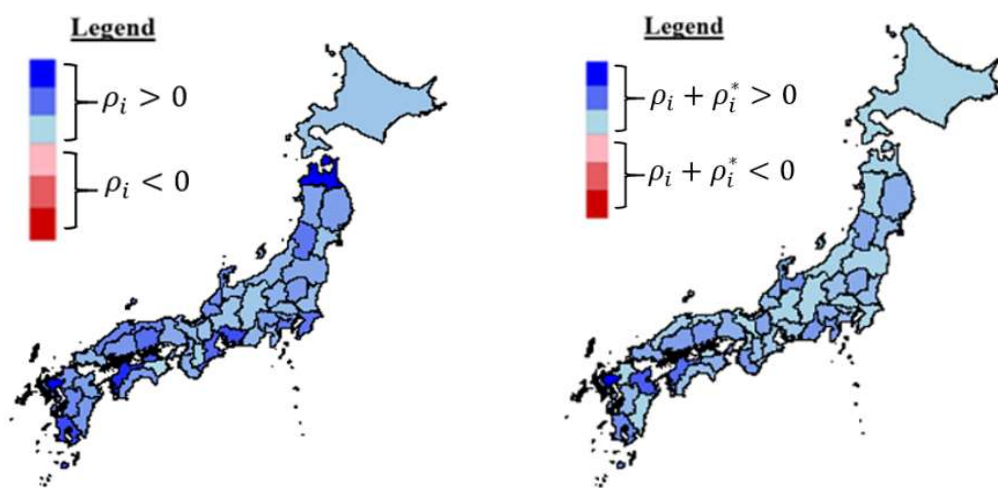


Figure 2.12. The spatial correlation before (left) and after (right) breakpoint in Japan.

2.4. Discussion and Conclusion

Several statistical methods for structural change, such as F-test and Wald-test based on broken time-trend model are used to analyze the effect of Lehman's crisis towards regional economic growth in US and Japan.

F-test perform better compared to the Wald test for spatially-independent model to detect spatial cluster. The Wald test produced better results for spatially-dependent model. The endogeneity in spatially-dependent model might imply the F-test become non-robust for autocorrelated disturbances (Krämer, 2003).

In the US, it was revealed that the negative impact of crisis clustered in West Coast, Southeastern, and Great Lake region. States in those regions with good manufacturing, construction, insurance, and finance as the main contributor for their GRP. On the other hand, states that relied on agriculture, forestry, fishing, hunting, and mining sectors had resilience.

In Japan, the negative impact spread-out across all the regions. After the crisis, most prefectures showed recoveries, except several other prefectures, such as Nagasaki. The negative trend in Nagasaki mainly affected by decline in the ship building industry, fisheries industry, and small enterprise (Miyao, 2014).

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Chapter 3

Generic Methodology for Variable Selection in Spatial Regression Analysis to Attest Regional Interlinkages among SDG Indicators: A Study Case of Sumatra Island, Indonesia

3.1. Introduction

Spatial regression models in economic analysis often cause estimation difficulties, but the biggest spatial Durbin error models manifest tremendous power to unravel interlinkages among SDG indicators capturing neighboring interactions (LeSage & Pace, 2009; Elhorst, 2014).

This chapter focused on the usage of full spatial regression that capture all spatial information to unravel the regional linkages. Not all information nonetheless is reliable to explain the data, thus the usage of variable selection based on Akaike information criteria (AIC) and Bayesian information criteria (BIC).

Variable selection in **spatial regression method (VSSR) developed here** not only to avoid the difficulties but also to select the best variables to attest the interlinkages. This chapter utilize the Sumatra data and used VSSR method to analyze the relationship between palm oil production and regional income inequality in conjunction with child labor contribution.

3.2. Various Spatial Regression Models

Following Elhorst (2014), the full model capturing the spatial effect in different ways. Let the model be expressed as follows,

$$\begin{aligned} \mathbf{y}_t &= \alpha \mathbf{1} + \delta \mathbf{W} \mathbf{y}_t + \mathbf{X}_t \boldsymbol{\beta} + \mathbf{W} \mathbf{X}_t \boldsymbol{\theta} + \mathbf{v}_t \\ \mathbf{v}_t &= \lambda \mathbf{W} \mathbf{v}_t + \boldsymbol{\epsilon}_t, \quad \boldsymbol{\epsilon}_t \sim \text{i.i.d. } N(0, \sigma^2 \mathbf{I}), \quad t = 1, \dots, T \end{aligned} \quad (3.1)$$

where \mathbf{y}_t gives $N \times 1$ vector of dependent variable at time t with N being the number of regions. $\mathbf{X}_t = [x_{1t}, \dots, x_{Kt}]$ is $N \times K$ matrix which consists of K number of independent variables. The \mathbf{W} is a spatial neighbor matrix of size $N \times N$ with $w_{ii} = 0$, which stores the neighborhood information between regions. The α represents a common intercept and $\mathbf{1} = [1, \dots, 1]'$ is $N \times 1$ vector of one. $\boldsymbol{\beta}$ and $\boldsymbol{\theta}$ are $K \times 1$ vectors of regression coefficients and spatial regression coefficients for explanatory variables respectively.

The model (3.1) captures the spatial effect in three different ways through δ , λ and $\boldsymbol{\theta}$. The δ and λ are spatial regression coefficients called endogenous and error term interaction effect. Based on Elhorst (2014), there are the three spatial components in model configuration: 1) endogenous interaction effect δ ; 2) exogenous interaction effect $\boldsymbol{\theta}$; and 3) interaction effect among the error terms, λ .

The interaction effect captures the impact of change in dependent and independent variables in neighboring regions toward each region value, respectively. The error terms interaction effect captured the shock of unobserved variables in the neighboring regions that may affect the dependent variable in each region.

Table 3.1 shows the types of spatial configuration from the full model in equation (3.1). Each configuration is constructed based on the combination of those three spatial effects with some conditions are hold. However, those limited conditions restrict the model and eliminate the potential information for the analysis. LeSage and Pace (2009) emphasized that omitting spatial error terms will increase the loss of efficiency in the estimates and will become less of a problem

relative to bias as sample is increased. Elhorst (2014) also showed that the full spatial model produced unbiased coefficient estimator compared to the other models with restrictions.

Table 3.1. Spatial Configuration and Maximum Combination Required for Variable Selection Process to Attest Interlinkages.

Model Names	Linear Models	Max. Combination
Pure Spatial Autoregressive Model	$y_t = \alpha \mathbf{1} + \delta \mathbf{W}y_t + \epsilon_t$ $\epsilon_t \sim N(0, \sigma^2 \mathbf{I})$	0
Spatial Autoregressive Model (SAR)	$y_t = \alpha \mathbf{1} + \delta \mathbf{W}y_t + \mathbf{X}_t \boldsymbol{\beta} + \epsilon_t$ $\epsilon_t \sim N(0, \sigma^2 \mathbf{I})$	2^k
Spatial Error Model (SEM)	$y_t = \alpha \mathbf{1} + \mathbf{X}_t \boldsymbol{\beta} + v_t$ $v_t = \lambda \mathbf{W}v_t + \epsilon_t, \quad \epsilon_t \sim N(0, \sigma^2 \mathbf{I})$	2^k
Spatial Lag Model (SLM)	$y_t = \alpha \mathbf{1} + \delta \mathbf{W}y_t + \mathbf{W}X_t \boldsymbol{\theta} + \epsilon_t$ $\epsilon_t \sim N(0, \sigma^2 \mathbf{I})$	2^k
Spatial Lag of X Model (SLX)	$y_t = \alpha \mathbf{1} + \mathbf{X}_t \boldsymbol{\beta} + \mathbf{W}X_t \boldsymbol{\theta} + \epsilon_t$ $\epsilon_t \sim N(0, \sigma^2 \mathbf{I})$	2^{2k}
Spatial Autocorrelation (SAC)	$y_t = \alpha \mathbf{1} + \delta \mathbf{W}y_t + \mathbf{X}_t \boldsymbol{\beta} + v_t$ $v_t = \lambda \mathbf{W}v_t + \epsilon_t, \quad \epsilon_t \sim N(0, \sigma^2 \mathbf{I})$	2^k
Spatial Durbin Model (SDM)	$y_t = \alpha \mathbf{1} + \delta \mathbf{W}y_t + \mathbf{X}_t \boldsymbol{\beta} + \mathbf{W}X_t \boldsymbol{\theta} + \epsilon_t$ $\epsilon_t \sim N(0, \sigma^2 \mathbf{I})$	2^{2k}
Spatial Durbin Error Model (SDEM)	$y_t = \alpha \mathbf{1} + \mathbf{X}_t \boldsymbol{\beta} + \mathbf{W}X_t \boldsymbol{\theta} + v_t$ $v_t = \lambda \mathbf{W}v_t + \epsilon_t, \quad \epsilon_t \sim N(0, \sigma^2 \mathbf{I})$	2^{2k}
Non-dynamic General Nesting Spatial (GNS) Model	$y_t = \alpha \mathbf{1} + \delta \mathbf{W}y_t + \mathbf{X}_t \boldsymbol{\beta} + \mathbf{W}X_t \boldsymbol{\theta} + v_t$ $v_t = \lambda \mathbf{W}v_t + \epsilon_t, \quad \epsilon_t \sim N(0, \sigma^2 \mathbf{I})$	2^{2k}
Total Maximum Combination		$4 \cdot 2^{16} + 4 \cdot 2^8$

Note: k is the number of independent variables.

3.3. Estimation Methods in Spatial Regression Models and the Difficulty

There are several methods to estimate the spatial model such as, maximum likelihood (MLE), instrumental variable (IV), two-step least squares (2SLS), and generalized method of moments (GMM). However, those methods still have weakness regarding instability of parameter estimation.

Ord (1975), and Anselin (1988) used the maximum likelihood estimation method to solve the spatial dependence model that correlated with disturbance form. However, there is disadvantage of computational burden especially for large sample size (Pace & Barry, 1997). Therefore, the other methods are developed as alternative techniques.

Kelejian and Prucha (1998, 1999, 2010) proposed instrumental variable with 2SLS and GMM to overcome this problem. The advantages of both alternative methods are that they are not relied upon normality assumptions of error disturbance and provide easy estimation technique Baltagi and Liu (2011) then extend the estimation method into three-staged least squares (3SLS)

that based on 2SLS. However, the estimation of δ and λ may outside its parameter space becomes the weaknesses. This happened because IV and GMM did not restrict the parameter space. The other problem arose in this method is how to choose appropriate instrumental variables for spatial Durbin configuration.

Elhorst (2014) then proposed concentrated maximum likelihood estimation (CMLE) based on Anselin and Hudak (1992) and LeSage and Pace (2010) to provide less computational burden and coefficient estimator that are asymptotically similar to MLE. This method consists of two parts: 1) OLS estimation for α , β and θ ; then 2) use iteration process to estimate δ and λ parameters. However, there is computational problem arose during the iteration process. The parameter estimation will change slightly every running routine. **Table 3.2** summarizes the advantage and weakness of existing estimation methods for spatial models. Note that SDEM estimation will be the most difficult in terms of accuracy and computation.

Table 3.2. Summary of Estimation Methods in Spatial Models

Estimation Method	Precedent Researches	Advantages	Weaknesses
Maximum Likelihood	Ord (1975) Anselin (1988) Pace and Barry (1997)	Full information estimation process.	1. Computational burden for large data size. 2. In large sample size there may occurred a problem during the Jacobian calculation.
CMLE	Anselin and Hudak (1992) LeSage and Pace (2009) Lee and Yu (2010) Elhorst (2014)	Computational burden is reduced due to the estimation problem only focused on spatial coefficient regression.	1. Spatial coefficient parameters can only be solved numerically. 2. The parameter estimation will change slightly every running routine. 3. Bias correction is needed for the parameter estimate of $\hat{\sigma}^2$.
IV 2SLS 3SLS	Anselin (1988) Kelejian and Prucha (1998) Lee (2003) Baltagi and Liu (2011)	1. Does not relied upon normality assumptions of disturbances errors. 2. Calculation of spatial model with neighboring effect of dependent variable is straightforwardly estimated.	1. Parameter estimation for spatial correlation coefficients may outside of parameter space, due to the fact there is no restriction on the parameters range. 2. Instrument selection becomes a problem in SDM and SDEM model.
GMM	Kelejian and Prucha (1999) Fingleton and Le Gallo (2008) Drukker et al. (2013)	1. Does not relied upon normality assumptions of disturbances errors. 2. Calculation of large sample size is direct. 3. It is beneficial for one or more endogenous explanatory variables (Liu & Lee, 2013).	Parameter estimation for spatial correlation coefficients may outside of parameter space. This occurred due to there is no restriction on the parameter range.

3.4. Variable Selection and Interlinkages

Inclusion of all information into the analysis will not guarantee to provide the best model to explain the data. There are several information those may not be reliable. By including more explanatory variables, a better fitted model will be obtained hence the decrease in the error variance and standard errors of OLS estimator (Greene, 2012).

The addition of new explanatory variables should reflect the model selection which evaluates either the new variables improve fit the model. The traditional way to conduct this process is adjusted R-squared that penalizes degree of freedom that occurs when adding new variable in the model (Greene, 2012). However, this method has weakness not to consider loss function unlike Akaike information criteria (AIC) and Bayesian information criteria (BIC) (Amemiya, 1980). Those two information criteria take balance between the goodness of fit for model and the complexity of the model. As the model becoming more complex may obtain an overfit for the model and will not produce best model for forecasting. In some cases, for example, SDM should indicate the better criterion than the bigger SDEM (Credit, 2017; Montero, Minguez, & Fernández-Avilés, 2018; and Montmartin, Herrera, & Massard, 2018). BIC considers heavier penalty compared to AIC and select more simpler model, especially for larger number of parameters (Engle & Brown, 1986; and Greene, 2012).

To solve this problem, variable selection in spatial regression method (VSSR) is employed. This method will keep the best selected variables (Bendel & Afifi, 1977) and able to avoid loss of efficiency in the estimation.

The variable selection was conducted by stepwise regression which by default use of backward elimination. This selection process evaluates the model using AIC by dropping one explanatory variable at a time until there is no significant drop in AIC value (Venables & Ripley, 2002). This process is combined with the estimation process and each iteration the AIC value is evaluated. This criteria is used to select the best model from a set of alternative models, which selected one provides the minimum value (Teräsvita & Mellin, 1986).

This variable selection in spatial analysis ideally conducted toward the best configuration to explain the data. Even it is difficult to determine the best configuration to explain the data, then the process ideally conducted for all possible configuration. There is another problem however regarding huge computational burden.

By using this study that used *eight* explanatory variables (detailed in **Section 3.6**), then there are 263,168 ($4 \cdot 2^{16} + 4 \cdot 2^8$) maximum combination required for variable selection process for all spatial configuration. But this study only need to focus on the full model (3.1) that consists of all spatial configuration and conducts the variable selection. This method uses all possible reliable information and reduces the computational burden that considered 65,536 (2^{16}) maximum combination, which should produce the subsets of the models in **Table 3.1** from pure spatial autoregressive to SDEM.

It is not easy to apply the variable selection for non-linear form of equation (3.1). In VSSR process, linearized transformation form of equation (3.1) is used for the estimation process (detailed in **Methodology** section). By this form least square estimation method can easily use and avoid several weaknesses arisen for existing estimation methods in **Table 3.2**.

3.5. Methodology

3.5.1. Variable Selection in Spatial Regression Method (VSSR)

Transform equation (3.1) into the linearized model as follows,

$$(\mathbf{I} - \lambda \mathbf{W})\mathbf{y}_t = (\mathbf{I} - \lambda \mathbf{W})\{\alpha \mathbf{1} + \delta \mathbf{W}\mathbf{y}_t + \mathbf{X}_t\boldsymbol{\beta} + \mathbf{W}\mathbf{X}_t\boldsymbol{\theta}\} + \boldsymbol{\epsilon}_t \quad (3.2)$$

where \mathbf{y}_t gives $N \times 1$ vector of incomes at time t with $N = 10$ being the number of provinces in Sumatra island. $\mathbf{X}_t = [x_{1t}, \dots, x_{Kt}]$ is $N \times K$ matrix which consists of K number of independent variables. The \mathbf{W} is a spatial neighbor matrix of size 10×10 with $w_{ii} = 0$, which stores the neighborhood information between provinces in Sumatra. In this empirical analysis the row-standardized \mathbf{W} matrix is used. Therefore, the row-standardization simplifies the intercept estimation since it holds that,

$$(\mathbf{I} - \lambda \mathbf{W})\alpha \mathbf{1} = \alpha(1 - \lambda)\mathbf{1} \equiv \tilde{\alpha}\mathbf{1}.$$

Entries of the error term $\boldsymbol{\epsilon}_t$ follow the Gaussian distribution with common variance σ^2 independently.

Let $\tilde{\mathbf{y}}_t = (\mathbf{I} - \lambda \mathbf{W})\mathbf{y}_t$, $\tilde{\mathbf{W}} = (\mathbf{I} - \lambda \mathbf{W})$, and $\tilde{\mathbf{X}}_t = (\mathbf{I} - \lambda \mathbf{W})\mathbf{X}_t$. Then, consider the linear model:

$$\tilde{\mathbf{y}}_t = \tilde{\alpha}\mathbf{1} + \delta \tilde{\mathbf{W}}\mathbf{y}_t + \tilde{\mathbf{X}}_t\boldsymbol{\beta} + \tilde{\mathbf{W}}\mathbf{X}_t\boldsymbol{\theta} + \boldsymbol{\epsilon}_t \quad (3.3)$$

The variable selection in spatial regression (VSSR) can be obtained from following procedures⁴.

Step 1. Fix λ in the interval $[0, \phi)$ for grid search, where ϕ is the reciprocal of the maximum eigen value of matrix \mathbf{W} .

Step 2. Obtain the least square estimates $\hat{\alpha}(\lambda), \hat{\delta}(\lambda), \hat{\boldsymbol{\beta}}(\lambda), \hat{\boldsymbol{\theta}}(\lambda)$ and $\hat{\sigma}^2(\lambda)$ for given λ .

Step 3. Find the best model minimizing $\text{AIC}(\lambda)$ for variable selection based on following calculation,

$$\text{AIC}(\lambda) = NT \log(2\pi e) + NT \log \hat{\sigma}^2(\lambda) + 2 \cdot T \log |\mathbf{I} - \lambda \mathbf{W}| + 2 \cdot d \quad (3.4)$$

where N is the number of province in Sumatra island, T is number of time period, and d is the number of parameters given by $3 + \dim \{\hat{\boldsymbol{\beta}}(\lambda)\} + \dim \{\hat{\boldsymbol{\theta}}(\lambda)\}$, where 3 is derived by $\tilde{\alpha}, \delta$ and σ^2 . The $\dim \{\hat{\boldsymbol{\beta}}(\lambda)\}$ and $\dim \{\hat{\boldsymbol{\theta}}(\lambda)\}$ denote the number of non-zero entries under consideration.

The variable selection was conducted by stepwise regression which by default use of backward elimination. This selection process evaluates the model by dropping one

⁴ The source programs, data, and logs are available at https://github.com/shojiro-tanaka/2020_VSSR

explanatory variable at a time, which minimizes the AIC value, until there is no significant drop in AIC value. This process conducted by using *step* function in R library.

Step 4. Repeat Steps 1 – 3.

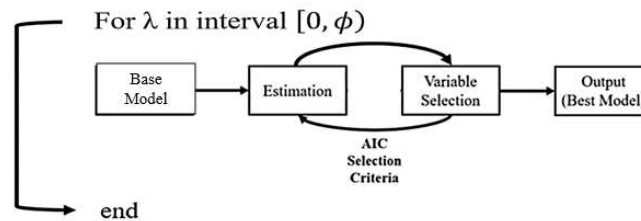


Figure 3.1. Generic Flow Chart of VSSR Process.

3.6. Data and Variables

3.6.1. List of Variables

Average of Income per month. This variable used as a proxy variable to represents the poverty and income inequality. Statistics Indonesia actually provides more relevance indicator, percentage of poor people by province. However, due to the complicated definition and sampling method⁵, which may have bigger measurement error, thus income used as proxy variable.

Average of income is calculated by nominal wage divided by the number of laborers for each month. Laborer is casual employee in agriculture and non-agriculture. **Total laborer** as defined by BPS (Bureau of Statistics Indonesia) as follows,

- Casual employee in agriculture:** a person who works based on daily or contract payment system permanently for other people/employer/institution (more than 1 employer during the last 1 month) in agricultural sector either home industry or not home industry.
- Casual employee in non-agriculture:** a person who works based on daily or contract payment system permanently for other people/employer/institution (more than 1 employer during the last 1 month) in non-agricultural sector, such as mining, electricity, gas, building construction, warehousing, etc.

Growth of gross regional product (GRP) per capita with production approach. Based on BPS (2018), GRP is the total value added of the goods and services produced by the various production unit in a region. Production units in the display are grouped into 17 industrial origin.

Crude palm oil production. The production data is referred to the industrial output after transform the palm oil into the crude palm oil. This output counted in 1043 industrial classification code in manufacturing industry.

⁵ The percentage of poor people indicator is calculated based on the percentage of population that are below of poverty line. The poverty line itself is defined as many poverty calculations is a food energy intake requirement of 2,100 calories per person per day based on 52 commodity items (BPS, Bappenas, & UNDP, 2001). Once the food basket has been chosen, the food poverty line in each region is then established using the basket of quantities of the national reference group, but region-specific commodity prices

Gross enrollment ratio for secondary school. Bureau of Statistics Indonesia defines the number of students enrolled in school for secondary school and show the ratio of the number of students who live in that province to those who qualify for the particular grade level.

Mining and wholesale industry. Mining and wholesale industries have significant contributions towards economic activities in Sumatra Island (see **Section 1.2**). Therefore, it is necessary to include both sector into the analysis. Both mining and wholesale industry data are compiled from related departments/institutions. The compilation from each sector consists of production data, data on prices at producer level, production cost, and expenditure data acquired either from survey or estimation.

Child ratio to population variable used to approximate the contribution of child labor to support family economies. Child worker is better data, but due to data limitation the child population (less than 15 years old) to total population is used instead.

3.6.2. Source of Data

All of data are provided by Bureau of Statistics Indonesia websites⁶ and available in specific topics that are relevant to the list of variables. The number of laborers and average of income per months data obtained from labor statistics publication. Crude palm oil production data retrieved from an annual oil palm statistics publication. The proportion of child to total population ratio obtained from *Welfare Statistics* publication.

3.6.3. Descriptive Statistics

There is large difference between largest income province (Riau Islands province) and the other provinces in Sumatra Island. To obtain the clear relationship the data from Riau Islands is excluded, which implies the number of provinces reduced to $N = 9$.

There are two main reasons for this exclusion. The first reason is geographical characteristics of Riau Islands is different to other provinces. The archipelago structure and the closeness to the Singapore may imply different economic activities compared to the other provinces in Sumatra.

The second reason regarding the industrial structure of Riau Islands is different compared to the other provinces. Due to their geographical features that consist a lot of small islands, agricultural sector has a small contribution to total GRP only 3.58% in 2017. After the removal the descriptive statistics result shows in **Table 3.3**.

Table 3.3. Descriptive Statistics after Riau Islands Removal (datasize = 63).

Aceh					
Variables (Unit)	Min.	Median	Mean	Max.	Std. dev.
Income per month (Rupiah)	1,510,050.00	1,742,500.00	1,789,857.14	2,151,200.00	237,632.88
Income per year (Rupiah)	18,120,600.00	20,910,000.00	21,478,285.71	25,814,400.00	2,851,594.53
Growth (%)	-0.73	3.28	2.58	4.18	1.69

⁶ Accessed on: www.bps.go.id

School (%)	75.09	81.53	81.69	87.52	4.76
Population Growth (0 - 1)	0.018	0.020	0.021	0.028	0.003
Palm Oil Production per Labor (Kg)	7,27.71	861.48	958.07	1,176.46	182.67
Mining per Labor (Rupiah)	8,069,242.87	15,714,234.74	14,584,052.51	20,717,274.11	5,452,164.45
Wholesale Industry per Labor (Rupiah)	18,184,472.64	20,261,362.57	20,037,735.40	22,131,339.98	1,335,032.55
Child Ratio to Population (0 - 1)	0.310	0.322	0.320	0.325	0.006
Sumatra Utara					
Variables (Unit)	Min.	Median	Mean	Max.	Std. dev.
Income per month (Rupiah)	1,431,450.00	1,703,150.00	1,742,264.29	2,178,600.00	260,102.56
Income per year (Rupiah)	17,177,400.00	20,437,800.00	20,907,171.43	26,143,200.00	3,121,230.77
Growth (%)	5.1	5.23	5.69	6.66	0.68
School (%)	77.15	82.96	84.42	93.64	6.59
Population Growth (0 - 1)	0.011	0.013	0.014	0.018	0.002
Palm Oil Production per Labor (Kg)	1,388.94	1,560.61	1,643.77	1,889.00	184.81
Mining per Labor (Rupiah)	1,440,806.80	2,072,276.57	1,971,158.32	2,361,480.47	327,991.61
Wholesale Industry per Labor (Rupiah)	23,632,197.47	27,910,543.43	27,427,325.27	31,307,500.64	2,489,825.81
Child Ratio to Population (0 - 1)	0.315	0.332	0.328	0.336	0.008
Sumatra Barat					
Variables (Unit)	Min.	Median	Mean	Max.	Std. dev.
Income per month (Rupiah)	1,664,550.00	1,871,050.00	1,912,085.71	2,206,100.00	210,038.23
Income per year (Rupiah)	19,974,600.00	22,452,600.00	22,945,028.57	26,473,200.00	2,520,458.76
Growth (%)	5.27	5.88	5.81	6.34	0.46
School (%)	70.00	80.46	78.36	88.39	7.22
Population Growth (0 - 1)	0.012	0.013	0.013	0.018	0.002
Palm Oil Production per Labor (Kg)	1,033.37	1,107.17	1,118.27	1,250.27	74.99
Mining per Labor (Rupiah)	5,865,563.44	6,188,678.33	6,294,130.96	6,998,800.63	409,276.93
Wholesale Industry per Labor	19,964,201.72	22,589,604.49	22,125,327.28	23,776,874.97	1,316,752.07

(Rupiah)					
Child Ratio to Population (0 - 1)	0.301	0.313	0.312	0.324	0.009
Riau					
Variables (Unit)	Min.	Median	Mean	Max.	Std. dev.
Income per month (Rupiah)	1,760,550.00	2,111,900.00	2,088,128.57	2,415,400.00	239,666.89
Income per year (Rupiah)	21,126,600.00	25,342,800.00	25,057,542.86	28,984,800.00	2,876,002.72
Growth (%)	0.22	2.68	2.80	5.57	1.62
School (%)	68.73	76.16	75.14	85.05	5.68
Population Growth (0 - 1)	0.024	0.026	0.027	0.034	0.003
Palm Oil Production per Labor (Kg)	4,863.37	5,468.17	5,371.03	5,736.90	306.33
Mining per Labor (Rupiah)	68,930,590.71	95,698,593.59	92,521,207.37	117,897,303.96	19,802,633.76
Wholesale Industry per Labor (Rupiah)	27,085,650.85	30,279,129.67	29,652,951.95	31,375,013.13	1,594,008.77
Child Ratio to Population (0 - 1)	0.310	0.326	0.325	0.338	0.010
Jambi					
Variables (Unit)	Min.	Median	Mean	Max.	Std. dev.
Income per month (Rupiah)	1,354,700.00	1,804,450.00	1,762,200.00	2,140,100.00	290,558.88
Income per year (Rupiah)	16,256,400.00	21,653,400.00	21,146,400.00	25,681,200.00	3,486,706.54
Growth (%)	4.21	6.84	6.04	7.86	1.57
School (%)	65.61	73.63	73.10	83.54	7.33
Population Growth (0 - 1)	0.016	0.018	0.018	0.024	0.003
Palm Oil Production per Labor (Kg)	2,178.57	2,740.99	2,639.04	2,978.36	301.72
Mining per Labor (Rupiah)	42,307,672.71	46,280,167.15	46,187,340.16	51,972,888.52	3,501,901.04
Wholesale Industry per Labor (Rupiah)	12,906,990.58	16,559,003.81	16,414,480.02	19,095,199.28	2,094,238.84
Child Ratio to Population (0 - 1)	0.279	0.298	0.296	0.310	0.011
Sumatra Selatan					
Variables (Unit)	Min.	Median	Mean	Max.	Std. dev.
Income per month (Rupiah)	1,388,500.00	1,708,550.00	1,764,150.00	2,154,000.00	274,216.88
Income per year	16,662,000.00	20,502,600.00	21,169,800.00	25,848,000.00	3,290,602.62

(Rupiah)					
Growth (%)	4.42	5.31	5.47	6.83	0.86
School (%)	63.78	72.51	72.81	83.44	7.83
Population Growth (0 - 1)	0.013	0.014	0.015	0.020	0.002
Palm Oil Production per Labor (Kg)	1,824.36	1,933.32	1,919.33	2,023.12	79.76
Mining per Labor (Rupiah)	35,560,084.81	36,657,150.73	36,859,880.90	38,733,265.81	970,232.86
Wholesale Industry per Labor (Rupiah)	15,388,211.79	16,400,117.83	16,397,980.43	17,435,362.83	726,836.90
Child Ratio to Population (0 - 1)	0.287	0.297	0.298	0.310	0.008
Bengkulu					
Variables (Unit)	Min.	Median	Mean	Max.	Std. dev.
Income per month (Rupiah)	1,466,550.00	1,877,850.00	1,853,400.00	2,163,000.00	252,416.18
Income per year (Rupiah)	17,598,600.00	22,534,200.00	22,240,800.00	25,956,000.00	3,028,994.17
Growth (%)	4.98	5.48	5.80	6.85	0.79
School (%)	67.42	79.49	77.24	87.10	7.99
Population Growth (0 - 1)	0.015	0.017	0.017	0.022	0.002
Palm Oil Production per Labor (Kg)	1,960.39	2,498.42	2,487.91	2,711.11	253.35
Mining per Labor (Rupiah)	3,795,846.99	4,375,788.44	4,278,886.16	4,677,492.82	332,182.67
Wholesale Industry per Labor (Rupiah)	12,773,216.88	15,986,879.20	15,954,045.86	18,889,812.76	1,848,892.33
Child Ratio to Population (0 - 1)	0.280	0.298	0.297	0.313	0.012
Lampung					
Variables (Unit)	Min.	Median	Mean	Max.	Std. dev.
Income per month (Rupiah)	1,099,900.00	1,629,950.00	1,563,585.71	1,873,100.00	300,030.94
Income per year (Rupiah)	13,198,800.00	19,559,400.00	18,763,028.57	22,477,200.00	3,600,371.23
Growth (%)	5.08	5.16	5.61	6.56	0.65
School (%)	61.76	68.49	71.16	85.16	9.80
Population Growth (0 - 1)	0.010	0.012	0.012	0.017	0.002
Palm Oil Production per Labor (Kg)	276.11	325.87	317.07	340.19	25.83

Mining per Labor (Rupiah)	7,721,600.30	8,286,036.96	8,344,199.91	9,214,202.99	471,216.48
Wholesale Industry per Labor (Rupiah)	15,651,190.80	16,340,045.53	16,372,789.40	17,193,024.70	493,570.55
Child Ratio to Population (0 - 1)	0.281	0.294	0.291	0.299	0.007
Bangka Belitung					
Variables (Unit)	Min.	Median	Mean	Max.	Std. dev.
Income per month (Rupiah)	1,519,300.00	1,948,750.00	1,950,978.57	2,452,000.00	347,500.09
Income per year (Rupiah)	18,231,600.00	23,385,000.00	23,411,742.86	29,424,000.00	4,170,001.05
Growth (%)	4.08	4.67	4.99	6.9	1.00
School (%)	59.69	75.51	71.92	82.88	8.92
Population Growth (0 - 1)	0.021	0.022	0.023	0.029	0.003
Palm Oil Production per Labor (Kg)	1,559.30	1,720.85	1,870.30	2,375.94	313.62
Mining per Labor (Rupiah)	19,293,351.32	20,979,334.50	20,664,346.35	21,383,020.66	735,379.88
Wholesale Industry per Labor (Rupiah)	16,759,934.94	20,270,794.26	19,853,648.07	21,998,325.85	1,764,291.19
Child Ratio to Population (0 - 1)	0.274	0.289	0.288	0.301	0.010

3.7. Model Specification

Model used in this study expressed based on equation (3.1),

$$(\mathbf{I} - \lambda \mathbf{W})\mathbf{y}_t = (\mathbf{I} - \lambda \mathbf{W})\{\alpha \mathbf{1} + \delta \mathbf{W}\mathbf{y}_t + \mathbf{X}_t\boldsymbol{\beta} + \mathbf{W}\mathbf{X}_t\boldsymbol{\theta}\} + \boldsymbol{\epsilon}_t \quad (3.5)$$

where \mathbf{y}_t gives $N \times 1$ vector of incomes at time t with $N = 10$ being the number of provinces in Sumatra island. $\mathbf{X}_t = [x_{1t}, \dots, x_{Kt}]$ is $N \times K$ matrix which consists of $K = 7$ number of independent variables: 1) GRP per capita growth; 2) secondary school enrollment ratio; 3) population growth; 4) CPO production per labor; 5) mining output per labor; 6) wholesale output per labor; and 7) child ratio to population.

The \mathbf{W} is a spatial neighbor matrix of size 10×10 with $w_{ii} = 0$, which stores the neighborhood information between provinces in Sumatra. In this empirical analysis the row-standardized \mathbf{W} matrix is used.

3.8. Interim Result

VSSR method is developed to answer the instability problem from the existing estimation method. The estimation based on the Sumatra data after outlier removal ($N = 9$ and $T = 7$). Based on this condition, the row-standardized spatial \mathbf{W} matrix is defined as follows,

$$W_{9 \times 9} = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.33 & 0 & 0.33 & 0.33 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.25 & 0 & 0.25 & 0.25 & 0 & 0.25 & 0 & 0 \\ 0 & 0.33 & 0.33 & 0 & 0.33 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.25 & 0.25 & 0 & 0.25 & 0.25 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.33 & 0 & 0.33 & 0.33 & 0 \\ 0 & 0 & 0.25 & 0 & 0.25 & 0.25 & 0 & 0.25 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.50 & 0.50 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

where row and column index represent each provincial index in Sumatra Island. The ninth index is Bangka Belitung province. Hence this province is separated to the other provinces in mainland, then based on common border condition, this province have no neighbor.

The result is that school enrollment, palm oil production, and wholesale industry positively affected regional income. On the other hand, mining industry and child labor ratio has negative relations. The neighboring school, palm oil production, and wholesale industry positively affected to each province in Sumatra. The neighboring income and child population ratio from neighboring provinces has negative effect. For the error term λ in equation (3.3), it showed strongly positive value in **Figure 3.2**.

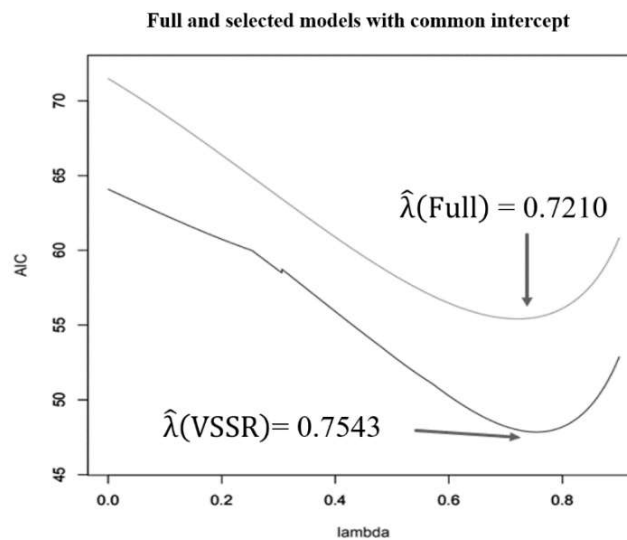


Figure 3.2. Parameter estimation of λ with respect to AIC for full and VSSR models.

An interesting finding showed that regional income from neighboring province has negative and significant impact for each region. It was suggested that this result may have occurred due to the presence of large enterprise in manufacturing and natural resources industries, such as palm oil, coal, oil and gas in Sumatra Island. Large enterprise then attracts foreign capital to invest in this sector (Lipsey & Sjöholm, 2004).

This condition caused the wage gap based on financial capability to provide better wage between enterprise with large capital inducement or not. This condition driven a wage inequality that triggered by inflow of foreign capital in Indonesia (Tomohara & Takii, 2011). Therefore, the province with a lot of large enterprise may attract more people, especially the skilled labor. The increase of skilled labor will increase the income. On the other hand, low-skilled labor may have negative effect toward regional income in the short-run (Okun & Richardson, 1961). This

absorption from neighboring province would affect the negative and significant endogenous effect in the result.

This positive relationship also observed in several studies, such as Lim and Kim (2015) that observed spatial dependencies over 177 economic areas in US states from 1969-2009. The spatial interaction in support of regional policy will generates sustainable economic activities.

