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Urban Land Expansion and Economic Development in Thailand from 2000 to 2020

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ABSTRACT

This study utilizes information gathered from satellites and economic sources spanning two decades (2000–2020) to estimate the effect of income shocks from industrialization on urbanization at the provincial level in Thailand. To measure urbanization, the study relies on the observable increase in urban land area as seen from space, serving as a proxy for the country's urban growth. Four regression models—fixed-effects, spatial autoregressive, spatial error model, and dynamic panel—are employed to assess the short-term impact of income shock on urbanization. The results suggested that increased productivity from industrialization positively affected urbanization in Thailand. This study also revealed that natural factors such as water accessibility and rainfall played a role in driving city expansion. A higher proportion of educated workers was found to strongly influence urban growth. Moreover, the expansion of urban land in one province spurred land growth in neighboring areas, demonstrating the spatial spillover effect of urban land expansion throughout Thailand.

Keywords: urbanization, industrialization, Thailand, satellite data, spatial analysis

INTRODUCTION

Urbanization, defined as the conversion of arable land into urban settlements, has been advancing rapidly worldwide, significantly impacting the density and spatial extent of cities (Elmqvist et al., 2021). This expansion trend, evident from satellite observations, reveals a substantial increase in urbanized areas worldwide, particularly in developing nations, with over 1,459 cities expanding, a considerable number of which are located in China's special economic zones (Asian Development Bank, 2019). Research suggests that continuous urban land expansion will continue globally until at least the 2040s, predominantly driven by ongoing population and economic growth (Chen et al., 2020).

Thailand, as a developing Asian nation, has undergone rapid urbanization, transitioning from an agrarian economy to one centered around industry and services since the 1960s. Over six decades, significant economic growth and extensive infrastructure investments have spurred substantial rural-to-urban migration, expanding urban cores outward into previously agricultural regions. Recent urban development strategies, including Smart City initiatives, Tourism Cities, and Special Economic Zones, have further accelerated this expansion, notably reshaping Thailand's urban landscape (Tonguthai, 2019).

Advancements in remote-sensing technologies have enabled the observation of Thailand's urban expansion from space. Data derived from satellite imagery, Terra and Aqua Moderate-Resolution Imaging Spectroradiometer (MODIS), between 2000 and 2020, indicates a notable increase of urban areas in Thailand from 5,422 to 6,296 square kilometers.

However, despite consistent urban land expansion, growth primarily concentrated in specific provinces reflects Thailand's monocentric urban growth pattern. The country's urban development exhibits significant regional inequality, notably witnessed in the disproportionate growth of the Bangkok Metropolitan Region[1] compared to other areas (Rodríguez-Pose, 2018). Bangkok's urban size dwarfs that of other major cities, making Thailand stand out globally with the highest urban primacy index (Short & Pinet-Peralta, 2009). Urbanization trends from 1992 to 2019 primarily concentrated in the Bangkok Metropolitan Region and a few eastern provinces, highlighting extreme regional disparities (Sangkasem & Puttanapong, 2022).

Using data collected from MODIS, a detailed examination of specific provinces and their urban land expansion further underscores this inequality. Figure 1 shows that urbanization between 2000 and 2020 mostly took place in the Bangkok Metropolitan Region and three provinces in the Eastern Economic Corridor (Chachoengsao, Chonburi, Rayong). Urban land expansion in the top twenty provinces accounted for 91 percent of Thailand's total urban land growth. The regional distribution of this expansion resembles a long-tail distribution, showcasing substantial growth in a few primary cities while the majority show minimal to no increase in urban areas.

The disproportionate urban growth aligns with the unequal economic progress across provinces, notably reflected in the distribution of real Gross Provincial Product (GPP). The economic boom predominantly favored the Bangkok Metropolitan Region and provinces in the Eastern Economic Corridor.

