International Journal of Humanities, Arts and Social Sciences
volume 6 issue 1 pp. 44-62 doi: https://dx.doi.org/10.20469/ijhss.6.20005-1

Effect of Transportation Development on the Urbanization in Thailand

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Abstract: This study examines the spatial effect of road density on urbanization in Thailand from 2013-2017. The urban density is proxied by the nighttime light data obtained from the Visible Infrared Imaging Radiometer Suite Day/Night band satellite. The Open Streep Map (OSM) database provided the road network data of each subdistrict (or tambon in Thailand's administrative classification) and other explanatory variables, including building footprints and points of interest. These data represent the geospatial locations of human settlements and economic activities, such as residential areas, retailers, commonplace spots, and public agencies. The first analysis utilized the local indicators of spatial association to investigate geographical correlations. The result shows the statistically significant correlation between road density and nighttime light. The second analysis used spatial regressions to examine the spatial casualties of road density and other variables on urbanization. Results econometrically reveal that road density exerts a statistically significant and positive effect on urban expansion. These findings confirm the significance of road density on urbanization and affirm the necessity of transportation infrastructure investment. This study further suggests future expansions involving the integration of satellite images, geospatial data, and spatial econometric methods to quantitatively explore the spatial relationships.

Keywords: *Transportation infrastructure, urbanization, spatial econometrics, night time light, open street map, Thailand*

Received: 11 October 2019; ***Accepted:*** 31 January 2020; ***Published:*** 28 February 2020

INTRODUCTION

This study aims to analyze the spatial effect of transportation development on the urbanization in Thailand, particularly on the road and highway network sprawl. When people have numerous possibilities to travel via an excellent transportation system, such development changes the social, economic, and city structures. Geographical conditions change with city growth. Therefore, the effect of transportation development must be analyzed using the techniques in spatial economics because the data are dependent on their neighbors.

Motivation

Urbanization is a result of economic growth, which refers to the significantly increasing number of people in urban areas compared with the surrounding ones. The structural transformation and innovation of the city attract the people to migrate from rural areas to cities for jobs and enhanced well-being. The principal institutions and amenities located in the urban areas facilitate the firms for achieving efficient production because of the concentration of workers and entrepreneurs. The United Nations Population Fund reported that more than 50% of the world's population resides

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in towns and cities since 2016, and the urban population will swell to 5 billion people before 2030. This growth will result in large-scale social, economic, and environmental transformations, particularly in developing Asian countries. The urban population in Asia is expected to increase from more than 1.8 billion in 2017 to nearly 3.0 billion by 2050, thereby increasing the proportion of the urban population from 46% to 64%.

In Thailand, the entire economic system continuously expands since the introduction of The National Economic Plans in 1960. The nature of the country shifted from agriculture-intensive into manufacturing, owing to the contribution of the foreign direct investment. The outcome of this development can be measured using the gross products of the nation (e.g., Gross Domestic Product (GDP), gross national product, and gross national income).

Bangkok, which has a population of more than 10 million (including latent population), is one of the fast-growing Asian Metropolis. The majority of the key industries cluster in the Bangkok Metropolitan Region (BMR). The geographical and institutional conditions around BMR develop over the years as the cities expand. The prime agricultural lands and habitats, such as forests and water basins, are transformed into areas for housing, roads, and industries. The high economic growth and increased employment opportunities in the region caused a substantial influx of labor immigration (Hung & Yasuoka, 2000).

Table 1 *Thailand Population Data from 2013-2017*

	Total Population	
Year	Entire Kingdom (Person)	Density (Person/sq. km)
2013	65,321,509	127.31
2014	65,664,880	127.97
2015	66,275,727	129.16
2016	66,491,853	129.58
2017	66,708,736	130.01

Table 2 *BMR Population Data from 2013-2017*

	BMR	
Year	BMR Population (Person)	Density (Person/sq. km)
2013	9,409,109	1,522.07
2014	9,474,946	1,532.72
2015	9,539,604	1,543.18
2016	9,580,228	1,549.75
2017	9,596,820	1,552.44

Source: DOPA2

Many previous studies have stated that the degree of urbanization can be considered as the degree of congestion because the increase in transportation infrastructures, such as new road, highway, and mass transit, elevates the amount of traffic inside the city. Therefore, congestion occurs and increases when the travel demand exceeds the maximum capacity of the transportation system in the city. However, Duranton and Puga (2019) proved that increasing road supply in the regions of the United States fails to relieve the urban congestion in the long run because many roads cater the drivers from inside and outside (i.e., newcomers) of the city. The positive correlation estimate between road length and congestion may also disregard several factors.

Urban transportation directly reflects how a government manages a city, particularly in metropolitan areas that cover multiple jurisdictions (Okpala, Omojuwa, Elenwo, & Opoko, 2017; Osra, 2017; Slack, 2007; Qiu, Song, & He, 2019). Michalopoulos and Papaioannou (2013) report that the roads and highways in Spain emanating from the central cities decrease the proportion of the primary area's population by 8%-9%. However, the aggregate population rapidly grows by 20% per highway. Cervero and Day (2008) find that the development of transportation in Asia significantly increases the urbanization rate in China.

The Transport Infrastructure Investment Action Plan of the Ministry of Transport in 2017 indicates that six plans are in progress and more than 30 future plans are underway, with a total value of over 25,000 million US dollars. Rujopakarn (1992) suggests that this plan considerably affects the growth of the city, and the rapid economic growth will facilitate the rural-urban migration and influence the population well-being.

Table 3 *Road and Highway Data from 20132017*

	Road and Highway	
Year	Entire Kingdom (m)	Density (m/sq. km)
2013	3,886,760.371	2478.719
2014	9,043,244.321	5767.184
2015	9,820,077.717	6262.597
2016	10,490,562.89	6690.188
2017	13,186,456.95	8409.452

Source: Calculation from Open Street Map database

On the basis of the above discussion, the study on city growth must consider that the road is related to road capacity and congestion. Studies on urbanization have consistently use the official statistics of the urban areas in each country. However, the traditional method for quantifying socioeconomic variables lacks accuracy and spatial information (Li, Zhao, & Li, 2016). Several methods can be applied to define or classify the city area. For example, the urban population data obtained by the government merely cover the city because of administrative boundaries. The data failed to include the residents in adjacent suburban areas and the people residing far from the center city but connected through transport networks. A comparable city dataset can improve the understanding of how urbanization evolves across the area.

The study on urban growth and transportation development must utilize the technique of geographical economics. The lack of data consistency negatively affects urban statistics. Remote Sensing (RS) and Geographic Information Systems (GIS) data are suitable for integration with the data for urbanization analysis. The data and methodology for RS and GIS yield can be used to obtain accurate results of urban growth studies.

The recent studies on spatial economics indicate that Nighttime Light Data (NTL) can be used to quantify these variables. Since 1992, satellites have been used to capture the NTL of human settlements. The obtained data are analyzed to study critical economic issues, such as the effect of national institutions on subnational development (Michalopoulos & Papaioannou, 2013) and the relationship between intercity transportation costs and economic activities of cities (Storeygard, 2016). These data can be directly obtained from many open sources, such as OSM and Google Map, or downloaded from the National Oceanic and Atmospheric Administration (NOAA) website.

This study aims to analyze the effect of transportation improvement on the changes in an urban area in Thailand at the subdistrict level (i.e., tambon in the administrative classification of Thailand) using the spatial economics method. The NTL is used to represent the city growth to analyze the influence of each implicated variable.

Statement of the Problem and Research Question

Urbanization is influenced by transportation development because the nature of the system bounds the regions with each other around the country. The traditional Ordinary Least squares (OLS) model cannot provide an accurate estimation because of the omitted spatial implicated variables. The geographical conditions for each area may exert different effects on city growth because of the spatial effect or spatial externality from the neighbors.