Lima and Neto (2015) also observed positive spatial regional income for 522 micro-regions in Brazil for the period 1970-2010. This spatial dependence result suggested an investment in human and capital are important toward Brazilian regional economies. The positive spatial dependence in Brazil also observed by Cravo, Becker, and Gourlay (2014).

The capital movement also caused by the interlinkages between corporates groups that owned the palm oil mills to produce the palm oil. By this internal relationship, the possibility of capital flows between company is high.

Table 3.4 shows positive returns of education as part of human capital investment to combat the income inequality (Psacharopoulos, 1985; Tilak, 1989; O'Neill, 1995; Krueger & Lindahl, 2001; E.A. Jamison, D.T. Jamison, & Hanushek, 2006; and Gyimah-Brempong, Paddison, & Mitiku, 2006). The positive neighboring effect of educational factor may also caused by migration of the educated population from adjacent provinces (Olejnik, 2008; Pijnenburg & Kholodilin, 2012; and Cravo, Becker, & Gourlay, 2014). Hence, more qualified and educated student seeking for better educational infrastructure and stayed to look better opportunities.

Positive and significant effect of palm industry from each province and the neighboring provinces toward regional income in Sumatra Island triggered by the interlinkages between corporates group that owned the palm oil enterprise. The relationship shown by their oil palm mills area expansion and ownership across provinces (see examples in **Appendix 3**). Each parent company hereafter may distribute the capital factor of production transfer toward their respective oil palm mills. Therefore, if those parent company has mills in different province, this may be observed by positive neighboring effect of oil palm industry.

The expansion conducted by large palm oil companies due to their limitation of land area to compete in this industry. Examples of several companies has several mills across Sumatra Island in **Appendix 3** were retrieved from Global Forest Watch (2019).

Table 3.4. Estimation Result

Parameters	Full Model	Best Model with VSSR Method
Intercept	-0.0325	-0.0215
W*Income	-1.2378***	-1.4556***
Growth	0.0821	-
School	0.4029***	0.4436***
Population Growth	-0.0576	-
Palm Oil Production per	0.6350**	0.5621***

Labor		
Mining per Labor	-0.2393 ^a	-0.1809*
Wholesale per Labor	0.4941***	0.4363***
Child Labor	-0.6512***	-0.6267***
W*Growth	0.1846	-
W*School	0.6994**	0.8612***
W*(Population Growth)	0.0043	-
W*(Palm Oil Production per Labor)	0.8622**	0.8622***
W*(Mining per Labor)	-0.2704	-
W*(Wholesale per Labor)	0.8720**	0.7057**
W*(Child Labor)	-1.1088***	-1.0765***
Lambda ($\hat{\lambda}$)	0.7210	0.7543
Adj. R-squared	0.8270	0.8403
AIC	55.4083	47.8445
BIC	93.9847	75.7053
Note: ***) Significant at level < 1%. **) Significant at 1%. *) Significant at 5%. a) Significant at 10%.		

Positive relationship between neighboring wholesale industry and the given province are observed. The result occurred due to the increasing of industrial competition from neighboring enterprises thus affected economic activities in that given province (Cravo, Becker, & Gourlay, 2015). Pijnenburg and Kholodilin (2014) also emphasized the competitiveness-improving effect occurred to explain the more competition in the business in the region of location will triggered incentive for each firm to increase their productivity. Therefore, the business relocation to neighborhood region in the long-run will increase job opportunities for the local region and generate greater regional income.

The last variable that affected regional income in Sumatra Island is child ratio to population as proxy variable of child labor. The finding indicated the negative and significant relationship between this variable toward regional income. This negative sign implies the insignificant role of child labor to support their family and more represents as an increasing dependent member and expense burden to the family.

Based on the regression results, a positive effect of palm oil production for Sumatra regional income is observed. However, there are of lot precedent researches that found the relation between mining and palm oil activities and environmental degradation, such as forest cover loss. Therefore, the usage of satellite data in incorporated analysis (Tanaka & Nishii, 2009) will enhance the analysis and provide deeper understanding for regional analysis in Sumatra.

3.9. Additional Variables and The Effect to Attest Interlinkages

The estimation result offers the initial result prior to more comprehensive regional analysis by adding the environmental factors, such as fire emission, forest cover loss, or vegetation quality

that reflect the negative impact caused by palm oil industry activities. The addition of more explanatory variables will obtain an in-depth regional analysis and select additional reliable information to attest the interlinkages.

Those additional explanatory variable in the model will change the parameter results hence all variables are jointly estimated. Even the parameter sign can be reversed (Mosteller & Tukey, 1977). Therefore, selecting best variable process in the VSSR method is essential to capture the best model with new additional variables that explain the regional interlinkages.

3.9.1. Inclusion of Environmental Variables

The inclusion of environmental factors to capture the issue that happened in Sumatra Island and the relation with economic activities focused on oil palm plantation and mining industries as discuss in **Chapter 1**. Variable, such as forest cover area data, are important in this analysis. By including forest cover data, it is also required to include topographic profile that support forest cover area and oil palm plantation analysis.

To obtain the environment factors such as vegetation qualities, forest cover loss, land cover use, soil degeneration, or urban concentration, satellite data from remote sensing technology is used. The source of satellite data is explained in detail in **Appendix 4**. The other sources that can be used to obtain this factor are grid-based dataset and data provided by official government.

3.9.1.1. Data Limitation for Forest Cover Data

Table 3.5 shows that a grid-based dataset can be used to extract forest cover area data. However, during this research is done, there are limitations for this type of data that can be used for the analysis. Those sources do not provide the required needed data for the required time slot analysis.

For example, the global forest change (GFC) provided tree canopy cover and forest tree gain. Tree canopy cover data based on forest definition for all vegetation taller than 5m in height. The value for this data ranges from 0-100. Forest tree gain calculated based on their definition as the inverse of forest loss, or non-forest to forest change. This data encoded as either 1 or 0 to represent forest gain and no gain respectively. Unfortunately, tree cover only contains year 2000 data, and forest tree gain measured change in the forest between 2000-2012. Therefore, this study could not include those data in the analysis.

Table 3.5. Analysis-ready Dataset for Forest Area

Data Sources	Data Availability	Spatial Resolution	Data Limitation
Global Forest Change	Tree canopy cover	1 arc-second per pixel approximately 30 x 30 meters resolution.	Provide only for year 2000 data
	Forest tree gain	1 arc-second per pixel approximately 30 x 30 meters resolution.	The change measure gain from 2000-2012. Therefore, only 2012 data can be obtained.

Global PALSAR-2/ PALSAR Forest/Non- Forest Map	Forest Map	1. 25 meters 2. 100 meters	The dataset provide only year 2007-2010, and 2016-2018.
Global Forest Canopy Height	Global 1km Forest Canopy Height	30 x 30 arc seconds or approximately 1 x 1 kilo meters resolution	The dataset provided only 2005 data.
Global Land Analysis & Discovery	Primary Humid Tropical Forest	30 x 30 meters resolution.	The dataset provided only 2001 data

The data limitation for grid-based dataset in **Table 3.5** lead this study to consider government data provided by Ministry of Forestry and Environments⁷ (MoFE) of Indonesia. The data source for forest cover area provided in *Buku Rekalkulasi Penutupan Lahan di Indonesia*⁸ (Book of Indonesian Land Cover Recalculation).

However, there are no consistent forest cover data provided by MoFE Statistics Publication. **Figure 3.3** shows the sudden increase in 2016 data for total forest cover in Sumatra Island. Margono et al. (2016) explained that there were updates in terms of calculation of forest cover area after 2015 in relation to joint work between Ministry of Forestry and National Institute of Aeronautics and Space of Indonesia (LAPAN). This set up focusing on data selection and data preparation, simple pre-processing data, and data-handling. Therefore, the inclusion of forest cover area provided by MoFE in this study is not appropriate.

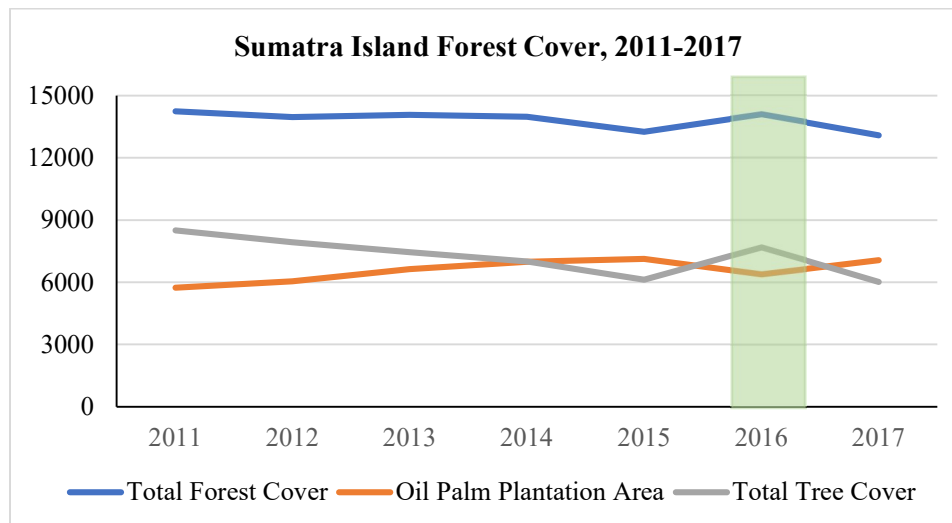


Figure 3.3. Total forest cover and oil palm area in Sumatra Island based on MoFE.

The inconsistency occurred due to the update on class classification from 22 classes based on National Indonesian Standard (SNI) 9645-2010 to 23 classes based on National Indonesian Standard (SNI) 7645-1:2014. The difference of forest definitions between these classes compared

⁷ Before 2014, MoFE is called Ministry of Forestry (MoF) of Indonesia.

⁸ Available at (only in Bahasa Indonesia):

<http://appgis.dephut.go.id/appgis/download/1.1.%20Buku%20REKALKULASI%20PENUTUPAN%20LAHAN%20INDONESIA/>

by Margono et al (2016) in **Figure 3.4**. **Figure 3.5** showed the inconsistency for all provinces in Sumatra Island.

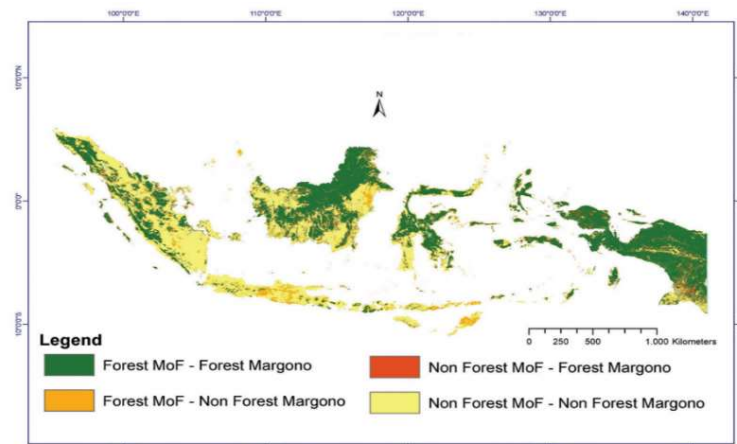


Figure 3.4. Map agreement and disagreement for forest and non-forest classes of the Ministry of Forestry and Class set based on Margono et al. (2014).



Figure 3.5. Forest Cover for each Province in Sumatra Island based on MoFE Publications.

3.9.1.2. The Inclusion of Altitude Data

Due to this data limitation, this study decided not to include forest cover data into the analysis. Therefore, the topography profile is the only environmental variable that included as an additional variable. Topological profile for each province used to incorporate the geographical profile based on altitude data in relation to oil palm plantation. For altitude data, this study used GTOPO30 dataset, provided by United States Geological Survey (USGS). GTOPO30 is a global digital elevation model (DEM) with a horizontal grid spacing of 30 arc seconds (approximately 1 km) covering around the world, resulting the GTOPO30 has 21,600 rows and 43,200 columns showed in **Figure 3.6** (USGS, 2009).

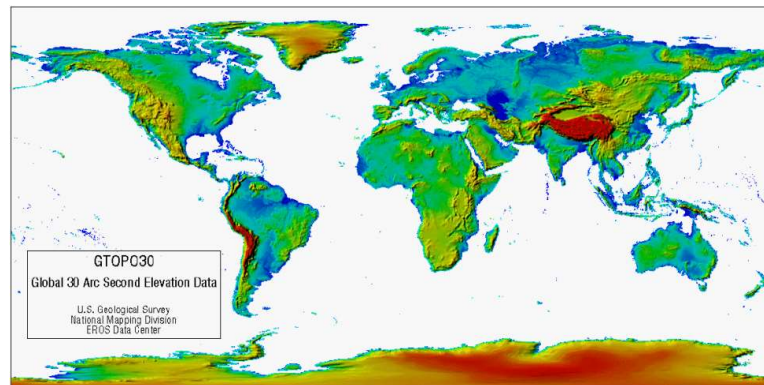


Figure 3.6. Global Altitude Map from GTOPO30 Dataset (USGS, 2001).

In this dataset, ocean areas have been masked as "no data" and have been assigned a value of -9999. Lowland coastal areas have an elevation of at least 1 meter. Small islands in the ocean with less than approximately 1 square kilometer will not be represented (USGS, 2009).

The GTOPO30 raster data set mainly derived from two sources: Digital Terrain Elevation Data (DTED) and Digital Chart of the World (DCW). DTED is a raster topographic data base with a horizontal grid spacing of 3-arc seconds (approximately 90 meters) produced by the National Imagery and Mapping Agency (NIMA). DTED was used as the source for most of Eurasia and large parts of Africa, South America, Mexico, Canada, and Central America.

Digital Chart of the World (DCW) is a vector cartographic data set based on the 1:1,000,000-scale Operational Navigation Chart (ONC) series, which is the largest scale base map source with global coverage (Danko, 1992).

Based on this grid-based data, the standard deviation value of altitude data is calculated to obtain the representative value for each province. This incorporation process based on following steps:

Step 1. Download the GTOPO30 raster image from USGS and Indonesia's level 1 shapefile.

GTOPO30 downloaded from USGS Earth Explorer⁹ and Indonesia shapefile can be obtained from Database of Global Administrative Areas¹⁰ (GADM).

⁹ Available at: <https://earthexplorer.usgs.gov/>

¹⁰ Available at: <https://gadm.org>.

```
# Open "sp", "raster", "rgdal" libraries.

library(sp); library(raster); library(rgdal)

# GTOPO30 Data #
tif1 <- raster("~/gt30e100n40.tif")
tif2 <- raster("~/gt30e060n40.tif")
# Merge two GTOPO30 raster images
tif_list <- list(tif1, tif2)
sum_topo <- do.call(merge, tif_list)
# ----- #

## Read Indonesia Shapefile for 1st Level Administrative Boundary Data
ina.shp.lv1 <- readOGR("~/gadm36_IDN_1.shp")

# Check the data structure and Find Polygon Data for Provinces in Sumatra
Island #
ina.shp.lv1@data$NAME_1

#####
# > ina.shp.lv1@data$NAME_1
# [1] Aceh          Bali          Bangka Belitung  Banten
# [5] Bengkulu     Gorontalo    Jakarta Raya     Jambi
# [9] Jawa Barat   Jawa Tengah   Jawa Timur       Kalimantan Barat
# [13] Kalimantan Selatan  Kalimantan Tengah  Kalimantan Timur
Kepulauan Riau
# [17] Lampung      Maluku        Maluku Utara      Nusa Tenggara
Barat
# [21] Nusa Tenggara Timur Papua          Papua Barat      Riau
# [25] Sulawesi Barat   Sulawesi Selatan  Sulawesi Tengah
Sulawesi Tenggara
# [29] Sulawesi Utara    Sumatera Barat    Sumatera Selatan
Sumatera Utara
# [33] Yogyakarta
# 33 Levels: Aceh Bali Bangka Belitung Banten Bengkulu Gorontalo
Jakarta Raya ... Yogyakarta
#####

# Riau Province has index number 24
```

Script 3.1. R Script for Step 1 process

Step 2. Obtain the *rectangular extent* and *polygon object* from shapefile image.

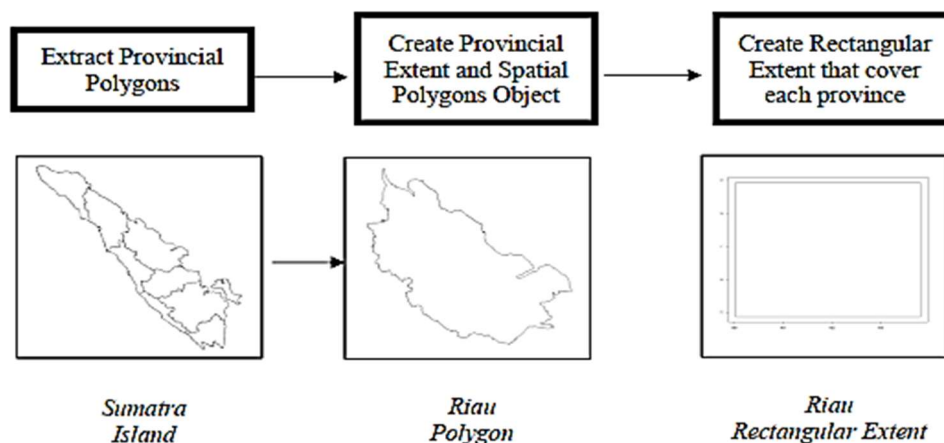


Figure 3.7a. Riau polygon object and rectangular extent.

This step focusing on extract the polygon information from Indonesia shapefile for each province. For example, **Figure 3.7a** showed the extract information for Riau province's *polygon object* and *rectangular extent*.

```
# Extract Polygon Data for Provinces in Sumatra
riau.shp.pol  <- ina.shp.lv1@polygons[[24]]@Polygons    # Riau Province

# Extract Polygon Data
## ----- Riau Province ----- ##
nlist = length(riau.shp.pol)
riau.range <- matrix(NA, nrow = nlist, ncol = 6)
for (i6 in 1:nlist) {
  riau.range[i6,1] <- min(coordinates(riau.shp.pol[[i6]]),[,1])
  riau.range[i6,2] <- max(coordinates(riau.shp.pol[[i6]]),[,1])
  riau.range[i6,3] <- riau.range[i6,2] - riau.range[i6,1]
  riau.range[i6,4] <- min(coordinates(riau.shp.pol[[i6]]),[,2])
  riau.range[i6,5] <- max(coordinates(riau.shp.pol[[i6]]),[,2])
  riau.range[i6,6] <- riau.range[i6,5] - riau.range[i6,4]
}
## Riau spatial polygon object
riau.sel  <- which(riau.range[,3] == max(riau.range[,3]), arr.ind = T)
pol       = Polygon(riau.shp.pol[[riau.sel]]@coords)
polys     = Polygons(list(pol),1)
riau.Spolys.t = SpatialPolygons(list(polys))

## ----- ##

riau.e <- c(min(riau.shp.pol[[riau.sel]]@coords[,1]),
            max(riau.shp.pol[[riau.sel]]@coords[,1]),
            min(riau.shp.pol[[riau.sel]]@coords[,2]),
            max(riau.shp.pol[[riau.sel]]@coords[,2]))

riau.x <- extent(riau.e)    # Riau's rectangular extent
## ----- ##
```

Script 3.2. R Script to obtain Riau's *polygon object* and *rectangular extent*

Step 3. Obtain the *rectangular raster image* of altitude for each province by using 'crop' for GTOPO30 based on *rectangular extent*.

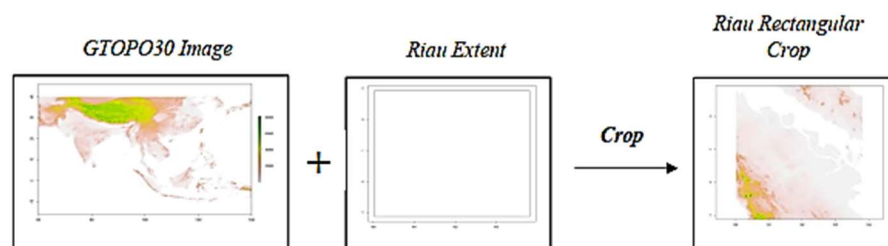


Figure 3.7b. Cropping GTOPO30 image to obtain Riau Rectangular Image.

Riau rectangular image crop is obtained by cropping GTOPO30 image with Riau extent.

This process done to narrow down target image for masking process.

```
# Cropping Raster Image
riau.rec.crop <- crop(sum_topo, riau.x, snap="out")

# Provincial Rectangular Crop
```

Script 3.3. R Script to obtain Riau's *rectangular image crop*

Step 4. Obtain the *provincial raster image* for altitude data by masking *rectangular raster image* with *polygon object*.

Use masking process for *Riau rectangular image crop* with *Riau polygon object* to obtain *Riau provincial raster image* for altitude data.



Figure 3.7c. Obtain Riau Provincial Raster Image for Altitude Data.

```
# Masking Process
riau.mask <- mask(riau.rec.crop, riau.spolys.t)
```

Script 3.4. R Script to obtain Riau's *provincial raster image*

Step 5. Calculate the standard deviation by using *aggregate* function in R.

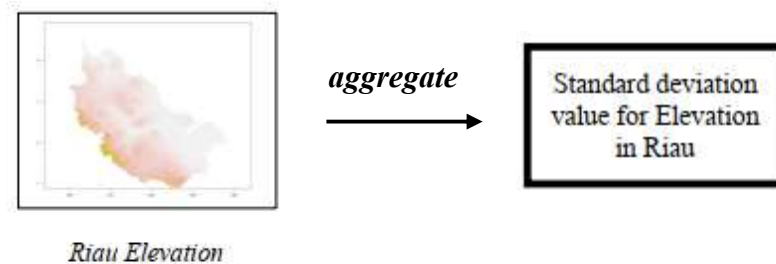


Figure 3.7d. Obtain Standard Deviation of Altitude for Riau Province.

```
# Descriptive Statistics

riau.mean <- aggregate(riau.mask, ncell(riau.mask), fun=mean)
riau.max <- aggregate(riau.mask, ncell(riau.mask), fun=max)
riau.min <- aggregate(riau.mask, ncell(riau.mask), fun=min)
riau.med <- aggregate(riau.mask, ncell(riau.mask), fun=median)
riau.sd <- aggregate(riau.mask, ncell(riau.mask), fun=sd)

riau.des <- data.frame(ncell(riau.mask),
                      values(riau.min),
                      values(riau.med),
                      values(riau.mean),
                      values(riau.max),
                      values(riau.sd))
```

Script 3.4. R Script to compute descriptive statistics of Riau's altitude

Figure 3.8 shows the complete flow chart of incorporation process for GTOPO30 raster image data. The main objective of this process is used the polygon object for each province to obtain provincial altitude by masking the GTOPO30 raster image with this information (shows in **Figure 3.9**).

Flow Chart of Extracting Elevation Data from GTOPO30 Image

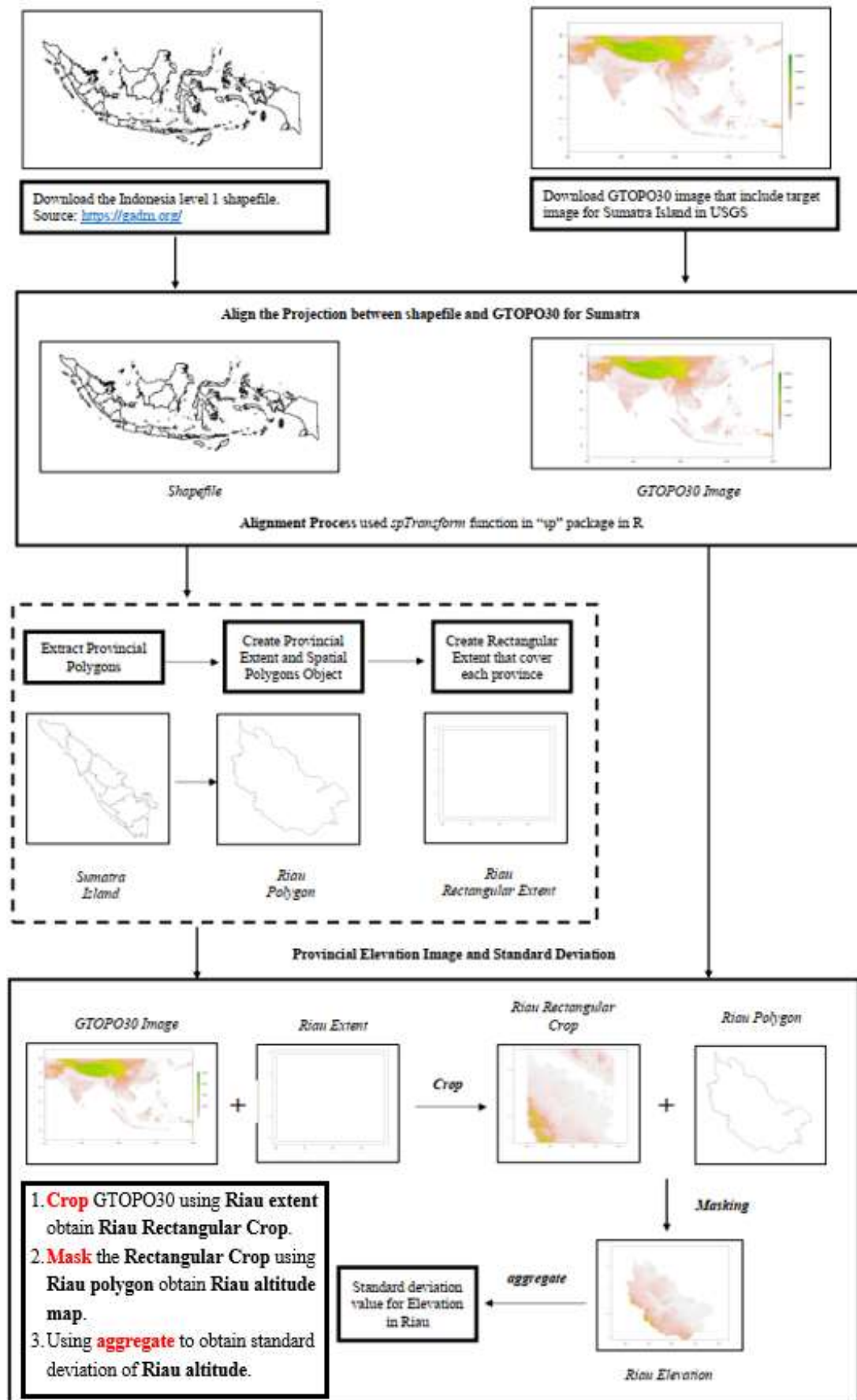


Figure 3.8 Flow Chart of Incorporated Process GTOPO data into the Analysis.

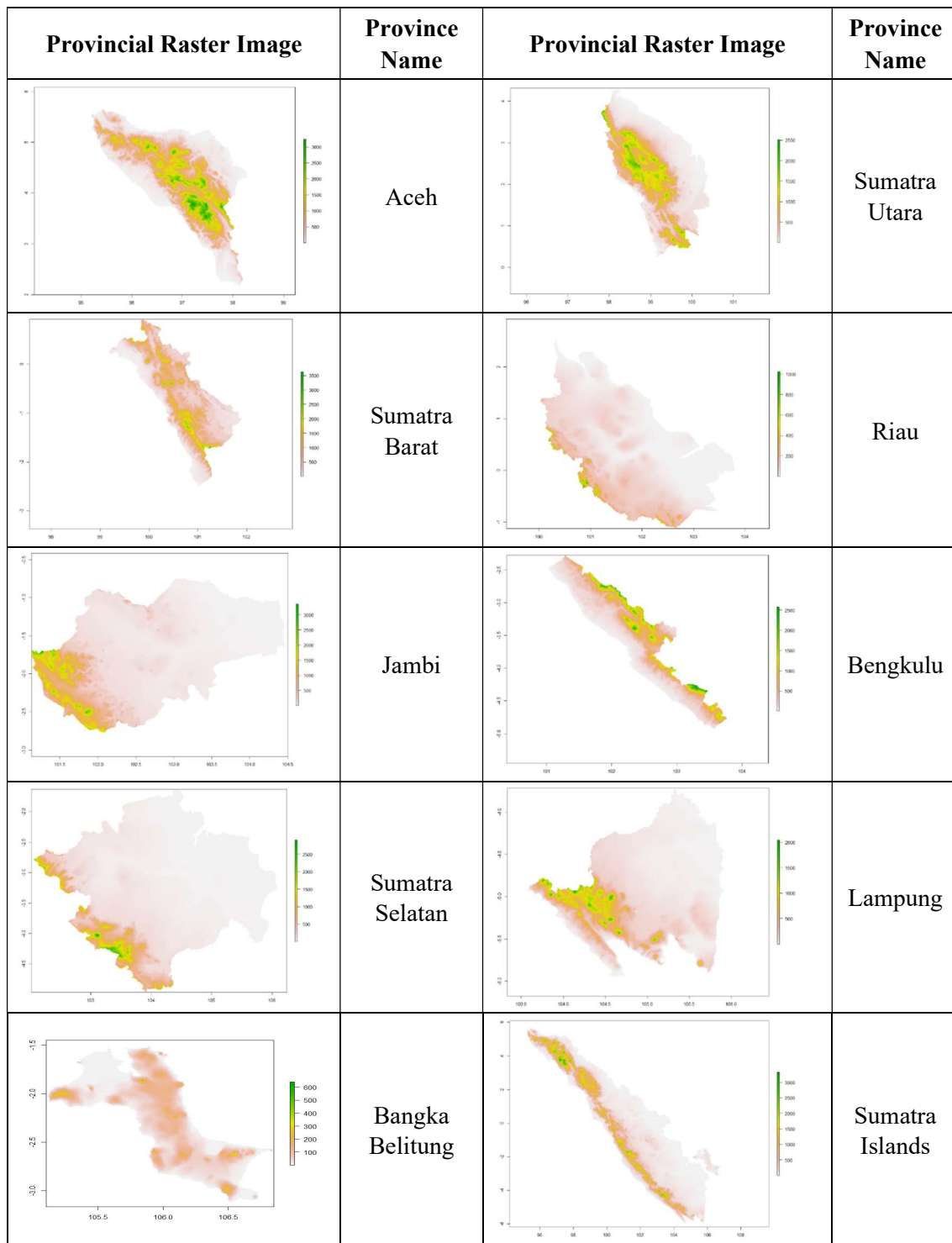


Figure 3.9. Provincial Raster Image based on GTOPO30 Dataset

3.9.2. New Model Specification

To demonstrate this change in interlinkages, this subchapter added environmental variable into the analysis. Hence, the inclusion of forest cover is not appropriate, due to the limitation in available data, the new variable added is standard deviation of provincial altitude to capture the geographical profile. The geographical profile for each province is hand-in-hand with the plantation of oil palm tree.

By this inclusion, then the new model specification become as follows,

$$\begin{aligned} \mathbf{y}_t &= \alpha \mathbf{1} + \delta \mathbf{W} \mathbf{y}_t + \mathbf{X}_t \boldsymbol{\beta} + \mathbf{Z} \boldsymbol{\gamma} + \mathbf{W} \mathbf{X}_t \boldsymbol{\theta} + \mathbf{W} \mathbf{Z} \boldsymbol{\phi} + \boldsymbol{\nu}_t \\ \boldsymbol{\nu}_t &= \lambda \mathbf{W} \boldsymbol{\nu}_t + \boldsymbol{\epsilon}_t, \quad \boldsymbol{\epsilon}_t \sim \text{i.i.d. } N(0, \sigma^2 \mathbf{I}), \quad t = 1, \dots, T \end{aligned} \quad (3.6)$$

where \mathbf{y}_t gives $N \times 1$ vector of incomes at time t with $N = 9$ being the number of provinces in Sumatra island (after Riau Island province is excluded). $[\mathbf{X}_t \quad \mathbf{Z}]$ is $N \times K$ matrix which consists of $K = 8$ number of independent variables: 1) GRP per capita growth; 2) secondary school enrollment ratio; 3) population growth; 4) CPO production per labor; 5) mining output per labor; 6) wholesale output per labor; 7) child ratio to population; and 8) standard deviation of altitude.

Let, $\boldsymbol{\beta}$ be 8×1 coefficient vector up to child ratio to population variable, and $\boldsymbol{\gamma}$ be a coefficient to **standard deviation of altitude**, thus equation (3.6) will have an additional independent variable,

$$\mathbf{X}_t \boldsymbol{\beta} + \mathbf{Z} \boldsymbol{\gamma} = \begin{bmatrix} \mathbf{X}_1 \\ \mathbf{X}_2 \\ \mathbf{X}_3 \\ \vdots \\ \mathbf{X}_K \end{bmatrix} \boldsymbol{\beta} + \begin{bmatrix} \mathbf{Z} \\ \mathbf{Z} \\ \mathbf{Z} \\ \vdots \\ \mathbf{Z} \end{bmatrix} \boldsymbol{\gamma} = \begin{bmatrix} \mathbf{X}_1 & \mathbf{Z} \\ \mathbf{X}_2 & \mathbf{Z} \\ \mathbf{X}_3 & \mathbf{Z} \\ \vdots & \vdots \\ \mathbf{X}_K & \mathbf{Z} \end{bmatrix} \begin{bmatrix} \boldsymbol{\beta} \\ \boldsymbol{\gamma} \end{bmatrix} = \mathbf{X}_t^* \boldsymbol{\beta}^*$$

and,

$$\mathbf{W} \mathbf{X}_t \boldsymbol{\theta} + \mathbf{W} \mathbf{Z} \boldsymbol{\phi} = \mathbf{W} \mathbf{X}_t^* \boldsymbol{\theta}^*$$

where \mathbf{Z} is standard deviation for each province, given $i = 1, \dots, 9$, and the value of \mathbf{Z} same for all time-series data. Therefore, equation (3.6) become,

$$\begin{aligned} \mathbf{y}_t &= \alpha \mathbf{1} + \delta \mathbf{W} \mathbf{y}_t + \mathbf{X}_t^* \boldsymbol{\beta}^* + \mathbf{W} \mathbf{X}_t^* \boldsymbol{\theta}^* + \boldsymbol{\nu}_t \\ \boldsymbol{\nu}_t &= \lambda \mathbf{W} \boldsymbol{\nu}_t + \boldsymbol{\epsilon}_t, \quad \boldsymbol{\epsilon}_t \sim \text{i.i.d. } N(0, \sigma^2 \mathbf{I}), \quad t = 1, \dots, T \end{aligned}$$

where can be transformed into linearized form based on equation,

$$\begin{aligned} (\mathbf{I} - \lambda \mathbf{W}) \mathbf{y}_t &= (\mathbf{I} - \lambda \mathbf{W}) \{ \alpha \mathbf{1} + \delta \mathbf{W} \mathbf{y}_t + \mathbf{X}_t^* \boldsymbol{\beta}^* + \mathbf{W} \mathbf{X}_t^* \boldsymbol{\theta}^* \} + \boldsymbol{\epsilon}_t \\ \tilde{\mathbf{y}}_t &= \tilde{\alpha} \mathbf{1} + \delta \tilde{\mathbf{W}} \mathbf{y}_t + \tilde{\mathbf{X}}_t^* \boldsymbol{\beta}^* + \tilde{\mathbf{W}} \mathbf{X}_t^* \boldsymbol{\theta}^* + \boldsymbol{\epsilon}_t \end{aligned} \quad (3.7)$$

Table 3.6 shows the descriptive statistics for this data. Based on **Table 3.6**, Riau has the largest area and has a flatter topography profile with the smallest standard deviation. Aceh has the largest standard deviation of altitude represents the higher topography profile. This result corresponds to the provincial raster image in **Figure 3.8**.

Table 3.6. Descriptive Statistics for Altitude Variable by Province

Province Name	Datasize*	Min.	Median	Mean	Max.	Std. dev.
Aceh	156240	1	377	644.1524	3245	664.0254
Sumatra Utara	154350	1	210	459.3604	2511	486.8602
Sumatra Barat	133496	1	438	548.6358	3633	454.0585
Riau	201096	1	37	55.6365	1027	73.6608
Jambi	99630	1	97	251.9984	3357	406.2576
Bengkulu	194084	1	45	150.8311	2910	306.4240

Sumatra Selatan	105589	1	289	463.2694	2571	466.6640
Lampung	75844	1	76	184.5690	2043	276.3898
Bangka Belitung	40740	1	45	56.7566	640	52.9437

Note: *) Datasize calculated the number of cells in gridded raster image, where each cell value represents 30 x 30 arc second (approximately 1 km) area.

3.9.3. Results after Addition of A New Variable

Table 3.7 showed changes in regression results due to the addition of altitude variable as described by Mosteller and Tukey (1977). The spatial interlinkages of λ parameters also reduced from 0.7543 to 0.6302 (**Figure 3.10**) which indicated the altitude variable able to obtain the neighboring effect of residual term which is not captured by model in equation (3.5). By adding this variable, the model is improved by decreasing AIC value from 47.8445 to 45.0998.