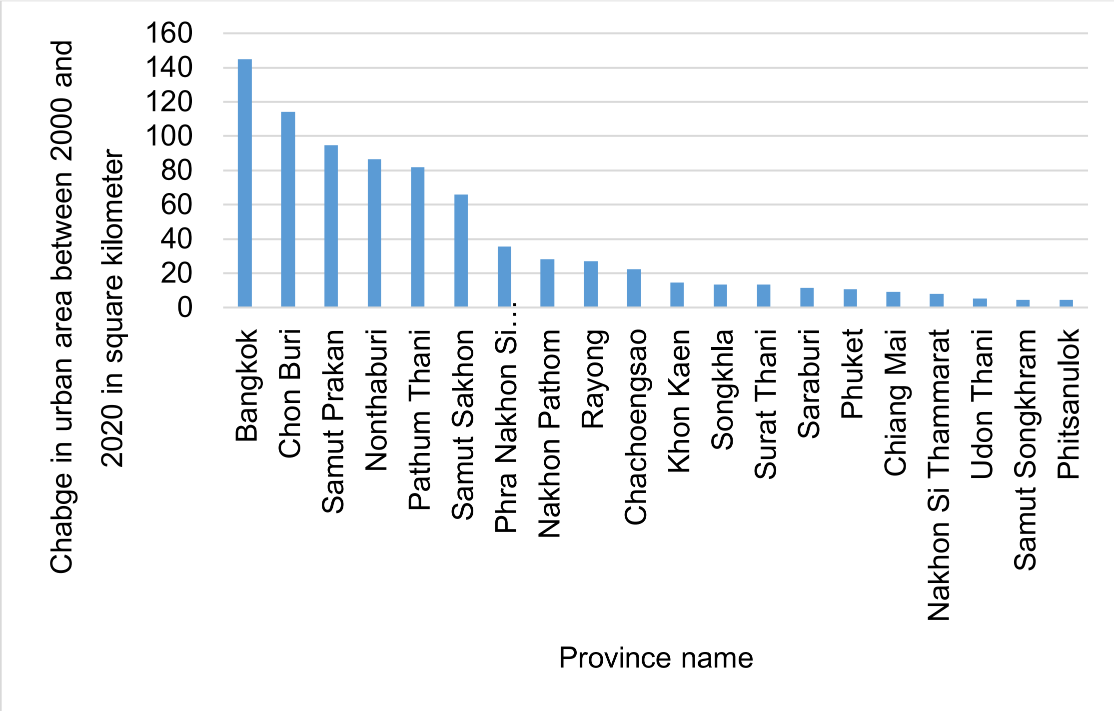
Analyzing the relationship between urban land expansion and GPP growth reinforces the correlation between the two variables. Figure 2 shows that higher GPP growth rates correspond with increased urban land expansion, with GPP growth alone explaining 63 percent of the variance in urban land growth. This highlights how unequal economic growth aligns with Thailand's monocentric urban system.

The skewed patterns of territorial development and economic growth pose significant social, economic, and political challenges in Thailand (Hewison, 2014; Rodríguez-Pose, 2018). Addressing these disparities requires redistributive policies that prioritize regional city growth over concentrating resources in a few prosperous provinces. Understanding the drivers of urban growth becomes pivotal in crafting such policies.

[1] Bangkok Metropolitan Region consists of Bangkok, Nakhon Pathom, Pathum Thani, Nonthaburi, Samut Prakan, and Samut Sakhon.

Figure 1

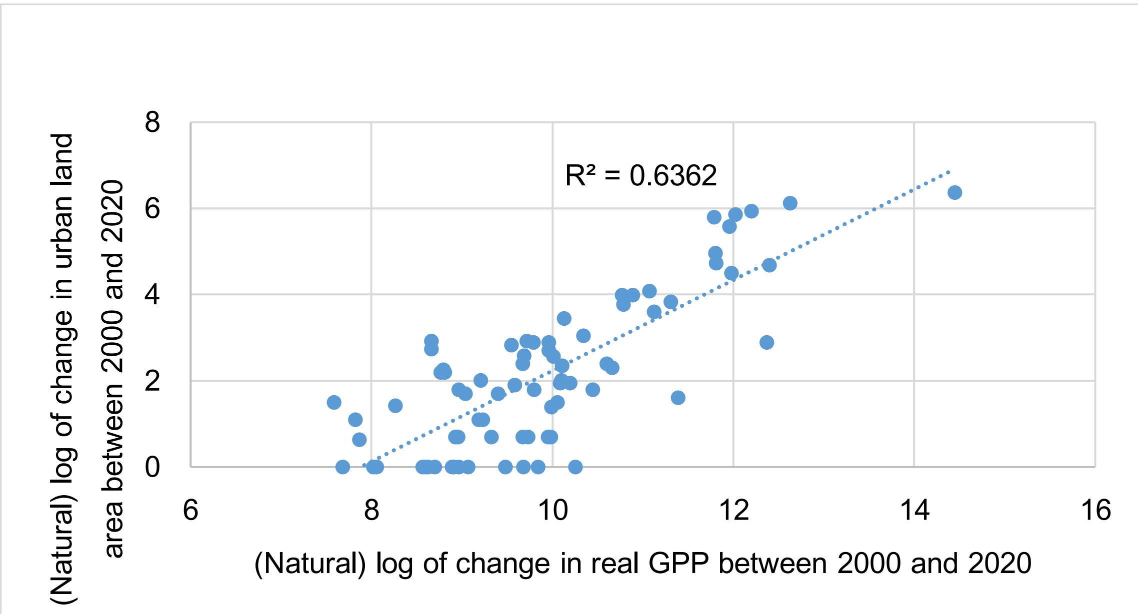
Distribution of Top 20 Provinces With the Highest Increase in Urban Areas Between 2000 and 2020 in Square Kilometers