This study examines the effect of road, building, and each type of facility that represents the urban growth of each area using a spatial econometric method that involves the data from an official source of the GIS technique. Moreover, this paper aims to realize the distribution and concentration of city growth in each subdistrict in Thailand. The results are presented through a gradient map to illustrate the differentiation of the geographical effects in each area.

Objectives of the Study

1. This paper aims to determine the effect of transportation development on the urban growth of Thailand at the subdistrict level using the NTL as the substitute for city growth.
2. This paper aims to investigate the urbanization process in Thailand by combining the spatial and ground survey data using spatial statistical methods.

Scope of the Study

This study collected the road and building data from OSM, administrative and population data at the subdistrict level in Thailand, and satellite data from Google Earth Engine.

OSM is a free editable map that contains various geographic data of the surface of the earth, including road networks, building footprints, and Point of Interest (POI). Geographical software, such as Quantum GIS (QGIS) and Aeronautical Reconnaissance Coverage GIS (ArcGIS) can transform these data into a quantitative format. This study used the population data at the tambon level from DOPA as the independent variable to investigate the urbanization process. The data from DOPA also contain the location ID and subdistrict name, which can be combined with the satellite data from Google Earth Engine to create the NTL data for each tambon. Thus, the integrated data represent economic growth and urban density. The NTL data are obtained from the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night band satellite, which observes and collects earth surface data since 2012.

LITERATURE REVIEW

The effect of transportation development can be explained through city growth theory. The introduction of land use theory or bid rent theory has advanced the research on the relationship between urban development and its components (Alonso, 1964). Transportation development is a critical variable for urban growth that depends on the individual characteristics of each city and those of the neighboring areas. The geographical technique is combined with an econometric application to investigate the spatial influence of the neighbors surrounding each area. The estimation result is explained using a map that shows the spatial correlation across the areas. This chapter reviews the related literature on transportation development and spatial influence and presents the theoretical framework for urbanization and geographical theory.

Theory of Urbanization and City Growth

Urban economics theory originated from the analyses on city growth. Von Thunen studied the land use patterns since 1826 in a local city and reported that the location of each economic activity is related to many factors. An individual chooses the area for economic activity depending on the corresponding cost-benefit relationship. The land located near the center of an essential economic activity has the highest rent, which is allocated for high-profit activities. For distant areas, the land rent decreases as the distance from the center city with the essential economic activity increases.

Land use theory, or bid rent theory, introduced the explanation of the urban growth process. Bid rent theory refers to the change in the demand for real estate depending on the distance from the center of economic activity or the Central Business District (CBD) and effect to the price of that asset. The land rent and value decrease as the distance from the CBD increases. Alonso (1964) describes the behavior of an individual in selecting the location of economic activity or housing using the monocentric city model. People residing near the CBD benefit from communication time cost but incur high rental costs.

Bid rent theory is one of the most popular core models for urbanization research. The study on urban growth has been consistently adapted and improved through the newest research, along with the economic argument. Recent studies have reported the effect of exogenous variables on the actual development of infrastructure and growth of cities with different physical geographies and histories.

Klaassen, Molle, and Paelinck (1981) introduced Spatial Cycle Theory (SCT) to explain the different stages of urban development from a regional perspective. The first stage in this cycle is urbanization, which is defined as the process of urban growth when people migrate to the city. The stages of SCT are explained as follows:

Urbanization phase: The population migrates to the urban area, which increases the population of the core city at the expense of that of the rural area.

Suburbanization (exurbanization) phase: The population of the core city considers shifting back to the surrounding area (i.e., suburban area), thereby reducing the population density of the inner city.
Disurbanization (counter-urbanization) phase: The decrease in population of the urban core is higher than the increase in the population of the surrounding area, consequently declining the overall city population.
Reurbanization phase: After two decreasing states, the core city gradually attracts the population again while the population of the rural areas continues to decline.

The urbanization stage involves a large-scale migration of people and economic activities from the surrounding area (i.e., rural and suburban areas) to the inner city. The development of infrastructure, along with the increase in the financial and institutional power of the metropolis, enhances the urbanization of a city. Recent studies have shown that the travel behavior of the population is a response to the change in transit infrastructure. Therefore, human behavior should be considered in the model. Duranton and Puga (2019) explain the urban growth using two model families.

The first is the random growth models, which consider growth as the result of the aggregation of random shocks. These models, which are constructed on the basis of the law of Gibrat (lognormal distribution), provide realistic city size distributions but disregard the systematic determinants of growth. The second model family is the systematic growth models, which define growth as the result of systematic drivers, such as human capital, infrastructure, and amenities. These models deliver consistent results but fail to generate realistic city size distributions.

The two model families can be combined and supplemented with necessary assumptions to develop an integrated model. Human capital accumulation and some idiosyncratic shook (e.g., government policy) are the main factors of an integrated urban growth model. In addition, the change in computation time and costs is another crucial element, similar to the factor in land use theory. The integrated model can be used to explain urban growth at a microeconomic level.

Urban and Transportation Development

Urban studies have indicated that transport infrastructure is crucial for the development of cities, regions, and countries. The government spends a considerable amount on public capital, helps increase the productivity of private factors, reduces transportation costs for firms, and enhances the accessibility to territories. Several empirical studies have used production or cost functions to examine the effect of infrastructure on economic growth; most studies focus on the aggregate amounts of public capital, whereas some distinguish between roads and other types of infrastructure. The geographical unit of analysis varies from the national level to the regional or local one (Fageda & Gonzalez-Arregall, 2014).

Many studies state that regional growth rate depends on observable and unobservable regional characteristics, such as basic factors of production (labor and capital), geographic condition, climate, and spillovers nearby regions. The transport infrastructure has found that effects on the growth at the regional and national levels vary in different studies. Spillovers affect regional growth rate better than do other unobservable regional characteristics and can be considered as equally important as the observable regional effects (Conley & Ligon, 2002).

The spillover effects of transportation infrastructure on regional economic growth can be both positive and negative. That difference is due to the presence of the significant spillover effects among regions. A spillover indicates that the benefits or the advantage of investing in infrastructure are obtained from the investments in each area and the positive and negative side effects of the investments in the transport networks of neighboring areas.

The studies on the effects of transportation infrastructure on economic growth can be categorized into two strands. The first strand covers the studies that investigated the relationship between transportation infrastructure and economic growth without consideration of the spatial spillover effects, whereas the second one includes those that focused on the effects of spatial spillover from transportation infrastructure on economic growth.

There are three varying results from many studies. Transportation infrastructure may exert positive or negative spillover effects on economic growth. Otherwise, transportation infrastructure lacks any spatial or mixed spatial spillover effect on economic growth. Singapore and Hong Kong demonstrate how this can be executed by booming economies that are susceptible to rapid motorization (Newman & Kenworthy, 1996). Idiosyncratic shook and human capital accumulation are sufficient in the advent of time and cost of commuting. When the government needs to extend the city, high spending is allocated on transport infrastructure development to cater to the exponential growth of the demand for car travel. These charges exclude the cost of environmental effect. Hence, cities must establish a transportation development plan to address this issue.

In summary, infrastructure development (e.g., roads and highways) directly affects the city sprawl through the increasing demand for residence. Therefore, cities must establish a transportation development plan to address relevant issues.

Spatial Influence

Researchers have continuously investigated the mechanisms of city growth. From bid rent theory, which merely focuses on the distance among economic activities, urban growth analysis is now developed and practised to investigate the influence of many physical factors. Given that the related studies constantly consider many areas with different geographic conditions, the studies on regional economic growth and development assume that the economic conditions in one region influence those in other regions; such an assumption of mutual influence extends to economic growth (Shabani & Safaie, 2018).