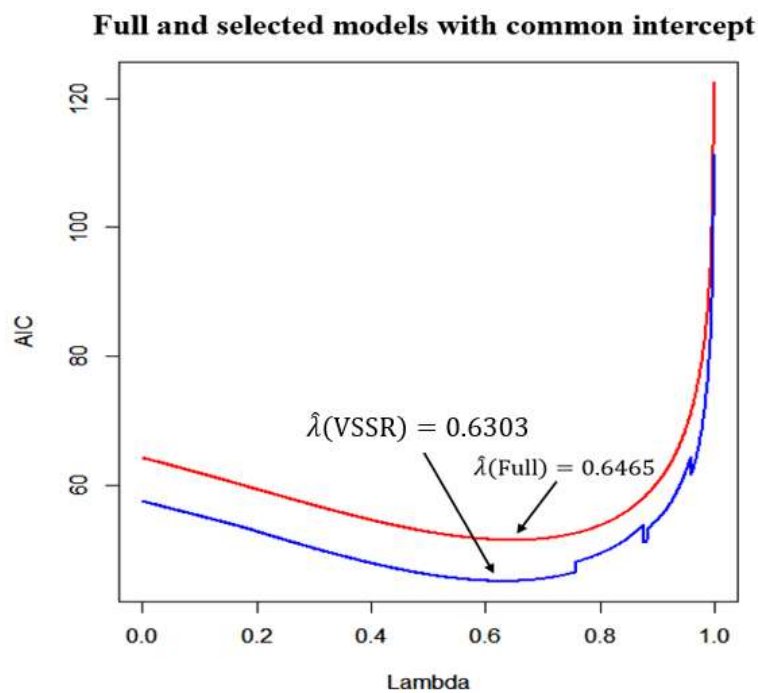


Figure 3.10. Parameter estimation of λ with respect to AIC for full and VSSR models.

The negative and significant coefficient of altitude variable indicated that highly produced oil palm plantation only occurred in several provinces. For example, the Riau province has higher production of palm oil compared to the neighboring Sumatra Barat province. This also may be due to that Riau also has a vast areas and flat topography profiles that more suitable for palm oil industry, compared to the Sumatra Barat province.

Table 3.7. New Estimation Result

Parameters	Full Model	Best Model with VSSR Method
Intercept	0.0807	0.0812 ^a
W*Income	-1.2149***	-1.3289***
Growth	0.0273	-

School	0.4550***	0.4464***
Population Growth	-0.2590 ^a	-0.1964 ^a
Palm Oil Production per Labor	0.4362 ^a	0.2447*
Mining per Labor	-0.1333	-
Wholesale per Labor	0.4742**	0.5566***
Child Labor	-0.3475*	-0.3924**
Altitude	-0.3235 ^a	-0.2545 ^a
W*Growth	0.2752	0.2543 ^a
W*School	0.8062**	0.8413***
W*(Population Growth)	-0.2496	-0.4493 ^a
W*(Palm Oil Production per Labor)	0.2038	-
W*(Mining per Labor)	-0.5761	-
W*(Wholesale per Labor)	0.9912***	0.9582***
W*(Child Labor)	-0.7298*	-0.7530**
W*(Altitude)	-2.4943*	-2.4154***
Lambda ($\hat{\lambda}$)	0.6465	0.6303
Adj. R-squared	0.8381	0.8474
AIC	51.4633	45.0998
BIC	94.3260	79.3899
Note: ***) Significant at level < 1%. **) Significant at 1%. *) Significant at 5%. a) Significant at 10%.		

3.10. Concluding Remarks

The usage of SDG indicators for regional analysis captures a wider perspective of environmental implications as an impact of economic activities. Both factors can be constructed through econometric spatial regression.

This chapter provided a novel calculation of VSSR method for looking the best combination. The method exposed major factors between economic and environmental interlinkages by variable selection among the spatial models without a priori assumptions.

By using Sumatra Island data between 2011-2017, the results showed that regional income has negative relationships with neighboring regions' income, mining, and child ratio to population. On the other hand, secondary school enrollment ratio, palm oil production per capita, and wholesale per capita positively affected regional income.

The inclusion of standard deviation value for altitude as an additional variable into the analysis provide a better model to explain the data, based on a decreasing value of AIC. The negative and significant coefficient of altitude variable indicated that highly produced oil palm

plantation only occurred in several provinces that has a vast areas and flat topography profiles that more suitable for this industry.

3.11. Future Works

The result offers an initial preparation for further spatial analysis by incorporating satellite data to quantify the environmental implication of palm oil and mining industry in Sumatra (SDG **Goals 15, Target 15.1**), such as forest cover loss (Hansen et al., 2013) or vegetation indicators from Normalized Difference Vegetation Index (NDVI) for the future works.

NDVI is an index used to determine density of green on land as an indicator of vegetation density and calculated as follows (NASA Earth Observatory, 2000),

$$NDVI = (NIR - Red)/(NIR + Red)$$

where NIR is near infrared and red (visible) value of satellite product that captures the sunlight reflected by the plants. If NDVI value close to one, then the region has denser vegetation area. Otherwis, if NDVI close to zero, then there is no vegetation in the observed area.

For future research, the remote sensing technique also can be used to overcome the data limitation that occurred in this analysis, especially to obtain a consistent forest cover area data for Sumatra Island. The other solution is to use analysis ready data, such as NASA Open Data Cube. This dataset storing rich information for full spatial and temporal coverage of earth observation (Lewis et al., 2017). Unfortunately, at this current stage, this dataset still an ongoing project and does not provide data for Sumatra Island. The other solution is to obtain consistent forest cover data is using Google Earth Engine (GEE). Kumar and Mutanga (2018) explore the potential of GEE as a platform for study earth observation data.

This chapter shows the brief explanation for future works of data incorporation between socio-economic variable (e.g. income inequality, and child labor participation) and satellite data (e.g. forest cover loss, CO₂ and fire emission). Hence this chapter used municipal based data, then the future works will use the mean or median value for satellite data products that represents for each region in **Figure 1.7**.

The VSSR method in this chapter also offer the possibility the inclusion of previous time value by extending equation (3.1) into dynamic spatial panel model (Elhorst, 2014). This model expressed as follows,

$$\begin{aligned} \mathbf{y}_t &= \alpha \mathbf{1} + \tau \mathbf{y}_{t-1} + \delta \mathbf{W} \mathbf{y}_t + \eta \mathbf{W} \mathbf{y}_{t-1} + \mathbf{X}_t \boldsymbol{\beta}_1 + \mathbf{W} \mathbf{X}_t \boldsymbol{\beta}_2 + \mathbf{X}_{t-1} \boldsymbol{\beta}_3 + \mathbf{W} \mathbf{X}_{t-1} \boldsymbol{\beta}_4 + \mathbf{v}_t \\ \mathbf{v}_t &= \rho \mathbf{v}_{t-1} + \lambda \mathbf{W} \mathbf{v}_t + \boldsymbol{\epsilon}_t, \quad \boldsymbol{\epsilon}_t \sim \text{i.i.d. } N(0, \sigma^2 \mathbf{I}), \quad t = 1, \dots, T \end{aligned}$$

By this inclusion, then not only spatial correlation but also there are three other problem need to deal with. Those are: 1) serial dependence between observations on each spatial unit over time; 2) serial correlation among error terms across time; and 3) correlation between independents variable with error terms.

Cochrane-Orcutt procedure (Cochrane & Orcutt, 1949) commonly used to overcome this serial correlation condition for time series model may be applied into the analysis. However, very few precedent researches that deal with those conditions in dynamic spatial panel model.

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Chapter 4

**Formulation of Huge Lattice Spatial Adjacency Matrices
With Non-rectangular Shape of Socio-economic Grid-Cell
Data for the Analysis of Sustainable Economy With High
Computational Efficiency**

4.1. Introduction

The goals and targets of SDGs example of related analysis that can be achieved by the incorporated data (**Table 4.1**). This approach comprehends not only for sustainable per capita economic growth by increasing economic productivity in the agricultural sector (**Goal 8**) but also for the impact of improper action for agricultural production causing deforestation and desertification (**Goal 15**).

In order to simultaneously analyze those two elements, the incorporation of grid-cell data for socio-economic variables and satellite data shall become a key role. The advantage of using this grid-cell data type of socio-economic variable enriches the regional analysis by incorporating satellite data (Tanaka & Nishii, 2015), such as night-time lights, carbon-dioxide concentration, and vegetation index. It becomes realized due to the availability of grid-cell database for socio-economic variables such as GPWv4, GRUMP, Landscan, Worldpop, and GeoStat (see examples in **Table 4.2**).

Table 4.1. Examples of related sustainable goals and targets for incorporated analysis

Goals	Targets
Goal 8. Promote sustained, inclusive and sustainable economic growth, full and productive employment and decent work for all.	<p>8.1 Sustain per capita economic growth in accordance with national circumstances and, in particular, at least 7 per cent gross domestic product growth per annum in the least developed countries.</p> <p>8.2 Achieve higher levels of economic productivity through diversification, technological upgrading and innovation, including through a focus on high value added and labor-intensive sectors.</p>
Goal 15. Protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss	<p>15.2 By 2020, promote the implementation of sustainable management of all types of forests, halt deforestation, restore degraded forests and substantially increase afforestation and reforestation globally.</p> <p>15.3 By 2030, combat desertification, restore degraded land and soil, including land affected by desertification, drought and floods, and strive to achieve a land degradation-neutral world.</p>

This incorporated dataset should become more convenient due to the improvement of accessibility for earth observation satellite data provided by a database such as NASA ongoing project Open Data Cube (ODC) (ODC Documentation, 2017). The ODC allows storing rich information for full spatial and temporal coverage of earth observation (Lewis et al., 2017).

The objective of this project is to provide an open and freely accessible analysis ready data to increase developing countries capability for the usage space-based Earth observation technologies (Killough, 2017). The web-based architecture providing user-friendly features for data preparation, processing, and visualization. There are ten features available in the ODC such as cloud-free mosaic, NDVI anomaly, water quality, landslide, and urbanization (Open Data Cube, 2018). This recent improvement allows future research to analyze the interrelation between socio-economics and satellite data as a component of achieving the SDG goals and targets.

Table 4.2. Examples of grid-cell data source for socio-economic variables

Database	Method	Data Sets	Data Availability
GPWv4 (source: CIESIN, Columbia University)	Population estimates are created by extrapolating the raw census estimates and proportionally allocated to raster cells using a uniform areal weighting approach to produce the population surfaces.	a. Population density. b. Population count. c. Land and water area d. National identifier grid.	All data contains 2000, 2005, 2010, 2015 with 1 km ² grid resolutions.
LandScan (source: Oak Ridge National Laboratory)	The modeling process uses sub-national level census counts for each country and primary geospatial input or ancillary datasets. For each country, they calculate a “likelihood” coefficient for each cell and applies it to total population.	Global population distribution data.	There are data from 1998 to 2016 (except 1999 data) with 1 km ² grid resolutions.
Worldpop (source: GeoData Institute, University of Southampton)	The dataset produced by disaggregating census data for population mapping using random forest with remotely-sensed and ancillary data (Stevens et al., 2015)	a. Population b. Birth c. Pregnancies d. Urban change e. Age structure The data covers for Africa, Asia, Latin America and the Caribbean.	Dataset a , d , and e are created based on 100 m resolution data. Dataset b and c are 1 km resolution data.
PRIO_GRID	PRIO-GRID is a spatio-temporal grid structure constructed to aid the compilation, management, and analysis of spatial data within a time-consistent framework. PRIO-GRID is constructed by imposing a quadratic grid on the two-dimensional terrestrial plane using vector shapefiles, where each cell in the grid is represented by a square polygon vector feature. (Tollefsen et al, 2012).	Several variables are: a. Agricultural land (Bontemps et al, 2009). b. Child malnutrition (CIESIN, 2005). c. Forest land (Bontemps et al, 2009). d. Gross cell product (GCP) (Nordhaus, 2006) e. Infant mortality rate (Storeygard et al, 2008).	PRIO-GRID is a standardized spatial grid structure dataset with global coverage at a resolution of 0.5 x 0.5 decimal degrees. This roughly 55 x 55 kilometers at the Equator.

		f. Main crop's harvested area (Portmann et al, 2010). g. Total land area (Weidman et al, 2010)	
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Let consider an instance of a spatial analysis with socio-economic variables based on Anselin (1988) spatially lagged autoregressive model,

$$\mathbf{Y} = \alpha \mathbf{i}_N + \delta \mathbf{WY} + \beta_1 \mathbf{x}_1 + \beta_2 \mathbf{x}_2 + \varepsilon$$

where \mathbf{Y} is the crime rate, \mathbf{x}_1 and \mathbf{x}_2 represent household income and housing value respectively, the data size N is the 49 areas in Columbus, Ohio, α is a constant, \mathbf{i}_N is a column vector, δ is the spatial regression coefficient, and $\varepsilon \sim N(0, \sigma^2 \mathbf{I}_N)$. All of the variable matrices have $N \times 1$ dimension. The spatial \mathbf{W} matrix stores the neighborhood relationship for each area, which is an $N \times N$ adjacency matrix. Therefore, the \mathbf{WY} variable represents the influence of neighborhood's crime rate.

The role of \mathbf{W} matrix in the above model is to represent the impact of each neighborhood's crime rate to the neighboring locations. Anselin (1988) and Anselin (1992) showed that based on several estimation methods, the $\hat{\delta}$ values are always positive ($0.3 < \hat{\delta} < 0.5$) and significant. This implies the existence of strong spatial spillover that the crime rate for each location affected by the neighboring values. Those results showed the importance of the \mathbf{W} matrix to capture the spatial relationship of neighboring locations on the analysis.

Bivand, Pebesma, and Gómez-Rubio (2008), Arbia (2014), Dmowska and Stepinski (2017), and Baddeley, Turner, and Rubak (2018), proceeded to carry out the grid-cell data analysis with the extraction of base data by overlaying it with specific regional shapefile in general (ESRI, 1998). The output object and data created by this process then become the base information for the succeeding analysis, which is summarized in **Figure 4.1**. Based on those data types, analysis the neighborhood relation captures inside the data and store it in spatial adjacency matrix \mathbf{W} .

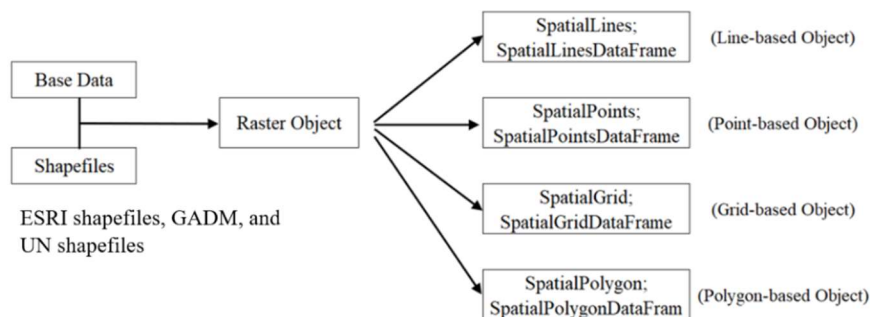
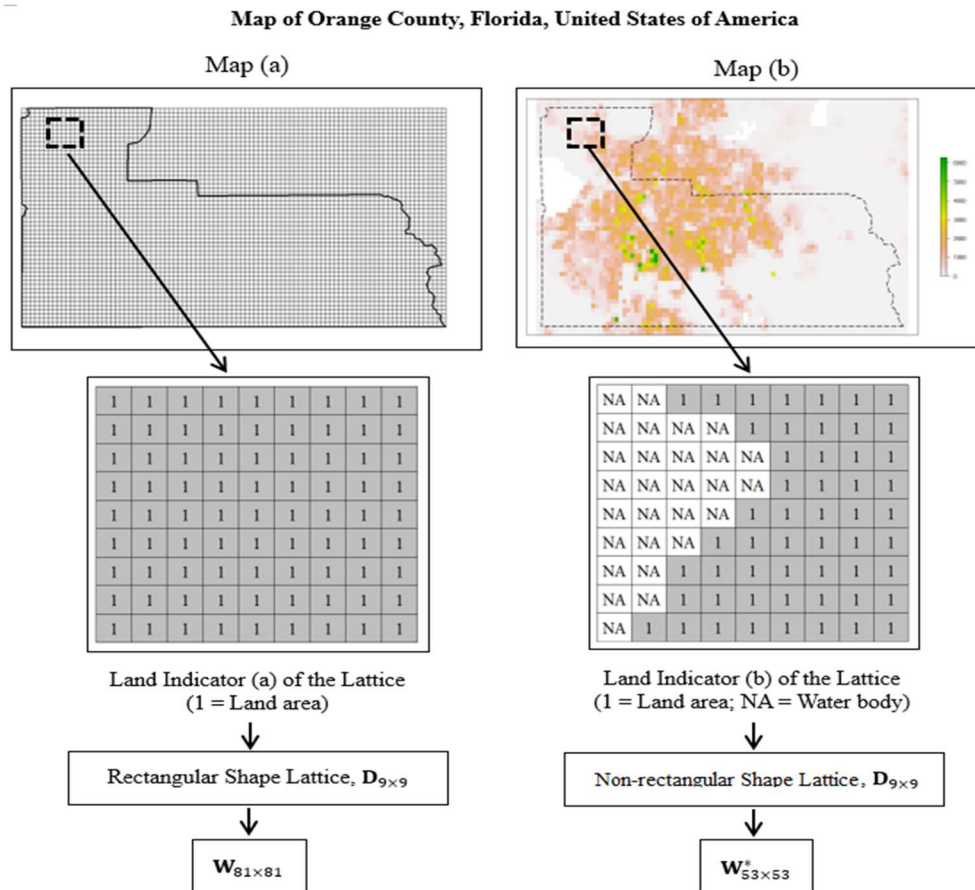


Figure 4.1. General shapefile handling process for spatial analysis

However, this general process based on shapefile is not suitable to derive the \mathbf{W} matrix from grid-cell data because it does not exclude the NA cells inside the administrative area. Lake Apopka, Florida is selected to demonstrate this drawback as shown in **Figure 4.2**.

Figure 4.2 map (a) shows that the shapefile does not reflect the surface information of the lake area in map (b). It is clear that there is no population in water body areas in map (b), which are denoted by NA cells. By using the shapefile rectangular lattice matrix $\mathbf{D}_{9 \times 9}$ is created without identifying the non-inhabitant area as seen on land indicator (a). Thus, misidentification for the possibility of a human settlement exists over non-inhabitant areas will happened. By applying a projection matrix (Tanaka & Nishii, 2009) to exclude the NA cells of non-rectangular $\mathbf{D}_{9 \times 9}$ lattice based on land indicator (b), the correct $\mathbf{W}_{53 \times 53}^*$ can be constructed instead of $\mathbf{W}_{81 \times 81}$.



Source: Map (a): Plot of Administrative Boundaries, from ESRI Shapefile.

Map (b): Plot of Population Density of Orange County, Florida based on GPWv4 for 2010 World Population Density.

Figure 4.2. Comparison of formulation of \mathbf{w} for the neighborhood of eastern area of Lake Apopka, Florida

The importance of correctly formulate \mathbf{W}^* are shown by several precedent researches such as: residential values analysis based on surrounding land use (Geoghegan, Wainger, & Bockstael, 1997), land use change impact to economic and ecological condition (Irwin & Geoghegan, 2001) or rural-urban interface (Bell & Irwin, 2002), and roads impact on deforestation (Nelson & Hellerstein, 1997). Their analysis, in particular, indicated the role of spatial \mathbf{W} matrix to represent windborne seeding effects that the neighboring locations are more likely to have the same vegetation type. By using the correct \mathbf{W}^* , they exactly observed that effect for a vegetative cover area.

Hence this importance of **W** matrix, there should be researches which are focused on how to develop this matrix. Based on the search attempted for precedent research of spatial neighbor matrix, there are 180 researches focused on this subject based on the keyword: *allintitle*: “spatial * matrix” on Google Scholar on 16-20 August 2017. This attempt used to consider a research that focused on the development of spatial neighbor matrix. The result shown on **Appendix 5A**.

This study also found several researches which are not directly related to the development of the **W** matrix by using “spatial * matrix” as their term. Some examples, based on **Appendix 5A** are: Tegmark (1996), Gershman *et al* (1997), Roberts (1999), Roberts (2000), and Snel and Fuller (2010). Those researches are eliminated and summarize only the related topics in **Appendix 5B**. **Appendix 5B** showed 32 of 180 papers, which are considered to have an impact on the development of the matrix formulation.

Aldstald and Getis (2006) do not only provide theoretical construction but also practical technique to apply their theoretical formulation. Unfortunately, the paper used their technique on the distance-based **W** matrix. Therefore, this study could not find any precedent research of the theoretical and practical formulation of binary spatial neighbor matrix **W** in lattice data structure. Row-standardized **W** matrix can be easily derived from the binary process.

This chapter aims to provide not only the theoretical but also practical formulation of spatial neighbor matrix, **W**. The practical section provides several techniques to formulate **W** matrix. There are two methods, that will be compared regarding their efficiency, 1) Kronecker product; and 2) ‘cell2nb’ and ‘poly2nb’ function on *spdep* package in R. *Spdep* package is chosen hence the package is regularly used by the applications of spatial analysis with R language program, such as Bivand *et al* (2008), Arbia (2014), and Kelejian and Piras (2017).

The most efficient method provides a future reference for spatial analysis. This condition is directly correspond to provide minimum computational cost to do spatial analysis research. For example, to analyze satellite data, then the data will contains large lattice structure. For example, satellite data for Jakarta and its neighborhood areas from Landsat Data 8¹¹. The satellite image has 2061×1688 pixels dimension which can be translated into a 2061×1688 dimension matrix. Later section (**Section 4.4**) shows that the efficient methods will have big different impact to deal the large data structure.

4.2. Weighted Neighbor Relation Matrices

4.2.1. Rectangular Lattice

Construction of spatial adjacency matrix based on a spatial lattice matrix, **D**, inherit a spatial information of a lattice cell denoted by s_i at (x_i, y_i) position

$$\mathbf{D} = \{s_i = (x_i, y_i) : i = 1, \dots, Z\} \quad (4.1)$$

¹¹ Data source United States Geological Survey (USGS)

where, $x_i = 1, \dots, c$ and $y_i = 1, \dots, r$, given that r and c are row and column of \mathbf{D} respectively, and $Z = rc$ is the data size on a given rectangular lattice. The neighborhood information for each s_i cell is defined as follows (Cressie 1991, pp. 384-385),

$$N_i = \{s_j = (x_j, y_j) : s_j \text{ is a neighbor cell of } s_i\}, \quad i \neq j, \quad i, j = 1, \dots, Z \quad (4.2)$$

N_i consists of horizontal-vertical and diagonal neighborhood of each cell. There will be $N_i = 8$, which are found by following properties:

$$N_i = \left\{ \begin{array}{l} s(x_j^+, y_i) = (x_i + 1, y_i) \\ s(x_j^+, y_j^+) = (x_i + 1, y_i + 1) \\ s(x_i, y_j^+) = (x_i, y_i + 1) \\ s(x_j^-, y_j^+) = (x_i - 1, y_i + 1) \\ s(x_j^-, y_i) = (x_i - 1, y_i) \\ s(x_j^-, y_j^-) = (x_i - 1, y_i - 1) \\ s(x_i, y_j^-) = (x_i, y_i - 1) \\ s(x_j^+, y_j^-) = (x_i + 1, y_i - 1) \end{array} \right. \quad (4.3)$$

The relation on equation (4.3) can be constructed into following figure based on Tanaka and Nishii (2009),

$s(x_j^-, y_j^+)$	$s(x_i, y_j^+)$	$s(x_j^+, y_j^+)$
$s(x_j^-, y_i)$	$s_i(x, y)$	$s(x_j^+, y_i)$
$s(x_j^-, y_j^-)$	$s(x_i, y_j^-)$	$s(x_j^+, y_j^-)$

Figure 4.3. Nearest Neighbors Grid System of $s(x_i, y_i)$

Construction of N_i on equation (4.3) and **Figure 4.3** defined as *Nearest Neighbor Set* (Cressie, 1991) that captures all possible neighbor cells. N_i structure can be partitioned into two subsets, which are called *Primary Nearest Neighbor* and *Secondary (Oblique) Nearest Neighbor*.

A. Primary Nearest Neighbor Cells (1N)

The 1N structure captures horizontal and vertical neighborho relationships **Figure 4.4a**.

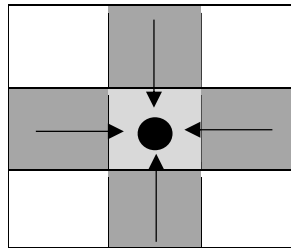


Figure 4.4a. Neighbor Cell Construction of 1N

The list of 1N Cells denotes as $s_1(x_j, y_j)$, which consists of

$$1N_i = \begin{cases} s_1(x_j^+, y_i) = (x_i + 1, y_i) \\ s_1(x_i, y_j^+) = (x_i, y_i + 1) \\ s_1(x_j^-, y_i) = (x_i - 1, y_i) \\ s_1(x_i, y_j^-) = (x_i, y_i - 1) \end{cases}$$

B. Secondary (Oblique) Nearest Neighbors (2N)

The 2N system capture diagonal neighbor relationship that constructed on **Figure 4.4b**.

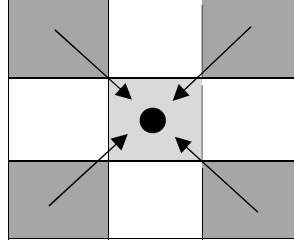


Figure 4.4b. Neighbor Cell Construction of 2N

The list of 2N Cells denotes as $s_2(x_j, y_j)$ consists of,

$$2N_i = \begin{cases} s_2(x_j^+, y_j^+) = (x_i + 1, y_i + 1) \\ s_2(x_j^-, y_j^+) = (x_i - 1, y_i + 1) \\ s_2(x_j^-, y_j^-) = (x_i - 1, y_i - 1) \\ s_2(x_j^+, y_j^-) = (x_i + 1, y_i - 1) \end{cases}$$

Based on those two subsets then $N_i = 1N_i + 2N_i$ as follows,

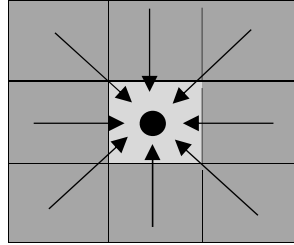


Figure 4.4c. Neighbor Cell Construction of N_i

Therefore, given any **D** image matrix, then the neighbor relation matrix **W** become,

$$\mathbf{W}_{Z \times Z} = \mathbf{W}\mathbf{P}_{Z \times Z} + \mathbf{W}\mathbf{S}_{Z \times Z} \quad (4.4)$$

where, Z is the last cell formed by a (x, y) formation. $\mathbf{W}\mathbf{P}_{Z \times Z}$ is the *primary neighbor* and $\mathbf{W}\mathbf{S}_{Z \times Z}$ is the *secondary neighbor* matrices. The Z value represents “datasize” of matrix $\mathbf{D}_{r \times c}$ hence each $Z \equiv r \times c$ row is represented all $s(x_i, y_i)$.

4.2.2. Non-rectangular Lattice

This subsection showed the construction of spatial **W** matrix corresponds to non-rectangular grid-cell structure, such in **Figure 4.5**. **Figure 4.6** shows an example to construct the neighborhood of cell (1,1), (2,2), and (3,2) on non-rectangular $D_{3 \times 3}$.

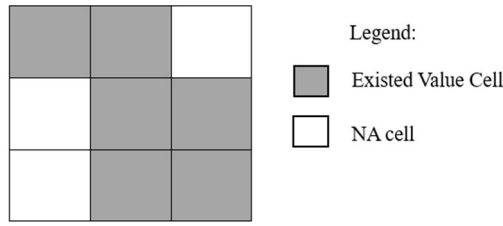


Figure 4.5. Nonrectangular Lattice $\mathbf{D}_{3 \times 3}$

All the neighborhood information is stored on spatial adjacency matrix, $\mathbf{W}_{Z \times Z}$ which includes NA cells. However, as shown in Figure 4, NA cells should be excluded from the analysis. Therefore, the projection matrix on a rectangular case \mathbf{W} based on Tanaka and Nishii (2009) is applied to obtain the real projected \mathbf{W}^* .

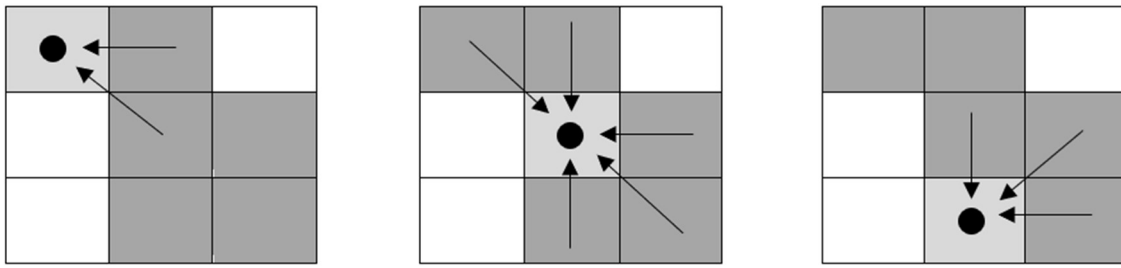


Figure 4.6. Neighborhood Examples for cell (1,1), (2,2), and (3,2) on $\mathbf{D}_{3 \times 3}$

4.3. Formulation of \mathbf{W} Matrices

Formulation of \mathbf{W} as the basis neighborhood information prior to the projection matrix. In nearest neighbor case, based on Cressie and Wikle (2011, p. 167), the $\mathbf{W} \equiv (w_{ij})$ as a $Z \times Z$ matrix with $w_{ii} = 0$ and $w_{ij} = 1$ if cell s_j is the neighbor of s_i as defined on equation (4.2).

4.3.1. Kronecker Product

The formulation utilizes Kronecker product of an identity matrix \mathbf{I}_m and an \mathbf{A}_m matrix which constructed as follows,

$$\mathbf{A}_m = \begin{bmatrix} 0 & 1 & 0 & & 0 & 0 \\ 1 & 0 & 1 & \dots & 0 & 0 \\ 0 & 1 & 0 & & 0 & 0 \\ & \vdots & & \ddots & & \vdots \\ 0 & 0 & 0 & \dots & 0 & 1 \\ 0 & 0 & 0 & \dots & 1 & 0 \end{bmatrix}_{(m \times m)} \quad (4.5)$$

where \mathbf{A}_m has a $m \times m$ dimension which is either $r \times r$, or $c \times c$ given that r and c is the number of row and column of \mathbf{D} respectively. Thus, \mathbf{W} matrix formulated as follows,

$$\mathbf{W}_{\mathbf{P}, Z \times Z} = \mathbf{A}_r \otimes \mathbf{I}_c + \mathbf{I}_r \otimes \mathbf{A}_c, \quad \mathbf{W}_{\mathbf{S}, Z \times Z} = \mathbf{A}_r \otimes \mathbf{A}_c, \quad \text{and} \quad \mathbf{W}_{Z \times Z} = \mathbf{W}_{\mathbf{P}, Z \times Z} + \mathbf{W}_{\mathbf{S}, Z \times Z} \quad (4.6)$$

By using $\mathbf{D}_{3 \times 3}$ image matrix will produce $\mathbf{W}_{(3 \cdot 3) \times (3 \cdot 3)}$. The neighbor searching process constructed the neighbor relation matrix of $\mathbf{W}_{9 \times 9}$ on following **Table 4.3** and **Table 4.4**.

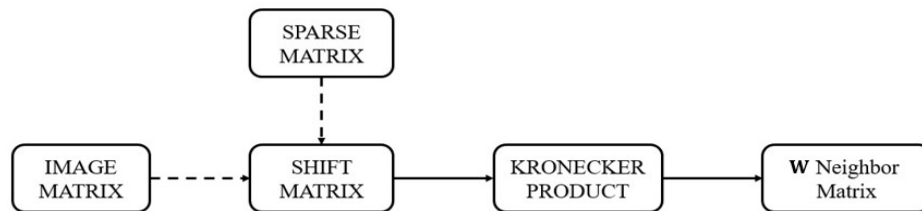
Table 4.3. Construction $\mathbf{W}_{9 \times 9}$ Spatial Weighted Neighborhood Matrix

$s_N(1,1)$	0	1	0	1	1	0	0	0	0
$s_N(1,2)$	1	0	1	1	1	1	0	0	0
$s_N(1,3)$	0	1	0	0	1	1	0	0	0
$s_N(2,1)$	1	1	0	0	1	0	1	1	0
$s_N(2,2)$	1	1	1	1	0	1	1	1	1
$s_N(2,3)$	0	1	1	0	1	0	0	1	1
$s_N(3,1)$	0	0	0	1	1	0	0	1	0
$s_N(3,2)$	0	0	0	1	1	1	1	0	1
$s_N(3,3)$	0	0	0	0	1	1	0	1	0

Table 4.4. Construction $\mathbf{W}_{9 \times 9}$ Weighted Neighborhood Matrix for $1N_i$

$s_1(1,1)$	0	1	0	1	0	0	0	0	0
$s_1(1,2)$	1	0	1	0	1	0	0	0	0
$s_1(1,3)$	0	1	0	0	0	1	0	0	0
$s_1(2,1)$	1	0	0	0	1	0	1	0	0
$s_1(2,2)$	0	1	0	1	0	1	0	1	0
$s_1(2,3)$	0	0	1	0	1	0	0	0	1
$s_1(3,1)$	0	0	0	1	0	0	0	1	0
$s_1(3,2)$	0	0	0	0	1	0	1	0	1
$s_1(3,3)$	0	0	0	0	0	1	0	1	0

The $\mathbf{W}_{Z \times Z}$ consists of two components, primary ($\mathbf{W}_{P,Z \times Z}$) and secondary neighborhood ($\mathbf{W}_{S,Z \times Z}$). Practically, in R language program, equation (4.6) can be run by Script 4.1 which applies sparse matrix library by using *Matrix* package (Bates & Maechler, 2017). As general, the process for Kronecker product methods as follows,

**Figure 4.7.** Kronecker Product Method by using Shift Matrix

```

## Constructing the Function* ##
A.mat <- function(dims){
  B <- as(diag(1, dims-1, dims-1), "CsparseMatrix")

```

```

D ← as(matrix(rep(0, dims), nrow = dims, ncol = 1), "CsparseMatrix")
E ← cbind(rbind(t(D[1:(dims-1),]),B), D)
return(t(E) + E)
}

library(Matrix)
r = r; c = c
ic ← as(diag(1, ncol = c, nrow = c), "CsparseMatrix")
ir ← as(diag(1, ncol = r, nrow = r), "CsparseMatrix")
ac ← A.mat(c); ar ← A.mat(r)

# Construct the Spatial W Matrix #
W ← kronecker(ar, ic) + kronecker(ir, ac) + kronecker(ar, ac)

```

Script 4.1. Kronecker Product to Construct W

Note: *) r and c is the number of rows and columns of **D** and ‘dims’ is referred to the value of r or c .

4.3.2. Polygon and Cell Based on *spdep* R Package

The *spdep* R package is a widely used library to analyze spatial research. One of two functions are ‘poly2nb’ and ‘cell2nb’. As general, process of execution of those two functions is shown on **Figure 8a** and **Figure 8b**.

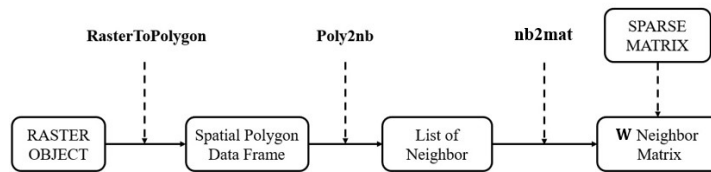


Figure 4.8a. Illustration of ‘poly2nb’ Process

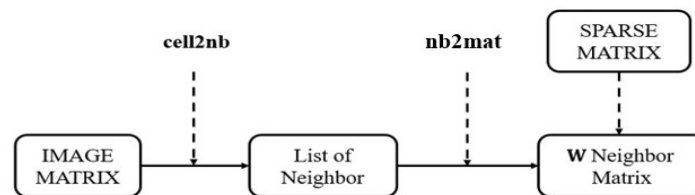


Figure 4.8b. Illustration of ‘cell2nb’ Process

Based on **Figure 4.8a** and **Figure 4.8b**, the ‘cell2nb’ and ‘poly2nb’ function are used to generate a neighbor list class for each cell within an image matrix. In order to convert that list into spatial neighbor matrix, ‘nb2mat’ functionality within the package is needed.

```

library(raster); library(sp); library(spdep)

# Block 1–Block 3 #
poly.sim ← rasterToPolygons(raster.sim)
nb.sim ← poly2nb(poly.sim, queen = T)
mat.nb.sim ← as(nb2mat(nb.sim, style = "B"), "CsparseMatrix")

```

Script 4.2. Poly2nb Method

```
library(raster); library(sp); library(spdep)

# Block 1 and Block 2 #
nb.cell      ← cell2nb(nrow = row, ncol = col, type = "queen")
nb.mat.cell ← as(nb2mat(nb.cell, style = "B"), "CsparseMatrix")
```

Script 4.3. Cell2nb Method

Unfortunately, the ‘nb2mat’ functionality does not provide the *sparse* option. In order to create a **W** sparse matrix for the matrix output, the matrix output from ‘nb2mat’ function should be transformed using ‘CsparseMatrix’ function. In this case, the combine the *spdep* package with *Matrix* package is needed.