*Note***.** The figure was created by the author's calculation.

Figure 2

Relationship Between Change in Urban Land Area and Change in Real GPP at Provincial Level (In Natural Log Terms)



*Note***.** The figure was created by the author's calculation.

Theoretical literature has explored the relationship between economic development and urbanization. Theoretical frameworks developed by Bertinelli and Black (2004), Gollin et al. (2016), Henderson (2005), and Wheaton (1974) suggest a reciprocal link between economic growth and urban expansion, emphasizing the role of human capital, technological advancements, institutions, and international trade in driving urbanization.

Besides theoretical work, recent literature on the relationship between economic development and urbanization has focused on China's experience of economic boom and rapid urban growth. According to this literature, rapid urbanization in China has been characterized by the expansion of urban land, converting agricultural areas into built-up areas. Satellite data has often been used to observe the urbanization process in China.

Some studies directly investigated the relationship between urban land expansion and GDP (Bai et al., 2012; Deng et al., 2008; Gollin et al., 2016; Li et al., 2018; Liu & Feng, 2016), while other key socio-economic variables (such as population, wage, foreign direct investment, institution, technology) also used by researchers to explore how these factors affected urbanization process (Ades & Glaeser, 1995; Duranton, 2016; Gao et al., 2014; Gao et al., 2015; Henderson & Wang, 2007; Li et al., 2015; Tontisirin & Anantsuksomsri, 2021; Ustaoglu & Williams, 2017; Xu et al., 2020).

Empirical studies generally support the idea that economic development and urban expansion are related. However, Bloom et al. (2008) did not find a connection between economic growth and the level of urbanization globally between 1970 and 2000. This lack of a significant link between urbanization and the rate of economic growth might be explained by the occurrence of high urbanization rates in several African countries despite having extremely low GDP growth rates. This finding by Bloom et al. (2008) aligns with Henderson (2003) argument. Henderson cautioned against viewing urbanization as a cure-all for improving productivity, citing empirical evidence that showed rapid urbanization happening during periods of economic stagnation.

Bai et al. (2012) contested the insignificant impact of urbanization and economic development highlighted by Bloom et al. (2008), suggesting that this lack of effect could be attributed to the inadequacy of using demographic data to gauge the urbanization rate, given variations in the definition of urban population across countries. As an alternative to using population as a representation of urbanization, Bai et al. opted for a clearer measure—the built-up area derived from satellite data—to proxy the urbanization process. Following Bai et al.'s approach, subsequent researchers employed satellite data to explore how economic development influenced the expansion of urban land in China over the last decade.

Viewed from a spatial angle, the urbanization and economic progress in Thailand aligned with the monocentric theory of urban growth (Puttanapong, 2018; Thinnakorn, 2019). Despite economic advancements benefiting rural regions, Tonguthai (2019) contended that the bulk of the generated wealth from this growth clustered in the Bangkok Metropolitan Region (BMR). Governmental policies notably influenced the urbanization rate in Thailand. For instance, strategies regarding agricultural goods, a focus on infrastructure investment, and the push for industrialization in Bangkok spurred significant rural-to-urban migration, accelerating the rapid expansion of Thailand's capital city.