Spatial econometrics is developed to deal with the aforementioned assumption. The spatial analysis focuses on the spatial dependence of individual variables. The traditional analysis of cross-sectional data, particularly that of spatial data, experiences significant concern in regression analysis, including the differences in locations (heteroscedasticity) and the relationship among data observations, which indicates that the neighbor variable (autocorrelation). In addition, the explanatory power of the parameters may result in overestimation because the data are dependent. For example, the relationship among the locations of economic activities, such as market, firm, and private housing, is determined in accordance with city growth theory. The spatial correlation implies that this relationship depends on the distance between the two points on the locations or geographical contiguity (Miller & Wentz, 2003). The numerous advances in spatial econometric techniques enabled the researchers to address other concerns in this research field, particularly the quantification of the spatial spillovers among neighboring regions on the basis of infrastructure. Thus, determining whether territories benefit from their own infrastructure and the endowment of their neighbors is possible. Positive and negative regional spillovers are present in the transport infrastructure.

In conclusion, geographical influence cannot be disregarded because the correlation of the error term, which represents the spatial correlation variation across neighbors, results in a biased estimation model. That is, if the geological process is responsible for the geographical effect, then the spatial model is more efficient and suitable than the traditional one. Moreover, spatial modelling can provide appropriate policy recommendations for the taxation and provision of public goods.

Limitation of the Traditional Approach

Faraji, Qingpinga, Valinoorib, and Komijanib (2016) claims that Thailand has the highest urban primacy index score, which reflects that the country possesses a monocentric growth pole. Thus, the characteristic of cities in Thailand may yield a different pattern of urbanization process, which must be examined using the corresponding unique data of each city. With regard to the spatial econometric study on urbanization in Thailand, the research gap requires a new kind of research on the urban economic field of the country.

RESEARCH METHODOLOGY

This study analyzes the development of the transportation system and city growth using the combination of statistical and geographic data. Most of the data used are obtained from the satellite database, which contains highly accurate and useful data. To investigate the development of the transportation system in the Thailand metropolis and the surrounding cities, the digital maps generated through GIS are combined with other economic data to establish the measurement for road growth though spatial analysis.

Standard Model

This study focuses on the spatial effects of transportation infrastructure on city growth. Therefore, a model that considers transportation infrastructure and spillovers as essential factors must be adopted. Among the regional growth models, the new economic-geographic model versions are spatial models that consider the neighborhood as a decisive factor for efficiency and growth. This model is appropriate for this study, in which the concentration of transportation and industrial activities is a crucial stimulating factor for economic growth.

Shabani and Safaie (2018) indicate that the model specification starts with a Cobb-Douglas production function, which represents the correlation between the production and input factors in a region. The transportation infrastructure, along with the concentration of industrial activities, is regarded as an external factor. Transportation infrastructure and industrial concentration are treated as production function frontier shifters, which increase the efficiency of other inputs The production function of the neighbors of region i is expressed as

$$Y_{it} = A_{it}\left(Z_{it}^{W}\right)K_{it}^{\beta_k}L_{it}^{\beta_h} \tag{1}$$

where Y represents the GDP, A is the total factor productivity, Z_{it}^{W} denotes the concentration of the transportation infrastructure (e.g., roads and highways) and industrial activities in subdistrict *i* at time *t*; K and L represent the capital and labor, respectively. The construction of interstate transportation infrastructure can improve a network through the efficient connection of states, thereby enabling the redistribution of the existing resources for production. An improved transportation network can provide a highly efficient and integrated network, and thus contributes to the economic activities in spatially related states.

Therefore, the construction or improvement of transportation infrastructure in one state can adversely affect the output of the private sectors in neighboring states with developing transportation infrastructure (Tong, Yu, Cho, Jensen, & Ugarte, 2013). If the total factor productivity shares an exponential relationship with transportation infrastructure and industrial concentration, then

$$A_{it} = Road_{it}^{\beta_{Ra}}Ag_{it}^{\beta AG}\varepsilon_{it} \tag{2}$$

where Road refers to the total and primary road lengths in each subdistrict (km), and Ag represents the concentration of industrial activities. The linear log transformation of Equation 2 can be written as

$$Ly_{it} = \beta_{ro}Lroad_{it} + \beta_{ag}Lag_{it} + \beta_k Lk_{it} + \varepsilon_{it} \tag{3}$$

where *y* is the logarithm of the real GDP per capita, $Lroad_{it}$ is the logarithm of the total road length per capita, and Lk_{it} denotes the real capital stock per capita. Many previous studies reveal that NTL data can be used as a substitute for income per capita, GDP, and economic growth. Hence, Lk_{it} is replaced by the NTL data. Ag_{it}, which represents the industrial sector concentration in region *j*, is set as the number of POIs in the area. The building and population densities are referred to as the capital stock and labor force in the production function. The final model can be expressed as

$$\text{Lntl }_{it} = \beta_{ro}\text{ Lroad }_{it} + \beta_{po}Lpop_{it} + \beta_{bu}Lbulid_{it} + \beta_{svcs}\Sigma_{i=0}^{3}SVCS + \varepsilon_{it} \tag{4}$$

where L$pop_i t$is the logarithm of the population density, $Lbulid_i ti$ s the logarithm of the building area, and SVCS is the density of the POI in each type. This model can be used to investigate the effect of transportation development on city growth while analyzing the influences of other external factors. Nevertheless, in the spatial dimension analysis, the OLS regression result may be influenced by an unexpected spatial factor. This problem can be solved using spatial statistic techniques.

Spatial Model

The spatial model refers to the estimation that uses spatial data (i.e., GIS data) and their technology to describe the basic properties of a set of spatial features. The essential difference between the ordinary and spatial methods is the weight matrix, which includes the inverse distance criterion for the area or the geographical contiguity status of the neighbor set that represents the geographical dimension.

Spatial weight matrix: In the spatial analysis, the spatial weight matrix is the most crucial part of the model and the process. This matrix determines the proximity of the neighbor; a spatial model estimation with different definitions of the spatial weight matrix generates different model specifications and estimated values.

A spatial weight matrix is a non-negative matrix created by two spatial-based ideas. The idea of contiguity or adjacent areas can be divided into queen and rook contiguities. Another idea is to separate a distance-based spatial weight matrix as distance band weight and k-nearest neighbors.Rook is a spatial weight matrix creation method that merely considers the adjacent locations that share a common line boundary and excludes the corner neighbors. The locations sharing a common line boundary and the corner or common vertex are defined as adjacent neighbors and are considered in the queen contiguity method. High-order neighbors may also be included to consider the effect from indirect neighbors or the neighbor of direct neighbors (i.e., second-order neighbor).

Several areas in Thailand are islands that lack neighbor or direct adjacent boundary. Therefore, the distance band criterion, which is based on the distance from the center of each polygon, is applied. If the linear distance between cities is less than the imposed threshold, then the cities are classified as neighbors, despite that some adjacent neighbors are located on the island. Figure 3.1 presents the borders and neighbors of the central area and the islands under the rook, queen, and the distance threshold criterion