4.3.3. Kronecker Product for Non-rectangular Case

To eliminate NA cells in the non-rectangular case, a projection matrix (**P**) based on Tanaka and Nishii (2009) is needed.

$$\mathbf{W}_{\mathcal{V} \times \mathcal{V}}^* = \mathbf{P}_{\mathcal{Z} \times \mathcal{V}}^T \mathbf{W}_{\mathcal{Z} \times \mathcal{Z}} \mathbf{P}_{\mathcal{Z} \times \mathcal{V}} \quad (4.7)$$

where \mathcal{V} represents the number of valid value cells (see Script 4.4 to run equation (4.7)).

```
# Let us assume the spatial lattice matrix D as ‘base’ object #
# Identify the valid value cells on D and store the information in ‘no.na’ object* #
# The ‘NA’ values are originated from grid-cells such as GPWv4 #
no.na ← which(as.numeric(t(base)) != 'NA', arr.ind = TRUE)

library(Matrix)
P ← as(matrix(0, nrow = (ncol(base)*nrow(base)), ncol = length(no.na)), "CsparseMatrix")

count = 0
for (i in 1:nrow(P)){
  if (is.element(i, no.na)){
    count = count+1;
    P[i, count] ← 1;
  }
}

# NA Removal through multiplication of projection matrix
W_star ← t(P) %*% W %*% P
```

Script 4.4. R Script for projection matrix

Note: *) The transpose of D matrix is necessary due to the default system of cell-indexing matrix in R which started from the row and the cell-indexing format for equation (4.4) is inserted by column.

4.4. Computational Efficiency Comparison: A Simulation

This section also compared the actual computational among the existing methods. The method computations are executed by each block within each method's Script and calculated by using R Core utility function called 'system.time' for elapsed time and 'object.size'. 'system.time' function calculated how long CPU times need to return each R expression execute (R v.3.4.0 Documentation, 2017). All computational simulations are conducted by using following computational environment on **Table 4.5**.

This section compared the performance of Kronecker Product method with 'cell2nb' and 'nb2mat' functions in *spdep* package. Note that 'poly2nb' function is commonly used based on the polygon object, but that is not suitable for the purposes of this article focusing only on grid-cell data. The actual computational space and time are measured based on several **D** matrices. All simulations were conducted using the computational environment in **Table 4.5** and a basic assumption there are no NA cells for all **D**. The assumption is used to simplify the simulation process since the processes.

Table 4.5. Computational environments for simulations

Computational Environment		
Processor		Intel core i7-6700K, 4 GHz, 8 MB
Memory		DDR4-2133 64 GB (16 GB x 4 slots)
R version	Main Body	3.4.2 (64-bit)
	Library (<i>Matrix</i>)	1.2-11
	Library (<i>spdep</i>)	0.7-7
	Library (<i>raster</i>)	2.5-8

This chapter also build the matrix simulation for $\mathbf{W}_{Z \times Z}$ in form of *Sparse Matrix* using R language. Sparse matrix used in order to avoid overflow. Overflow is occurred when the memory space that is needed to construct any object is surpassed memory limit in the system. For example, if an integer value input as an element value of a matrix, then the object will have 208 bytes memory object, where an integer object itself consume 48 bytes memory¹² in R language. On the other hand, sparse matrix object generally built to under construction that zero entries need not to be represented, which has impact to decrease amounts of memory (Knuth, 1973) by using Boolean or logical value, instead of integer value. This condition will derive an advantage of sparse matrix object.

¹² The value is defined by computing one integer value space in R by using 'object.size' function of R. On the other hand, 208 bytes is needed to store one integer value on 1×1 dimension regular matrix. Even though, 1×1 dimension sparse matrix need 1632 bytes to store 1 integer value, but in the bigger dimension will have less memory space for sparse matrix object.

This advantages of using sparse matrix method instead of the regular matrix illustrated by comparing space requirement to build the adjacency matrix, $\mathbf{W}_{Z \times Z}$, for every spatial lattice matrices, $\mathbf{D}_{r \times c}$. Space requirement is calculated by using ‘object.size’ function. This function provides an estimate of each memory that is being used to store an R object (R Core, 2017).

To build Sparse Matrix by R language, ‘sparseMatrix’ function on *Matrix* package is used, especially build as ‘dgCMatrix’ class. dgCMatrix class is a class of sparse numeric matrices in the compressed, sparse, column-oriented format (Maechler and Bates, 2006).

Table 4.6, showed that Kronecker product method is more than 2000 times faster for the largest \mathbf{W} . All the results obviously indicate that the Kronecker product method produces the best result, especially for larger dimension cases. **Table 4.7** showed actual object memory size comparison of both methods. The results also show that this method consumed 1/3 times less memory compared to ‘cell2nb’ and ‘nb2mat’.

The reason why the two *spdep* methods (especially ‘poly2nb’ method) are consumed a lot of space because during the construction process is not based on matrix sparse class but in form of list class. Furthermore, in the original function of ‘poly2nb’ in *spdep* function, there is no methods to convert list class on neighbor list class (the result of ‘poly2nb’ function) into \mathbf{W} sparse matrix class. However, there is the tricky part to convert the list into \mathbf{W} sparse matrix class, by using ‘as’ and ‘CsparseMatrix’.

The original steps to construct spatial neighbor matrix based on *spdep* guidance as follows,

$$\text{polygon} \xrightarrow{\text{'poly2nb'}} \text{neighbor list} \xrightarrow{\text{'nb2mat'}} \mathbf{W} \text{ matrix}$$

Based on those original steps, then will create a sparse matrix class object. Therefore, the combination *spdep* with *Matrix* package as follows,

$$\text{polygon} \xrightarrow{\text{'poly2nb'}} \text{neighbor list} \xrightarrow[\text{as "CsparseMatrix"}]{\text{'nb2mat' +}} \mathbf{W} \text{ matrix}$$

However, even though this step is applied into this simulations, ‘poly2nb’ method still requires most space during construction of \mathbf{W} matrix. **Table 4.7** is provided in sparse matrix construction, rather than the original one. **Figures 4.9** and **4.10** provides graphics comparison of memory size and elapsed time between Kronecker product and *spdep* method.

Table 4.6. Total elapsed time comparison for all methods *

Spatial Lattice Matrix ($\mathbf{D}_{r \times c}$)	W Elements (Z^2)	Script 4.1	‘cell2nb’ and ‘nb2mat’
$\mathbf{D}_{3 \times 3}$	81	0.005	0.012
$\mathbf{D}_{60 \times 60}$	1.296×10^7	0.006	1.223

$\mathbf{D}_{120 \times 120}$	2.074×10^8	0.008	4.838
$\mathbf{D}_{180 \times 180}$	1.050×10^9	0.011	10.932
$\mathbf{D}_{240 \times 240}$	3.318×10^9	0.018	19.722
$\mathbf{D}_{300 \times 300}$	8.100×10^9	0.025	31.117
$\mathbf{D}_{330 \times 330}$	1.186×10^{10}	0.052	37.790
$\mathbf{D}_{500 \times 500}$	6.250×10^{10}	0.137	108.191
$\mathbf{D}_{1000 \times 1000}$	1.000×10^{12}	0.234	492.589

Note: *) Each elapsed time for generic function in **Script 4.1** is an average of 100 times iteration. On the other hand, ‘cell2nb’ and ‘nb2mat’ method is measured once by considering the amount of time needed to run.

Table 4.7. Actual object memory size comparison between all methods* (in MB)

Spatial Lattice Matrix ($\mathbf{D}_{r \times c}$)	W Elements (Z^2)	Script 4.1	‘cell2nb’ and ‘nb2mat’
$\mathbf{D}_{3 \times 3}$	81	0.008	0.006
$\mathbf{D}_{60 \times 60}$	1.296×10^7	0.462	1.247
$\mathbf{D}_{120 \times 120}$	2.074×10^8	1.838	4.997
$\mathbf{D}_{180 \times 180}$	1.050×10^9	4.136	11.252
$\mathbf{D}_{240 \times 240}$	3.318×10^9	7.355	20.013
$\mathbf{D}_{300 \times 300}$	8.100×10^9	11.496	31.280
$\mathbf{D}_{330 \times 330}$	1.186×10^{10}	13.912	37.853
$\mathbf{D}_{500 \times 500}$	6.250×10^{10}	31.955	86.931
$\mathbf{D}_{1000 \times 1000}$	1.000×10^{12}	127.903	347.902

Note: *) All the simulations were done by one-shot run due to the same results produced by any iteration.

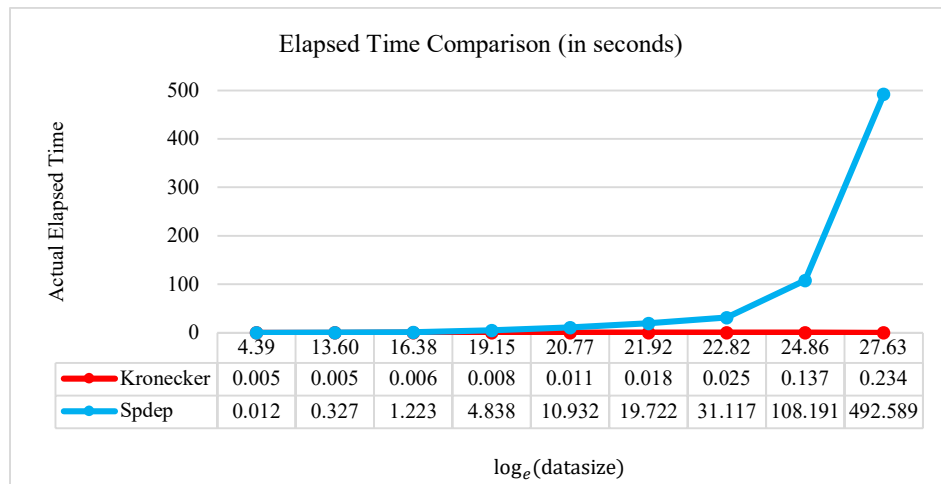


Figure 4.9. Comparison of elapsed time between Script 4.1 and *spdep* method

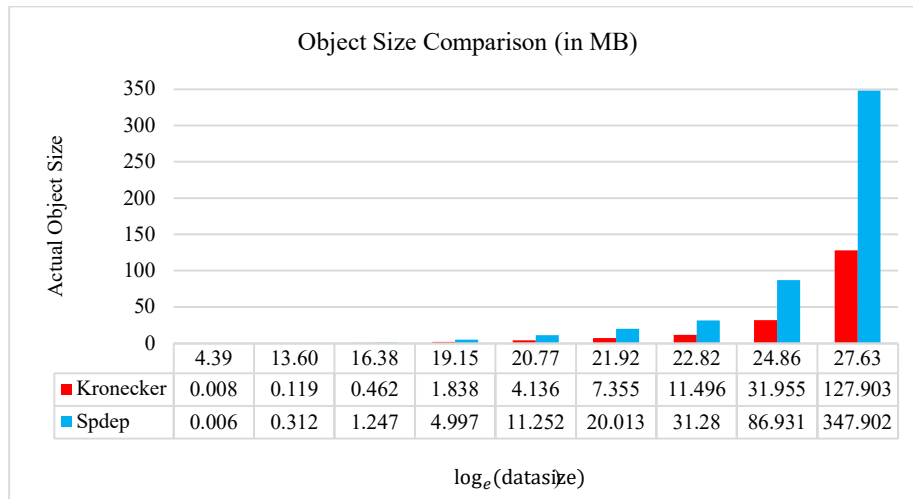


Figure 4.10. Object size comparison between Script 4.1 and *spdep* method

4.5. Kronecker Product Method Performance for Very Large \mathbf{W} Matrices

The simulation for larger \mathbf{W} matrices is essential due to the attempt to incorporate satellite images for higher resolution. Note that Landsat 8 image of Jakarta around the size of 4650×2571 pixels and will generate \mathbf{W} matrix with more than 1.42×10^{15} elements.

Table 4.8 summarizes the experiment for the elapsed time and object memory size. The results show the Kronecker product's handy availability to the formulation of huge \mathbf{W} . Even for 5.063×10^{16} (more than 50 quadrillion) elements, it can produce the matrix in less than one minute.

Table 4.8. Kronecker product method performances for larger \mathbf{W} Matrices*

Spatial Lattice Matrix ($\mathbf{D}_{r \times c}$)	\mathbf{W} Elements (Z^2)	Elapsed Time (in seconds)	Object Memory Size
$\mathbf{D}_{2500 \times 2500}$	3.906×10^{13}	1.45404	799.75 MB
$\mathbf{D}_{5000 \times 5000}$	6.250×10^{14}	5.91074	3.20 GB
$\mathbf{D}_{7500 \times 7500}$	3.164×10^{15}	13.49425	7.20 GB
$\mathbf{D}_{10000 \times 10000}$	1.000×10^{16}	25.14439	12.80 GB
$\mathbf{D}_{15000 \times 15000}$	5.063×10^{16}	55.90863	28.80 GB

Note: *) Each elapsed time is an average of 100 iteration times, but for the memory size run once.

4.6. Concluding Remarks

To achieve the SDGs, focus study not only on the increasing economic growth, but also on the environmental sustainability are equally related and important. To observed them, the incorporation of grid-cell data for socio-economic variables and satellite data plays the key role.

Nonetheless, there were still few precedent researches that utilize those data for the analysis, which counts the adjacency interaction, such as Nelson and Hellerstein (1997) and Tanaka and Nishii (2015). It should be more desirable to carry out multi-dimensional quantitative analysis,

such as dynamic spatial panel analysis (Elhorst, 2014). Spatio-temporal model will generate more sophisticated analysis for sustainable development based on SDG indicators (UNSTATS, 2018).

To capture the interrelations between the two indicators, the use of spatial adjacency matrices (\mathbf{W}) provides much more precise and sophisticated analysis as stated in the Introduction. The general approach by using shapefiles is failed to project NA cells inside the municipal body. The utilization of Kronecker product used to formulate a rectangular \mathbf{W} and apply the projection matrix to correctly construct the non-rectangular \mathbf{W}^* .

This chapter provides an eminent efficiency to construct the \mathbf{W} . The results showed that Kronecker product method can generate them more than 2000 times faster and with three times less space than the commonly used R package, ‘cell2nb’ and ‘nb2mat’ functions of *spdep*. Efficient process is important to handle huge data size, due to the increase of resolution, especially to deal with the satellite data. This approach would give practical insights for statistical imputation such as NA cell case of the neighbors and spatial interpolation.

4.7. Future Works

The advantage of procedure in this chapter is to provide highly efficient to formulate spatial neighborhood matrix in regular lattice structure with very large datasize. This supports the future work on how to incorporate regional analysis between socio-economic and satellite data in gridded structure.

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Appendix 1

**List of Global Indicator Framework for the Sustainable
Goals and Targets**

**Global indicator framework for the Sustainable Development Goals
and targets of the 2030 Agenda for Sustainable Development
(UNSTATS, 2018)¹³**

Goals and Targets	Indicator(s)	Statistics Indonesia Data*
Goal 1 End poverty in all its forms everywhere		
1.1. By 2030, eradicate extreme poverty for all people everywhere, currently measured as people living on less than \$1.25 a day.	1.1.1. Proportion of population below the international poverty line, by sex, age, employment status and geographical location (urban/rural).	1.1.1. Proportion of population below the international poverty line (1,90 USD a day), 1990-2016. 1.1.2. Poverty severity index by districts/cities, 2015-2017. 1.1.3. Number and percentage of poor people, poverty line, poverty gap index, poverty severity index by province, 2007-2009 (March), 2010-2011, 2012 (March-September).
1.2. By 2030, reduce at least by half the proportion of men, women and children of all ages living in poverty in all its dimensions according to national definitions.	1.2.1. Proportion of population living below the national poverty line, by sex and age. 1.2.2. Proportion of men, women and children of all ages living in poverty in all its dimensions according to national definitions.	
1.3. Implement nationally appropriate social protection systems and measures for all, including floors, and by 2030 achieve substantial coverage of the poor and the vulnerable.	1.3.1. Proportion of population covered by social protection floors/systems, by sex, distinguishing children, unemployed persons, older persons, persons with disabilities, pregnant women, newborns, work-injury victims and the poor and the vulnerable.	
1.4. By 2030, ensure that all men and women, in particular the poor and the vulnerable, have equal rights to economic resources, as well as access to basic services, ownership and control over land and other forms of property, inheritance, natural resources, appropriate new technology and financial services, including microfinance.	1.4.1. Proportion of population living in households with access to basic services. 1.4.2. Proportion of total adult population with secure tenure rights to land, (a) with legally recognized documentation, and (b) who perceive their rights to land as secure, by sex and type of tenure.	
1.5. By 2030, build the resilience of the poor and those in vulnerable situations and reduce their exposure and vulnerability to climate-related extreme events and other	1.5.1. Number of deaths, missing persons and directly affected persons attributed to disasters per 100,000 population. 1.5.2. Direct economic loss attributed to disasters in relation to	Number of deaths, missing persons and directly affected persons attributed to disasters per 100,000 population, 2011-2016.

¹³ Retrieved from: <https://unstats.un.org/sdgs/indicators/indicators-list/>

economic, social and environmental shocks and disasters.	global gross domestic product (GDP). 1.5.3. Number of countries that adopt and implement national disaster risk reduction strategies in line with the Sendai Framework for Disaster Risk Reduction 2015–2030. 1.5.4. Proportion of local governments that adopt and implement local disaster risk reduction strategies in line with national disaster risk reduction strategies.	
1.a. Ensure significant mobilization of resources from a variety of sources, including through enhanced development cooperation, in order to provide adequate and predictable means for developing countries, in particular least developed countries, to implement programs and policies to end poverty in all its dimensions.	1.a.1. Proportion of domestically generated resources allocated by the government directly to poverty reduction programs 1.a.2. Proportion of total government spending on essential services (education, health and social protection). 1.a.3. Sum of total grants and non-debt-creating inflows directly allocated to poverty reduction programs as a proportion of GDP.	
1.b. Create sound policy frameworks at the national, regional and international levels, based on pro-poor and gender-sensitive development strategies, to support accelerated investment in poverty eradication actions.	1.b.1. Proportion of government recurrent and capital spending to sectors that disproportionately benefit women, the poor and vulnerable groups	
Goal 2		
End hunger, achieve food security and improved nutrition and promote sustainable agriculture.		
2.1. By 2030, end hunger and ensure access by all people, in particular the poor and people in vulnerable situations, including infants, to safe, nutritious and sufficient food all year round.	2.1.1. Prevalence of undernourishment 2.5.2. Prevalence of moderate or severe food insecurity in the population, based on the Food Insecurity Experience Scale (FIES).	2.1.1. Proportion of population with minimum calories intake 1440 per day by residences, expenditure level, or province, 2015-2017. 2.1.2. Prevalence of food insecurities, 2011 and 2017. 2.1.3. Prevalence of food insecurities among population, based on Food Insecurity Experience Scale (FIES).
2.2. By 2030, end all forms of malnutrition, including achieving, by 2025, the internationally agreed targets on stunting and wasting in children under 5 years of age, and address the nutritional needs of adolescent girls, pregnant and	2.2.1. Prevalence of stunting (height for age <- 2 standard deviation from the median of the World Health Organization (WHO) Child Growth Standards) among children under 5 years of age. 2.2.2. Prevalence of malnutrition (weight for height >+2 or <-2	2.2.1. Percentage of infant (less than 6 months) that received exclusive breast-feeding program by province and gender, 2015-2016. 2.2.2. Percentage of short and very short children under 5 years of age, 2015-2016.

lactating women and older persons.	standard deviation from the median of the WHO Child Growth Standards) among children under 5 years of age, by type (wasting and overweight).	2.2.3. Percentage of short and very short children under 2 years of age, 2015-2016. 2.2.4. Prevalence of anemia for pregnant mother, 2013.
2.3. By 2030, double the agricultural productivity and incomes of small-scale food producers, in particular women, indigenous peoples, family farmers, pastoralists and fishers, including through secure and equal access to land, other productive resources and inputs, knowledge, financial services, markets and opportunities for value addition and non-farm employment.	2.3.1. Volume of production per labor unit by classes of farming/pastoral/forestry enterprise size. 2.3.2. Average income of small-scale food producers, by sex and indigenous status.	2.3.1. Ratio of agricultural value added and labor force in agricultural sector, 2015-2016.
2.4. By 2030, ensure sustainable food production systems and implement resilient agricultural practices that increase productivity and production, that help maintain ecosystems, that strengthen capacity for adaptation to climate change, extreme weather, drought, flooding and other disasters and that progressively improve land and soil quality	2.4.1. Proportion of agricultural area under productive and sustainable agriculture.	
2.a. Increase investment, including through enhanced international cooperation, in rural infrastructure, agricultural research and extension services, technology development and plant and livestock gene banks in order to enhance agricultural productive capacity in developing countries, in particular least developed countries.	2.a.1. The agriculture orientation index for government expenditures.	
2.b. Correct and prevent trade restrictions and distortions in world agricultural markets, including through the parallel elimination of all forms of agricultural export subsidies and all export measures with equivalent effect, in accordance with the mandate of the Doha Development Round	2.b.1 Agricultural export subsidies.	
2.c. Adopt measures to ensure the proper functioning of food commodity markets and their derivatives and facilitate timely access to market information, including on food reserves, in order to help limit extreme food price volatility.	2.c.1. Indicator of food price anomalies.	

Goal 3 Ensure healthy lives and promote well-being for all at all ages.		
3.1. By 2030, reduce the global maternal mortality ratio to less than 70 per 100,000 live births.	3.1.1. Maternal mortality ratio. 3.1.2. Proportion of births attended by skilled health personnel.	
3.2. By 2030, end preventable deaths of newborns and children under 5 years of age, with all countries aiming to reduce neonatal mortality to at least as low as 12 per 1,000 live births and under-5 mortality to at least as low as 25 per 1,000 live births.	3.2.1. Maternal mortality ratio. 3.2.2. Proportion of births attended by skilled health personnel. 3.2.3. Under-5 mortality rate.	3.2.1. Mortality rate for mother by island, 2015. 3.2.2. Percentage of obese children under 5 year of age. 3.2.3. Under-5 mortality rate per 1,000 live births by province, 2012.
3.3. By 2030, end the epidemics of AIDS, tuberculosis, malaria and neglected tropical diseases and combat hepatitis, water-borne diseases and other communicable diseases.	3.3.1. Number of new HIV infections per 1,000 uninfected population, by sex, age and key populations. 3.3.2. Tuberculosis incidence per 100,000 population. 3.3.3. Malaria incidence per 1,000 population. 3.3.4. Hepatitis B incidence per 100,000 population. 3.3.5. Number of people requiring interventions against neglected tropical diseases.	3.3.1. Malaria incidence per 1000 population by province, 2015-2016.
3.4. By 2030, reduce by one third premature mortality from non-communicable diseases through prevention and treatment and promote mental health and well-being.	3.4.1. Mortality rate attributed to cardiovascular disease, cancer, diabetes or chronic respiratory disease. 3.4.2. Suicide mortality rate.	
3.5. Strengthen the prevention and treatment of substance abuse, including narcotic drug abuse and harmful use of alcohol.	3.5.1. Coverage of treatment interventions (pharmacological, psychosocial and rehabilitation and aftercare services) for substance use disorders. 3.5.2. Harmful use of alcohol, defined according to the national context as alcohol per capita consumption (aged 15 years and older) within a calendar year in liters of pure alcohol.	3.5.1. Annual alcohol consumption by population over 15 years of age, 2015-2017.
3.6. By 2020, halve the number of global deaths and injuries from road traffic accidents.	3.6.1. Death rate due to road traffic injuries.	
3.7. By 2030, ensure universal access to sexual and reproductive health-care services, including for family planning, information and education, and the integration of reproductive health into national strategies and programs.	3.7.1. Proportion of women of reproductive age (aged 15–49 years) who have their need for family planning satisfied with modern methods. 3.7.2. Adolescent birth rate (aged 10–14 years; aged 15–19 years) per 1,000 women in that age group.	3.7.1. Proportion of married women (aged 15–49 years) who have their need for family planning satisfied with modern methods, 2012. 3.7.2. Proportion of married women (aged 15–49 years) who gave birth by skilled health worker by residences, expenditure level, or province, 2015-2016.

		<p>3.7.3. Proportion of married women (aged 15–49 years) who gave birth in medical facility by residences, expenditure level, or province, 2015-2016.</p> <p>3.7.4. Proportion of women of reproductive age (aged 15–49 years) who have their need for family planning satisfied with modern methods, 2012.</p>
3.8. Achieve universal health coverage, including financial risk protection, access to quality essential health-care services and access to safe, effective, quality and affordable essential medicines and vaccines for all.	<p>3.8.1. Coverage of essential health services (defined as the average coverage of essential services based on tracer interventions that include reproductive, maternal, newborn and child health, infectious diseases, non-communicable diseases and service capacity and access, among the general and the most disadvantaged population).</p> <p>3.8.2. Proportion of population with large household expenditures on health as a share of total household expenditure or income.</p>	
3.9. By 2030, substantially reduce the number of deaths and illnesses from hazardous chemicals and air, water and soil pollution and contamination.	<p>3.9.1. Mortality rate attributed to household and ambient air pollution.</p> <p>3.9.2. Mortality rate attributed to unsafe water, unsafe sanitation and lack of hygiene (exposure to unsafe Water, Sanitation and Hygiene for All (WASH) services).</p> <p>3.9.3. Mortality rate attributed to unintentional poisoning.</p>	
3.a. Strengthen the implementation of the World Health Organization Framework Convention on Tobacco Control in all countries, as appropriate.	3.a.1. Age-standardized prevalence of current tobacco use among persons aged 15 years and older.	
3.b. Support the research and development of vaccines and medicines for the communicable and non-communicable diseases that primarily affect developing countries, provide access to affordable essential medicines and vaccines, in accordance with the Doha Declaration on the TRIPS Agreement and Public Health, which affirms the right of developing countries to use to the full the provisions in the Agreement on Trade-Related Aspects of Intellectual Property Rights regarding flexibilities to protect public	<p>3.b.1. Proportion of the target population covered by all vaccines included in their national program.</p> <p>3.b.2. Total net official development assistance to medical research and basic health sectors.</p> <p>3.b.3. Proportion of health facilities that have a core set of relevant essential medicines available and affordable on a sustainable basis.</p>	

health, and, in particular, provide access to medicines for all.		
3.c. Substantially increase health financing and the recruitment, development, training and retention of the health workforce in developing countries, especially in least developed countries and small island developing States.	3.c.1. Health worker density and distribution.	3.c.1. Health worker density and distribution.
3.d. Strengthen the capacity of all countries, in particular developing countries, for early warning, risk reduction and management of national and global health risks.	3.d.1. International Health Regulations (IHR) capacity and health emergency preparedness.	
Goal 4 Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all.		
4.1. By 2030, ensure that all girls and boys complete free, equitable and quality primary and secondary education leading to relevant and effective learning outcomes.	4.1.1. Proportion of children and young people (a) in grades 2/3; (b) at the end of primary; and (c) at the end of lower secondary achieving at least a minimum proficiency level in (i) reading and (ii) mathematics, by sex.	4.1.1. Proportion of children in grades 4 achieving at least a minimum proficiency level in (i) reading and (ii) mathematics, 2017.
4.2. By 2030, ensure that all girls and boys have access to quality early childhood development, care and pre-primary education so that they are ready for primary education.	4.2.1. Proportion of children under 5 years of age who are developmentally on track in health, learning and psychosocial well-being, by sex. 4.2.2. Participation rate in organized learning (one year before the official primary entry age), by sex.	
4.3. By 2030, ensure equal access for all women and men to affordable and quality technical, vocational and tertiary education, including university.	4.3.1. Participation rate of youth and adults in formal and non-formal education and training in the previous 12 months, by sex.	4.3.1. Elementary school net enrolment rate (NER), by gender and region type, 2009-2017. 4.3.2. Junior high school NER, by gender and region type, 2009-2017. 4.3.3. Senior high school NER by gender and region type, 2009-2017. 4.3.4. Gender ratio of NER in the college by expenditure level, 2015-2016.
4.4. By 2030, substantially increase the number of youth and adults who have relevant skills, including technical and vocational skills, for employment, decent jobs and entrepreneurship.	4.4.1. Proportion of youth and adults with information and communications technology (ICT) skills, by type of skill.	4.4.1. Proportion of youth and adults (15-59 years of age) with information and communications technology (ICT) skills, by province, 2015-2016. 4.4.2. Proportion of youth and adults (15-24 years of age) with information and

		communications technology (ICT) skills, by province, 2015-2016.
4.5. By 2030, eliminate gender disparities in education and ensure equal access to all levels of education and vocational training for the vulnerable, including persons with disabilities, indigenous peoples and children in vulnerable situations.	4.5.1. Parity indices (female/male, rural/urban, bottom/top wealth quintile and others such as disability status, indigenous peoples and conflict-affected, as data become available) for all education indicators on this list that can be disaggregated.	
4.6. By 2030, ensure that all youth and a substantial proportion of adults, both men and women, achieve literacy and numeracy.	4.6.1. Proportion of population in a given age group achieving at least a fixed level of proficiency in functional (a) literacy and (b) numeracy skills, by sex.	
4.7. By 2030, ensure that all learners acquire the knowledge and skills needed to promote sustainable development, including, among others, through education for sustainable development and sustainable lifestyles, human rights, gender equality, promotion of a culture of peace and non-violence, global citizenship and appreciation of cultural diversity and of culture's contribution to sustainable development.	4.7.1. Extent to which (i) global citizenship education and (ii) education for sustainable development, including gender equality and human rights, are mainstreamed at all levels in (a) national education policies; (b) curricula; (c) teacher education; and (d) student assessment.	
4.a. Build and upgrade education facilities that are child, disability and gender sensitive and provide safe, non-violent, inclusive and effective learning environments for all.	4.a.1. Proportion of schools with access to (a) electricity; (b) the Internet for pedagogical purposes; (c) computers for pedagogical purposes; (d) adapted infrastructure and materials for students with disabilities; (e) basic drinking water; (f) single-sex basic sanitation facilities; and (g) basic handwashing facilities (as per the WASH indicator definitions).	
4.b. By 2020, substantially expand globally the number of scholarships available to developing countries, in particular least developed countries, small island developing States and African countries, for enrolment in higher education, including vocational training and information and communications technology, technical, engineering and scientific programs, in developed countries and other developing countries.	4.b.1. Volume of official development assistance flows for scholarships by sector and type of study.	

4.c. By 2030, substantially increase the supply of qualified teachers, including through international cooperation for teacher training in developing countries, especially least developed countries and small island developing States.	4.c.1. Proportion of teachers in: (a) pre-primary; (b) primary; (c) lower secondary; and (d) upper secondary education who have received at least the minimum organized teacher training (e.g. pedagogical training) pre-service or in-service required for teaching at the relevant level in a given country.	
Goal 5 Achieve gender equality and empower all women and girls		
5.1. End all forms of discrimination against all women and girls everywhere.	5.1.1. Whether or not legal frameworks are in place to promote, enforce and monitor equality and non-discrimination on the basis of sex.	
5.2. Eliminate all forms of violence against all women and girls in the public and private spheres, including trafficking and sexual and other types of exploitation.	5.2.1. Proportion of ever-partnered women and girls aged 15 years and older subjected to physical, sexual or psychological violence by a current or former intimate partner in the previous 12 months, by form of violence and by age. 5.2.2. Proportion of women and girls aged 15 years and older subjected to sexual violence by persons other than an intimate partner in the previous 12 months, by age and place of occurrence.	5.2.1. Proportion of women and girls aged 15 years and older subjected to sexual violence by persons other than an intimate partner in the previous 12 months, 2016. 5.2.2. Prevalence of the crime for female children, 2013.
5.3. Eliminate all harmful practices, such as child, early and forced marriage and female genital mutilation.	5.3.1. Proportion of women aged 20–24 years who were married or in a union before age 15 and before age 18. 5.3.2. Proportion of girls and women aged 15–49 years who have undergone female genital mutilation/cutting, by age.	5.3.1. Proportion of women aged 20–24 years who were married or in a union before age 15 and before age 18 by residence or province, 2015–2017.
5.4. Recognize and value unpaid care and domestic work through the provision of public services, infrastructure and social protection policies and the promotion of shared responsibility within the household and the family as nationally appropriate.	5.4.1. Proportion of time spent on unpaid domestic and care work, by sex, age and location.	
5.5. Ensure women's full and effective participation and equal opportunities for leadership at all levels of decision-making in political, economic and public life.	5.5.1. Proportion of seats held by women in (a) national parliaments and (b) local governments. 5.5.2. Proportion of women in managerial positions.	5.5.1. Distribution of managerial positions by gender, 2016.
5.6. Ensure universal access to sexual and reproductive health and reproductive rights as agreed in accordance with the Program of Action of the	5.6.1. Proportion of women aged 15–49 years who make their own informed decisions regarding sexual relations, contraceptive use and reproductive health care.	5.6.1. Percentage of the knowledge and understanding from couples of reproductive-age about

International Conference on Population and Development and the Beijing Platform for Action and the outcome documents of their review conferences.	5.6.2. Number of countries with laws and regulations that guarantee full and equal access to women and men aged 15 years and older to sexual and reproductive health care, information and education.	contraceptive by residency, education level, 2012. 5.6.2. Maternity rate for women 15-19 years of age by province, 2012.
5.a. Undertake reforms to give women equal rights to economic resources, as well as access to ownership and control over land and other forms of property, financial services, inheritance and natural resources, in accordance with national laws.	5.a.1. (a) Proportion of total agricultural population with ownership or secure rights over agricultural land, by sex; and (b) share of women among owners or rights-bearers of agricultural land, by type of tenure. 5.a.2. Proportion of countries where the legal framework (including customary law) guarantees women's equal rights to land ownership and/or control.	
5.b. Enhance the use of enabling technology, in particular information and communications technology, to promote the empowerment of women.	5.b.1. Proportion of individuals who own a mobile telephone, by sex.	5.b.1. Proportion of individuals who own a mobile telephone, by age groups or sex, 2015-2016.
5.c. Adopt and strengthen sound policies and enforceable legislation for the promotion of gender equality and the empowerment of all women and girls at all levels.	5.c.1. Proportion of countries with systems to track and make public allocations for gender equality and women's empowerment.	
Goal 6		
Ensure availability and sustainable management of water and sanitation for all.		
6.1. By 2030, achieve universal and equitable access to safe and affordable drinking water for all.	6.1.1. Proportion of population using safely managed drinking water services	6.1.1. Proportion of population using safely managed drinking water services by residency or province, 2015-2017.
6.2. By 2030, achieve access to adequate and equitable sanitation and hygiene for all and end open defecation, paying special attention to the needs of women and girls and those in vulnerable situations.	6.2.1. Proportion of population using (a) safely managed sanitation services and (b) a hand-washing facility with soap and water.	6.2.1. Proportion of population using (a) safely managed sanitation services and (b) a hand-washing facility with soap and water by residency or province, 2016.
6.3. By 2030, improve water quality by reducing pollution, eliminating dumping and minimizing release of hazardous chemicals and materials, halving the proportion of untreated wastewater and substantially increasing recycling and safe reuse globally.	6.3.1. Proportion of wastewater safely treated. 6.3.2. Proportion of bodies of water with good ambient water quality.	
6.4. By 2030, substantially increase water-use efficiency across all sectors and ensure	6.4.1. Change in water-use efficiency over time.	6.4.1. Numbers of dams, 2011-2015.

sustainable withdrawals and supply of freshwater to address water scarcity and substantially reduce the number of people suffering from water scarcity.	6.4.2. Level of water stress: freshwater withdrawal as a proportion of available freshwater resources.	6.4.2. Numbers of dams construction, 2011-2015.
6.5. By 2030, implement integrated water resources management at all levels, including through transboundary cooperation as appropriate.	6.5.1. Degree of integrated water resources management implementation (0–100). 6.5.2. Proportion of transboundary basin area with an operational arrangement for water cooperation.	
6.6. By 2020, protect and restore water-related ecosystems, including mountains, forests, wetlands, rivers, aquifers and lakes.	6.6.1. Change in the extent of water-related ecosystems over time.	
6.a. By 2030, expand international cooperation and capacity-building support to developing countries in water- and sanitation-related activities and programs, including water harvesting, desalination, water efficiency, wastewater treatment, recycling and reuse technologies.	6.a.1. Amount of water- and sanitation-related official development assistance that is part of a government-coordinated spending plan.	
6.b. Support and strengthen the participation of local communities in improving water and sanitation management.	6.b.1. Proportion of local administrative units with established and operational policies and procedures for participation of local communities in water and sanitation management.	
Goal 7		
Ensure access to affordable, reliable, sustainable and modern energy for all.		
7.1. By 2030, ensure universal access to affordable, reliable and modern energy services.	7.1.1. Proportion of population with access to electricity. 7.1.2. Proportion of population with primary reliance on clean fuels and technology.	7.1.1. Proportion of primary energy allocation, 2009-2016. 7.1.2. Proportion of household consumption for gas, 2015-2016. 7.1.3. Per capita electricity consumption, 2009-2016. 7.1.4. Electrification ratio, 2009-2016. 7.1.5. Percentage of poor and vulnerable households that are the main source is electricity, 2015-2016.
7.2. By 2030, increase substantially the share of renewable energy in the global energy mix.	7.2.1. Renewable energy share in the total final energy consumption.	
7.3. By 2030, double the global rate of improvement in energy efficiency.	7.3.1. Energy intensity measured in terms of primary energy and GDP.	
7.a. By 2030, enhance international cooperation to facilitate access to clean energy research and technology, including renewable energy,	7.a.1. International financial flows to developing countries in support of clean energy research and development and renewable	

energy efficiency and advanced and cleaner fossil-fuel technology, and promote investment in energy infrastructure and clean energy technology.	energy production, including in hybrid systems.	
7.b. By 2030, expand infrastructure and upgrade technology for supplying modern and sustainable energy services for all in developing countries, in particular least developed countries, small island developing States and landlocked developing countries, in accordance with their respective programs of support.	7.b.1. Investments in energy efficiency as a proportion of GDP and the amount of foreign direct investment in financial transfer for infrastructure and technology to sustainable development services.	
Goal 8 Promote sustained, inclusive and sustainable economic growth, full and productive employment and decent work for all.		
8.1. Sustain per capita economic growth in accordance with national circumstances and, in particular, at least 7 per cent gross domestic product growth per annum in the least developed countries.	8.1.1. Annual growth rate of real GDP per capita.	8.1.1. Per capita GDP growth by labor force, 2011-2016.
8.2. Achieve higher levels of economic productivity through diversification, technological upgrading and innovation, including through a focus on high-value added and labor-intensive sectors.	8.2.1. Annual growth rate of real GDP per employed person.	
8.3. Promote development-oriented policies that support productive activities, decent job creation, entrepreneurship, creativity and innovation, and encourage the formalization and growth of micro-, small- and medium-sized enterprises, including through access to financial services.	8.3.1. Proportion of informal employment in non-agriculture employment, by sex.	8.3.1. Proportion of informal employment in non-agriculture employment, by province, residency, group of age, or education level, 2015-2017.
8.4. Improve progressively, through 2030, global resource efficiency in consumption and production and endeavor to decouple economic growth from environmental degradation, in accordance with the 10-Year Framework of Programs on Sustainable Consumption and Production, with developed countries taking the lead.	8.4.1. Material footprint, material footprint per capita, and material footprint per GDP. 8.4.2. Domestic material consumption, domestic material consumption per capita, and domestic material consumption per GDP.	
8.5. By 2030, achieve full and productive employment and decent work for all women and men, including for young people	8.5.1. Average hourly earnings of female and male employees, by occupation, age and persons with disabilities.	8.5.1. Open unemployment rate, by residency, education level, or group of age, 2015-2017.

and persons with disabilities, and equal pay for work of equal value.	8.5.2. Unemployment rate, by sex, age and persons with disabilities.	8.5.2. Underemployment rate, by residency, education level, or group of age, 2015-2017. 8.5.3. Average hourly earnings of employees, by province, group of age, education level, or sex, 2015-2016.
8.6. By 2020, substantially reduce the proportion of youth not in employment, education or training.	8.6.1. Proportion of youth (aged 15–24 years) not in education, employment or training.	
8.7. Take immediate and effective measures to eradicate forced labor, end modern slavery and human trafficking and secure the prohibition and elimination of the worst forms of child labor, including recruitment and use of child soldiers, and by 2025 end child labor in all its forms.	8.7.1. Proportion and number of children aged 5–17 years engaged in child labor, by sex and age.	
8.8. Protect labor rights and promote safe and secure working environments for all workers, including migrant workers, in particular women migrants, and those in precarious employment.	8.8.1. Frequency rates of fatal and non-fatal occupational injuries, by sex and migrant status. 8.8.2. Level of national compliance with labor rights (freedom of association and collective bargaining) based on International Labor Organization (ILO) textual sources and national legislation, by sex and migrant status.	
8.9. By 2030, devise and implement policies to promote sustainable tourism that creates jobs and promotes local culture and products.	8.9.1. Tourism direct GDP as a proportion of total GDP and in growth rate. 8.9.2. Proportion of jobs in sustainable tourism industries out of total tourism jobs.	8.9.1. Tourism direct GDP as a proportion of total GDP, 2015. 8.9.2. Total foreign exchange from tourism sector, 2015. 8.9.3. Number of foreign tourists per months from the immigration gate, 2008-2017. 8.9.4. Number of foreign tourists per months from the immigration gate, 2017-2018.
8.10. Strengthen the capacity of domestic financial institutions to encourage and expand access to banking, insurance and financial services for all.	8.10.1. (a) Number of commercial bank branches per 100,000 adults and (b) number of automated teller machines (ATMs) per 100,000 adults. 8.10.2. Proportion of adults (15 years and older) with an account at a bank or other financial institution or with a mobile-money-service provider.	8.10.1. Proportion of credit for small-sized enterprise by total credit, 2011-2016.
8.a. Increase Aid for Trade support for developing countries, in particular least developed countries, including through the Enhanced Integrated Framework for Trade-related	8.a.1. Aid for Trade commitments and disbursements.	