Due to a lack of thorough quantitative analysis, this study aims to empirically assess urban land expansion in Thailand using satellite-based geospatial data, providing new insights into the pace, pattern, and determinants of urbanization at the provincial level. Unlike traditional studies that rely on demographic or administrative definitions of urbanization, this study utilizes high-resolution remote sensing data to capture the actual spatial extent of urban land expansion.

Additionally, this study combines geospatial analysis with econometric modeling to investigate the impact of economic development and structural transformation on urban land expansion. Specifically, it integrates panel data from MODIS satellite imagery with provincial-level economic indicators to investigate whether increases in income—particularly from tradable sectors—correlate with urban growth. A unique contribution of this paper is the simulation of rural versus urban labor allocation responses, derived from a theoretical framework based on Gollin et al. (2016), to model how income shocks affect spatial labor movement and urban land demand over time. The empirical strategy employs fixed-effects, spatial, and dynamic panel regression models to quantify these effects.

The remainder of this paper is divided into six sections. The second section discusses the theoretical framework of this paper. The third section provides an overview of the estimation method used in this paper. The fourth section gives details of the data used in the analysis. The estimation results are discussed in Section 5. The last section concludes this paper.

RESEARCH METHODOLOGY

Theoretical Framework

The basic theoretical foundation of this paper is based on the theoretical work of Gollin et al. (2016). The model was specifically developed to address urbanization and the increasing levels of income resulting from the discovery of natural resources and rising industrial productivity. The model could be assessed empirically in the context of data availability in a developing country.

Model of Urbanization and Structural Change

Urbanization is driven by income shocks, either from the discovery of natural resources or an increase in industrial productivity. The income shock causes workers to structurally shift away from an agricultural-based economy in rural areas to an industrial and service-based economy in urban areas. The economy comprises both tradable and non-tradable sectors. The tradable sectors produce manufactured goods and services that can be traded internationally, such as finance, insurance, and business services. Some tradable goods, such as agricultural products, are produced in rural areas. The non-tradable sectors comprise government and personal services, as well as local retail, transportation, construction, education, and healthcare.

Household Utility Function

A household sector is assumed to have the following utility function:

$$U = \beta_f \ln\left(c_f - \overline{c_f}\right) + \beta_d \ln c_d + \beta_n \ln c_n, \tag{1}$$

where $\overline{c_f}$ is the subsistence requirement for food, c_f is food consumption (rural tradable goods), c_d is urban tradable goods (manufacturing as well as tradable services such as finance, insurance, and business services), c_n is urban non-tradable goods (government and personal services, as well as local retail, transportation, construction, education, and health). The values of $\beta_f + \beta_d + \beta_n$ are between zero and one and $\beta_f + \beta_d + \beta_n = 1$.

Production Function

The production function of each sector takes the following form:

$$Y_j = A_j L_j^{1-\alpha}, \tag{2}$$

where $j\epsilon(f, d, n)$ and the sum of the number of workers in each sector is equal to the total number of workers in the economy. Mathematically, $L_f + L_d + L_n = 1$ and L_f, L_d, and L_n represent the share of workers in each sector.

Budget Constraint

In addition to the utility and production function, the household sector has the following budget constraints.

$$p_f^* c_f + p_d^* c_d + p_n c_n = m, \tag{3}$$

$$p_f^*\left(c_f - \overline{c_f}\right) + p_d^* c_d + p_n c_n = m - p_f^* \overline{c_f}, \tag{4}$$

where p_f^* and p_d^* denote the international price of tradable goods and p_n represents the domestic price of urban non-tradable goods. The RHS of Eq. (4), $m - p_f^* \overline{c_f}$, is surplus income after purchasing the subsistence requirement for food. Since urban non-tradable goods are assumed to be produced domestically, the total consumption of urban non-tradable goods is equal to the total value of production, which could be written in mathematical form as:

$$\beta_n(m - p_f^* c_f) = p_n Y_n, \quad (5)$$

where the LHS of Eq. (5), $\beta_n(m - p_f^* c_f)$, is the total consumption of urban non-tradable goods, and the RHS of Eq. (5), $p_n Y_n$, is the total value of production of urban non-tradable goods.