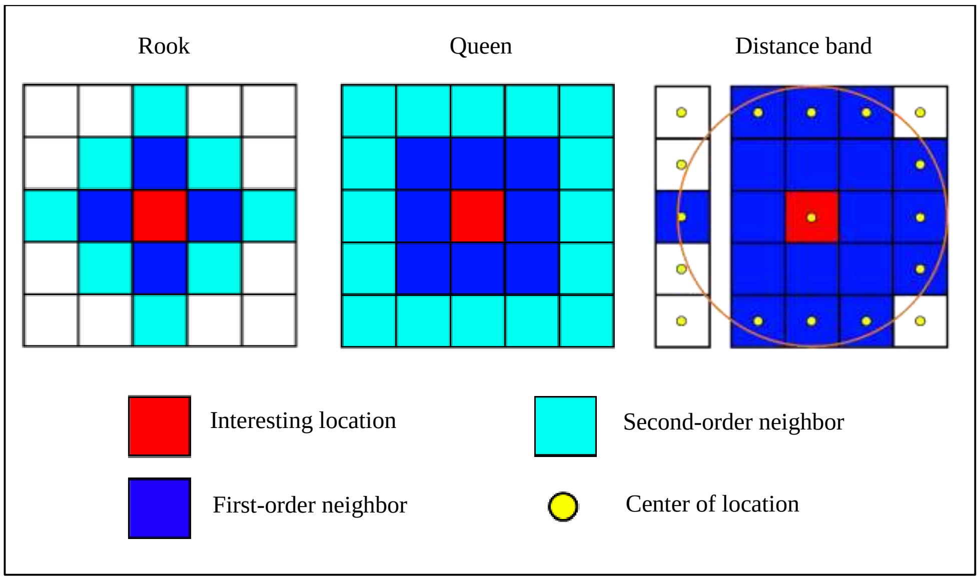


Figure 1 *Spatial neighbors under the rook, queen, and distance band criterion*

The weight matrix definitions are recorded as 0 and 1 for queen and rook contiguities. $w_{ij} = 1$ if locations i and j are neighbors (have the same border), and w_{ij} =0 otherwise. For the distance band criterion, the weight matrix is generated as an inverse distance matrix. In this matrix, each element in the spatial weights for i and j is computed using the following inverse distance function.

$$w_{ij} = f(d_{ij}, \alpha) \tag{5}$$

where w_{ij} is the weight of locations, in which is the decay parameter. i and j, d_{ij} represents the inverse distance between locations i and j, The attribute of the distance decay effect decreases the distance function as the distance increases, that is, $\frac{\partial wi}{\partial dij} < 0$. The functional form is typically expressed as w_{ij} =1/dij, where is a fixed parameter that is equal to 1 for the inverse distance, and 2 for gravity weights. This study sets the value to 1 for the inverse distance matrix. $w_i j$ =1/dij if the distance between locations i and j (d_{ij}) is less than the distance threshold $(d_{threshold}$, the linear distance remains in the band). T The areas are not neighbor to each other if the distance exceeds the threshold, that is w_{ij} =0.

Moran's I test: Developed by Moran (1948), Moran's I test is a statistical test applied to regression residuals to identify the correlation with the neighbors. If the test rejects the null hypothesis (i.e., no spatial autocorrelation), then the OLS estimate will be wrongly specified because the estimation disregards the relationship in spatial dimensions. The spatial lag and spatial error models (SLM and SEM, respectively) are applied to solve this problem according to the statistical outcomes of the Lagrange Multiplier (LM) lag and error tests of the model (Anselin, n.d.).

$$I = \frac{\left[L_i \Sigma_j w_{ij} \left(A_i - \bar{A}\right)\left(A_j - \bar{A}\right)\right]}{\Sigma_i \Sigma_j w_{ij} \left(A_i - \bar{A}\right)^2} \tag{6}$$

where w_{ij} is the spatial weight matrix, and A_i and A_j are the data of the interest area. Moran's I test value (I) generally ranges between +1 and 1; I = 0 signifies the null hypothesis or no clustering. A positive and negative I of the neighboring areas indicate positive and negative spatial autocorrelation, respectively; the neighboring areas tend to have similar or dissimilar attribute values, respectively. If Moran's I specification test produces a significant result, then the existence of the spatial effect is confirmed. The LM test is subsequently conducted to assess whether the result represents a spatial lag or a spatial error. The LM test can be separated into LM lag and LM error; among them, at least one must generate significant results to reveal the spatial dependency pattern in the model. If the LM lag and LM error results are substantial, then the robust results must be evaluated to confirm the spatial pattern.

SLM: SLM is a model used to verify the spatial dependence or similarity of nearby observations. In this case, the NTL data that represent the economic growth may be affected by other external factors in their neighbor. The model can be mathematically expressed as

$$y = \rho W y + x\beta + \varepsilon \tag{7}$$

where ρWy is the vector of the dependent variable y multiplied by the spatial weight matrix W, which represents an additional spatially lagged dependent variable; x is the vector of explanatory variables; β is a vector of parameters. This matrix reflects the effect of the neighboring endogenous variable, including how the city growth is affected by the transportation infrastructure development of the neighboring area (i.e., nearby subdistrict). An example of this specification (with three cities) is shown in Equation 7.

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} = \rho \begin{bmatrix} (w_{11}y_1 + w_{12}y_2 + w_{13}y_3) \\ (w_{21}y_1 + w_{22}y_2 + w_{23}y_3) \\ (w_{31}y_1 + w_{32}y_2 + w_{33}y_3) \end{bmatrix} + \begin{bmatrix} x_{11} & x_{12} & x_{13} \\ x_{21} & x_{22} & x_{23} \\ x_{31} & x_{32} & x_{33} \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \end{bmatrix} + \begin{bmatrix} u_1 \\ u_2 \\ u_3 \end{bmatrix} \tag{8}$$

where w_{11}, w_{11}, and w_{11} are equal to zero. Therefore, Wy can neighbor as another vector of the independent variable. The SLM in Equation 5 can be applied to Equation 4 to create the combined model, which can be represented as

$$\text{Lntl}_{it} = \rho W ntl_{it} + \beta_{ro} Lroad_{it} + \beta_{po} Lpop_{it} + \beta_{bu} Lbulid_{it} + \beta_{svcs} \Sigma_{i=0}^{3} SVCS + e_{it} \tag{9}$$

where ρ is a spatial autocorrelation coefficient that ranges between 1 and 1 (1<ρ<1) to avoid the explosive processes (the neighboring factors should not produce an effect that is more significant than that of the internal factors), W is the spatial weight matrix that represents the spatial relationships between each pair of locations or subdistricts in the dataset of Thailand, and the other variables follow the previously mentioned specifications.

SEM: SEM is used to verify the spatial heterogeneity. When the spatial influence of the omitted variable and the error term across locations are correlated, the model can be written as

$$y = x\beta + u; u = \rho W u + \varepsilon \tag{10}$$

where u is a function of the neighbor's disturbance. The endogenous and exogenous u values are the same vectors. However, the latter is multiplied by the spatial matrix W to define the disturbance effect of the neighboring subdistrict. Therefore, Equations 4 and 8 are combined to establish the following expression.

$$\begin{aligned} &\text{Lntl}_{it} = \beta_{ro} \text{ Lroad}_{it} + \beta_{po} Lpop_{it} + \beta_{bu} Lbulid_{it} + \beta_{svcs} \sum_{i=0}^{3} SVCS + u_{it} \\ &; u_{it} = \rho W u + \varepsilon \end{aligned} \tag{11}$$

In SEM, ρ represents the cross-location effect through error terms of the model. In addition, SEM uses the same weight matrix as SLM.

Data Description

OSM: OSM is the primary data source of the present study. As previously mentioned, OSM is a free editable map of the world that contains much geographic data, such as road, place, location, point, and area size. The OSM member can edit and download data from the website for free in a geospatial vector form (shapefile) under copyright schemes. The map comprises three primitive types of flexible data.

- Nodes (POI) consist of an ID and a location with longitude and latitude coordinates
- Ways involve an ordered list of nodes. Depending on the context, this data type can represent a line (e.g., a street) or an area.
- Relations contain an arbitrary number of other primitives (including other relationships) and can be used to model high-level structures.

Using geographical software (e.g., QGIS and ArcGIS), the data can be extracted from the shapefile to obtain the following statistical data that can be used in the regression process.