Technical Assistance to Least Developed Countries.		
8.b. By 2020, develop and operationalize a global strategy for youth employment and implement the Global Jobs Pact of the International Labor Organization.	8.b.1. Existence of a developed and operationalized national strategy for youth employment, as a distinct strategy or as part of a national employment strategy.	
Goal 9 Build resilient infrastructure, promote inclusive and sustainable industrialization and foster innovation.		
9.1. Develop quality, reliable, sustainable and resilient infrastructure, including regional and transborder infrastructure, to support economic development and human well-being, with a focus on affordable and equitable access for all.	9.1.1. Proportion of the rural population who live within 2 km of an all-season road. 9.1.2. Passenger and freight volumes, by mode of transport.	9.1.1. Total distance of railway in Indonesia, 2011-2015. 9.1.2. Accessibility of national highway, 2011-2014. 9.1.3. Percentage of operated highway, by the operators, 2014. 9.1.4. Number of airports, 2010-2016. 9.1.5. Number of ports in Indonesia, 2010-2016.
9.2. Promote inclusive and sustainable industrialization and, by 2030, significantly raise industry's share of employment and gross domestic product, in line with national circumstances, and double its share in least developed countries.	9.2.1. Manufacturing value added as a proportion of GDP and per capita. 9.2.2. Manufacturing employment as a proportion of total employment.	9.2.1. GDP growth in manufacturing industry, 2015-2016. 9.2.2. Manufacturing employment as a proportion of total employment, 2015-2016.
9.3. Increase the access of small-scale industrial and other enterprises, in particular in developing countries, to financial services, including affordable credit, and their integration into value chains and markets.	9.3.1. Proportion of small-scale industries in total industry value added. 9.3.2. Proportion of small-scale industries with a loan or line of credit.	9.3.1. Proportion of small-scale industries in total industry value added, 2010-2015. 9.3.1. Proportion of manufacturing industries in value added per capita, 2015-2016. 9.3.2. Proportion of small-scale industries with a loan or line of credit, 2015.
9.4. By 2030, upgrade infrastructure and retrofit industries to make them sustainable, with increased resource-use efficiency and greater adoption of clean and environmentally sound technologies and industrial processes, with all countries taking action in accordance with their respective capabilities.	9.4.1. CO ₂ emission per unit of value added.	
9.5. Enhance scientific research, upgrade the technological capabilities of industrial sectors	9.5.1. Research and development expenditure as a proportion of GDP.	

in all countries, in particular developing countries, including, by 2030, encouraging innovation and substantially increasing the number of research and development workers per 1 million people and public and private research and development spending.	9.5.2. Researchers (in full-time equivalent) per million inhabitants.	
9.a. Facilitate sustainable and resilient infrastructure development in developing countries through enhanced financial, technological and technical support to African countries, least developed countries, landlocked developing countries and small island developing States.	9.a.1. Total official international support (official development assistance plus other official flows) to infrastructure.	
9.b. Support domestic technology development, research and innovation in developing countries, including by ensuring a conducive policy environment for, inter alia, industrial diversification and value addition to commodities.	9.b.1. Proportion of medium and high-tech industry value added in total value added.	
9.c. Significantly increase access to information and communications technology and strive to provide universal and affordable access to the Internet in least developed countries by 2020.	9.c.1. Proportion of population covered by a mobile network, by technology.	9.c.1. Proportion of individuals covered by a mobile network, 2015-2016. 9.c.2. Proportion of individuals covered by a mobile network, by sex, group of age, 2015-2016. 9.c.3. Proportion of individuals covered by an internet access, by province, residency, group of age, sex, or media access, 2015-2016.
Goal 10 Reduce inequality within and among countries.		
10.1. By 2030, progressively achieve and sustain income growth of the bottom 40 per cent of the population at a rate higher than the national average.	10.1.1. Growth rates of household expenditure or income per capita among the bottom 40 per cent of the population and the total population.	10.1.1. Gini ratio by province, 2002-2018. 10.1.2. Percentage of poor population by province, 2007-2018. 10.1.3. Percentage of poor population by district/cities, 2015-2017.
10.2. By 2030, empower and promote the social, economic and political inclusion of all, irrespective of age, sex, disability, race, ethnicity, origin, religion or economic or other status.	10.2.1. Proportion of people living below 50 per cent of median income, by sex, age and persons with disabilities.	10.2.1. Average of economic growth in underdeveloped regions, 2011-2015. 10.2.2. Percentage of poor population in underdeveloped regions, 2015.
10.3. Ensure equal opportunity and reduce inequalities of outcome, including by eliminating discriminatory laws,	10.3.1. Proportion of population reporting having personally felt discriminated against or harassed in the previous 12 months on the	10.3.1. Numbers of handling cases of the violation for human rights law, 2015-2016.

policies and practices and promoting appropriate legislation, policies and action in this regard.	basis of a ground of discrimination prohibited under international human rights law.	
10.4. Adopt policies, especially fiscal, wage and social protection policies, and progressively achieve greater equality.	10.4.1. Labor share of GDP, comprising wages and social protection transfers.	
10.5. Improve the regulation and monitoring of global financial markets and institutions and strengthen the implementation of such regulations.	10.5.1. Financial Soundness Indicators.	
10.6. Ensure enhanced representation and voice for developing countries in decision-making in global international economic and financial institutions in order to deliver more effective, credible, accountable and legitimate institutions.	10.6.1 Proportion of members and voting rights of developing countries in international organizations.	10.6.1. Indonesia Democracy Index (IDI), by aspects and province, 2009-2016.
10.7. Facilitate orderly, safe, regular and responsible migration and mobility of people, including through the implementation of planned and well-managed migration policies.	10.7.1. Recruitment cost borne by employee as a proportion of yearly income earned in country of destination. 10.7.2. Number of countries that have implemented well-managed migration policies.	
10.a. Implement the principle of special and differential treatment for developing countries, in particular least developed countries, in accordance with World Trade Organization agreements.	10.a.1. Proportion of tariff lines applied to imports from least developed countries and developing countries with zero-tariff.	
10.b. Encourage official development assistance and financial flows, including foreign direct investment, to States where the need is greatest, in particular least developed countries, African countries, small island developing States and landlocked developing countries, in accordance with their national plans and programs.	10.b.1. Total resource flows for development, by recipient and donor countries and type of flow (e.g. official development assistance, foreign direct investment and other flows).	
10.c. By 2030, reduce to less than 3 per cent the transaction costs of migrant remittances and eliminate remittance corridors with costs higher than 5 per cent.	10.c.1. Remittance costs as a proportion of the amount remitted.	
Goal 11		
Make cities and human settlements inclusive, safe, resilient and sustainable.		
11.1. By 2030, ensure access for all to adequate, safe and	11.1.1. Proportion of urban population living in slums,	11.1.1. Percentage of urban slums households by province, 2015-2016.

affordable housing and basic services and upgrade slums.	informal settlements or inadequate housing.	
11.2. By 2030, provide access to safe, affordable, accessible and sustainable transport systems for all, improving road safety, notably by expanding public transport, with special attention to the needs of those in vulnerable situations, women, children, persons with disabilities and older persons.	11.2.1. Proportion of population that has convenient access to public transport, by sex, age and persons with disabilities.	11.2.1. Household percentage of using primary transportation that used to workplace, 2014. 11.2.2. Percentage of households that has access for decent and affordable housing by province or residency, 2015-2016.
11.3. By 2030, enhance inclusive and sustainable urbanization and capacity for participatory, integrated and sustainable human settlement planning and management in all countries.	11.3.1. Ratio of land consumption rate to population growth rate. 11.3.2. Proportion of cities with a direct participation structure of civil society in urban planning and management that operate regularly and democratically.	
11.4. Strengthen efforts to protect and safeguard the world's cultural and natural heritage.	11.4.1. Total expenditure (public and private) per capita spent on the preservation, protection and conservation of all cultural and natural heritage, by type of heritage (cultural, natural, mixed and World Heritage Centre designation), level of government (national, regional and local/municipal), type of expenditure (operating expenditure/investment) and type of private funding (donations in kind, private non-profit sector and sponsorship).	
11.5. By 2030, significantly reduce the number of deaths and the number of people affected and substantially decrease the direct economic losses relative to global gross domestic product caused by disasters, including water-related disasters, with a focus on protecting the poor and people in vulnerable situations.	11.5.1. Number of deaths, missing persons and directly affected persons attributed to disasters per 100,000 population. 11.5.2. Direct economic loss in relation to global GDP, damage to critical infrastructure and number of disruptions to basic services, attributed to disasters.	11.5.1. Number of provinces based on the disaster risk level, 2011-2013. 11.5.2. Number of districts/cities based on the disaster risk level, 2011-2013. 11.5.3. Number of deaths, missing persons and directly affected persons attributed to disasters per 100,000 population, 2011-2016.
11.6. By 2030, reduce the adverse per capita environmental impact of cities, including by paying special attention to air quality and municipal and other waste management.	11.6.1. Proportion of urban solid waste regularly collected and with adequate final discharge out of total urban solid waste generated, by cities. 11.6.2. Annual mean levels of fine particulate matter (e.g. PM2.5 and PM10) in cities (population weighted).	
11.7. By 2030, provide universal access to safe, inclusive and accessible, green and public spaces, in particular	11.7.1. Average share of the built-up area of cities that is open space for public use for all, by sex, age and persons with disabilities.	11.7.1. Number of victims in the last 12 months that reported to the police by sex, 2015.

for women and children, older persons and persons with disabilities.	11.7.2. Proportion of persons victim of physical or sexual harassment, by sex, age, disability status and place of occurrence, in the previous 12 months.	
11.a. Support positive economic, social and environmental links between urban, peri-urban and rural areas by strengthening national and regional development planning.	11.a.1. Proportion of population living in cities that implement urban and regional development plans integrating population projections and resource needs, by size of city.	
11.b. By 2020, substantially increase the number of cities and human settlements adopting and implementing integrated policies and plans towards inclusion, resource efficiency, mitigation and adaptation to climate change, resilience to disasters, and develop and implement, in line with the Sendai Framework for Disaster Risk Reduction 2015–2030, holistic disaster risk management at all levels.	11.b.1. Number of countries that adopt and implement national disaster risk reduction strategies in line with the Sendai Framework for Disaster Risk Reduction 2015–2030. 11.b.2. Proportion of local governments that adopt and implement local disaster risk reduction strategies in line with national disaster risk reduction strategies.	
11.c. Support least developed countries, including through financial and technical assistance, in building sustainable and resilient buildings utilizing local materials.	11.c.1. Proportion of financial support to the least developed countries that is allocated to the construction and retrofitting of sustainable, resilient and resource-efficient buildings utilizing local materials.	
Goal 12		
Ensure sustainable consumption and production patterns.		
12.1. Implement the 10-Year Framework of Programs on Sustainable Consumption and Production Patterns, all countries taking action, with developed countries taking the lead, taking into account the development and capabilities of developing countries.	12.1.1. Number of countries with sustainable consumption and production (SCP) national action plans or SCP mainstreamed as a priority or a target into national policies.	
12.2. By 2030, achieve the sustainable management and efficient use of natural resources.	12.2.1. Material footprint, material footprint per capita, and material footprint per GDP. 12.2.2. Domestic material consumption, domestic material consumption per capita, and domestic material consumption per GDP.	
12.3. By 2030, halve per capita global food waste at the retail and consumer levels and reduce food losses along production and supply chains, including post-harvest losses.	12.3.1. Global food loss index.	
12.4. By 2020, achieve the environmentally sound management of chemicals and all wastes throughout their life	12.4.1. Number of parties to international multilateral environmental agreements on hazardous waste, and other	12.4.1. Number of hazardous wastes that managed per sector, 2015.

cycle, in accordance with agreed international frameworks, and significantly reduce their release to air, water and soil in order to minimize their adverse impacts on human health and the environment.	chemicals that meet their commitments and obligations in transmitting information as required by each relevant agreement. 12.4.2. Hazardous waste generated per capita and proportion of hazardous waste treated, by type of treatment.	
12.5. By 2030, substantially reduce waste generation through prevention, reduction, recycling and reuse.	12.5.1. National recycling rate, tons of material recycled.	
12.6. Encourage companies, especially large and transnational companies, to adopt sustainable practices and to integrate sustainability information into their reporting cycle.	12.6.1. Number of companies publishing sustainability reports.	
12.7. Promote public procurement practices that are sustainable, in accordance with national policies and priorities.	12.7.1. Number of countries implementing sustainable public procurement policies and action plans.	
12.8. By 2030, ensure that people everywhere have the relevant information and awareness for sustainable development and lifestyles in harmony with nature.	12.8.1. Extent to which (i) global citizenship education and (ii) education for sustainable development (including climate change education) are mainstreamed in (a) national education policies; (b) curricula; (c) teacher education; and (d) student assessment.	
12.a. Support developing countries to strengthen their scientific and technological capacity to move towards more sustainable patterns of consumption and production.	12.a.1. Amount of support to developing countries on research and development for sustainable consumption and production and environmentally sound technologies.	
12.b. Develop and implement tools to monitor sustainable development impacts for sustainable tourism that creates jobs and promotes local culture and products.	12.b.1. Number of sustainable tourism strategies or policies and implemented action plans with agreed monitoring and evaluation tools.	
12.c. Rationalize inefficient fossil-fuel subsidies that encourage wasteful consumption by removing market distortions, in accordance with national circumstances, including by restructuring taxation and phasing out those harmful subsidies, where they exist, to reflect their environmental impacts, taking fully into account the specific needs and conditions of developing countries and minimizing the possible adverse impacts on their development in a manner	12.c.1. Amount of fossil-fuel subsidies per unit of GDP (production and consumption) and as a proportion of total national expenditure on fossil fuels.	

that protects the poor and the affected communities.		
<p align="center">Goal 13</p> <p align="center">Take urgent action to combat climate change and its impacts.</p>		
13.1. Strengthen resilience and adaptive capacity to climate-related hazards and natural disasters in all countries.	<p>13.1.1. Number of deaths, missing persons and directly affected persons attributed to disasters per 100,000 population.</p> <p>13.1.2. Number of countries that adopt and implement national disaster risk reduction strategies in line with the Sendai Framework for Disaster Risk Reduction 2015–2030.</p> <p>13.1.3. Proportion of local governments that adopt and implement local disaster risk reduction strategies in line with national disaster risk reduction strategies.</p>	<p>13.1.1. Number of deaths, missing persons and directly affected persons attributed to disasters per 100,000 population, 2011-2016.</p> <p>13.1.2. Percentage of households that knowledgeable for disaster signs and able to participate for after disaster construction in the neighborhood, 2014.</p> <p>13.1.3. Percentage of households that participate on natural disaster rescue simulation, 2014.</p>
13.2. Integrate climate change measures into national policies, strategies and planning.	13.2.1. Number of countries that have communicated the establishment or operationalization of an integrated policy/strategy/plan which increases their ability to adapt to the adverse impacts of climate change, and foster climate resilience and low greenhouse gas emissions development in a manner that does not threaten food production (including a national adaptation plan, nationally determined contribution, national communication, biennial update report or other).	
13.3. Improve education, awareness-raising and human and institutional capacity on climate change mitigation, adaptation, impact reduction and early warning.	<p>13.3.1. Number of countries that have integrated mitigation, adaptation, impact reduction and early warning into primary, secondary and tertiary curricula.</p> <p>13.3.2. Number of countries that have communicated the strengthening of institutional, systemic and individual capacity-building to implement adaptation, mitigation and technology transfer, and development actions.</p>	
13.a. Implement the commitment undertaken by developed-country parties to the United Nations Framework Convention on Climate Change to a goal of mobilizing jointly \$100 billion annually by 2020 from all sources to address the needs of developing countries in the context of meaningful mitigation actions and transparency on implementation	13.a.1. Mobilized amount of United States dollars per year between 2020 and 2025 accountable towards the \$100 billion commitment.	

and fully operationalize the Green Climate Fund through its capitalization as soon as possible.		
13.b. Promote mechanisms for raising capacity for effective climate change-related planning and management in least developed countries and small island developing States, including focusing on women, youth and local and marginalized communities.	13.b.1. Number of least developed countries and small island developing States that are receiving specialized support, and amount of support, including finance, technology and capacity-building, for mechanisms for raising capacities for effective climate change-related planning and management, including focusing on women, youth and local and marginalized communities.	
Goal 14 Conserve and sustainably use the oceans, seas and marine resources for sustainable development.		
14.1. By 2025, prevent and significantly reduce marine pollution of all kinds, in particular from land-based activities, including marine debris and nutrient pollution.	14.1.1. Index of coastal eutrophication and floating plastic debris density.	
14.2. By 2020, sustainably manage and protect marine and coastal ecosystems to avoid significant adverse impacts, including by strengthening their resilience, and take action for their restoration in order to achieve healthy and productive oceans.	14.2.1. Proportion of national exclusive economic zones managed using ecosystem-based approaches.	
14.3. Minimize and address the impacts of ocean acidification, including through enhanced scientific cooperation at all levels.	14.3.1. Average marine acidity (pH) measured at agreed suite of representative sampling stations.	
14.4. By 2020, effectively regulate harvesting and end overfishing, illegal, unreported and unregulated fishing and destructive fishing practices and implement science-based management plans, in order to restore fish stocks in the shortest time feasible, at least to levels that can produce maximum sustainable yield as determined by their biological characteristics.	14.4.1. Proportion of fish stocks within biologically sustainable levels.	
14.5. By 2020, conserve at least 10 per cent of coastal and marine areas, consistent with national and international law and based on the best available scientific information.	14.5.1. Coverage of protected areas in relation to marine areas.	14.5.1. Coverage of protected areas in relation to marine areas, 2014-2015.

14.6. By 2020, prohibit certain forms of fisheries subsidies which contribute to overcapacity and overfishing, eliminate subsidies that contribute to illegal, unreported and unregulated fishing and refrain from introducing new such subsidies, recognizing that appropriate and effective special and differential treatment for developing and least developed countries should be an integral part of the World Trade Organization fisheries subsidies negotiation.	14.6.1. Progress by countries in the degree of implementation of international instruments aiming to combat illegal, unreported and unregulated fishing.	
14.7. By 2030, increase the economic benefits to small island developing States and least developed countries from the sustainable use of marine resources, including through sustainable management of fisheries, aquaculture and tourism.	14.7.1. Sustainable fisheries as a proportion of GDP in small island developing States, least developed countries and all countries.	
14.a. Increase scientific knowledge, develop research capacity and transfer marine technology, taking into account the Intergovernmental Oceanographic Commission Criteria and Guidelines on the Transfer of Marine Technology, in order to improve ocean health and to enhance the contribution of marine biodiversity to the development of developing countries, in particular small island developing States and least developed countries.	14.a.1. Proportion of total research budget allocated to research in the field of marine technology.	
14.b. Provide access for small-scale artisanal fishers to marine resources and markets.	14.b.1. Progress by countries in the degree of application of a legal/regulatory/policy/institutional framework which recognizes and protects access rights for small-scale fisheries.	
14.c. Enhance the conservation and sustainable use of oceans and their resources by implementing international law as reflected in the United Nations Convention on the Law of the Sea, which provides the legal framework for the conservation and sustainable use of oceans and their resources, as recalled in paragraph 158 of “The future we want”.	14.c.1. Number of countries making progress in ratifying, accepting and implementing through legal, policy and institutional frameworks, ocean-related instruments that implement international law, as reflected in the United Nations Convention on the Law of the Sea, for the conservation and sustainable use of the oceans and their resources.	

Goal 15 Protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss.		
15.1. By 2020, ensure the conservation, restoration and sustainable use of terrestrial and inland freshwater ecosystems and their services, in particular forests, wetlands, mountains and drylands, in line with obligations under international agreements.	15.1.1. Forest area as a proportion of total land area. 15.1.2. Proportion of important sites for terrestrial and freshwater biodiversity that are covered by protected areas, by ecosystem type.	15.1.1. Proportion of covered forest area over total land area, 2014. 15.1.2. Proportion of hazardous wastes that managed by the regulation, 2015.
15.2. By 2020, promote the implementation of sustainable management of all types of forests, halt deforestation, restore degraded forests and substantially increase afforestation and reforestation globally.	15.2.1. Progress towards sustainable forest management.	15.1.1. Proportion of rehabilitated land that is degraded over total land area, 2011-2015. 15.1.2. Number of conservation areas that reached 70% minimum Mett Index, 2016.
15.3. By 2030, combat desertification, restore degraded land and soil, including land affected by desertification, drought and floods, and strive to achieve a land degradation-neutral world.	15.3.1. Proportion of land that is degraded over total land area.	
15.4. By 2030, ensure the conservation of mountain ecosystems, including their biodiversity, in order to enhance their capacity to provide benefits that are essential for sustainable development.	15.4.1. Coverage by protected areas of important sites for mountain biodiversity. 15.4.2. Mountain Green Cover Index.	
15.5. Take urgent and significant action to reduce the degradation of natural habitats, halt the loss of biodiversity and, by 2020, protect and prevent the extinction of threatened species.	15.5.1. Red List Index.	15.5.1. Number of endangered animals, 2015.
15.6. Promote fair and equitable sharing of the benefits arising from the utilization of genetic resources and promote appropriate access to such resources, as internationally agreed.	15.6.1. Number of countries that have adopted legislative, administrative and policy frameworks to ensure fair and equitable sharing of benefits.	
15.7. Take urgent action to end poaching and trafficking of protected species of flora and fauna and address both demand and supply of illegal wildlife products.	15.7.1. Proportion of traded wildlife that was poached or illicitly trafficked.	15.7.1. Percentage of settlements for environmental criminal act over total case, 2015.
15.8. By 2020, introduce measures to prevent the introduction and significantly reduce the impact of invasive alien species on land and water ecosystems and control or eradicate the priority species.	15.8.1. Proportion of countries adopting relevant national legislation and adequately resourcing the prevention or control of invasive alien species.	

15.9. By 2020, integrate ecosystem and biodiversity values into national and local planning, development processes, poverty reduction strategies and accounts.	15.9.1. Progress towards national targets established in accordance with Aichi Biodiversity Target 2 of the Strategic Plan for Biodiversity 2011–2020.	
15.a. Mobilize and significantly increase financial resources from all sources to conserve and sustainably use biodiversity and ecosystems.	15.a.1. Official development assistance and public expenditure on conservation and sustainable use of biodiversity and ecosystems.	
15.b. Mobilize significant resources from all sources and at all levels to finance sustainable forest management and provide adequate incentives to developing countries to advance such management, including for conservation and reforestation.	15.b.1. Official development assistance and public expenditure on conservation and sustainable use of biodiversity and ecosystems.	
15.c. Enhance global support for efforts to combat poaching and trafficking of protected species, including by increasing the capacity of local communities to pursue sustainable livelihood opportunities.	15.c.1. Proportion of traded wildlife that was poached or illicitly trafficked.	
<p style="text-align: center;">Goal 16</p> <p style="text-align: center;">Promote peaceful and inclusive societies for sustainable development, provide access to justice for all and build effective, accountable and inclusive institutions at all levels.</p>		
16.1. Significantly reduce all forms of violence and related death rates everywhere.	<p>16.1.1. Number of victims of intentional homicide per 100,000 population, by sex and age.</p> <p>16.1.2. Conflict-related deaths per 100,000 population, by sex, age and cause.</p> <p>16.1.3. Proportion of population subjected to (a) physical violence, (b) psychological violence and (c) sexual violence in the previous 12 months.</p> <p>16.1.4. Proportion of population that feel safe walking alone around the area they live.</p>	<p>16.1.1. Number of murder cases in the previous year, 2011-2015.</p> <p>16.1.2. Proportion of population subjected to physical violence, in the previous 12 months by sex, group of age, regional classification, or province, 2015-2016.</p> <p>16.1.3. Proportion of population that feel safe walking alone around the area they live, 2014.</p>
16.2. End abuse, exploitation, trafficking and all forms of violence against and torture of children.	<p>16.2.1. Proportion of children aged 1-17 years who experienced any physical punishment and/or psychological aggression by caregivers in the past month.</p> <p>16.2.2. Number of victims of human trafficking per 100,000 population, by sex, age and form of exploitation.</p> <p>16.2.3. Proportion of young women and men aged 18–29 years</p>	<p>16.2.1. Proportion of children aged 1-17 years who experienced any physical punishment and/or psychological aggression by caregivers in the past 12 months by residency or province, 2014.</p> <p>16.2.2. Prevalence of children abused, 2013.</p> <p>16.2.3. Proportion of young women and men aged 18–</p>

	who experienced sexual violence by age 18.	29 years who experienced sexual violence by age 18, 2013.
16.3. Promote the rule of law at the national and international levels and ensure equal access to justice for all.	16.3.1. Proportion of victims of violence in the previous 12 months who reported their victimization to competent authorities or other officially recognized conflict resolution mechanisms. 16.3.2. Unsensitized detainees as a proportion of overall prison population.	16.3.1. Proportion of victims of violence in the previous 12 months who reported their victimization to the police, 2012-2016. 16.3.2. Unsensitized detainees as a proportion of overall prison population, 2014-2016.
16.4. By 2030, significantly reduce illicit financial and arms flows, strengthen the recovery and return of stolen assets and combat all forms of organized crime.	16.4.1. Total value of inward and outward illicit financial flows (in current United States dollars). 16.4.2. Proportion of seized, found or surrendered arms whose illicit origin or context has been traced or established by a competent authority in line with international instruments.	
16.5. Substantially reduce corruption and bribery in all their forms.	16.5.1. Proportion of persons who had at least one contact with a public official and who paid a bribe to a public official or were asked for a bribe by those public officials, during the previous 12 months. 16.5.2. Proportion of businesses that had at least one contact with a public official and that paid a bribe to a public official or were asked for a bribe by those public officials during the previous 12 months.	
16.6. Develop effective, accountable and transparent institutions at all levels.	16.6.1. Primary government expenditures as a proportion of original approved budget, by sector (or by budget codes or similar). 16.6.2. Proportion of population satisfied with their last experience of public services.	16.6.1. Primary government expenditures as a proportion of original approved budget, 2015-2016.
16.7. Ensure responsive, inclusive, participatory and representative decision-making at all levels.	16.7.1. Proportions of positions (by sex, age, persons with disabilities and population groups) in public institutions (national and local legislatures, public service, and judiciary) compared to national distributions. 16.7.2. Proportion of population who believe decision-making is inclusive and responsive, by sex, age, disability and population group.	
16.8. Broaden and strengthen the participation of developing countries in the institutions of global governance.	16.8.1. Proportion of members and voting rights of developing countries in international organizations.	
16.9. By 2030, provide legal identity for all, including birth registration.	16.9.1. Proportion of children under 5 years of age whose births	

	have been registered with a civil authority, by age.	
16.10. Ensure public access to information and protect fundamental freedoms, in accordance with national legislation and international agreements.	16.10.1. Number of verified cases of killing, kidnapping, enforced disappearance, arbitrary detention and torture of journalists, associated media personnel, trade unionists and human rights advocates in the previous 12 months. 16.10.2. Number of countries that adopt and implement constitutional, statutory and/or policy guarantees for public access to information.	
16.a. Strengthen relevant national institutions, including through international cooperation, for building capacity at all levels, in particular in developing countries, to prevent violence and combat terrorism and crime.	16.a.1. Existence of independent national human rights institutions in compliance with the Paris Principles.	
16.b. Promote and enforce non-discriminatory laws and policies for sustainable development.	16.b.1. Proportion of population reporting having personally felt discriminated against or harassed in the previous 12 months on the basis of a ground of discrimination prohibited under international human rights law.	
<p style="text-align: center;">Goal 17</p> <p style="text-align: center;">Strengthen the means of implementation and revitalize the Global Partnership for Sustainable Development.</p>		
Finance		
17.1. Strengthen domestic resource mobilization, including through international support to developing countries, to improve domestic capacity for tax and other revenue collection.	17.1.1. Total government revenue as a proportion of GDP, by source. 17.1.2. Proportion of domestic budget funded by domestic taxes.	17.1.1. Total government revenue as a proportion of GDP, by source, 2015-2016. 17.1.2. Proportion of domestic budget funded by domestic taxes, 2015-2017. 17.1.3. Growth of export products from non-oil and gas, 2012-2016. 17.1.4. Year on year growth rate of GDP by sectors, 2011-2018.
17.2. Developed countries to implement fully their official development assistance commitments, including the commitment by many developed countries to achieve the target of 0.7 per cent of gross national income for official development assistance (ODA/GNI) to developing countries and 0.15 to 0.20 per cent of ODA/GNI to least developed countries; ODA providers are encouraged to	17.2.1. Net official development assistance, total and to least developed countries, as a proportion of the Organization for Economic Cooperation and Development (OECD) Development Assistance Committee donors' gross national income (GNI).	

consider setting a target to provide at least 0.20 per cent of ODA/GNI to least developed countries.		
17.3. Mobilize additional financial resources for developing countries from multiple sources.	17.3.1. Foreign direct investment (FDI), official development assistance and South-South cooperation as a proportion of total domestic budget. 17.3.2. Volume of remittances (in United States dollars) as a proportion of total GDP.	17.3.1. Volume of remittances (in US dollars) as a proportion of total GDP, 2012-2016.
17.4. Assist developing countries in attaining long-term debt sustainability through coordinated policies aimed at fostering debt financing, debt relief and debt restructuring, as appropriate, and address the external debt of highly indebted poor countries to reduce debt distress.	17.4.1. Debt service as a proportion of exports of goods and services.	17.4.1. Debt service as a proportion of exports of goods and services, 2012-2016.
17.5. Adopt and implement investment promotion regimes for least developed countries.	17.5.1. Number of countries that adopt and implement investment promotion regimes for least developed countries.	
Technology		
17.6. Enhance North-South, South-South and triangular regional and international cooperation on and access to science, technology and innovation and enhance knowledge-sharing on mutually agreed terms, including through improved coordination among existing mechanisms, in particular at the United Nations level, and through a global technology facilitation mechanism.	17.6.1. Number of science and/or technology cooperation agreements and programs between countries, by type of cooperation. 17.6.2. Fixed Internet broadband subscriptions per 100 inhabitants, by speed.	
17.7. Promote the development, transfer, dissemination and diffusion of environmentally sound technologies to developing countries on favorable terms, including on concessional and preferential terms, as mutually agreed.	17.7.1. Total amount of approved funding for developing countries to promote the development, transfer, dissemination and diffusion of environmentally sound technologies.	
17.8. Fully operationalize the technology bank and science, technology and innovation capacity-building mechanism for least developed countries by 2017 and enhance the use of enabling technology, in particular information and communications technology.	17.8.1. Proportion of individuals using the Internet.	17.8.1. Proportion of individuals using the Internet by province, residency, sex, or group of age, 2015-2016.

Capacity-building		
17.9. Enhance international support for implementing effective and targeted capacity-building in developing countries to support national plans to implement all the Sustainable Development Goals, including through North-South, South-South and triangular cooperation.	17.9.1. Dollar value of financial and technical assistance (including through North-South, South-South and triangular cooperation) committed to developing countries.	
Trade		
17.10. Promote a universal, rules-based, open, non-discriminatory and equitable multilateral trading system under the World Trade Organization, including through the conclusion of negotiations under its Doha Development Agenda.	17.10.1. Worldwide weighted tariff-average.	
17.11. Significantly increase the exports of developing countries, in particular with a view to doubling the least developed countries' share of global exports by 2020.	17.11.1. Developing countries' and least developed countries' share of global exports.	
17.12. Realize timely implementation of duty-free and quota-free market access on a lasting basis for all least developed countries, consistent with World Trade Organization decisions, including by ensuring that preferential rules of origin applicable to imports from least developed countries are transparent and simple, and contribute to facilitating market access.	17.12.1. Average tariffs faced by developing countries, least developed countries and small island developing States.	
Systemic issues		
<i>Policy and institutional coherence</i>		
17.13. Enhance global macroeconomic stability, including through policy coordination and policy coherence.	17.13.1. Macroeconomic Dashboard.	
17.14. Enhance policy coherence for sustainable development.	17.14.1. Number of countries with mechanisms in place to enhance policy coherence of sustainable development.	
17.15. Respect each country's policy space and leadership to establish and implement policies for poverty eradication and sustainable development.	17.15.1. Extent of use of country-owned results frameworks and planning tools by providers of development cooperation.	