Like urban non-tradable goods, the total consumption of rural and urban tradable goods must equal the total value of production, as described in Eq. (6).

$$(\beta_f + \beta_d)(m - p_f^* \bar{c_f}) + p_f^* \bar{c_f} = R + p_f^* Y_f + p_d^* Y_d, \quad (6)$$

where R is the revenue from the natural resources that can be used to pay for imports. The LHS of Eq. (6), $(\beta_f + \beta_d)(m - p_f^* \bar{c_f}) + p_f^* \bar{c_f}$, is the total consumption of rural and urban tradable goods. The RHS of Eq. (6), $R + p_f^* Y_f + p_d^* Y_d$, is their total value of production plus revenue from natural resources.

Wage Equalization Between Sectors

Assuming free labor mobility between the sectors of the economy, wage between sectors is equalized for any sector j and k.

$$(1-\alpha) p_j A_j L_j^{-\alpha} = (1-\alpha) p_k^* A_k L_k^{-\alpha} \quad (7)$$

From the budget constraints and production function, Eq. (5), Eq. (6), Eq. (7), Eq. (2) and $L_f + L_d + L_n = 1$, the number of laborers in the urban non-tradable sector is given by Eq. (8) as:

$$L_n = \beta_n \left(1 + \frac{(1-L_n)^\alpha}{\bar{A}} \left(R - p_f^* \bar{c_f}\right)\right), \quad (8)$$

where $\bar{A} = \left[(p_d^* A_d)^{1/\alpha} + (p_f^* A_f)^{1/\alpha}\right]^\alpha$.

Equation (8) implies that the number of urban non-tradable sectors depends on the income level from either an increase in resource export or productivity level. The rising income level enables workers to meet their basic needs more easily, facilitating urban migration.

From Eq. (8), the allocation of labor to the other sector is given by Eq. (9) and (10) as:

$$L_d = (1 - L_n) \left(\frac{p_d^* A_d}{\bar{A}}\right)^{1/\alpha} \quad (9)$$

$$L_f = (1 - L_n) \left(\frac{p_f^* A_f}{\bar{A}}\right)^{1/\alpha}. \quad (10)$$

Like Eq. (8), Eq. (9), and Eq. (10), it is suggested that the number of workers in tradable sectors depends on the relative productivity level of that sector.

Urbanization and Comparative Statics

Labor allocation between sectors implies that urbanization equals the number of workers in the urban tradable and non-tradable sectors.

$$U = L_n + L_d. \quad (11)$$

- Proposition 1 *(*resource revenue and urbanization*)*

From Eq. (8), Eq. (9), and Eq. (10), it can be shown that:

$$(A)\ \frac{\partial U}{\partial R} > 0$$
$$(B)\ \frac{\partial L_n}{\partial R} > 0$$
$$(C)\ \frac{\partial L_d}{\partial R} < 0$$

Proposition 1 implies that increased resource revenue leads to higher demand for workers in urban non-tradable sectors, but it reduces demand for workers in rural and urban tradable sectors because the fall in tradables production can be compensated by imported goods paid for with the higher resource revenue. Yet, the increase in workers in urban non-tradable sectors outweighs the fall in workers in tradable sectors; therefore, the increased resource revenue leads to a higher urbanization rate.

- Proposition 2 *(*industrialization and urbanization*)*

When $R < p_{rd}^* \bar{c}_{rd}$, then the given Eq. (8) and Eq. (9) can be shown as:

$$(A)\ \frac{\partial U}{\partial p_d^* A_d} > 0$$
$$(B)\ \frac{\partial L_n}{\partial p_d^* A_d} > 0$$
$$(C)\ \frac{\partial L_d}{\partial p_d^* A_d} > 0$$

Proposition 2 applies in cases where resource revenue is less than income from tradable production. In this case, the rising productivity of tradable sectors not only shifts workers away from the food production sector to tradable sectors but also drives a shift towards urban non-tradable sectors. The effect of increased productivity in tradable sectors on the urbanization rate is straightforward; an increase in tradable sector productivity leads to a higher urbanization rate.

Hypotheses

Based on the theoretical framework and contextual background discussed above, this study tests the following hypotheses:

H1*:* An increase in real tradable Gross Provincial Product (GPP) per capita leads to a statistically significant expansion in urban land area.

H2*:* Resource GPP per capita has no statistically significant impact on urban land expansion in Thailand.

H3*:* Environmental factors (e.g., water availability, drought, temperature) and human capital (e.g., share of workers with higher education) significantly influence urban land growth.

These hypotheses are evaluated using panel regression models that incorporate both spatial and temporal dimensions of provincial data in Thailand.