- Road length; total and primary road lengths in each subdistrict (km)
- Building Area; total area covered by buildings, places, and other landmarks in the area (sq. km)
- POI from the Node data, which indicate the number of buildings, infrastructure, places, and other landmarks in the area. The POI can be divided into four types according to the criteria set by the Office of the National Economics and Social Development Council.
  - Type 0: mining and quarrying/manufacturing/electricity, gas, steam, and air conditioning/water supply, sewerage, waste management, and remediation activities/construction
  - Type 1: wholesale and retail trade and repair of motor vehicles/transportation and storage/accommodation and food service activities (point/sq. km)
  - Type 2: information and communication/financial and insurance/real estate /professional activities, scientific, and technical/administrative and support service activities
  - Type 3: public administration and defense, compulsory social security/education/human health activities, arts, entertainment, and recreation/other service activities

NTL: The NTL data are recorded using two sources, namely, the Defense Meteorological Satellite Program (DMSP) in the National Geophysical Data Center from 1992-2013 and the VIIRS Project from 2014 to present. The data are collected using polar-orbiting satellites with Operational Linescan System (OLS) that provides full coverage of the globe twice a day and allows the detection of low levels of visible-near infrared radiance at night.

The dataset can be selected, transformed, and downloaded through an open-access tool, such as Google Earth Engine, or directly downloaded as a tagged image file (.tiff) from the NOAA website, and then transformed into statistical data using a geographical software. In the tagged image file, each pixel refers to the geographic coverage of a square kilometer that represents the magnitude of illumination with scales of 0-63 and 0-132 for the NTL data from the DMSP and VIIRS, respectively. The data are then used to represent the economic growth in the areas.

Survey Data

The survey data include the population and household data of 7,367 subdistricts of Thailand, which are gathered from DOPA. These data contain the population and household headcount, location ID, and area size for each subdistrict. The DOPA website contains data from 1993 to 2018, but the present study merely used those from 2013 to 2017. The data are used to verify the accuracy of the location name and position and represent the labor force of each area in the model.

RESULTS AND DISCUSSION

This section summarizes the results of the empirical test using the model presented in Chapter 3. The traditional model (weight OLS) shows the test result without applying spatial factors in the equation; the LM test confirms the spatial correlation in the model. This chapter also compares the results of the SLM and SEM with that of the traditional model. The spatial correlation is illustrated using Moran's I map. Subsequently, the spatial model is adopted to illustrate the pattern of spatial dependence and the effect of transport development is described to answer the research question.

Traditional Model

Table 5 presents the empirical results of the traditional model for the effect of transportation development in the semi-log function. Results suggest that the NTL is significant with all independent factors at a significant level of 0.01 every year. Most of the expanding variables are positively related to city growth, except for Ln_SVCS3_D, which denotes the density of type 3 POIs. Therefore, each percent of road density increase elevates the city growth by 0.06%1.1 % from 2013-2016 and degrades by 0.09% in 2017 (still positive). The population growth and the increase in building density also exhibit a positive relationship with city growth. The type 0 POI displays the strongest effect on city growth for this test, thereby reaching 0.9%1.07% in 2016. Furthermore, types 2 and 3 POIs also exert a positive effect on city growth, but the degree of coefficient decreases annually.

Table 4 *Standard Model With the Spatial Specification Testing of the Spatial Distance Weight Matrix*

Ln-NTL-Den (Dependent)	2013	2014	2015	2016	2017
Ln-RDL-Den	0.0638***	0.0691***	0.0783***	0.1151***	0.0929***
	(0.0022)	(0.0028)	(0.0037)	(0.0068)	(0.0046)
Ln-Pop-Den	0.5281***	0.5799***	0.5231***	0.5541***	0.4425***
	(0.0121)	(0.0128)	(0.0122)	(0.0182)	(0.0102)
Ln-Bu-Den	0.0138***	0.0147***	0.0198***	0.0194***	0.0106***
	(0.0020)	(0.0121)	(0.0016)	(0.0022)	(0.0011)
Ln-SVCS0-D	0.8209***	0.9655***	0.9764***	1.075***	0.9844***
	(0.0331)	(0.031)	(0.0282)	(0.0350)	(0.0188)
Ln-SVCS1-D	0.392017***	0.334151***	0.305698***	0.3047***	0.301***
	(0.0253)	(0.0245)	(0.0217)	(0.0293)	(0.0144)
Ln-SVCS2-D	0.2425***	0.1863***	0.1399***	0.1056***	0.1008***
	(0.0414)	(0.0379)	(0.0383)	(0.0441)	(0.0231)
Ln-SVCS3-D	0.1742**	0.1605***	0.1328***	0.1762***	0.1729***
	(0.1742)	(0.0262)	(0.0224)	(0.0306)	(0.0148)
Constant	2.5273***	2.4966***	2.15274***	2.65802***	2.0226***
	(0.1103)	(0.1158)	(0.1095)	(0.1623)	(0.0913)
R-squared	0.8802	0.8747	0.8793	0.7883	0.9018
Log likelihood	8423.32	8964.65	8566.68	11351.5	7132.39
Jarque-Bera (*p*-value)	10236.4233***	8970.4143***	6818.6513***	15328.88***	14132.1361***
Moran's I (*p*-value)	166.9086***	166.7059***	191.1280***	103.6853***	171.2898***
LM (lag) (*p*-value)	2557.9443***	2887.9556***	3332.1791***	1744.59***	2799.3879***
LM robus (lag) (*p*-value)	741.2175***	891.0931***	954.7052***	477.7702***	990.6572***
LM (error) (*p*-value)	24396.9277***	24320.1374***	31970.3859***	9396.5606***	25648.4001***
LM robus (error) (*p*-value)	22580.2006***	22323.2749***	29592.9120***	8129.3308***	23839.6694***

Source: Calculation from Open Street Map database

Moran's I Test

In statistics, a spatial autocorrelation among proximal locations in space can be measured using global Moran's I, which evaluates whether the expressed pattern is clustered or dispersed. Each spatial weight matrix constructed under a specific spatial definition affects Moran's I index differently because of the different sets of neighbor. The Local Indicator of Spatial Association (LISA) is used to evaluate the existence of clusters in a specific location. The variables with high and low values are analyzed by comparing their statistical means. The average values of variables at the provincial level are used to measure the spatial influence across areas. The results presented in this section are estimated using the GeoDa software.

Spatial autocorrelation: The spatial weight matrix is defined by a spatial distance band that is automatically calculated by the GeoDa software to confirm the spatial pattern of the geographical relationship among tambons. Figure 2 displays a histogram of the number of connected neighbors that satisfy that criterion. The software showed a distance band at 39939.39 (or 496.18 km), which is the minimum value if no neighborless area is present.

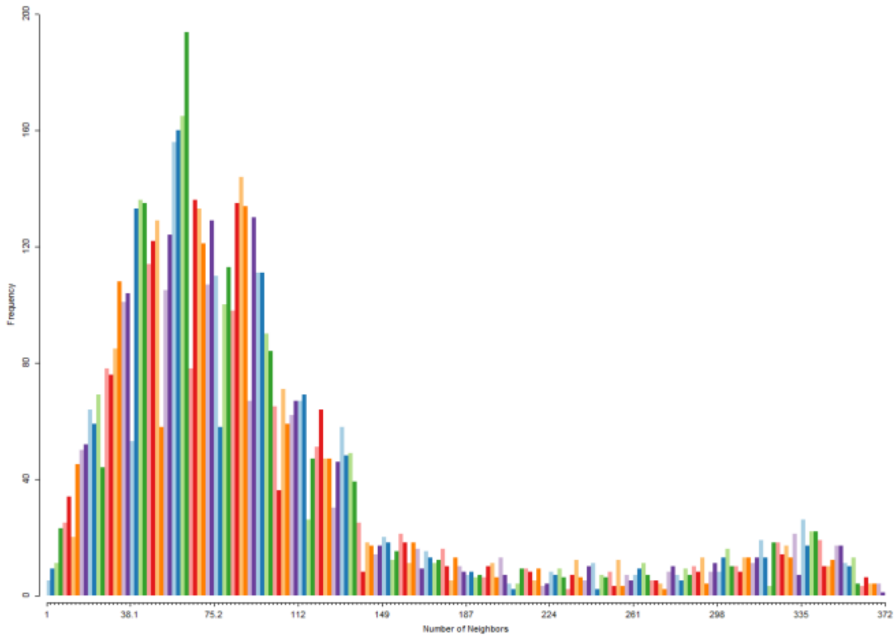


Figure 2 *Number of connected neighbors based on the spatial distance band*

Local Moran's I (LISA): In this section, the spatial autocorrelation of the natural logarithm of the NTL, road length, and population densities in the tambon is measured using LISA, which indicates the spatial relationship between each pair of tambon and the neighbors. The positive index reported in the previous section indicates that the tambons with high/low NTL, road length, and population are clustered together in the map.