<i>Multi-stakeholder partnerships</i>		
17.16. Enhance the Global Partnership for Sustainable Development, complemented by multi-stakeholder partnerships that mobilize and share knowledge, expertise, technology and financial resources, to support the achievement of the Sustainable Development Goals in all countries, in particular developing countries.	17.16.1. Number of countries reporting progress in multi-stakeholder development effectiveness monitoring frameworks that support the achievement of the sustainable development goals.	
17.17. Encourage and promote effective public, public-private and civil society partnerships, building on the experience and resourcing strategies of partnerships.	17.17.1. Amount of United States dollars committed to (a) public-private partnerships and (b) civil society partnerships.	
<i>Data, monitoring and accountability</i>		
17.18. By 2020, enhance capacity-building support to developing countries, including for least developed countries and small island developing States, to increase significantly the availability of high-quality, timely and reliable data disaggregated by income, gender, age, race, ethnicity, migratory status, disability, geographic location and other characteristics relevant in national contexts.	17.18.1. Proportion of sustainable development indicators produced at the national level with full disaggregation when relevant to the target, in accordance with the Fundamental Principles of Official Statistics.	
	17.18.2. Number of countries that have national statistical legislation that complies with the Fundamental Principles of Official Statistics. 17.18.3. Number of countries with a national statistical plan that is fully funded and under implementation, by source of funding.	
17.19. By 2030, build on existing initiatives to develop measurements of progress on sustainable development that complement gross domestic product, and support statistical capacity-building in developing countries.	17.19.1. Dollar value of all resources made available to strengthen statistical capacity in developing countries.	
	17.19.2. Proportion of countries that (a) have conducted at least one population and housing census in the last 10 years; and (b) have achieved 100 per cent birth registration and 80 per cent death registration.	

Note: *) List of Indicators of Statistics Indonesia are retrieved from: <https://www.bps.go.id/> (only available in Bahasa Indonesia)

Appendix 2

Breakpoint Test Results for The US Data

Appendix 2.1. F-test Result of Spatially-Independent Model for The US Data

State Name	F-test	Breakpoint Results
Alabama	1.8152	No Breakpoint
Alaska	0.6771	No Breakpoint
Arizona	14.0595	There is Breakpoint
Arkansas	0.5691	No Breakpoint
California	3.1819	There is Breakpoint
Colorado	1.6916	No Breakpoint
Connecticut	6.2798	There is Breakpoint
Delaware	0.6386	No Breakpoint
District of Columbia	3.0797	There is Breakpoint
Florida	10.8233	There is Breakpoint
Georgia	2.7252	There is Breakpoint
Hawaii	2.2023	There is Breakpoint
Idaho	4.5041	There is Breakpoint
Illinois	1.4618	No Breakpoint
Indiana	1.7006	No Breakpoint
Iowa	0.4945	No Breakpoint
Kansas	1.6267	No Breakpoint
Kentucky	0.9447	No Breakpoint
Louisiana	0.6491	No Breakpoint
Maine	1.3277	No Breakpoint
Maryland	0.9988	No Breakpoint
Massachusetts	0.6219	No Breakpoint
Michigan	0.7535	No Breakpoint
Minnesota	0.1657	No Breakpoint
Mississippi	3.6437	There is Breakpoint
Missouri	0.3400	No Breakpoint
Montana	1.8121	No Breakpoint
Nebraska	0.1785	No Breakpoint
Nevada	10.3578	There is Breakpoint
New Hampshire	0.5044	No Breakpoint
New Jersey	3.8466	There is Breakpoint
New Mexico	0.6134	No Breakpoint
New York	0.8221	No Breakpoint
North Carolina	3.2846	There is Breakpoint
North Dakota	2.4137	There is Breakpoint
Ohio	0.5382	No Breakpoint
Oklahoma	0.0845	No Breakpoint
Oregon	4.5691	There is Breakpoint
Pennsylvania	1.4347	No Breakpoint
Rhode Island	3.0632	There is Breakpoint
South Carolina	2.5315	There is Breakpoint
South Dakota	1.8449	No Breakpoint
Tennessee	1.2460	No Breakpoint

Texas	0.9486	No Breakpoint
Utah	12.0894	There is Breakpoint
Vermont	0.3830	No Breakpoint
Virginia	3.0855	There is Breakpoint
Washington	4.0605	There is Breakpoint
West Virginia	0.1223	No Breakpoint
Wisconsin	1.2423	No Breakpoint
Wyoming	2.2283	There is Breakpoint

Appendix 2.2. Wald Test Result of Spatially-Independent Model for The US Data

State Name	Wald test	Breakpoint Results
Alabama	1.31634	No Breakpoint
Alaska	1.60934	No Breakpoint
Arizona	9.77174	There is Breakpoint
Arkansas	0.38666	No Breakpoint
California	2.86352	No Breakpoint
Colorado	1.89895	No Breakpoint
Connecticut	4.38178	No Breakpoint
Delaware	0.42900	No Breakpoint
District of Columbia	2.09138	No Breakpoint
Florida	9.70887	There is Breakpoint
Georgia	4.35174	No Breakpoint
Hawaii	1.48491	No Breakpoint
Idaho	3.26176	No Breakpoint
Illinois	1.02726	No Breakpoint
Indiana	1.20623	No Breakpoint
Iowa	0.33017	No Breakpoint
Kansas	1.27829	No Breakpoint
Kentucky	0.63312	No Breakpoint
Louisiana	0.55721	No Breakpoint
Maine	1.33266	No Breakpoint
Maryland	0.71483	No Breakpoint
Massachusetts	0.57093	No Breakpoint
Michigan	2.52781	No Breakpoint
Minnesota	0.41064	No Breakpoint
Mississippi	2.65415	No Breakpoint
Missouri	0.23100	No Breakpoint
Montana	1.40252	No Breakpoint
Nebraska	0.22567	No Breakpoint
Nevada	8.50179	No Breakpoint
New Hampshire	0.61055	No Breakpoint
New Jersey	2.75147	No Breakpoint
New Mexico	0.40926	No Breakpoint
New York	0.54933	No Breakpoint
North Carolina	2.19136	No Breakpoint
North Dakota	2.85921	No Breakpoint
Ohio	1.14833	No Breakpoint
Oklahoma	0.17669	There is Breakpoint
Oregon	3.50537	No Breakpoint
Pennsylvania	1.00454	No Breakpoint
Rhode Island	2.15985	No Breakpoint
South Carolina	2.19966	No Breakpoint
South Dakota	1.33590	No Breakpoint
Tennessee	1.56849	No Breakpoint

Texas	0.72263	No Breakpoint
Utah	8.11168	No Breakpoint
Vermont	0.27908	No Breakpoint
Virginia	2.05704	No Breakpoint
Washington	3.24658	No Breakpoint
West Virginia	0.10815	There is Breakpoint
Wisconsin	1.22280	No Breakpoint
Wyoming	2.38970	No Breakpoint

Appendix 2.3. F-test Result of Spatially-Dependent Model for The US Data

State Name	F-test	Breakpoint Results
Alabama	2.5625	There is Breakpoint
Alaska	NA	NA
Arizona	4.7735	There is Breakpoint
Arkansas	0.4836	No Breakpoint
California	0.8390	No Breakpoint
Colorado	0.4546	No Breakpoint
Connecticut	7.8489	There is Breakpoint
Delaware	0.4310	No Breakpoint
District of Columbia	3.0635	There is Breakpoint
Florida	5.9091	There is Breakpoint
Georgia	0.3936	No Breakpoint
Hawaii	NA	NA
Idaho	0.8606	No Breakpoint
Illinois	1.3407	No Breakpoint
Indiana	2.2604	There is Breakpoint
Iowa	0.1017	No Breakpoint
Kansas	0.9462	No Breakpoint
Kentucky	0.0516	No Breakpoint
Louisiana	1.4969	No Breakpoint
Maine	1.5841	No Breakpoint
Maryland	1.9343	No Breakpoint
Massachusetts	5.7848	There is Breakpoint
Michigan	1.7290	No Breakpoint
Minnesota	0.3789	No Breakpoint
Mississippi	6.7100	There is Breakpoint
Missouri	0.1318	No Breakpoint
Montana	2.2438	There is Breakpoint
Nebraska	0.8299	No Breakpoint
Nevada	1.1719	No Breakpoint
New Hampshire	0.6024	No Breakpoint
New Jersey	3.5281	There is Breakpoint
New Mexico	0.9848	No Breakpoint
New York	1.0756	No Breakpoint
North Carolina	3.9278	There is Breakpoint
North Dakota	2.2760	There is Breakpoint
Ohio	0.2489	No Breakpoint
Oklahoma	0.6878	No Breakpoint
Oregon	0.3468	No Breakpoint
Pennsylvania	2.6503	There is Breakpoint
Rhode Island	6.6654	There is Breakpoint
South Carolina	0.2673	No Breakpoint
South Dakota	1.2076	No Breakpoint
Tennessee	2.2505	There is Breakpoint

Texas	1.0348	No Breakpoint
Utah	4.2603	There is Breakpoint
Vermont	1.0809	No Breakpoint
Virginia	3.8089	There is Breakpoint
Washington	0.6196	No Breakpoint
West Virginia	0.2345	No Breakpoint
Wisconsin	0.6561	No Breakpoint
Wyoming	1.3708	No Breakpoint

Note: Alaska and Hawaii are excluded in the analysis due to no neighbours condition.

Appendix 2.4. Wald Test Result of Spatially-Dependent Model for The US Data

State Name	Wald test	Breakpoint Results
Alabama	22.48333	There is Breakpoint
Alaska	NA	NA
Arizona	14.95267	There is Breakpoint
Arkansas	2.99722	No Breakpoint
California	10.41001	There is Breakpoint
Colorado	9.22672	No Breakpoint
Connecticut	10.06619	There is Breakpoint
Delaware	0.26210	No Breakpoint
District of Columbia	2.25059	No Breakpoint
Florida	17.22667	There is Breakpoint
Georgia	16.50529	There is Breakpoint
Hawaii	NA	NA
Idaho	6.93209	No Breakpoint
Illinois	13.30177	There is Breakpoint
Indiana	27.37404	There is Breakpoint
Iowa	8.62154	No Breakpoint
Kansas	4.33341	No Breakpoint
Kentucky	33.86116	There is Breakpoint
Louisiana	2.81336	No Breakpoint
Maine	5.22105	No Breakpoint
Maryland	2.89259	No Breakpoint
Massachusetts	10.44928	There is Breakpoint
Michigan	16.90323	There is Breakpoint
Minnesota	3.48712	No Breakpoint
Mississippi	13.91655	There is Breakpoint
Missouri	2.46070	No Breakpoint
Montana	3.29077	No Breakpoint
Nebraska	1.33541	No Breakpoint
Nevada	12.27205	There is Breakpoint
New Hampshire	5.16954	No Breakpoint
New Jersey	2.31070	No Breakpoint
New Mexico	3.59109	No Breakpoint
New York	0.66361	No Breakpoint
North Carolina	6.63350	No Breakpoint
North Dakota	2.88614	No Breakpoint
Ohio	10.69355	There is Breakpoint
Oklahoma	4.64785	No Breakpoint
Oregon	9.44894	There is Breakpoint
Pennsylvania	4.67517	No Breakpoint
Rhode Island	5.39616	No Breakpoint
South Carolina	15.90283	There is Breakpoint
South Dakota	1.60396	No Breakpoint
Tennessee	14.64723	There is Breakpoint

Texas	4.18385	No Breakpoint
Utah	6.70508	No Breakpoint
Vermont	2.56494	No Breakpoint
Virginia	12.52128	There is Breakpoint
Washington	5.17264	No Breakpoint
West Virginia	2.15199	No Breakpoint
Wisconsin	22.08654	There is Breakpoint
Wyoming	1.38794	No Breakpoint

Note: Alaska and Hawaii are excluded in the analysis due to no neighbours condition.

Appendix 3

**Example of Oil Palm Mills Owned by the Same Parent
Company**

Appendix 3. Example of palm oil mills owned by the same parent company.

Palm Oil Mills Name	Parent Company	Location
Alno Agro Utama	Anglo Eastern Plantation	Bengkulu
Mitra Puding Mas	Anglo Eastern Plantation	Bengkulu
Tasik Raja	Anglo Eastern Plantation	Sumatra Utara
United Kingdom Indonesia Plantations	Anglo Eastern Plantation	Sumatra Utara
Bina Pitri Jaya	Anglo Eastern Plantation	Riau
Anugerah Tanjung Medan	Anugerah Tanjung Medan	Sumatra Utara
Cipta Agro Sejati	Anugerah Tanjung Medan	Riau
Merbau Jaya Indah Raya	Asam Jawa	Sumatra Utara
Asam Jawa	Asam Jawa	Sumatra Utara
Perkebunan Lembah Bhakti	Astra Agro Lestari	Aceh
Perkebunan Lembah Bhakti 2	Astra Agro Lestari	Aceh
Karya Tanah Subur	Astra Agro Lestari	Aceh
Sari Aditya Loka 1	Astra Agro Lestari	Jambi
Sari Aditya Loka 2	Astra Agro Lestari	Jambi
Sari Aditya Loka 2	Astra Agro Lestari	Jambi
Tunggal Perkasa Plantation	Astra Agro Lestari	Riau
Ekadura Indonesia	Astra Agro Lestari	Riau
Kimia Tirta Utama	Astra Agro Lestari	Riau
Sawit Asahan Indah	Astra Agro Lestari	Riau
Sari Lembah Subur 2	Astra Agro Lestari	Riau
Surya Indah Nusantara Pagi	Astra Agro Lestari	Riau
Pt Sumbertama Nusapertiwi	Bakrie Sumatera Plantation	Jambi
Pt Bakrie Sumatera Plantations Tbk, Unit Sumut I, Kisaran	Bakrie Sumatera Plantation	Sumatra Utara
Graha Dura Leidong Prima	Bakrie Sumatera Plantation	Sumatra Utara
Rapi Teknik Cv	Bakrie Sumatera Plantation	Sumatra Utara
Bakrie Pasaman Plantation (Air Balam)	Bakrie Sumatera Plantation	Sumatra Barat
Bukit Barisan Indah Prima	Bukit Barisan Indah Prima	Jambi
Batanghari Sawit Sejahtera	Bukit Barisan Indah Prima	Jambi
Pt. Karya Indorata Persada	Bukit Barisan Indah Prima	Riau

Palm Oil Mills Name	Parent Company	Location
Citra Riau Sarana 3	Citra Riau Sarana	Riau
Citra Riau Sarana	Citra Riau Sarana	Riau
Citra Riau Sarana 2	Citra Riau Sarana	Riau
Mekar Sari Alam Lestari	Darmex Agro	Riau
Banyu Bening Utama	Darmex Agro	Riau
Wanajingga Timur	Darmex Agro	Riau
Cerenti Subur	Darmex Agro	Riau
Duta Palma Nusantara	Darmex Agro	Riau
Samudera Sawit Nabati	Duta Marga	Aceh
Tales Inti Sawit	Duta Marga	Sumatra Utara
Gunung Selamat Lestari	Duta Marga	Sumatra Utara
Simpang Kanan Lestarindo	Duta Marga	Riau
Dharmasraya Lestarindo	Duta Marga	Sumatra Barat
Pt Surya Intisari Raya Sei Likut Mill	First Resources	Riau
Surya Dumai	First Resources	Riau
Ciliandra Perkasa	First Resources	Riau
Pt Subur Arum Makmur Semananenek Mill	First Resources	Riau
Muriniwood Indah Industry	First Resources	Riau
Meridan Sejatisurya Plant	First Resources	Riau
Kepehuan	First Resources	Riau
Perdana Intisawit Perkasa - Pisp 2	First Resources	Riau
Subur Arum Makmur 2	First Resources	Riau
Pt. Satya Kisma Usaha - Sungai Bengkal	Golden Agri	Jambi
Langling Mill - Pt. Kresna Duta Agroindo	Golden Agri-Resources Ltd.	Jambi
Jelatang Mill - Pt. Kresna Duta Agroindo	Golden Agri-Resources Ltd.	Jambi
Sungai Buaya Mill - Pt. Sumber Indah Perkasa	Golden Agri-Resources Ltd.	Lampung
Sungai Merah Mill - Pt. Sumber Indah Perkasa	Golden Agri-Resources Ltd.	Lampung
Nagasakti Palm Oil Mill - Pt Buana Wiralestari Mas	Golden Agri-Resources Ltd.	Riau

Palm Oil Mills Name	Parent Company	Location
Jamika Raya	Incasi Raya	Jambi
Pasamanmarama Sejahtera	Incasi Raya	Sumatra Barat
Incasi Raya (Pks Sodetan)	Incasi Raya	Sumatra Barat
Sumatera Jaya Agro Lestari (Pks Silaut)	Incasi Raya	Sumatra Barat
Incasi Raya (Pks Pangian)	Incasi Raya	Sumatra Barat
Sumbar Andalas Kencana	Incasi Raya	Sumatra Barat
Selago Makmur Plantation	Incasi Raya	Sumatra Barat
Bintara Tani Nusantara	Incasi Raya	Sumatra Barat
Bina Pratama Sakatojaya	Incasi Raya	Sumatra Barat
Agro Wira Ligatsa	Incasi Raya	Sumatra Barat
Bangun Tenera Riau	Indah Group	Riau
Pt Bastian Olah Sawit	Indah Group	Sumatra Utara
Sun Sawit	Indah Group	Sumatra Utara
Pt Pp London Sumatra Indonesia Tbk – Begerpang Mill	Indofood Agri	Sumatra Utara
Pt Salim Ivomas Pratama Tbk - Lubuk Raja Mill	Indofood Agri	Riau
Pt Salim Ivomas Pratama Tbk - Sungai Dua Mill	Indofood Agri	Riau
London Sumatra Indonesia (Sei Lakitan)	Indofood Agri	Sumatra Selatan
London Sumatra Indonesia (Pks Tirta Agun)	Indofood Agri	Sumatra Selatan
Mentari Subur Abadi	Indofood Agri	Sumatra Selatan
Arta Kencana	Indofood Agri	Sumatra Selatan
Sawindo Kencana	Kencana Agri	Bangka Belitung
Kencana Persada Nusantara (Arya Rama Prakarsa)	Kencana Agri	Riau
Kencana Permata Nusantara	Kencana Permata Nusantara	Sumatra Utara
Pt Arya Rama Prakarsa	Kencana Persada Nusantara	Riau
Kencana Persada Nusantara	Kencana Persada Nusantara	Riau
Kencana Andalan Nusantara	Kencana Persada Nusantara	Riau
Pt Steelindo Wahana Perkasa Pom	Kuala Lumpur Kepong Berhad	Bangka Belitung
Pt Langkat Nusantara Kepong	Kuala Lumpur Kepong Berhad	Sumatra Utara

Palm Oil Mills Name	Parent Company	Location
Pt Adei Plantation – Nilo 1 Palm Oil Mill	Kuala Lumpur Kepong Berhad	Riau
Pt Adei Plantation – Nilo 2 Palm Oil Mill	Kuala Lumpur Kepong Berhad	Riau
Pt Adei Plantations Mandau Palm Oil Mill	Kuala Lumpur Kepong Berhad	Riau
Sumber Sawit Nusantara	Lingga Tiga Sawit	Sumatra Utara
Torganda (Rantau Kasai)	Lingga Tiga Sawit	Riau
Pt Saudara Sejati Luhur - Gunung Melayu I Mill	London Sumatra Indonesia	Sumatra Utara
Pt Pp London Sumatra Indonesia Tbk - Gunung Melayu Mill	London Sumatra Indonesia	Sumatra Utara
Pt.Pp.London Sumatra Indonesia Tbk - Dolok Mill	London Sumatra Indonesia	Sumatra Utara
Pt Pp London Sumatra Indonesia Tbk – Turangie Mill	London Sumatra Indonesia	Sumatra Utara
Pt Pp London Sumatra Indonesia Tbk - Belani Elok Mill	London Sumatra Indonesia	Sumatra Selatan
London Sumatra Indonesia (Terawas Indah)	London Sumatra Indonesia	Sumatra Selatan
London Sumatra Indonesia (Gunung Bais)	London Sumatra Indonesia	Sumatra Selatan
Perkebunan Nusantara I (Tg Seumantoh)	Pt. Perkebunan Nusantara I	Aceh
Perkebunan Nusantara II (Sawit Hulu)	Pt. Perkebunan Nusantara II	Sumatra Utara
Perkebunan Nusantara III (Sei Meranti)	Pt. Perkebunan Nusantara III	Riau
Rimbo Duo	Pt. Perkebunan Nusantara IV	Jambi
Pks Sei Rokan Ptpn V	Pt. Perkebunan Nusantara V	Riau
Perkebunan Nusantara VI (Solok Selatan)	Pt. Perkebunan Nusantara VI	Sumatra Barat
Betung	Pt. Perkebunan Nusantara VII	Sumatra Selatan
Perkebunan Nusantara VII (Talo Pino)	Pt. Perkebunan Nusantara VII	Bengkulu
Rejosari	Pt. Perkebunan Nusantara VII	Lampung
Pt Inti Indosawit Subur - Tungkal Ulu	Pt. Inti Indosawit Subur	Jambi
Pt. Inti Indosawit Subur - Muara Bulian	Pt. Inti Indosawit Subur	Jambi
Pt Dasa Anugrah Sejati - Taman Raja Mill	Pt. Inti Indosawit Subur	Jambi

Palm Oil Mills Name	Parent Company	Location
Pt Rigunas Agri Utama - Bungo Tebo Mill	Pt. Inti Indosawit Subur	Jambi
Pt Supra Matra Abadi - Aek Nabara Mill	Pt. Inti Indosawit Subur	Sumatra Utara
Pt Hari Sawit Jaya - Negri Lama Ii Mill	Pt. Inti Indosawit Subur	Sumatra Utara
Pt Hari Sawit Jaya - Negri Lama I Mill	Pt. Inti Indosawit Subur	Sumatra Utara
Pt Inti Indosawit Subur - Buatan Ii	Pt. Inti Indosawit Subur	Riau
Pt. Rigunas Agri Utama - Peranap Mill	Pt. Inti Indosawit Subur	Riau
Prima Sauhur Lestari	Prima Sauhur Lestari	Sumatra Utara
Pt Mustika Agung Sawit Sejahtera Jl	Prima Sauhur Lestari	Riau
Karyabadi Sama Sejati	Prima Sauhur Lestari	Riau
Sukaramai	Prima Sauhur Lestari	Riau
Pt Inti Indosawit Subur - Tungkal Ulu	Pt. Inti Indosawit Subur	Jambi
Pt. Inti Indosawit Subur - Muara Bulian	Pt. Inti Indosawit Subur	Jambi
Pt Dasa Anugrah Sejati - Taman Raja Mill	Pt. Inti Indosawit Subur	Jambi
Pt Rigunas Agri Utama - Bungo Tebo Mill	Pt. Inti Indosawit Subur	Jambi
Pt Supra Matra Abadi - Aek Nabara Mill	Pt. Inti Indosawit Subur	Sumatra Utara
Pt Hari Sawit Jaya - Negri Lama Ii Mill	Pt. Inti Indosawit Subur	Sumatra Utara
Pt Hari Sawit Jaya - Negri Lama I Mill	Pt. Inti Indosawit Subur	Sumatra Utara
Pt Inti Indosawit Subur - Buatan Ii	Pt. Inti Indosawit Subur	Riau
Pt. Rigunas Agri Utama - Peranap Mill	Pt. Inti Indosawit Subur	Riau
Pt Salim Ivomas Pratama Tbk - Sungai Bangko Mill	Pt Salim Ivomas Pratama Tbk	Riau
Pt Salim Ivomas Pratama Tbk - Napal Mill	Pt Salim Ivomas Pratama Tbk	Riau
Pt Salim Ivomas Pratama Tbk - Balam Mill	Pt Salim Ivomas Pratama Tbk	Riau
London Sumatra Indonesia (Pks Artha Kencana)	Pt Salim Ivomas Pratama Tbk	Sumatra Selatan
Global Sawit Semesta	Raja Garuda Mas	Aceh
Pt Gunung Melayu - Gunung Melayu Ii Mill	Raja Garuda Mas	Sumatra Utara
Pt Supra Matra Abadi - Teluk Panjie Mill	Raja Garuda Mas	Sumatra Utara

Palm Oil Mills Name	Parent Company	Location
Pt Tunggal Yunus Estate - Topaz Mill	Raja Garuda Mas	Riau
Usaha Sawit Mandiri	Raja Garuda Mas	Sumatra Barat
Mazuma Agro Indonesia	Sawit Raya Nusantara	Sumatra Utara
Graha Permata Hijau	Sawit Raya Nusantara	Riau
Pt Socfin Indonesia - Seumanyam Mill	Socfin Indonesia	Aceh
Pt Socfin Indonesia - Sungai Liput Mill	Socfin Indonesia	Aceh
Pt Socfin Indonesia - Lae Butar Mill	Socfin Indonesia	Aceh
Pt Socfin Indonesia - Seunagan	Socfin Indonesia	Aceh
Pt Socfin Indonesia - Negeri Lama Mill	Socfin Indonesia	Sumatra Utara
Pt Socfin Indonesia - Aek Loba	Socfin Indonesia	Sumatra Utara
Pt Socfin Indonesia - Bangun Bandar Mill	Socfin Indonesia	Sumatra Utara
Pt Agromuko Bunga Tanjung Mill	Sipef	Bengkulu
Sipef - Pt Umbul Mas Wisesa	Sipef	Sumatra Utara
Pt Agromuko - Mukomuko Pom	Sipef Group	Bengkulu
Perlabian Palm Oil Mill - Pt Tolan Tiga	Sipef Group	Sumatra Utara
Bukit Maradja Palm Oil Mill - Pt. Eastern Sumatra Indonesia	Sipef Group	Sumatra Utara
Surya Andalan Primatama	Sungai Budi	Bengkulu
Terbanggi	Sungai Budi	Lampung
Budi Nabati Perkasa	Sungai Budi	Jambi
Tunas Baru Lampung	Sungai Budi	Lampung
Mesuji Pks 2	Sungai Budi	Lampung
SAML	Sriwijaya Palm Oil Group	Sumatra Selatan
CLS	Sriwijaya Palm Oil Group	Sumatra Selatan
Sriwijaya Palm Oil Indonesia	Sriwijaya Palm Oil Indonesia	Sumatra Selatan
Ensem Sawita	Tenera Lestari	Aceh
Ensem Lestari	Tenera Lestari	Aceh
Kwala Gunung Lima Puluh Mill	Tenera Lestari	Sumatra Utara
Sinar Bengkulu Selatan	Trinity Interlink	Bengkulu
Merangkai Artha Nusantara	Trinity Interlink	Riau
Agrindo Indah Persada 3	Wilmar	Bengkulu

Palm Oil Mills Name	Parent Company	Location
Agrindo Indah Persada 2	Wilmar	Jambi
Pt Asiatic Persada	Wilmar Group	Jambi
Agrindo Indah Persada	Wilmar	Sumatra Utara
Perkebunan Milano (Aek Batu)	Wilmar	Sumatra Utara
Varem Sawit Cemerlang	Wilmar	Sumatra Utara
Daya Labuhan Indah 1	Wilmar International	Sumatra Utara
Sinarsiak Dianpermai	Wilmar	Riau
Siak Prima Sakti	Wilmar	Riau
Salim Ivomas Pratama (Pks Balam)	Wilmar	Riau
Pt. Murini Sam Sam (Kandis)	Wilmar International Limited	Riau
Musi Banyuasin Indah	Wilmar	Sumatra Selatan
Pt Buluh Cawang Plantation	Wilmar	Sumatra Selatan
Pt. Tania Selatan	Wilmar International Limited	Sumatra Selatan
Pt. Agro Palindo Sakti	Wilmar International Limited	Sumatra Selatan
Pt. Gersindo Minang Plantation	Wilmar	Sumatra Barat
Pt. Amp Plantation Unit Pom	Wilmar	Sumatra Barat
Pt. Kencana Sawit Indonesia	Wilmar	Sumatra Barat
Usaha Inti Padang	Wilmar International	Sumatra Barat

Note: Pt. Perkebunan Nusantara is a state-owned enterprise. Wilmar, Wilmar Group, Wilmar International, and Wilmar International Limited are owned by the same corporate group (Wilmar Group)

Appendix 4

List of Satellite Data Products

Appendix 4. List of Satellite Data Product

Platform	Instrument	Type	Data Availability	Descriptions
ALOS (JP)	PALSAR (The Phased Array-type L-band Synthetic Aperture Radar)	Active	Free	<p>Mission Duration: 24 January 2006 – 12 May 2011</p> <p>Data File Format: NetCDF (Open Data Cube format)</p> <p>Spatial Resolution:</p> <ol style="list-style-type: none"> 1) Fine Resolution (FBS): 70 km swath, 10 × 10 m 2) Fine Resolution (FBD): 70 km swath, 20 × 20 m 3) ScanSAR: 250-300 km swath, 100 × 100 m 4) Polarimetric: 30 km swath, 30 × 30 m <p>Center Frequency: L-Band (1.27 GHz) to achieve cloud-free and day-and-night land observation.</p> <p>Coverage: Repeat cycle = 46 days, sub cycle = 2 days.</p> <p>Altitude: 691.65 km (at equator)</p> <p>Source: https://www.eorc.jaxa.jp/ALOS/en/dataset/dataset_index.htm</p>
ALOS-2 (JP)	PALSAR-2	Active	Free	<p>Mission Duration: 24 May 2014 –</p> <p>Data File Format: NetCDF</p> <p>Spatial Resolution:</p> <ol style="list-style-type: none"> 1) Spotlight: 25 × 25 km swath, 3 × 1 m 2) Ultrafine Resolution: 50 km swath, 3 × 3 m 3) High Sensitive Resolution: 50 km swath, 6 × 6 m 4) Fine Resolution: 70 km swath, 10 × 10 m 5) ScanSAR (Normal): 350 km swath (5 scans), 100 × 100 m 6) ScanSAR (Wide): 490 km swath (7 scans), 60 × 60 m <p>Center Frequency: L-Band Synthetic Aperture Radar to achieve cloud-free and day-and-night land observation in all weather conditions.</p> <p>Coverage: Revisit cycle = 14 days.</p> <p>Altitude: 628 km (at equator)</p> <p>Source: https://www.eorc.jaxa.jp/ALOS/en/dataset/dataset_index.htm</p>
GPM (NASA & JP)	GPM (Global Precipitation Measurement)	Active	Free	<p>Data File Format: NetCDF, HDF5. GIS TIFF + Wordfile, GDS, Giovanni.</p> <p>Data Resolutions and Regions:</p> <ol style="list-style-type: none"> 1) 0.1° – 30 minutes for area 90°N – 90°S (Latency 4 hours) 2) 0.1° – 30 minutes for area 90°N – 90°S (Latency 12 hours)

Platform	Instrument	Type	Data Availability	Descriptions
				3) 0.1° – 30 minutes for area 90°N – 90°S (Latency 2.5 months) 4) 0.1° – 3 hours for area 90°N – 90°S (Latency 4 hours) 5) 0.1° – 3 hours for area 90°N – 90°S (Latency 12 hours) 6) 0.1° – 1 day for area 90°N – 90°S (Latency 4 hours) 7) 0.1° – 1 day for area 90°N – 90°S (Latency 12 hours) 8) 0.1° – 1 day for area 90°N – 90°S (Latency 2.5 months) 9) 0.1° – 3 days for area 90°N – 90°S (Latency 12 hours) 10) 0.1° – 7 days for area 90°N – 90°S (Latency 4 hours) 11) 0.1° – 30 minutes for area 90°N – 90°S (Latency 2.5 months) Source: https://pmm.nasa.gov/data-access/downloads/gpm
LANDSAT 5 (USGS – NASA)	TM (Thematic Mapper)	Passive	Free	Mission Duration: 1 March 1984 – 5 June 2013 Data File Format: GeoTiff Ground Sampling Interval (pixel size): 1) Reflective: 30 × 30 m 2) Thermal: 120 × 120 m Spectral Bands: 1) Visible (0.45 – 0.52 µm): 30 × 30 m 2) Visible (0.52 – 0.60 µm): 30 × 30 m 3) Visible (0.63 – 0.69 µm): 30 × 30 m 4) Near Infrared (0.76 – 0.90 µm): 30 × 30 m 5) Near Infrared (1.55 – 1.75 µm): 30 × 30 m 6) Thermal (10.40 – 12.50 µm): 120 × 120 m 7) Mid-Infrared (2.08 – 2.35 µm): 30 × 30 m Coverage: Revisit cycle = 16 days. Swath width: 185 km Source: https://earthexplorer.usgs.gov/
LANDSAT 7 (NASA – USGS)	ETM (Enhanced Thematic Mapper)	Passive	Free	Mission Duration: 15 April 1999 – Data File Format: GeoTiff Ground Sampling Interval (pixel size): 1) Reflective: 30 × 30 m 2) Thermal: 60 × 60 m Spectral Bands: 1) Visible (0.45 – 0.52 µm): 30 × 30 m 2) Visible (0.52 – 0.60 µm): 30 × 30 m 3) Visible (0.63 – 0.69 µm): 30 × 30 m 4) Near Infrared (0.77 – 0.90 µm): 30 × 30 m 5) Near Infrared (1.55 – 1.75 µm): 30 × 30 m 6) Thermal (10.40 – 12.50 µm): 120 × 120 m

Platform	Instrument	Type	Data Availability	Descriptions
				<p>7) Mid-Infrared (2.08 – 2.35 μm): 30 \times 30 m</p> <p>8) Panchromatic (PAN) (0.52 – 0.90 μm): 15 \times 15 m</p> <p>Coverage: Revisit cycle = 16 minutes.</p> <p>Swath width: 185 km</p> <p>Source: https://earthexplorer.usgs.gov/</p>
LANDSAT 8 (NASA – USGS)	<p>OLI (Operational Land Imager)</p> <p>TIRS (Thermal Infrared Sensor)</p>	Passive	Free	<p>Mission Duration (Landsat 8): 11 February 2013 –</p> <p>Data File Format: GeoTiff</p> <p>Spatial Resolution:</p> <ol style="list-style-type: none"> 1) Panchromatic: 15 \times 15 m 2) Multispectral: 30 \times 30 m 3) Thermal: 100 \times 100 m <p>Spectral Bands:</p> <ol style="list-style-type: none"> 1) Coastal/Aerosol (0.43 – 0.45 μm): 30 \times 30 m 2) Blue (0.450 – 0.51 μm): 30 \times 30 m 3) Green (0.53 – 0.59 μm): 30 \times 30 m 4) Red (0.64 – 0.67 μm): 30 \times 30 m 5) Near Infrared (0.85 – 0.88 μm): 30 \times 30 m 6) Short Wavelength Infrared (1.57 – 1.65 μm): 30 \times 30 m 7) Short Wavelength Infrared (2.11 – 2.29 μm): 30 \times 30 m 8) Panchromatic (0.50 – 0.68 μm): 15 \times 15 m 9) Cirrus (1.36 – 1.38 μm): 30 \times 30 m 10) Long Wavelength Infrared (10.60 – 11.19 μm): 100 \times 100 m 11) Long Wavelength Infrared (11.50 – 12.51 μm): 100 \times 100 m <p>Coverage: Revisit cycle = 16 days.</p> <p>Source: https://earthexplorer.usgs.gov/</p>
SENTINEL 1 (ESA)	SAR (Synthetic Aperture Radar)	Active	Free	<p>Mission Duration: 3 April 2014 –</p> <p>Data File Format: Sentinel-SAFE Format (GeoTIFF format on ODC)</p> <p>Instrument: C-band synthetic aperture radar</p> <p>Spatial Resolution:</p> <ol style="list-style-type: none"> 1) Strip Map (SM): 80 km swath, 5 \times 5 m 2) Interferometric Wide Swath (IW): 250 km swath, 5 \times 20 m 3) Extra-Wide Swath (EW): 400 km swath, 20 \times 40 m 4) Wave (WV): 20 \times 20 km, 20 \times 40 m <p>Coverage: Map global landmasses once every 12 days.</p> <p>Source: https://scihub.copernicus.eu/dhus/#/home</p>
TERRA (NASA)	ASTER (The Advanced Spaceborne Thermal)	Active	Free	<p>Mission Duration: 18 December 1999 –</p> <p>There are 3 types of telescope:</p> <ol style="list-style-type: none"> 1) Visible Near Infrared (VNIR) <p>Bands: 1, 2, and 3N</p> <p>Pixel Size: 15 m</p>

Platform	Instrument	Type	Data Availability	Descriptions
	Emission and Reflection Radiometer) GDEM_v2 (Global Digital Elevation Model)			2) Shortwave Infrared (SWVIR) Bands: 4 – 9 Pixel Size: 30 m 3) Thermal Infrared (TIR) Bands: 10 – 14 Pixel Size: 90 m Data File Format: GeoTiff. Data Resolution: 1 × 1 arc second grid. Coverage: Revisit cycle 16 days. Source: https://earthexplorer.usgs.gov/
IBUKI (JP)	GOSAT 2 (Greenhouse gases Observing Satellite)	Passive	Free	Mission Duration: 23 January 2009 – Main Purpose: Observe the greenhouse gases concentration Instrument: 1) Fourier Transform Spectrometer (FTS) 2) Cloud and Aerosol Imager TANSO-CAI Specification: 1) Band 1 (central wavelength = 0.380 μm): 20 × 20 m 2) Band 2 (central wavelength = 0.674 μm): 20 × 20 m 3) Band 3 (central wavelength = 0.870 μm): 20 × 20 m 4) Band 4 (central wavelength = 1.600 μm): 90 × 90 m Coverage: Repeat cycle 6 days
SHIZUKU (JP)	GCOM-W1 (Global Change Observation Mission - Water)	Passive	Free	Mission Duration: 17 May 2012 – Instrument: Advanced Microwave Scanning Radiometer 2. Geophysical parameters observed by GCOM-W1: 1) Total Precipitable Water: Daily / Monthly: High res. = 0.1°, Low res. = 0.25° 2) Cloud Liquid Water: Daily / Monthly: High res. = 0.1°, Low res. = 0.25° 3) Precipitation: Daily / Monthly: High res. = 0.1°, Low res. = 0.25° 4) Sea Surface Temperature: Daily / Monthly: High res. = 0.1°, Low res. = 0.25° 5) Sea Ice Concentration: Daily / Monthly: High res. = 10 km, Low res. = 25 km 6) Snow Depth: Daily / Monthly: High res. = 0.1°, Low res. = 0.25° 7) Soil Moisture Content: Daily / Monthly: High res. = 0.1°, Low res. = 0.25° 8) Brightness Temperature: Daily / Monthly: High res. = 0.1°, Low res. = 0.25° Coverage: 1450 km swath for every 2 days.