Methodology

In this paper, four regression models were applied to examine whether an increase in income (either from resource revenue or productivity) significantly impacts urban land expansion at the provincial level in Thailand. However, as Thailand is an export-led growth country where income from the export of tradable goods and services is consistently higher than income from the export of natural resources, the prediction of proposition 2 is more suitable as a basic theoretical foundation for constructing the regression models. However, it is still interesting to see whether the prediction of proposition 1 is correct.

According to Proposition 2, increasing the productivity of urban tradable sectors, while holding resource revenue constant, is expected to have a positive and significant effect on urban land growth. Since urban land expansion occurs over time, selecting the lagged value of income, environmental factors, and human capital as explanatory variables in the regression models reveals the effects of income growth and the short-term effects of variation in the last two factors on urban land expansion. Following Gollin et al. (2016), the ten-year lag variables were used as explanatory variables in the regressions.

The first empirical approach is the fixed-effects panel regression model, which estimates the impact of productivity in tradable sectors on urban land expansion, while controlling for resource revenue and other variables. The second empirical approach is the spatial autoregressive model with spatial fixed effects, which is a basic specification of spatial panel-data models. The third empirical approach is the spatial error model with spatial fixed-effects, an extended version of the spatial autoregressive model. Both spatial autoregressive and spatial panel-data models were applied to control for the spatial correlation between geographic units, which is likely to occur when sample data are collected from geographically close entities (Belotti et al., 2017). Lastly, the dynamic panel-data model was applied to control the dynamic expectation of workers. Mathematical representations of each model are presented below.

Fixed-Effects Model

$$U_{i,t} = \alpha + \beta_1 tradable_{i,t-10} + \beta_2 resource_{i,t-10} + \beta_3 climate_{i,t-10} + \beta_4 education_{i,t-10} + u_i + \varepsilon_{i,t}. \quad (12)$$

Equation (12) shows the standard mathematical expression of the (non-spatial) fixed-effects model. The dependent variable, $U_{i,t}$, represents urban land area of the province i at time t. The urban land data were obtained from the combined MODIS data of Terra and Aqua. With its foundation on satellite images, the urban land cover types were measured by supervision from various sources, including the International Geosphere-Biosphere Programme, University of Maryland, Leaf Area Index, BIOME-Biogeochemical Cycles, and Plant Functional Types classification schemes. The primary classified land-use map was corrected with auxiliary information prior to its final release.

The key explanatory variable is the term $tradable_{i,t-10}$, which is the real tradable GPP per capita of province i at time $t-10$. The real tradable GPP per capita is meant to proxy the productivity of tradable sectors. The key control variable is $resource_{i,t-10}$ which is the real resource GPP per capita of province i at time $t-10$. The inclusion of resource revenue as the main control variable was based on theoretical modelling discussed in the previous section.

The other control variable is $climate_{i,t-10}$ which includes a set of environmental factors such as the yearly average value of NDDI, NDVI, NDWI, temperature, and precipitation of province i at time $t-10$. To avoid potential multicollinearity, each environmental factor was estimated separately. The last control variable is $education_{i,t-10}$ which is the share of workers with higher education in province i at time $t-10$. u_i represents an unobserved characteristic of province i. $\varepsilon_{i,t}$ is pure residual. The details of each variable will be discussed in the next section.

Spatial Autoregressive Model with Spatial Fixed Effects

$$U_{i,t} = \rho W U_{i,t} + \beta_1 tradable_{i,t-10} + \beta_2 resource_{i,t-10} + \beta_3 climate_{i,t-10} + \beta_4 education_{i,t-10} + u_i + \varepsilon_{i,t}. \quad (13)$$

Equation (13) elaborates the specification of the spatial autoregressive model with spatial fixed effects. Equation (13) includes the same set of control variables as did Eq. (12), but the term $\rho W U_{i,t}$ was added. According to Belotti et al. (2017), W is the $n \times n$ matrix that describes the spatial arrangement of the n units. Every geographic unit i is associated with the spatial matrix W. In other words, W could be thought of as a defined neighborhood, and the term rho would capture any spatial spillover effect. The spatial weight matrix used in this paper is the (Euclidean) Distance Weight matrix, as it accounts for the presence of island provinces such as Phuket in Thailand. Therefore, using a Distance Weight matrix is the most appropriate specification to ensure that all provinces are included in the analysis.