Figure 3 presents the local autocorrelation among the neighbors. Each color on the map has a specific meaning and reflects the spatial significance of the LISA index at the 0.05 level.

- The red portion (high-high) represents a spatial cluster of the high values of each variable and indicates that the neighbors spatially surround an area with a high natural logarithm of each value with a similarly high value.
- The dark blue portion (low-low) represents a cluster of an area with low values and indicates that the neighbors spatially surround a tambon with a low natural logarithm of each value with a similarly low value.
- The pink portion (high-low) indicates that the neighbors spatially surround an area with a high value of each variable with a low value.
- The light blue portion (low-high) indicates that the neighbors surround an area with a low labor income with a low value.
- The gray portion denotes the insignificant spatial autocorrelation of the values across locations and implies that the distribution of the labor force income in an area is spatially random.

The Moran's I test result for each variable (Figure 3) shows that the NTL and population densities follow the same pattern each year. The red portion shows that the clusters of the areas with high values of NTL and population are surrounded by the same type of neighbors, particularly the tambon in Bangkok Metropolitan areas. The areas marked in dark blue are mostly located in the northern and northeastern parts of Thailand. However, the areas around the Chiang Mai province at the center of the northern part remain red. With regard to the population data, certain tambons in the northeastern parts, which include the primary provinces of Nakhon Si Thammarat, Nong Khai, and Khon Kaen, are red. For the road density data, the dominant colors for the first year (2013) are red and pink. However, the pink areas gradually change to dark blue in 2014-2017, particularly the northeastern parts

Figure 4 shows the results of the bivariate Moran's I test. The traditional test (i.e., univariate Moran's I test) can be used to evaluate the spatial relationship between each pair of tambon and the neighbors, whereas the bivariate Moran's I test can be used to assess the spatial relationship between each pair of variables in the surrounding areas. Result shows that the relationship between road length, NTL, and population has the same pattern each year. In the results for 2013 and 2014, the tambon in Bangkok Metropolitan areas and the primary province of some parts, such as Nakhon Si Thammarat, Nong Khai, and Khon Kaen, are red. The pink areas that appeared during both years gradually change to dark blue in 2015-2017.

Figure 5 summarizes the results of the High/Low Clustering (Getis-Ord General G or G star), which determines the type of clustering condition for each area and the corresponding neighbors. Red denotes the zone with high variable values, whereas blue represents the zone with low ones. This test is a simple way to analyze the clustering of the data, which can be used to explain the spatial regression test result.

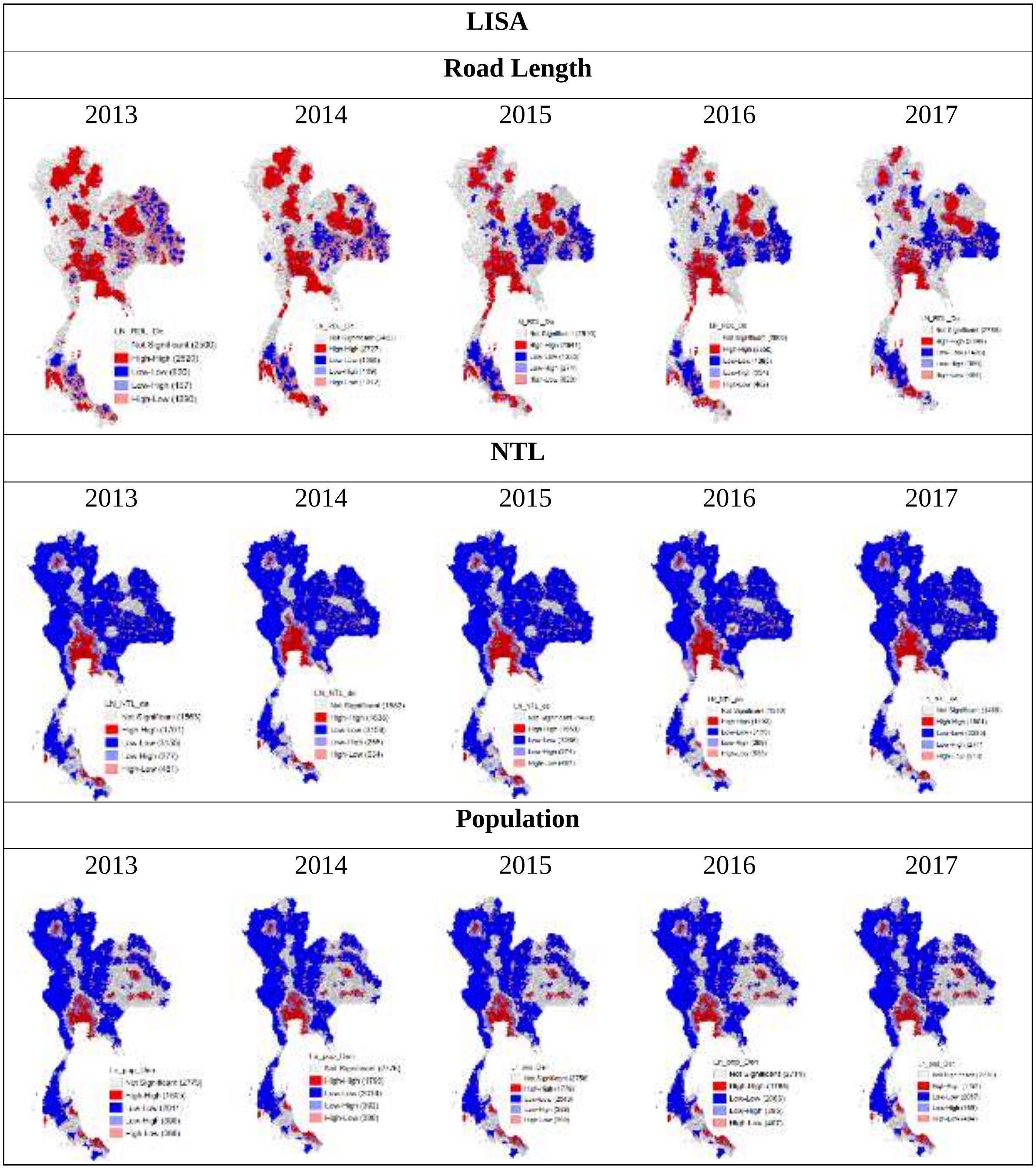
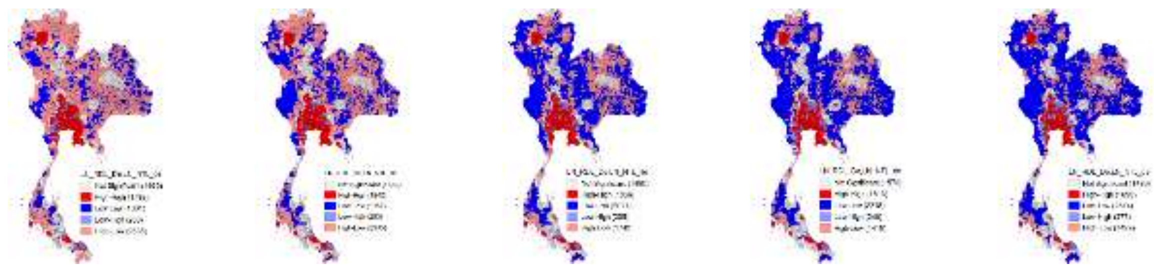