Platform	Instrument	Type	Data Availability	Descriptions
SHIKISAI (JP)	GCOM-C (Global Change Observation Mission - Climate)	Passive	Free	<p>Mission Duration: 23 December 2017 –</p> <p>Instrument: Second-Generation Global Imager.</p> <p>Instantaneous Field of View based on Sensor Channel:</p> <p><u>Visible Near Infrared (VNIR)</u></p> <ol style="list-style-type: none"> 1) VNIR1 (central wavelength 0.380 μm): 250 \times 250 m 2) VNIR2 (central wavelength 0.412 μm): 250 \times 250 m 3) VNIR3 (central wavelength 0.443 μm): 250 \times 250 m 4) VNIR4 (central wavelength 0.490 μm): 250 \times 250 m 5) VNIR5 (central wavelength 0.530 μm): 250 \times 250 m 6) VNIR6 (central wavelength 0.565 μm): 250 \times 250 m 7) VNIR7 (central wavelength 0.6735 μm): 250 \times 250 m 8) VNIR8 (central wavelength 0.6735 μm): 250 \times 250 m 9) VNIR9 (central wavelength 0.763 μm): 1000 \times 1000 m 10) VNIR10 (central wavelength 0.8685 μm): 250 \times 250 m 11) VNIR11 (central wavelength 0.8685 μm): 250 \times 250 m 12) Polarized VNIR (P1) (central wavelength 0.6765 μm): 1000 \times 1000 m 13) Polarized VNIR (P2) (central wavelength 0.8685 μm): 1000 \times 1000 m <p><u>Infrared Scanner (IRS)</u></p> <ol style="list-style-type: none"> 1) Short Wave Infrared (SWIR1) (central wavelength 1.05 μm): 1000 \times 1000 m 2) Short Wave Infrared (SWIR2) (central wavelength 1.38 μm): 1000 \times 1000 m 3) Short Wave Infrared (SWIR3) (central wavelength 1.63 μm): 250 \times 250 m 4) Short Wave Infrared (SWIR4) (central wavelength 2.21 μm): 1000 \times 1000 m 5) Thermal Infrared (TIR1) (central wavelength 10.80 μm): 500 \times 500 m 6) Thermal Infrared (TIR2) (central wavelength 12.00 μm): 500 \times 500 m <p>14) Coverage: 2-3 days</p>
HIMAWARI (JP)	HIMAWARI 8	Passive	Not Free	<p>Mission Duration: 7 October 2014 –</p> <p>Data File Format: NetCDF</p> <p>Instrument: The Advanced Himawari Imager (AHI)</p> <p>Spectral Bands:</p> <ol style="list-style-type: none"> 1) Visible 1 (0.46 μm): 1 \times 1 km 2) Visible 2 (0.51 μm): 1 \times 1 km 3) Visible 3 (0.64 μm): 0.5 \times 0.5 km 4) Near Infrared 1 (0.86 μm): 1 \times 1 km 5) Near Infrared 2 (1.6 μm): 2 \times 2 km

Platform	Instrument	Type	Data Availability	Descriptions
				6) Near Infrared 3 (2.3 μm): 2×2 km 7) Infrared 4 (3.9 μm): 2×2 km 8) WV (6.2 μm): 2×2 km 9) W2 (7.0 μm): 2×2 km 10) W3 (7.3 μm): 2×2 km 11) MI (8.6 μm): 2×2 km 12) O3 (9.6 μm): 2×2 km 13) IR (10.4 μm): 2×2 km 14) L2 (11.2 μm): 2×2 km 15) I2 (12.3 μm): 2×2 km 16) CO ₂ (13.3 μm): 2×2 km Coverage: Revisit cycle = 1436.13 minutes.
GOES (NASA – NOAA)	GOES-16	Passive	Free	Mission Duration: 19 November 2016 – Instrument: The Advanced Baseline Imager (ABI) Spectral Bands: 1) Blue (0.47 μm): 1×1 km 2) Red (0.64 μm): 0.5×0.5 km 3) Veggie (0.865 μm): 1×1 km 4) Cirrus (1.378 μm): 2×2 km 5) Snow/Ice (1.61 μm): 1×1 km 6) Cloud Particle Size (2.25 μm): 2×2 km 7) Shortwave Window (3.9 μm): 2×2 km 8) Upper-level Tropospheric Water Vapor (6.9 μm): 2×2 km 9) Mid-level Tropospheric Water Vapor (6.95 μm): 2×2 km 10) Lower-level Tropospheric Water Vapor (7.34 μm): 2×2 km 11) Cloud-Top Phase (8.5 μm): 2×2 km 12) Ozone (9.61 μm): 2×2 km 13) Clean Infrared Longwave Window (10.35 μm): 2×2 km 14) Infrared Longwave Window (11.2 μm): 2×2 km 15) Dirty Infrared Longwave Window (12.3 μm): 2×2 km 16) CO ₂ Longwave Infrared (13.3 μm): 2×2 km Coverage: Revisit cycle = 1436.1 minutes.
NOAA-20 (NOAA)	VIRS	Passive	Free	Mission Duration: 18 November 2017 – Instrument: Visible Infrared Imaging Radiometer Suite (VIRS) Spectral Bands: 1) M1. Ocean color, Aerosols (0.402 – 0.422 μm): 750×750 m 2) M2. Ocean color, Aerosols (0.436 – 0.454 μm): 750×750 m 3) M3. Ocean color, Aerosols (0.478 – 0.498 μm): 750×750 m 4) M4. Ocean color, Aerosols (0.545 – 0.565 μm): 750×750 m

Platform	Instrument	Type	Data Availability	Descriptions
				5) I1. Imagery (0.600 – 0.680 μm): 375 \times 375 m 6) M5. Ocean color, Aerosols (0.662 – 0.682 μm): 750 \times 750 m 7) M6. Ocean color, Aerosols (0.739 – 0.754 μm): 750 \times 750 m 8) I2. NDVI (0.846 – 0.885 μm): 375 \times 375 m 9) M7. Ocean color, Aerosols (0.846 – 0.885 μm): 750 \times 750 m 10) M8. Cloud particle size (1.23 – 1.25 μm): 750 \times 750 m 11) M9. Cirrus cover (1.371 – 1.386 μm): 750 \times 750 m 12) I3. Binary snow map (1.58 – 1.64 μm): 375 \times 375 m 13) M10. Snow fraction (1.58 – 1.64 μm): 750 \times 750 m 14) M11. Clouds (2.225 – 2.275 μm): 750 \times 750 m 15) I4. Cloud imagery (3.55 – 3.93 μm): 375 \times 375 m 16) M12. Sea surface temperature (3.66 – 3.84 μm): 750 \times 750 m 17) M13. Sea surface temperature (3.973 – 4.128 μm): 750 \times 750 m 18) M14. Cloud top properties (8.40 – 8.70 μm): 750 \times 750 m 19) M15. Sea surface temperature (10.263 – 11.263 μm): 750 \times 750 m 20) I5. Cloud imagery (10.50 – 12.40 μm): 375 \times 375 m 21) M16. Sea surface temperature (11.538 – 12.468 μm): 750 \times 750 m Altitude: 824 km Coverage: Revisit cycle 4 days
ADEOS-II (JP)	MIDORI-II	Active		Duration Mission: 14 December 2002 – 23 October 2003 Instrument: 1. Advanced Microwave Scanning Radiometer Spectral Bands: 1) 1 (central frequency 6.925 GHz): 40 \times 70 km 2) B2 (central frequency 10.65 GHz): 27 \times 46 km 3) B3 (central frequency 18.7 GHz): 14 \times 25 km 4) B4 (central frequency 23.8 GHz): 17 \times 29 km 5) B5 (central frequency 36.5 GHz): 8 \times 14 km 6) B6 (central frequency 50.3 GHz): 6 \times 10 km 7) B7 (central frequency 52.8 GHz): 6 \times 10 km

Platform	Instrument	Type	Data Availability	Descriptions
				<p>8) B8 (central frequency 89.0A GHz): 3×6 km</p> <p>9) B9 (central frequency 89.0B GHz): 3×6 km</p> <p>Swath: 1600 km</p> <p>2. Advanced Microwave Scanning Radiometer</p> <p><u>Spectral Bands:</u></p> <p>1) Visible and Near Infrared: 23 bands (0.38-0.83 μm)</p> <p>2) Short wavelength infrared: 6 bands (1.05-2.215 μm)</p> <p>3) Middle and Thermal IR: 7 bands (3.715-11.95 μm)</p> <p>Swath: 1600 km</p> <p>3. SeaWinds (NASA Scatterometer II)</p> <p><u>Radar:</u></p> <p>13.4 GHz (Ku-band); 110 W pulse at 189 Hz pulse repetition frequency (PRF)</p> <p>Spatial resolution: 50 km</p> <p>Swath: 1800 km</p> <p>4. Improved Limb Atmospheric Spectrometer-II (ILAS-II)</p> <p><u>Spectral Bands:</u></p> <p>1) Band 1: 44 IR channels from 6.21-11.76 μm</p> <p>2) Band 2: 22 IR channels from 3.0-5.7 μm</p> <p>3) Band 3: 22 IR channels from 12.78-12.85 μm</p> <p>4) VIS: 1024 channels from 0.753-0.784 μm</p> <p>Spatial coverage: 10 – 60 km</p> <p>5. Polarization and Directionality of the Earth's Reflectances (POLDER-2)</p> <p><u>Spectral Bands:</u></p> <p>1) Ocean color: wavelength 0.443 μm</p> <p>2) Aerosol, ERB: wavelength 0.443 μm</p> <p>3) Ocean color: wavelength 0.490 μm</p> <p>4) Ocean color: wavelength 0.565 μm</p> <p>5) Vegetation, aerosols, ERB: wavelength 0.670 μm</p> <p>6) Cloud top temperature: wavelength 0.763 μm</p> <p>7) Aerosols, CTP: wavelength 0.765 μm</p> <p>8) Vegetation, aerosols, ERB: wavelength 0.865 μm</p> <p>9) Water vapor content: wavelength 0.910 μm</p> <p>Swath: 2400 km</p> <p>Pixel size at nadir: $6 \text{ km} \times 7 \text{ km}$</p> <p>Coverage: Revisit cycle = 4 days.</p>

Platform	Instrument	Type	Data Availability	Descriptions
ENVISAT (ESA)	MERIS	Passive		<p>Mission Duration: 1 March 2002 – 8 April 2012</p> <p>Instrument: Medium Resolution Imaging Spectrometer</p> <p>Spectral Bands:</p> <ol style="list-style-type: none"> 1) Yellow substance and turbidity (band center = 0.4125 μm) 2) Chlorophyll absorption max (band center = 0.4425 μm) 3) Chlorophyll and other pigments (band center = 0.490 μm) 4) Turbidity, suspended sediment and red tides (band center = 0.510 μm) 5) Chlorophyll, suspended sediment (band center = 0.560 μm) 6) Suspended sediment (band center = 0.620 μm) 7) Chlorophyll absorption (band center = 0.665 μm) 8) Chlorophyll fluorescence, red edge (band center = 0.68125 μm) 9) Aerosol, red edge transition (band center = 0.70875 μm) 10) Oxygen absorption reference band, vegetation (band center = 0.75375 μm) 11) Oxygen absorption R-branch (band center = 0.760625 μm) 12) Aerosol correction over ocean (band center = 0.865 μm) 13) Water vapor absorption reference (band center = 0.885 μm) 14) Water vapor, vegetation (band center = 0.900 μm) <p>Spatial resolution: Open ocean observation: 1040 \times 1200 m Land and Coastal Zone: 260 \times 300 m</p> <p>Altitude: 790 km</p> <p>Coverage: Repeat cycle 35 days</p>
ENVISAT (ESA)	AATSR	Passive		<p>Mission Duration: 1 March 2002 – 8 April 2012</p> <p>Instrument: Advanced Along Track Scanning Radiometer (AATSR)</p> <p>Spectral Bands:</p> <ol style="list-style-type: none"> 1) Chlorophyll (band center = 0.555 μm) 2) Vegetation Index (band center = 0.659 μm) 3) Vegetation Index (band center = 0.865 μm) 4) Cloud clearing (band center = 1.61 μm) 5) SST (band center = 3.70 μm) 6) SST (band center = 10.85 μm) 7) SST (band center = 12.00 μm) <p>Spatial resolution: 1 km \times 1 km</p>

Platform	Instrument	Type	Data Availability	Descriptions
				Swath width: 500 km Altitude: 790 km Coverage: Repeat cycle 35 days
TERRA (NASA)	MODIS	Passive		Mission Duration: 15 April 1999 – Instrument: Moderate Resolution Imaging Spectroradiometer (MODIS) Spectral Bands: <ol style="list-style-type: none"> 1) Land/Cloud/Aerosols Boundaries (0.62 – 0.67 μm): 250 \times 250 m 2) Land/Cloud/Aerosols Boundaries (0.841 – 0.876 μm): 250 \times 250 m 3) Land/Cloud/Aerosols Properties (0.459 – 0.479 μm): 500 \times 500 m 4) Land/Cloud/Aerosols Properties (0.545 – 0.565 μm): 500 \times 500 m 5) Land/Cloud/Aerosols Properties (1.23 – 1.25 μm): 500 \times 500 m 6) Land/Cloud/Aerosols Properties (1.628 – 1.652 μm): 500 \times 500 m 7) Land/Cloud/Aerosols Properties (2.105 – 2.155 μm): 500 \times 500 m 8) Ocean color (0.405 – 0.420 μm): 1000 \times 1000 m 9) Ocean color (0.438 – 0.448 μm): 1000 \times 1000 m 10) Ocean color (0.483 – 0.493 μm): 1000 \times 1000 m 11) Ocean color (0.526 – 0.536 μm): 1000 \times 1000 m 12) Ocean color (0.546 – 0.556 μm): 1000 \times 1000 m 13) Ocean color (0.662 – 0.672 μm): 1000 \times 1000 m 14) Ocean color (0.673 – 0.683 μm): 1000 \times 1000 m 15) Ocean color (0.743 – 0.753 μm): 1000 \times 1000 m 16) Ocean color (0.862 – 0.877 μm): 1000 \times 1000 m 17) Water vapor (0.890 – 0.920 μm): 1000 \times 1000 m 18) Water vapor (0.931 – 0.941 μm): 1000 \times 1000 m 19) Water vapor (0.915 – 0.965 μm): 1000 \times 1000 m 20) Surface/Cloud temperature (3.660 – 3.840 μm): 1000 \times 1000 m 21) Surface/Cloud temperature (3.929 – 3.989 μm): 1000 \times 1000 m 22) Surface/Cloud temperature (3.929 – 3.989 μm): 1000 \times 1000 m 23) Surface/Cloud temperature (4.020 – 4.080 μm): 1000 \times 1000 m 24) Atmospheric temperature (4.433 – 4.498 μm): 1000 \times 1000 m 25) Atmospheric temperature (4.482 – 4.549 μm): 1000 \times 1000 m

Platform	Instrument	Type	Data Availability	Descriptions
				26) Cirrus clouds (1.360 – 1.390 μm): 1000 \times 1000 m 27) Cirrus clouds (6.535 – 6.895 μm): 1000 \times 1000 m 28) Cirrus clouds (7.175 – 7.475 μm): 1000 \times 1000 m 29) Cloud properties (8.40 – 8.70 μm): 1000 \times 1000 m 30) Ozone (9.580 – 9.880 μm): 1000 \times 1000 m 31) Surface/Cloud temperature (10.78 – 11.28 μm): 1000 \times 1000 m 32) Surface/Cloud temperature (11.77 – 12.27 μm): 1000 \times 1000 m 33) Cloud top altitude (13.185 – 13.485 μm): 1000 \times 1000 m 34) Cloud top altitude (13.485 – 13.785 μm): 1000 \times 1000 m 35) Cloud top altitude (13.785 – 14.085 μm): 1000 \times 1000 m 36) Cloud top altitude (14.085 – 14.385 μm): 1000 \times 1000 m Coverage: Revisit cycle = 1 – 2 days. Swath width: 2330 km
TANSAT (China)	CAPI (Cloud and Aerosol Polarimetry Imager)			CAPI Specification: 1) Band 1 (central wavelength = 0.380 μm): 0.5 \times 0.5 km 2) Band 2 (central wavelength = 0.674 μm): 0.5 \times 0.5 km 3) Band 3 (central wavelength = 0.870 μm): 0.5 \times 0.5 km 4) Band 4 (central wavelength = 1.375 μm): 0.5 \times 0.5 km 5) Band 5 (central wavelength = 1.640 μm): 0.5 \times 0.5 km Revisit cycle: 16 days Altitude: ~700 km
CBERS (China-Brazil)	MUXCam, PanMUX, IRS & IRMSS-2, WFI			CBERS Instrument specification: <u>Multispectral Camera (MUXCam)</u> 1) Band 1 (0.45 – 0.52 μm): 20 \times 20 m 2) Band 2 (0.52 – 0.59 μm): 20 \times 20 m 3) Band 3 (0.63 – 0.69 μm): 20 \times 20 m 4) Band 4 (0.77 – 0.89 μm): 20 \times 20 m <u>Panchromatic and Multispectral Camera (PanMUX)</u> 5) Band 5 (0.51 – 0.85 μm): 5 \times 5 m 6) Band 6 (0.52 – 0.59 μm): 10 \times 10 m 7) Band 7 (0.63 – 0.69 μm): 10 \times 10 m 8) Band 8 (0.77 – 0.89 μm): 10 \times 10 m <u>IRS and IRMSS-2</u> 1) Band 9 (0.50 – 0.90 μm): 40 \times 40 m 2) Band 10 (1.55 – 1.75 μm): 40 \times 40 m

Platform	Instrument	Type	Data Availability	Descriptions
				<p>3) Band 11 (2.08 – 2.35 μm): 40 \times 40 m 4) Band 12 (10.40 – 12.50 μm): 80 \times 80 m</p> <p><u>Wide-Field Imager (WFI)</u></p> <p>1) Band 13 (0.45 – 0.52 μm): 64 \times 64 m 2) Band 14 (0.52 – 0.59 μm): 64 \times 64 m 3) Band 15 (0.63 – 0.69 μm): 64 \times 64 m 4) Band 16 (0.77 – 0.89 μm): 64 \times 64 m</p> <p>Revisit cycle: 26 (MUXCam, IRS), 52 (PanMUX), 5 (WFI) days Altitude: 778 km</p>
SUOMI NPP (NOAA NASA)	VIIRS	Passive	Free	<p>Mission Duration: 28 October 2017 –</p> <p>Instrument: Visible Infrared Imaging Radiometer Suite (VIIRS)</p> <p>Spectral Bands:</p> <p>1) M1. Ocean color, Aerosols (0.402 – 0.422 μm): 750 \times 750 m 2) M2. Ocean color, Aerosols (0.436 – 0.454 μm): 750 \times 750 m 3) M3. Ocean color, Aerosols (0.478 – 0.498 μm): 750 \times 750 m 4) M4. Ocean color, Aerosols (0.545 – 0.565 μm): 750 \times 750 m 5) I1. Imagery (0.600 – 0.680 μm): 375 \times 375 m 6) M5. Ocean color, Aerosols (0.662 – 0.682 μm): 750 \times 750 m 7) M6. Ocean color, Aerosols (0.739 – 0.754 μm): 750 \times 750 m 8) I2. NDVI (0.846 – 0.885 μm): 375 \times 375 m 9) M7. Ocean color, Aerosols (0.846 – 0.885 μm): 750 \times 750 m 10) M8. Cloud particle size (1.23 – 1.25 μm): 750 \times 750 m 11) M9. Cirrus cover (1.371 – 1.386 μm): 750 \times 750 m 12) I3. Binary snow map (1.58 – 1.64 μm): 375 \times 375 m 13) M10. Snow fraction (1.58 – 1.64 μm): 750 \times 750 m 14) M11. Clouds (2.225 – 2.275 μm): 750 \times 750 m 15) I4. Cloud imagery (3.55 – 3.93 μm): 375 \times 375 m 16) M12. Sea surface temperature (3.66 – 3.84 μm): 750 \times 750 m 17) M13. Sea surface temperature (3.973 – 4.128 μm): 750 \times 750 m 18) M14. Cloud top properties (8.40 – 8.70 μm): 750 \times 750 m</p>

Platform	Instrument	Type	Data Availability	Descriptions
				<p>19) M15. Sea surface temperature (10.263 – 11.263 μm): 750 \times 750 m</p> <p>20) I5. Cloud imagery (10.50 – 12.40 μm): 375 \times 375 m</p> <p>21) M16. Sea surface temperature (11.538 – 12.468 μm): 750 \times 750 m</p> <p>Altitude: 824 km</p> <p>Coverage: Revisit cycle 16 days</p> <p>Data Source: https://www.bou.class.noaa.gov/saa/products/catSearch </p>
SUOMI NPP (NOAA NASA)	ATMS	Active	Free	<p>Mission Duration: 28 October 2017 –</p> <p>Instrument: Advanced Technology Microwave Sounder (ATMS)</p> <p>Channels:</p> <ol style="list-style-type: none"> 1) Window-water Vapor 100 mm (Center frequency: 23.8 GHz and max bandwidth: 0.27) 2) Window-water Vapor 500 mm (Center frequency: 31.4 GHz and max bandwidth: 0.18) 3) Window-surface emissivity (Center frequency: 50.30 GHz and max bandwidth: 0.18) 4) Window-surface emissivity (Center frequency: 51.76 GHz and max bandwidth: 0.40) 5) Surface air (Center frequency: 52.80 GHz and max bandwidth: 0.40) 6) Channel 6 (4 km ~ 700 mb) (Center frequency: 53.596 \pm 0.115 GHz and max bandwidth: 0.17) 7) Channel 7 (9 km ~ 400 mb) (Center frequency: 54.40 GHz and max bandwidth: 0.40) 8) Channel 8 (11 km ~ 250 mb) (Center frequency: 54.94 GHz and max bandwidth: 0.40) 9) Channel 9 (13 km ~ 180 mb) (Center frequency: 55.50 GHz and max bandwidth: 0.33) 10) Channel 10 (17 km ~ 90 mb) (Center frequency: 57.290334 GHz and max bandwidth: 0.33) 11) Channel 11 (19 km ~ 50 mb) (Center frequency: 57.290334 \pm 0.217 GHz and max bandwidth: 0.078) 12) Channel 12 (25 km ~ 25 mb) (Center frequency: 57.290334 \pm 0.3222 \pm 0.048 GHz and max bandwidth: 0.036) 13) Channel 13 (29 km ~ 10 mb) (Center frequency: 57.290334 \pm 0.3222 \pm 0.022 GHz and max bandwidth: 0.016) 14) Channel 14 (32 km ~ 6 mb) (Center frequency: 57.290334 \pm 0.3222 \pm 0.010 GHz and max bandwidth: 0.008)

Platform	Instrument	Type	Data Availability	Descriptions
				<p>15) Channel 15 (37 km ~ 3 mb) (Center frequency: $57.290334 \pm 0.3222 \pm 0.0045$ GHz and max bandwidth: 0.003)</p> <p>16) Window H₂O 150 mm (Center frequency: 87 – 91 GHz and max bandwidth: 2.0)</p> <p>17) Window H₂O 18 mm (Center frequency: 166.31 GHz and max bandwidth: 2.0)</p> <p>18) Window H₂O 8 mm (Center frequency: 188.31 ± 7.0 GHz and max bandwidth: 2.0)</p> <p>19) Window H₂O 4.5 mm (Center frequency: 188.31 ± 4.5 GHz and max bandwidth: 2.0)</p> <p>20) Window H₂O 2.5 mm (Center frequency: 188.31 ± 3.0 GHz and max bandwidth: 1.0)</p> <p>21) Window H₂O 1.2 mm (Center frequency: 188.31 ± 1.8 GHz and max bandwidth: 1.0)</p> <p>22) Window H₂O 0.5 mm (Center frequency: 188.31 ± 1.0 GHz and max bandwidth: 0.5)</p> <p>Altitude: 824 km Coverage: Revisit cycle 16 days Data Source: https://www.bou.class.noaa.gov/saa/products/catSearch</p>
SUOMI NPP (NOAA NASA)	OMPS	Passive	Free	<p>Mission Duration: 28 October 2017 –</p> <p>Instrument: Ozone Mapping and Profiler Suite (OMPS)</p> <p>Purpose:</p> <ol style="list-style-type: none"> 1. Global daily maps of the amount of ozone in the vertical column of the atmosphere. Measurement Parameter: <ol style="list-style-type: none"> 1) Horizontal cell size = 50 km at nadir. 2) Range = 50 – 650 Dobson Unit (DU) 3) Accuracy = 15 DU or better 4) Precision = 3 DU + 0.5% total ozone or better 5) Long time stability = 1% over 7 years or better 2. Provision of volumetric ozone concentration profiles in specified segments of a vertical column of the atmosphere with a 4-day revisit time. Measurement Parameter: <ol style="list-style-type: none"> 1) Vertical cell size = 3 km 2) Horizontal cell size = 250 km at nadir. 3) Vertical coverage = Tropopause height to 60 km 4) Range = 0.1 – 15 ppmv 5) Accuracy = Greater of (20%, 0.1 ppmv) above 15 km

Platform	Instrument	Type	Data Availability	Descriptions
				<p>6) Precision = Greater of (10%, 0.1 ppmv) above 15 km</p> <p>7) Long time stability = 3%, 15-50 km; 10% TH-15 and 50-60 km 2%</p> <p>Parameters:</p> <p>1. <u>Nadir Mapper:</u></p> <ol style="list-style-type: none"> 1) Spectral range = 300 – 380 nm 2) Spectral radiance range [photons/(s cm² sr nm)] = 9 el 3 (380 nm) and 8 el 1 (308 nm) 3) Minimum SNR = 1000 4) Integration time = 7.6 s 5) Spectral resolutions = 1 nm FWHM and 2.4 samples/FWHM 6) Field of view = $110^0 \times 1^0$ (cross-track \times along-track) 7) Cell size = 49 km \times 50 km (nadir) 8) Revisit time = Daily 9) Swath = 2800 km <p>2. <u>Nadir Profiler:</u></p> <ol style="list-style-type: none"> 1) Spectral range = 250 – 310 nm 2) Spectral radiance range [photons/(s cm² sr nm)] = 2 el 3 (310 nm) and 1.5 el 8 (252 nm) 3) Minimum SNR = 35 (252 nm) and 400 (310 nm) 4) Integration time = 38 s 5) Spectral resolutions = 1 nm FWHM and 2.4 samples/FWHM 6) Field of view = $16.6^0 \times 0.26^0$ 7) Cell size = 250 km \times 250 km (single cell at nadir) 8) Revisit time = Daily 9) Swath = 250 km <p>3. <u>Limb Sounding:</u></p> <ol style="list-style-type: none"> 1) Spectral range = 290 – 1000 nm 2) Spectral radiance range [photons/(s cm² sr nm)] = 9 el 3 (600 nm) and 5 el 0 (300 nm) 3) Minimum SNR = 320 (290 nm at 60 km) and 1200 (600 nm at 15 km) 4) Integration time = 38 s 5) Spectral resolutions = 2.8-54 nm FWHM and 1 samples/FWHM 6) Field of view = $8.5^0 \times 1.9^0$ (3 sets) 7) Cell size = 1 km vertical sampling interval 8) Revisit time = 4 days (average) 9) Swath = 3 vertical slits along-track and 500 km cross-track <p>Altitude: 824 km</p> <p>Data Source:</p> <p>https://www.bou.class.noaa.gov/saa/products/catSearch</p>

Platform	Instrument	Type	Data Availability	Descriptions
SUOMI NPP (NOAA NASA)	CrIS	Passive	Free	<p>Mission Duration: 28 October 2017 –</p> <p>Instrument: Cross-Track Infrared Sounder (CrIS)</p> <p>Spectral bands:</p> <ol style="list-style-type: none"> Longwave Infrared (Thermal Infrared) (TIR): <ol style="list-style-type: none"> Channel center wavenumber range = 650-1095 cm⁻¹; 15.38-9.14 μm No. of channels = 713 Spectral resolution = (<0.625 cm⁻¹) or 146 nm (at 15.3 μm) to 51.7 nm (at 9.1 μm) Absolute spectral uncertainty = < 10 (5) PPM Medium Wavelength Infrared (MWIR): <ol style="list-style-type: none"> Channel center wavenumber range = 1210-1750 cm⁻¹; 8.26-5.71 μm No. of channels = 433 Spectral resolution = (<1.25 cm⁻¹) or 92.8 nm (at 8.62 μm) to 40.6 nm (at 5.7 μm) Absolute spectral uncertainty = < 10 (5) PPM Short Wavelength Infrared (SWIR): <ol style="list-style-type: none"> Channel center wavenumber range = 2155-2550 cm⁻¹; 4.64-3.92 μm No. of channels = 159 Spectral resolution = (<2.5 cm⁻¹) or 5.4 nm (at 4.64 μm) to 38.4 nm (at 3.92 μm) Absolute spectral uncertainty = < 10 (5) PPM <p>Altitude: 824 km</p> <p>Data Source: https://www.bou.class.noaa.gov/saa/products/catSearch </p>
SUOMI NPP (NOAA NASA)	CERES	Passive	Free	<p>Mission Duration: 28 October 2017 –</p> <p>Instrument: Cloud and Earth's Radiant Energy System (CERES)</p> <p>Instruments:</p> <ol style="list-style-type: none"> Swath = limb to limb Spatial resolutions = 20 km at nadir Field of view = ± 78° cross-track, 360° azimuth Three channels in each radiometer = Total radiance (0.3 to 100 μm); Shortwave (0.3 to 5 μm); Window (8 to 12 μm) Data rate = 10.5 kbit/scanner (average) Field of view = 8.5° × 1.9° (3 sets) Atmospheric window: 8.0 - 12.0 μm (water vapor) Total channel radiance in the spectral range of 0.35 - 125 μm; reflected or emitted infrared radiation of the Earth

Platform	Instrument	Type	Data Availability	Descriptions
				<p>atmosphere system, measurement accuracy of 0.3%.</p> <p>9) Earth-atmosphere system, measurement accuracy of 0.3%</p> <p>10) VNIR + SWIR: 0.3 - 5.0 μm (also referred to as shortwave channel); measurement of reflected sunlight to an accuracy of 1%</p> <p>11) 3-channel deep convective cloud test =</p> <ol style="list-style-type: none"> Use night-time 8-12 μm window to predict longwave radiation (LW): cloud < 205K Total - SW = LW vs Window predicted LW in daytime for same clouds < 205K temperatures <p>12) 3-channel day/night tropical ocean test =</p> <ol style="list-style-type: none"> Rotate scan plane to align scanning instruments TRMM, Terra during orbital crossings (Haefelin: reached 0.1% LW, window, 0.5% SW 95% configuration in 6 weeks of orbital crossings of Terra and TRMM) <p>Altitude: 824 km</p> <p>Data Source: https://www.bou.class.noaa.gov/saa/products/catSearch </p>

Appendix 5

Prior Research in Constructing Spatial W Matrices

Appendix 5A. Table of Prior Researches

Source: Google Scholar				
Keyword: allintitle: ("spatial * matrix")				
Hit: 180 (without patents and citations)				
Retrieval Date: 16-20 August 2017				
No.	Title	Author(s)	Journal	Date of Publication
1	Constructing the Spatial Weights Matrix Using a Local Statistic	Getis, Arthur and Jared Aldstadt	<i>Perspectives on spatial data analysis</i>	2010
2	Using AMOEBA to Create a Spatial Weights Matrix and Identify Spatial Clusters	Aldstald and Getis	<i>Geographical Analysis</i>	2006
3	Spatial weights matrix	Zhou and Lin	<i>Encyclopedia of GIS</i>	2008
4	Matrix fitting approach to direction of arrival estimation with imperfect spatial coherence of wavefronts	Gershman <i>et al</i>	<i>IEEE Transactions on Signal Processing</i>	1997
5	Measuring the neighboring and environmental effects on residential property value: Using spatial weighting matrix	Hui <i>et al</i>	<i>Building and Environment</i>	2007
6	Minimal realization of a spatial stiffness matrix with simple springs connected in parallel	Roberts, R.G	<i>IEEE Transactions on Robotics and Automation</i>	1999
7	Direction of arrival estimation using the parameterized spatial correlation matrix	Dmochowski, Jacek <i>et al</i>	<i>IEEE Transactions on Audio, Speech, and Language Processing</i>	2007
8	Estimating a spatial autoregressive model with an endogenous spatial weight matrix	Xi Qu and Lung-fei Lee	<i>Journal of Econometrics</i>	2015
9	A low complexity algorithm to simulate the spatial covariance matrix for clustered MIMO channel models	Vorenza, A. <i>et al</i>	<i>Vehicular Technology Conference, 2004. VTC 2004-Spring, 2004 IEEE 59th</i>	2004
10	Estimating direct-to-reverberant energy ratio using D/R spatial correlation matrix model	Hioka, Yusuke <i>et al</i>	<i>IEEE Transactions on Audio, Speech, and Language Processing</i>	2011
11	Robust uplink to downlink spatial covariance matrix transformation for downlink beamforming	Chalise, B.K <i>et al</i>	<i>2004 IEEE International Conference on Communications</i>	2004
12	Estimation of spatial weights matrix in a spatial error model, with an application to diffusion in housing demand	Bhattacharjee, Arnab and Chris Jensen-Butler	n.a	n.a
13	Nonparametric Estimation of the Spatial Connectivity Matrix Using Spatial Panel Data	Beenstock and Felsenstein	<i>Geographical Analysis</i>	2012
14	Estimation of Spatial Weights Matrix, with an Application to Diffusion in Housing Demand	Bhattacharjee, Arnab and Chris Jensen-Butler	<i>Centre for Research into Industry, Enterprise, Finance and the Firm, (CRIEFF Discussion Papers)</i>	2006
15	Estimation of the spatial weights matrix under structural constraints	Bhattacharjee, Arnab and Chris Jensen-Butler	<i>Regional Science and Urban Economics</i>	2013

16	Computation of the information matrix for models with spatial interaction on a lattice	Smirnov, Oleg A.	<i>Journal of Computational and Graphical Statistics</i>	2004
17	High-spatial resolution matrix-assisted laser desorption ionization imaging analysis of glucosylceramide in spleen sections from a mouse model of Gaucher disease	Snel and Fuller	<i>Analytical Chemistry</i>	2010
18	The spatial autocorrelation matrix	Chessel, D.	<i>Vegetation dynamics in grasslands, healthlands and mediterranean ligneous formations</i>	1981
19	Minimal realization of an arbitrary spatial stiffness matrix with a parallel connection of simple and complex springs	Roberts, R.G	<i>IEEE Transactions on Robotics and Automation</i>	2000
20	Spatial regression models in criminology: Modeling social processes in the spatial weights matrix	Tita and Radil	<i>Handbook of quantitative criminology</i>	2010
21	Model boosting for spatial weighting matrix selection in spatial lag models	Kostov, Phillip	<i>Environment and Planning B: Urban Analytics and City Science</i>	2010
22	Direction of arrival estimation using eigenanalysis of the parameterized spatial correlation matrix	Dmochowski, Jacek <i>et al</i>	<i>2007 IEEE International Conference on Acoustics, Speech and Signal Processing</i>	2007
23	The spatial stiffness matrix from simple stretched springs	Sellig, J.M.	<i>Robotics and Automation, 2000. Proceedings</i>	2000
24	On the Four Types of Weight Functions for Spatial Contiguity Matrix	Yanguang Chen	<i>Letters in Spatial and Resource Sciences</i>	2012
25	A Dynamic Spatial Weight Matrix and Localised STARIMA for Network Modelling	Tao Cheng <i>et al</i>	<i>Geographical Analysis</i>	2014
26	Comparative analysis of spatial covariance matrix estimation methods in OFDM communication systems	Maltsev, Alexander <i>et al</i>	<i>2006 IEEE International Symposium on Signal Processing and Information Technology</i>	2006
27	Automatic selection of a spatial weight matrix in spatial econometrics: Application to a spatial hedonic approach	Seya, Hajime <i>et al</i>	<i>Regional Science and Urban Economics</i>	2013
28	Spatial Nonstationarity and Spurious Regression: The Case with Row-Normalized Spatial Weights Matrix	Lung-fei Lee and Jihai Yu	<i>Spatial Economic Analysis</i>	2009
29	Analyzing the Effect of Spatial Weighted Matrix On Spatial Autocorrelation——Taking Hunan's Income Gap between Urban and Rural Areas as A Case	Hongliang, Wang <i>et al</i>	<i>Journal of South China Normal University (Natural Science Edition)</i>	2010
30	Bounds on eigenvalues of a spatial correlation matrix	Choi and Love	<i>IEEE Communications Letters</i>	2014
31	Structure of the spatial stiffness matrix	Sellig and Ding	<i>Structure of the spatial stiffness matrix. International Journal of Robotics and Automation</i>	2002
32	On the normal form of a spatial stiffness matrix	Roberts, R.G	<i>Proceedings 2002 IEEE International Conference on Robotics and Automation</i>	2002