Figure 3 *Local Moran's I test results of the natural logarithm of each primary variable from 2013 to 2017*

Bivariate LISA

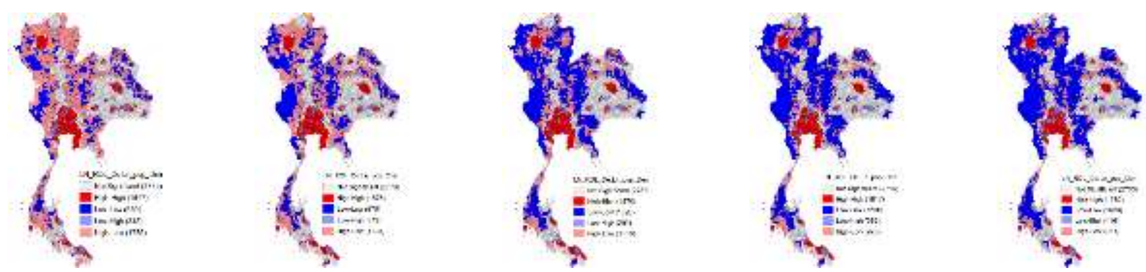
Road Length and NTL

2013	2014	2015	2016	2017



Road Length & Population

2013	2014	2015	2016	2017



NTL and Population

2013	2014	2015	2016	2017

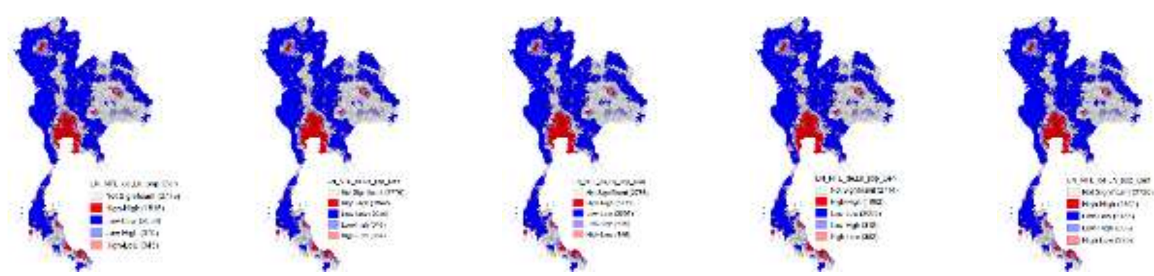


Figure 4 *Bivariate local Moran's I test results of the natural logarithm of each pair of primary variables from 2013 to 2017*

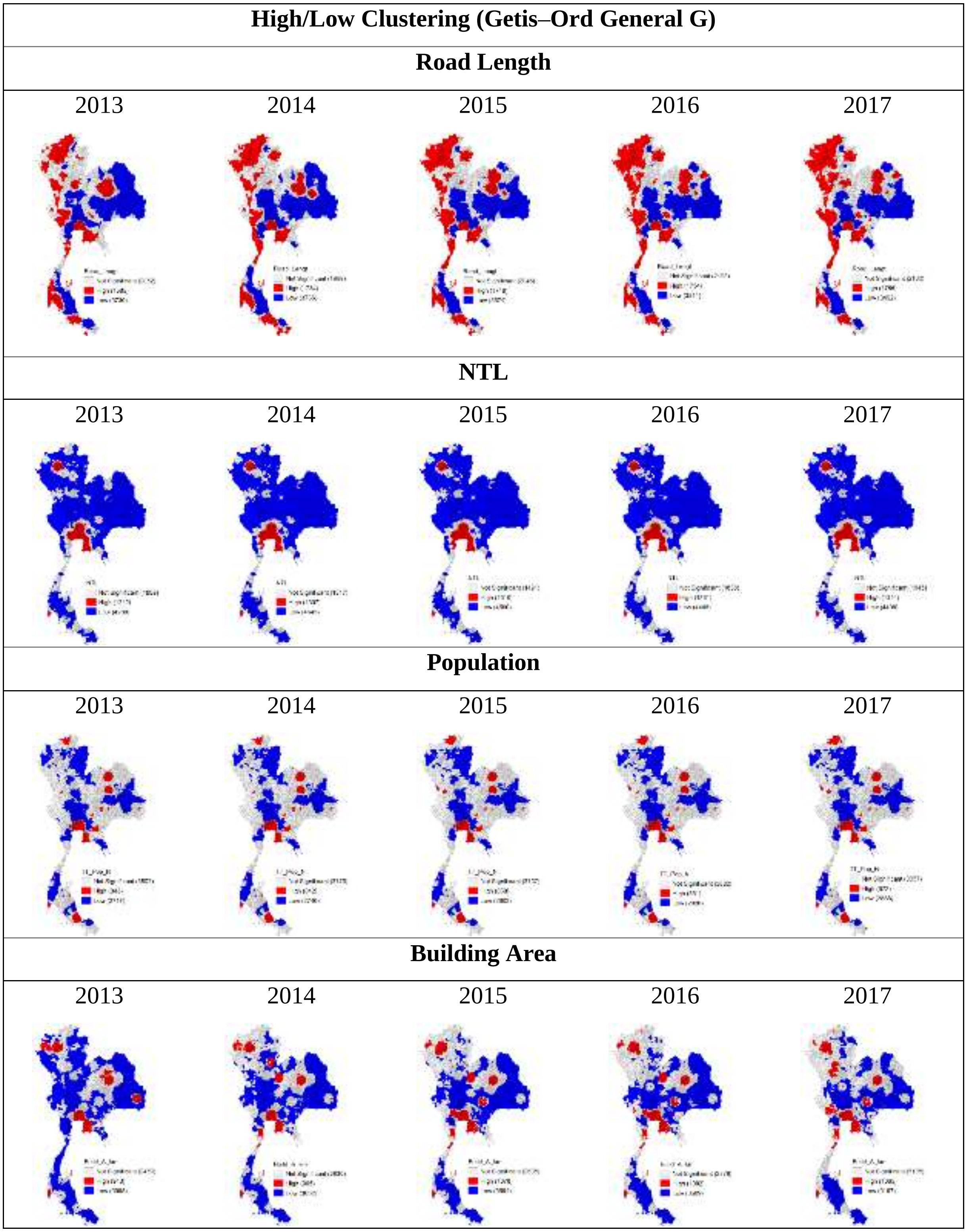


Figure 5 *High/Low Clustering (Getis-Ord General G) test results of the natural logarithm of each primary variable from 2013 to 2017*

Evidence from the Spatial Model

This section applies spatial regressions to investigate the effect of transportation development on city growth. The spatial models are also used to reveal the spatial pattern and spatial influence in the estimated model. These models are

subsequently compared to answer the research questions, achieve the research objectives, and generate critical findings.
Evidence from SLM: Figure 5 presents the results of the SLM, which uses the same spatial weight matrix to that in Table 1 (spatial distance band). Log_NTL_Den is an endogenous explanatory variable that represents the natural logarithm of the NTL density of the neighbors. The spatially lagged dependent variable exhibits a positive effect on all independent variables except on type 3 POI. The spatial test results are significant at the 0.01 level. Findings reveal that the increase in transportation supply elevates the city growth by 5%-9% from 2013-2017, and the spatial influence of neighboring areas also induces the growth of each other.
Evidence from SEM: Figure 5 shows the results of the SEM, which also uses the same spatial weight matrix to that in Table 1 (spatial distance band). Log_NTL_Den exerts a positive effect on all independent variables except on type 3 POI. However, in this test, this POI type is insignificant in 2014 and 2015 and significant at 0.05 level in 2016 and 2017. The other spatial test results are significant at the 0.01 level, except for the type 2 POI, which is significant at 0.05 level in 2016. Similar to that of SLM, the result of SEM indicates that the increase in transportation supply enhances the city growth by 5%9% from 2013-2017.