33	Measuring quantum states: Experimental setup for measuring the spatial density matrix	Tegmark, M.	<i>Physical Review A</i>	1996
34	Bayesians in Space: Using Bayesian Methods to Inform Choice of Spatial Weights Matrix in Hedonic Property Analyses	Mueller, Julie M. and John B. Loomis	<i>The Review of Regional Studies</i>	2010
35	Note on the normal form of a spatial stiffness matrix	Roberts, R.G	<i>IEEE Transactions on Robotics and Automation</i>	2001
36	Two-step lasso estimation of the spatial weights matrix	Ahrens, Achim and Arnab Bhattacharjee	<i>Econometrics</i>	2015
37	Detection and estimation of block structure in spatial weight matrix	Lam, Clifford and Pedro C.L. Souza	<i>Econometrics Review</i>	2016
38	Temporal convergence of phase spatial covariance matrix measurements in tomographic adaptive optics	Martin, O. <i>et al</i>	<i>Adaptive Optics Systems III. Proceedings of the SPIE</i>	2012
39	A matrix exponential spatial specification	LeSage and Pace	<i>Journal of Econometrics</i>	2007
40	DOA Estimation in Impulsive Noise Environments Using Fractional Lower Order Spatial-Temporal Matrix [J]	Jin and Zhong	<i>Acta Aeronautica Et Astronautica Sinica</i>	2006
41	Analysis and application on the specification methods of the spatial weight matrix	Liu and Wang	<i>Geo-information Science</i>	2002
42	Uplink to downlink spatial covariance matrix transformation concepts for downlink beamforming	Chalise, B.K <i>et al</i>	<i>Proceedings of the 3rd IEEE International Symposium on Signal Processing and Information Technology</i>	2003
43	A Proposal for an Alternative Spatial Weight Matrix under Consideration of the Distribution of Economic Activity	Perret, Jens K.	<i>Schumpeter Discussion Paper</i>	2011
44	On the eigenstructure of the signal-only tempo-spatial covariance matrix of broadband sources using a circular array	Messer and Rockah	<i>IEEE Transactions on Acoustics, Speech, and Signal Processing</i>	1990
45	The generalization of narrowband localization methods to broadband environments via parametrization of the spatial correlation matrix	Dmochowski, Jacek <i>et al</i>	<i>Signal Processing Conference, 2007 15th European</i>	2007
46	Computation of the information matrix for models of spatial interaction	Smirnov, Oleg A.	n.a	2003
47	Enhanced spatial covariance matrix estimation for asynchronous inter-cell interference mitigation in MIMO-OFDMA system	Jung Su Han <i>et al</i>	<i>VTC Spring 2009 - IEEE 69th Vehicular Technology Conference</i>	2009
48	Modelling a large, sparse spatial interaction matrix using data relating to a subset of possible flows	Bailey and Munford	<i>European journal of operational research</i>	1994
49	QML Estimation of the Spatial Weight Matrix in the MR-SAR Model	Benjanuvatra, Saruta	<i>VII World Conference of the Spatial Econometrics Association</i>	2013
50	The constitution and realization of spatial weight matrix based on ArcObjects [J]	Pan Hai-Yan <i>et al</i>	<i>Science of Surveying and Mapping</i>	2007

51	Choosing the right spatial weighting matrix in a quantile regression model	Kostov, Phillip	<i>ISRN Economics</i>	2013
52	Spatial Weighting Matrix Selection in Spatial Lag Econometric Model	Kostov, Phillip	<i>Econometrics</i>	2013
53	Spatial neighborhood matrix computation: inverse distance weighted versus binary contiguity	Negreiros, J	n.a	2009
54	Spatial heteroskedasticity and autocorrelation consistent estimation of covariance matrix	Kim and Sun	<i>Journal of Econometrics</i>	2011
55	Optimization of spatial filter matrix [J]	Zhou Hai <i>et al</i>	<i>Optics and Precision Engineering</i>	2007
56	On the spatial density matrix for the centre of mass of a one-dimensional perfect gas	Carazza, B.	<i>Foundations of Physics Letters</i>	1997
57	Quantitative Submonolayer Spatial Mapping of Arg-Gly-Asp-Containing Peptide Organomeraptan Gradients on Gold with Matrix-Assisted Laser Desorption/Ionization Mass Spectrometry	Qian Wang <i>et al</i>	<i>Analytical Chemistry</i>	2004
58	New spatial weight matrix and its application in China's regional foreign trade [J]	Zhang Jia-Wei <i>et al</i>	<i>Systems Engineering-Theory & Practice</i>	2009
59	Simulation of the spatial covariance matrix	Forenza, A. <i>et al</i>	<i>Simulation</i>	2003
60	Stata Implementation of the non-parametric spatial heteroskedasticity and autocorrelation consistent covariance matrix estimator	Jeanty, P.W.	<i>Stata conference San Diego</i>	2012
61	A robust algorithm based on spatial differencing matrix for source number detection and DOA estimation in multipath environment	Liu <i>et al</i>	<i>Physics Procedia</i>	2012
62	Investigation of basic imaging properties in digital radiography. 12. Effect of matrix configuration on spatial resolution	Fujita and Giger	<i>Medical Physics</i>	1988
63	Efficient multichannel nonnegative matrix factorization exploiting rank-1 spatial model	Kitamura, Daichi <i>et al</i>	<i>2015 IEEE International Conference on Acoustics, Speech and Signal Processing</i>	2015
64	One% Step Regularized Spatial Weight Matrix and Fixed Effects Estimation with Instrumental Variables	Lam and Souza	n.a	2015
65	Iterative receiver with enhanced spatial covariance matrix estimation in asynchronous interference environment for 3GPP LTE MIMO-OFDMA system	Jun-Hee Jang <i>et al</i>	<i>IEICE TRANSACTIONS on Communications</i>	2009
66	Model uncertainty in matrix exponential spatial growth regression models	Pribauer and Fischer	<i>Geographical Analysis</i>	2015
67	Model selection using J-test for the spatial autoregressive model vs. the matrix exponential spatial model	Han and Lee	<i>Regional Science and Urban Economics</i>	2013
68	Using matrix exponentials to explore spatial structure in regression relationships	LeSage and Pace	<i>researchgate</i>	2002

69	Momentum density and spatial form of correlated density matrix in model two-electron atoms with harmonic confinement	Akbari, A. <i>et al</i>	<i>Physical Review A</i>	2007
70	The spatial transfer matrix of curved box-girder bridge	Yan and Li	<i>Journal of Harbin Engineering University</i>	2014
71	A novel array calibration method based on spatial correlation matrix for HFSWR	Xiagou <i>et al</i>	<i>IEEE 10th International Conference On Signal Processing Proceedings</i>	2010
72	Synthesizing a positive definite spatial stiffness matrix with a hybrid connection of simple compliances	Roberts, R.G and Shirey	<i>Proceedings World Automation Congress, 2004</i>	2004
73	Large sample properties of the matrix exponential spatial specification with an application to FDI	Debarsy, N.	<i>Journal of Econometrics</i>	2015
74	Image classification using spatial relationship matrix based on color spatio-histogram	Woosaeng, Kim <i>et al</i>	<i>Proceedings. 2003 International Conference on Multimedia and Expo, 2003. ICME '03.</i>	2003
75	Determination of the reverberation chamber stirrer uncorrelated positions by means of the spatial and frequency correlation matrix	Gradoni, G. <i>et al</i>	<i>2013 International Symposium on Electromagnetic Compatibility (EMC EUROPE)</i>	2013
76	Spatial correlation matrix selection using Bayesian model averaging to characterize inter-tree competition in loblolly pine trees	Boone and Bullock	<i>Journal of Applied Statistics</i>	2008
77	Taking off some hoods: Estimating spatial models with a non-arbitrary W matrix	Fernandez-Vazquez, Esteban <i>et al</i>	<i>Spatial Econometrics Conference</i>	2007
78	A closer look at the spatial exponential matrix specification	Rodrigues, E <i>et al</i>	<i>Spatial Statistics</i>	2014
79	Robust spatial time-frequency distribution matrix estimation with application to direction-of-arrival estimation	Syariff, W. <i>et al</i>	<i>Signal Processing</i>	2011
80	Interference suppression with iterative channel and spatial covariance matrix estimation for LTE downlink	Fan, J <i>et al</i>	<i>Digital Signal Processing</i>	2014
81	Political interaction in the senate: estimating a political “spatial” weights matrix and an application to lobbying behavior	Chupp, B. A.	<i>Public Choice</i>	2014
82	Spatial weighting matrix selection in spatial lag econometric model	Kostov, Phillip	<i>Econometrics</i>	2013
83	A Combined Matrix Analysis on The Spatial Dislocation of Landscape Resources, Nameplate Scenery and Finance Achievement in China	Wang Mei-Hong <i>et al</i>	<i>Human Geography</i>	2009
84	Multichannel audio separation by direction of arrival based spatial covariance model and non-negative matrix factorization	Nikunen and Virtanen	<i>2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)</i>	2014
85	Noise robust direction of arrival estimation for speech source with weighted bispectrum spatial correlation matrix	Wei Xue <i>et al</i>	<i>IEEE Journal of Selected Topics in Signal Processing</i>	2015
86	Multibody mass matrix sensitivity analysis using spatial operators	Jain and Rodriguez	<i>International Journal for Multiscale Computational Engineering</i>	2003

87	Evaluating effects of low quality habitats on regional population growth in <i>Peromyscus leucopus</i> : insights from field-parameterized spatial matrix models	Grear and Burns	<i>Landscape Ecology</i>	2007
88	A new spatial interpolation algorithm to reduce the matrix fill time in the method of moments analysis of planar microstrip structures	Ogucu, G.O.	<i>IEEE Transactions on Antennas and Propagation</i>	2007
89	Estimation of a weights matrix for determining spatial effects	Lima and Macedo	n.a	1999
90	Robustness of the affine equivariant scatter estimator based on the spatial rank covariance matrix	Kai Yu <i>et al</i>	<i>Communications in Statistics - Theory and Methods</i>	2015
91	Selecting the Most Adequate Spatial Weighting Matrix:A Study on Criteria	Gomez, Marcus Herrera <i>et al</i>	<i>EconPapers</i>	2012
92	MUSIC algorithm of spatial prefiltering for vector hydrophones in an array matrix [J]	He Yiyi <i>et al</i>	<i>Journal of Huazhong University of Science and Technology(Natural Science Edition)</i>	2011
93	Correlative Analysis of Regional Economy Based on Transportation Network Spatial Weight Matrix——Taking Gansu Province as An Example [J]	Ma Qing-Yuan <i>et al</i>	<i>Areal Research and Development</i>	2007
94	Analysis on Forestland Change by Using Spatial Transition Matrix Model [J]	Zheng Chung-Yang <i>et al</i>	<i>Forest Resources Management</i>	2012
95	The construction of spatial weight matrix based on discrete points through building a searching area for each point	Wenii Yu <i>et al</i>	<i>2010 International Conference on Computer Application and System Modeling</i>	2010
96	An Improved Multichannel Spatial Correlation Matrix Based ARMA Model for Short-Term Wind Forecasting	Filik, T.	n.a	n.a
97	Alternative neighbourhood specifications of the spatial weight matrix; effects on spatial autocorrelation index and multivariate analysis of health data	Bertazzon and Elikan	n.a	2009
98	Estimation of sound source orientation using eigenspace of spatial correlation matrix	Kenta Niwa <i>et al</i>	<i>2010 IEEE International Conference on Acoustics Speech and Signal Processing (ICASSP)</i>	2010
99	Uplink to downlink spatial covariance matrix transformation methods for downlink beamforming of a UMTS-FDD system	Chalise, B.K <i>et al</i>	<i>Vehicular Technology Conference, 2004. VTC 2004-Spring. 2004 IEEE 59th</i>	2004
100	Shape of turbulent lump in a circular pipe flow determined by spatial-dependence matrix	Kohei Ogawa <i>et al</i>	<i>Chemical Engineering Communications</i>	1988
101	Regularizing the covariance matrix using spatial information	Tax, D.M.J	n.a	2004
102	Rotation invariant texture feature based on spatial dependence matrix for timber defect detection	Hashim, Umami R. <i>et al</i>	<i>Intelligent Systems Design and Applications (ISDA), 2013 13th International Conference on</i>	2013
103	Nonparametric Estimation of the Spatial Connectivity Matrix by the Method of Moments Using Spatial Panel Data	Beenstock <i>et al</i>	n.a	2009

104	Daily activity prediction based on spatial-temporal matrix for ongoing videos	Hsin-Lin Yang <i>et al</i>	<i>Society of Instrument and Control Engineers of Japan (SICE), 2015 54th Annual Conference of the</i>	2015
105	Blind Suppression of Nonstationary Diffuse Acoustic Noise Based on Spatial Covariance Matrix Decomposition	Nobutaka Ito <i>et al</i>	<i>Journal of Signal Processing Systems</i>	2015
106	Matrix Powers and Marginal Effects in Spatial Autoregressive Models	Kripfganz, Sebastiaan	<i>SSSRN</i>	2015
107	Quantization and feedback of spatial covariance matrix for massive MIMO systems with cascaded precoding	Yinsheng Liu <i>et al</i>	<i>IEEE Transactions on Communications</i>	2017
108	Bayesian Estimation of A Spatial Autoregressive Model with An Unobserved Endogenous Spatial Weight Matrix and Unobserved Factors\$	Xiaoyi Han	<i>Manuscript, The Ohio State University</i>	2013
109	Spatial, Temporal, and Matrix Variability of Clostridium botulinum Type E Toxin Gene Distribution at Great Lakes Beaches	Wijesinghe, Rasanthi U.	<i>Applied and Environmental Microbiology</i>	2015
110	Discrete choice modeling with interdependencies: A spatial binary Probit model with endogenous weight matrix	Zhou Y.	n.a	2015
111	Testing for a structural break in the weight matrix of the spatial error or spatial lag model	Angulo, Ana <i>et al</i>	<i>Spatial Economic Analysis</i>	2017
112	Institutions and growth: Testing the spatial effect using weight matrix based on the institutional distance concept	Ahmad and Hall	<i>mpira.ub.uni-muenchen.de</i>	2012
113	Handloom Silk Defect Recognition and Categorization using Gray Level Weight Matrix & Multi Resolution Combined Statistical and Spatial Frequency Method	Sabeenian, R.S <i>et al</i>	<i>researchgate</i>	n.a
114	Spatial wavelet approach to local matrix crack detection in composite beams with ply level material uncertainty	Sarangapani, G. <i>et al</i>	<i>Applied Composite Materials</i>	2013
115	The Improbable Nature of the Implied Correlation Matrix from Spatial Regression Models	Sen, Monalisa and Anil K. Bera	<i>Regional Statistics</i>	2014
116	A matrix exponential spatial specification approach to panel data models	Figueiredo and Da Silva	<i>Empirical Economics</i>	2015
117	Interaction matrix selection in spatial econometrics with an application to growth theory	Debarsy and Ertur	n.a	2016
118	A New Selection Method of Spatial Weight Matrix	Ren Yinghua and You Wanhai	<i>Statistical Research</i>	2012
119	Comparison of Uniform and Kernel Gaussian Weight Matrix in Generalized Spatial Panel Data Model	Purwaningsih, Tuti <i>et al</i>	<i>Open Journal of Statistics</i>	2015
120	Estimating the impact of air quality with a spatial hedonic: Geostatistical versus weight matrix approaches	Tandon, S, <i>et al</i>	n.a	2007

121	Analyzing the impact of different spatial weight matrix for the western coast of the Taiwan straits	Chen and Huang	<i>Journal of Shangqiu Normal University</i>	2016
122	Model for Effect of Spatial Weighted Matrix on Spatial Autocorrelation	Zhilang Wang <i>et al</i>	<i>Jurnal of Applied Mathematics and Statistics</i>	2013
123	A novel soft spatial weights matrix method based on soft sets	Wang and Xiao	<i>International Journal of Applied Decision Sciences</i>	2016
124	An Estimation Method of Sound Source Orientation Using Eigenspace Variation of Spatial Correlation Matrix	Kenta Niwa <i>et al</i>	<i>IEICE Transactions on Fundamentals of Electronics, Communications and Computer Sciences</i>	2013
125	Spatial Lag Model Estimation with Sparse Adjustment for Spatial Weight Matrix	Lam, Clifford and Pedro C.L. Souza	n.a	n.a
126	Extracting geographical networks from online network resource: Building a spatial neighbourhood matrix of local municipalities using free online encyclopaedia information	Shikano and Meissner	<i>Annual meeting des Arbeitskreises Handlungs- und Entscheidungstheorie der Deutschen Vereinigung der Politischen Wissenschaft</i>	2013
127	A bearing fault diagnosis technique based on singular values of EEMD spatial condition matrix and Gath-Geva clustering	Kun Yu <i>et al</i>	<i>Applied Acoustics</i>	2017
128	Relative Spatial Distance Matrix: a Novel and Invariant Data Structure for Representation and Retrieval of Exact Match Symbolic Images	Punitha, P. <i>et al</i>	<i>Proceedings of the International Conference on Cognition and Recognition</i>	2005
129	The Influence of the Structure of Spatial Weight Matrix on Regression Analysis in the Presence of Spatial Autocorrelation	Tsutsumi, Morito <i>et al</i>	土木計画学研究・論文集	2000
130	Dynamic Large Spatial Covariance Matrix Estimation in Application to Semiparametric Model Construction via Variable Clustering: the SCE approach	Song, Song	arXiv	2011
131	Data-aided SIMO channel estimation with unknown noise spatial covariance matrix	Xin Meng <i>et al</i>	<i>IEICE Communications Express</i>	2014
132	A Note on Eigenstructure of a Spatial Design Matrix In R	Kim and Tarazaga	<i>Communications for Statistical Applications and Methods</i>	2005
133	Spatial Prominence and Spatial Weights Matrix in Geospatial Analysis	Changping Zhang	<i>Progress in Geospatial Analysis</i>	2012
134	Two-Stage Procedure Of Building A Spatial Weight Matrix With The Consideration Of Economic Distance	Pietrzak, M.B.	<i>Oeconomia Copernicana</i>	2010
135	The best-approximate realization of a spatial stiffness matrix with simple springs connected in parallel	Jue Yu <i>et al</i>	<i>Mechanism and Machine Theory</i>	2016
136	Iterative Receiver with Enhanced Spatial Covariance Matrix Estimation in Asynchronous Interference Environment for 3GPP LTE MIMO-OFDMA System	Jang, Jun-Hee <i>et al</i>	<i>PAPER-Wireless Communication Technologies</i>	2009
137	Spatial stiffness matrix corrected and dynamic analysis of short-leg shear wall	Guo Zeying and Zhougang	<i>Sichuan Building Science</i>	2007
138	Spatial Relationships in Rural Land Markets with Emphasis on a Flexible Weights Matrix	Soto, Patricia <i>et al</i>	<i>Paper session of the American Agricultural Economics</i>	2002

			<i>Association Long Beach, Florida</i>	
139	Transmit waveform synthesis for MIMO radar using spatial-temporal decomposition of correlation matrix	Tao Yang <i>et al</i>	<i>Radar Conference, 2014 IEEE</i>	2014
140	Robust spatial covariance matrix transformation techniques for downlink beamforming	Chalise, B.K. <i>et al</i>	<i>2004 International Zurich Seminar on Communications</i>	2004
141	Rotation Invariant Texture Feature Based on Spatial Dependence Matrix for Timber Defect Detection	Muda and Raba'ah	n.a	2013
142	Computational architecture for linear n-processor array implementations of composite rigid-body spatial inertial matrix algorithms	Howell, P.D.	<i>Proceedings of the 1992 International Conference on Industrial Electronics, Control, Instrumentation, and Automation, 1992. Power Electronics and Motion Control</i>	1992
143	On Misspecification of Spatial Weight Matrix for Small Area Estimation in Longitudinal Analysis	Zadlo, Tomasz	<i>Comparative Economic Research</i>	2012
144	Hyperspectral image super-resolution extending: An effective fusion based method without knowing the spatial transformation matrix	Yong Li <i>et al</i>	<i>2017 IEEE International Conference on Multimedia and Expo (ICME)</i>	2017
145	Evaluating Estimation of Direct-to-Reverberation Energy Ratio using D/R Spatial Correlation Matrix Model	Yusuke, Hioka <i>et al</i>	<i>Proceedings of 20th International Congress on Acoustics</i>	2010
146	Spatial weights matrix construction and economic space gravitational effects analysis-Empirical testing based on European debt crisis	Li Li <i>et al</i>	<i>Systems Engineering-Theory & Practice</i>	2015
147	Estimating Non-stationary Spatial Covariance Matrix using Multi-resolution Knots	Nandy, Siddharta <i>et al</i>	n.a	n.a
148	¿Cuál matriz de pesos espaciales?. Un enfoque sobre selección de modelos [Which spatial weighting matrix? An approach for model selection]	Herrera Gomez, Marcos <i>et al</i>	<i>mpra.ub.uni-muenchen.de</i>	2011
149	Model uncertainty in matrix exponential spatial growth regression models	Fischer and Piribauer	<i>ePubWU Institutional Repository</i>	2013
150	Enhanced Spatial Covariance Matrix Estimation for Asynchronous Inter-Cell Interference Mitigation in MIMO-OFDMA System	Moon, Jong-Gun <i>et al</i>	<i>The Journal of Korean Institute of Communications and Information Sciences</i>	2009
151	The normal form of a positive semi-definite spatial stiffness matrix	Roberts, R.G.	<i>2002 Proceedings of the 5th Biannual World Automation Congress</i>	2002
152	Objective Assessment and Design Improvement of a Staring, Sparse Transducer Array by the Spatial Crosstalk Matrix for 3D Photoacoustic Tomography	Wong P. <i>et al</i>	<i>PloS One</i>	2015
153	A Grid Based Approach to Spatial Weighting Matrix Specification	Rahal, Charles	<i>SSRN Papers</i>	2017

154	Spatial dependence matrix feature and redundancy elimination algorithm using AdaBoost for object detection	Wen Jia <i>et al</i>	<i>Optical Engineering</i>	2011
155	Eigenstructures of Spatial Design Matrices	Gorsich, David J. <i>et al</i>	<i>Journal of Multivariate Analysis</i>	2002
156	Dynamic nearest neighbours for generating spatial weight matrix	Mawarni, Mutiara and Imam Machdi	<i>2016 International Conference on Advanced Computer Science and Information Systems (ICACSIS)</i>	2017
157	Imaging through a scattering medium based on spatial transmission matrix	Bin Zhuang <i>et al</i>	<i>Proceedings Volume 10416, Optical Coherence Imaging Techniques and Imaging in Scattering Media II</i>	2017
158	Combined asymmetric spatial weights matrix with application to housing prices	Haiyong Zhang and Xinyu Wang	<i>Journal of Applied Statistics</i>	2017
159	Spatial elastic-plastic rigidity matrix of T short shearing wall	Wang Ning and Xu Xiao-xu	<i>Shanxi Architecture</i>	2006
160	Studies on the Spatial Homogeneity and Flexural Strength of Several sic Fiber-Reinforced Cvi-Sic Matrix Composites	Araki, H. <i>et al</i>	<i>Materials for Advanced Energy Systems and Fission & Fusion Engineering</i>	2003
161	Spatial Dependence in Financial Data: Importance of the Weights Matrix	Bera, Anil K.	<i>researchgate</i>	2016
162	Dependence of spatial effects on the level of regional aggregation, weights matrix, and estimation method	Demidova, Olga <i>et al</i>	<i>EconSTOR</i>	2015
163	Lecture 6: Matrix Exponential Spatial models	LeSage, James P.	<i>researchgate</i>	2004
164	Effects of Mixer Intermodulation Distortion on the Spatial Cross Correlation Matrix of Received Signals in Wireless Communication Systems	Dadashzadeh, G. <i>et al</i>	<i>researchgate</i>	n.a
165	A method of estimation of turbulent diffusion in a circular pipe based on spatial-dependence matrix	Ogawa and Yoshikawa	<i>Chemical Engineering Communications</i>	1990
166	Spatial Lag Model with Time-lagged Effects and Spatial Weight Matrix Estimation	Lam, Clifford and Cheng Qian	n.a	n.a
167	Measuring quantum states: an experimental setup for measuring the spatial density matrix Measuring quantum states	Tegmark, M.	n.a	1996
168	Inferring the contiguity matrix for spatial autoregressive analysis with applications to house price prediction	Sarkar and Chawla	<i>arXiv</i>	2016
169	A structured matrix approach for spatial-domain approximation of 2-D IIR filters	Shaw and Pokala	<i>IEEE Transactions on Circuits and Systems II: Analog and Digital Signal Processing</i>	1997
170	Visualizing the spatial localization of active matrix metalloproteinases (MMPs) using MALDI imaging MS	Muruganantham, Sasirekha	<i>ProQuest (Book)</i>	2011
171	Is a matrix exponential specification suitable for the modeling of spatial correlation structures?	Strauß, M.E <i>et al</i>	<i>Spatial Statistics</i>	2017

172	Division of Weight Matrix Based on Pair-Distances and Resulting Nonlinear Spatial Dependency in Spatial Autoregressive Models	Yokoi, Takahisa	n.a	2012
173	A Study for Gender Classification Based on Gait via Incorporating Spatial and Temporal Feature Matrix	Wang and Yu	<i>Computational and Information Sciences (ICCIS), 2013 Fifth International Conference on</i>	2013
174	Supplement to “Irregular N2SLS and LASSO estimation of the matrix exponential spatial specification model”	Fei Jin and Lung-fei Lee	<i>econ.shufe.edu.cn</i>	2017
175	The W Matrix in Network and Spatial Econometrics: Issues Relating to Specification and Estimation	Corrado and Fingleton	<i>CEIS Working Paper No. 369</i>	2016
176	Spatial Weights Matrix and its Application	Changping Zhang	<i>Journal of Regional Development Studies</i>	2012
177	The Best Spatial Weight Matrix Order of Radius for GSTARIMA	Mubarak, Fadhlul <i>et al</i>	<i>International Journal of Engineering and Management Research</i>	2017
178	Enhanced Spatial Covariance Matrix Estimation for Asynchronous Inter-Cell Interference Mitigation in MIMO-OFDMA System	Moon, Jong-Gun <i>et al</i>	<i>The Journal of The Korean Institute of Communication Sciences</i>	2009
179	Modified local getis statistic on AMOEBA weights matrix for spatial panel model and its performance	Jajang	<i>repository.ipb.ac.id</i>	2014
180	Which spatial weighting matrix? An approach for model selection	Gomez, Marcos Herrera <i>et al</i>	<i>mpira.ub.uni-muenchen.de</i>	2011

Appendix 5B. List of Related Precedent Researches of Spatial Neighbor Matrix

No.	Title	Author(s)	Date of Publication	Summary
1	Constructing the Spatial Weights Matrix Using a Local Statistic	Getis, Arthur and Jared Aldstadt	2010	Constructing spatial weights matrix based on G_i^* local statistic
2	Using AMOEBA to Create a Spatial Weights Matrix and Identify Spatial Clusters	Aldstald and Getis	2006	The creation of a spatial weights matrix by a procedure called AMOEBA, A Multidirectional Optimum Ecotope-Based Algorithm, is dependent on the use of a local spatial autocorrelation statistic. The result are: 1) a vector that identifies those spatial units that are related and unrelated to contiguous spatial units; and 2) a matrix of weights whose values are a function of the relationship of the i th spatial unit with all other nearby spatial units for which there is a spatial association.
3	Estimating a spatial autoregressive model with an endogenous spatial weight matrix	Xi Qu and Lung-fei Lee	2015	In this paper, authors are constructed the W matrix based on endogenous approach.
4	Nonparametric Estimation of the Spatial Connectivity Matrix Using Spatial Panel Data	Beenstock and Felsenstein	2012	The authors use the moments from the covariance matrix for spatial panel data to estimate the parameters of the spatial autoregression model, including the spatial connectivity matrix W.
5	A Dynamic Spatial Weight Matrix and Localised STARIMA for Network Modelling	Tao Cheng <i>et al</i>	2014	In this paper, authors are aims to describe autocorrelation in network data with a dynamic spatial weight matrix and a localized STARIMA (LSTARIMA) model that captures the heterogeneity and nonstationarity.
6	Estimation of the spatial weights matrix under structural constraints	Bhattacharjee, Arnab and Chris Jensen-Butler	2013	The authors propose new methodology to estimate spatial weights matrix under spatial error model based an assumption that symmetrical spatial weights with extensions to other important spatial models
7	On the Four Types of Weight Functions for Spatial Contiguity Matrix	Yanguang Chen	2012	The aim of this study is at how to select a proper weight function to construct a spatial contiguity matrix for spatial analysis. The scopes of application of different weight functions are defined in terms of the characters of their spatial autocorrelation function (ACFs) and partial autocorrelation function (PACFs).
8	Automatic selection of a spatial weight matrix in spatial econometrics: Application to a spatial hedonic approach	Seya, Hajime <i>et al</i>	2013	

9	Spatial Nonstationarity and Spurious Regression: The Case with Row-Normalized Spatial Weights Matrix	Lung-fei Lee and Jihai Yu	2009	This paper investigates the spurious regression in the spatial setting where the regressant and regressors may be generated from possible nonstationary spatial autoregressive processes. Under the near unit root specification with a row-normalized spatial weights matrix, it is shown that the possible spurious regression phenomena in the spatial setting are relatively weaker than those in the nonstationary time series scenario.
10	Bayesians in Space: Using Bayesian Methods to Inform Choice of Spatial Weights Matrix in Hedonic Property Analyses	Mueller, Julie M. and John B. Loomis	2010	This paper found that improper choice of spatial weight matrix triggered 5% differences on the analysis of Bayesian approach a spatial hedonic model. The model estimates the impact of repeated wildfire on house prices in Southern California
11	Two-step lasso estimation of the spatial weights matrix	Ahrens, Achim and Arnab Bhattacharjee	2015	This study considers a two-step estimation strategy for estimating the $n(n-1)$ interaction effects in a spatial autoregressive panel model where the spatial dimension is potentially large. The identifying assumption is approximate sparsity of the spatial weights matrix.
12	Detection and estimation of block structure in spatial weight matrix	Lam, Clifford and Pedro C.L. Souza	2016	The authors propose a method that captures group affiliation or, equivalently, estimates the block structure of a neighboring matrix embedded in a Spatial Econometric model.
13	A Proposal for an Alternative Spatial Weight Matrix under Consideration of the Distribution of Economic Activity	Perret, Jens K.	2011	The author proposes a new measuring concept where takes into account the regional economic or demographic structures and constructs distances between regions accordingly.
14	QML Estimation of the Spatial Weight Matrix in the MR-SAR Model	Benjanuvatra, Saruta	2013	In this paper, we introduce a sub-model for spatial weights and estimate a variable weight matrix for the mixed regressive, spatial autoregressive (MR-SAR) model by maximum Gaussian likelihood.
15	Spatial Weighting Matrix Selection in Spatial Lag Econometric Model	Kostov, Phillip	2013	This paper investigates the choice of spatial weighting matrix in a spatial lag model framework. This article expands the latter transformation approach on Kostov (2010) into a two-step selection procedure. The proposed approach aims at reducing the arbitrariness in the selection of spatial weighting matrix in spatial econometrics.
16	Selecting the Most Adequate Spatial Weighting Matrix: A Study on Criteria	Gomez, Marcus Herrera <i>et al</i>	2012	In this paper, authors revise the literature looking for criteria to select the proper spatial weight matrix. Also, a new nonparametric procedure is introduced. Their proposal is based on a measure of the information, conditional entropy. We compare these alternatives by means of a Monte Carlo experiment.

17	The construction of spatial weight matrix based on discrete points through building a searching area for each point	Wenii Yu <i>et al</i>	2010	In this paper, authors present an algorithm to construct a spatial weight matrix by employing the threshold method to measure the spatial connectivity among discrete spatial points. This method can save searching costs by building a searching area for each point when we set values for each element of the weight matrix, and achieve optimization in the process of constructing a spatial weight matrix
18	The Improbable Nature of the Implied Correlation Matrix from Spatial Regression Models	Sen, Monalisa and Anil K. Bera	2014	This paper suggests a way that the weight matrix can capture the underlying dependence structure of the observations. the possibility of constructing the weight matrix (or the overall spatial dependence in the data) that is consistent with the underlying correlation structure of the dependent variable is explored.
19	A New Selection Method of Spatial Weight Matrix	Ren Yinghua and You Wanhai	2012	The paper applies a component-wise boosting algorithm to deal with the selection issue of a spatial weight matrix in spatial lag models.
20	Comparison of Uniform and Kernel Gaussian Weight Matrix in Generalized Spatial Panel Data Model	Purwaningsih, Tuti <i>et al</i>	2015	In this paper, the authors try to compare the differences between uniform and Kernel Gaussian weight matrix. The construction of spatial weight matrix is based on R programming language.
21	Model for Effect of Spatial Weighted Matrix on Spatial Autocorrelation	Zhilang Wang <i>et al</i>	2013	The authors constructed their W matrix based on three approaches: 1) adjacency relationship, 2) distance relationship, and 3) comprehensive factor relationship.
22	Testing for a structural break in the weight matrix of the spatial error or spatial lag model	Angulo, Ana <i>et al</i>	2017	Authors studied the W matrix in the two generic spatial econometric models, allowing the friction-of-distance parameter to be freely estimated.
23	Spatial Lag Model Estimation with Sparse Adjustment for Spatial Weight Matrix	Lam, Clifford and Pedro C.L. Souza	n.a	The authors propose a linear combination of spatial weight matrix specifications, added with a potentially sparse adjustment matrix in order to choose a good spatial weight matrix for modelling.
24	The Influence of the Structure of Spatial Weight Matrix on Regression Analysis in the Presence of Spatial Autocorrelation	Tsutsumi, Morito <i>et al</i>	2000	
25	Spatial Prominence and Spatial Weights Matrix in Geospatial Analysis	Changping Zhang	2012	The author analyzed the impact of regional division analysis into small area units, such as a prominent areal unit, which is obtained by Markov chains method from a W matrix.

26	Dynamic nearest neighbours for generating spatial weight matrix	Mawarni, Mutiara and Imam Machdi	2017	Authors propose Dynamic Nearest Neighbours algorithm instead of commonly used nearest neighbour algorithm. In their evaluation, they found DNN algorithm outperforms other techniques of Rook, Queen, and k-Nearest Neighbours since it can be applied to both contiguous and sparse regions and produce two-way relations.
27	A Grid Based Approach to Spatial Weighting Matrix Specification	Rahal, Charles	2017	The author used an exogenously set of weighting matrix to analyze its sensitive specification on spatial econometric model.
28	Combined asymmetric spatial weights matrix with application to housing prices	Haiyong Zhang and Xinyu Wang	2017	A combined asymmetric spatial weights matrix is proposed by authors to capture the unequal spatial dependence and estimated by using non-nested hypothesis test.
29	Spatial Lag Model with Time-lagged Effects and Spatial Weight Matrix Estimation	Lam, Clifford and Cheng Qian	n.a	This paper considers a spatial lag model with different spatial weight matrices for different time lagged spatial effects
30	Division of Weight Matrix Based on Pair-Distances and Resulting Nonlinear Spatial Dependency in Spatial Autoregressive Models	Yokoi, Takahisa	2012	In this paper, author purposes to discuss realistic models by dividing spatial terms. The resulting nonlinear dependency function is represented through the coefficients of a pair of spatial weight matrices.
31	The W Matrix in Network and Spatial Econometrics: Issues Relating to Specification and Estimation	Corrado, Luisa and Bernard Fingleton	2016	The authors analyzed the impact of misspecifying of W matrix on spatial econometric model. W matrix are used as part of model specification and used in estimation model.
32	Spatial Weights Matrix and its Application	Changping Zhang	2012	In this paper, author used several W matrix construction concept, such as: 1) binary weight, 2) distance decay-weight, 3) generalized weight, and 4) k-order neighbors weight.