The spatial error coefficient (lambda) is the most crucial variable for this model. In this test, all lambda is significant at 0.01 level every year. The spatial error dependence is considered as a spatial nuisance in the use of data due to the omission of several unobserved spatial variables in nearby locations. Therefore, the inferential errors from disregarding such effects should be assessed using the SEM. The spatial regression results highlight a spatial effect that is not induced by the externality of the transportation development in the neighbors but occurs on account of other reasons that are not analyzed by the traditional method, as well as other unobserved factors that are commonly found in nearby locations.

Table 5 *Spatial Lagged Model of the Spatial Distance Weight (Autogenerated)*

-DenLog-NTL-Den (Dependent)	2013	2014	2015	2016	2017
LN–DenW-LN-NTL-Den	0.3186***	0.3384***	0.3492***	0.3451***	0.3053***
	(0.0067)	(0.0066)	(0.0063)	(0.0097)	(0.0059)
Ln-RDL-Den	0.0563***	0.0601***	0.0629***	0.0904***	0.0706***
	(0.0019)	(0.0024)	(0.0031)	(0.0063)	(0.0039)
Ln-Pop-Den	0.4184***	0.4518***	0.4011***	0.4256***	0.3397***
	(0.0107)	(0.0113)	(0.0104)	(0.0171)	(0.0089)
Ln-Bu-Den	0.0074***	0.0084***	0.0139***	0.0137***	0.0084***
	(0.0017)	(0.0016)	(0.0013)	(0.0020)	(0.0009)
Ln-SVCS0-D	0.6492***	0.7371***	0.7543***	0.8465***	0.8198***
	(0.0029)	(0.0261)	(0.0219)	(0.0327)	(0.0163)
Ln-SVCS1-D	0.3293***	0.2816***	0.2591***	0.2964***	0.2787***
	(0.0221)	(0.0291)	(0.0181)	(0.0268)	(0.0122)
Ln-SVCS2-D	0.2171***	0.0324***	0.1441***	0.07431***	0.0631***
	(0.0360)	(0.0324)	(0.0273)	(0.0404)	(0.0196)
Ln-SVCS3-D	0.1272***	0.1109***	0.1096***	0.1531***	0.1344***
	(0.0245)	(0.0324)	(0.0187)	(0.0281)	(0.3493)
Constant	1.4203***	1.3668***	1.0178***	1.4093***	0.9443***
	(0.0982)	(0.1011)	(0.0933)	(0.0097)	(0.0801)
R-squared	0.9094	0.9083	0.9161	0.8217	0.9286
Log likelihood	7400.87	7823.01	7241.79	10726	5966.27

Note: ***, **, and * denote the significance level at 1%, 5%, and 10% respectively; the values inside the parentheses are the standard errors.
Source:Calculation from Open Street Map database

Table 6 *SEM of the Spatial Distance Weight (Autogenerated)*

Log-NTL-Den (Dependent)	2013	2014	2015	2016	2017
lambda	0.9336***	0.9329***	0.9378***	0.8485***	0.9335***
	(0.0106)	(0.0107)	(0.0102)	(0.0185)	(0.0107)
Ln_RDL_Den	0.0503***	0.0588***	0.0611***	0.0855***	0.0738***
	(0.0018)	(0.0024)	(0.0029)	(0.0064)	(0.0037)
Ln_Pop_Den	0.4522***	0.4877***	0.4368***	0.4672***	0.3413***
	(0.0102)	(0.0109)	(0.0099)	(0.0177)	(0.008)
Ln_Bu_Den	0.01338***	0.01526***	0.0161***	0.0165***	0.0011***
	(0.0016)	(0.0015)	(0.0012)	(0.0021)	(0.3901)
Ln_SVCS0_D	0.7818***	0.8491***	0.8556***	0.9085****	0.8578***
	(0.0263)	(0.0242)	(0.0202)	(0.3299)	(0.0152)
Ln_SVCS1_D	0.2597***	0.2065***	0.1924***	0.2515***	0.2298***
	(0.0207)	(0.0201)	(0.0171)	(0.0275)	(0.0121)
Ln_SVCS2_D	0.1838***	0.1339***	0.1106***	0.0697*	0.0586***
	(0.0321)	(0.0291)	(0.0241)	(00388)	(0.0175)
Ln_SVCS3_D	0.0566***	0.01501	0.0041	0.0555**	0.0272**
	(0.0227)	(0.0210)	(0.0102)	(0.0286)	(0.0122)
Constant	2.5757***	2.6201***	2.2851***	2.6408***	1.8561***
	(0.1315)	(0.1456)	(0.1373)	(0.1711)	(0.1122)
R-squared	0.9291	0.9265	0.9356	0.8374	0.9444
Log likelihood	6600.9681	7110.5071	6365.6218	10456.3812	5144.1227

Note: ***, **, and * denote the significance level at 1%, 5%, and 10% respectively; the values inside the parentheses are the standard errors.
Source: Calculation from Open Street Map database

CONCLUSION AND IMPLICATIONS

As previously stated, this study aims to analyze the effect of transportation development on urbanization with consideration of the spatial influence by combining the data from GIS with the ground survey data of Thailand. Two main conclusions are obtained from the regression at the tambon level using the standard and spatial models.

First, the estimates show that the effect of transportation development on urbanization is consistent with the theory discussed in the literature review. The results of the traditional and spatial models show that road density exhibits a positive effect on city growth. Almost all independent variables display a similar trend with the growth, except for the type 3 POI (i.e., public administration and defense, compulsory social security, education, human health activities, entertainment, and other service activities), which demonstrates a negative relationship with the city sprawl. In addition, the data obtained from GIS is appropriate for urban growth study in Thailand. The OSM road, building area, and POI data, as well as the NTL data from Google Earth Engine, are also suitable for the present study.

This study finds that the data cluster in many areas. The NTL, population, and transportation infrastructure at the tambon level display a strong clustering around the Metropolitan Region, thereby confirming that Thailand has only one growth pole (i.e., monocentric growth).

In conclusion, the development of infrastructures, such as roads and highways that encourage the transit possibility of the population, is one of the factors that contribute to the growth of the cities in Thailand. Consistent with many geographical theories, such as the theory of urban growth, central place theory, and spatial clustering theory, the findings emphasize the spatial effect among neighboring areas.

Policy Implications

The development of the economy and society in Thailand attracts the movement of the population toward the core city, namely, Bangkok. The population of the capital city of the country is more than ten million people, and primary intensive economic activities occur in the BMR. The study conclusions reveal that the development of the transportation system will encourage people to migrate to the city, thereby inducing serious inequality issues between the residents of urban and rural areas. Therefore, the effect of road construction should be considered because the outcome of such development depends on the size and place where the development occurs. Investments in transportation infrastructure investment remain necessary for the economic growth of Thailand. A new road, highway, or railway in other regions may bring a new growth pole through the spatial effect and spillover from the cluster. This strategy can encourage equitable development and relieve congestion in the Metropolitan Region.

Limitations and Recommendations for Future Study

The present study poses two major limitations. The first limitation is the hardware used in the analyses. Spatial regression processes with many observations consume a considerable amount of time, and a regular computer cannot calculate complicated formulas, such as spatial panel regression. Therefore, future studies should consider the limitation of the available hardware before starting the process.

The second limitation involves the integrity of the data. The NTL data before 2013 are collected from the DMSP-OLS satellite, and the succeeding ones are gathered from the VIIRS satellite, which possesses higher frequency and quality than the former. Therefore, this study utilized the data from 2013 to maintain data integrity. Future studies should include the data before 2013 to expand the border of urbanization growth study in Thailand. A variable from the GIS data can also be added to the model to investigate an undiscovered factor that may influence city growth.

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