Spatial Error Model with Spatial Fixed Effects

$$U_{i,t} = \beta_1 tradable_{i,t-10} + \beta_2 resource_{i,t-10} + \beta_3 climate_{i,t-10} + \beta_4 education_{i,t-10} + u_i + v_{i,t}, \quad (14)$$

where $v_{i,t} = \lambda M v_{i,t} + \varepsilon_{i,t}$.

The spatial error model shares similarities with the spatial autoregressive model but focuses explicitly on spatial spillover effects that operate through the error term as described by $v_{i,t} = \lambda M v_{i,t} + \varepsilon_{i,t}$. The matrix M is a spatial weight matrix that may or may not be equal to W.

The difference in specifications of each model can reveal whether increased productivity in tradable sectors significantly impacts provincial urban land expansion. Furthermore, they highlight the pathway by which spatial spillovers function—whether through a direct change in the dependent variable or through a change in the error term.

Dynamic Panel Model

$$U_{i,t} = \theta + \gamma U_{i,t-1} + \beta_1 tradable_{i,t-10} + \beta_2 resource_{i,t-10} + \beta_3 climate_{i,t-10} + \beta_4 education_{i,t-10} + u_i + \varepsilon_{i,t}. \quad (15)$$

As migration takes time to occur and cities take time to build, urban land expansion in province i at time $t-1$ could affect the urban land expansion of province i at time t. Because workers had observed that urban land expansion was taking place in province i at time $t-1$ and decided to move to that province in the next period, generating an inertia effect on urban land expansion. Moreover, urban land expansion is a process of accumulation, where the current value of urban land represents the accumulation of urban land from previous periods. Failing to control the dynamic mechanisms could cause biased coefficient estimators. To econometrically address this problem, this study also employed the dynamic panel-data model. The lagged dependent variable, $U_{i,t-1}$, was included in the model to control for a partial adjustment mechanism. The model could potentially reveal the effect of urban land expansion at time $t-1$ on urban land expansion at time t. Equation (15) was estimated via the Arellano–Bond estimation technique.

DISCUSSION

Data

The data for this paper consists of conventional economic indicators and satellite data. The conventional economic indicators obtained from the NESDC contain information on the GPP of various sectors and the population of each province. LFS provided by the NSO of Thailand also contains information on the characteristics of workers, which is a key explanatory variable in the regression, such as the level of education.

Besides the conventional economic indicators and ground survey, various satellite data from the Google Earth Engine platform service were used as dependent and explanatory variables in the regression. These data consist of urban land areas, Normalized Difference Drought Index (NDDI), Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Land Surface Temperature (at nighttime), and Precipitation (rainfall), which is available from 2000 to 2020. More details of these variables will be discussed below.

Dependent Variable

The urban land area at the provincial level from 2000 to 2020 was used as the dependent variable in the regression. Similar to the work of Sangawongse and Ruangrit (2015), who applied geospatial data to estimate city boundaries, the urban land area was extracted from Terra and Aqua MODIS reflectance data using supervised classification techniques. Each data point was mapped to the political boundaries of each province in Thailand. The concentration of urbanization (as measured by urban land area) in 2000, 2010, and 2020 is shown in Figure 3.

Using the total urban land area obtained from the remote sensing technique as a proxy for urbanization has two advantages. First, when compared to conventional data sources such as construction permits or population counts, satellite data better capture the true extent of urbanization in Thailand because the tempo of urbanization is directly observable from space. In contrast, the data collected by the government may only include the formally registered population, thereby missing the large informal sectors in developing countries.

Second, the most refined unit of analysis in Thailand is available at the provincial level. However, the political boundaries of each province in Thailand could be starkly different in size. Thus, using the total urban land as a proxy for urbanization helps attenuate statistical bias arising from the modifiable areal unit problem (MAUP).

Specifically, using the urbanization rate or density at the provincial level (instead of the absolute total land area) as a proxy for urbanization may produce biased results by artificially inflating or deflating the degree of urbanization in some provinces. For example, the total land area of Nakhon Ratchasima is larger than that of the Bangkok Metropolitan Area. However, its urbanization rate differs because the political area of Nakhon Ratchasima is significantly larger than that of Bangkok. Thus, regressing total urban land on a set of economic and natural factors should reveal how explanatory factors affect the tempo of urbanization at the provincial level in Thailand.

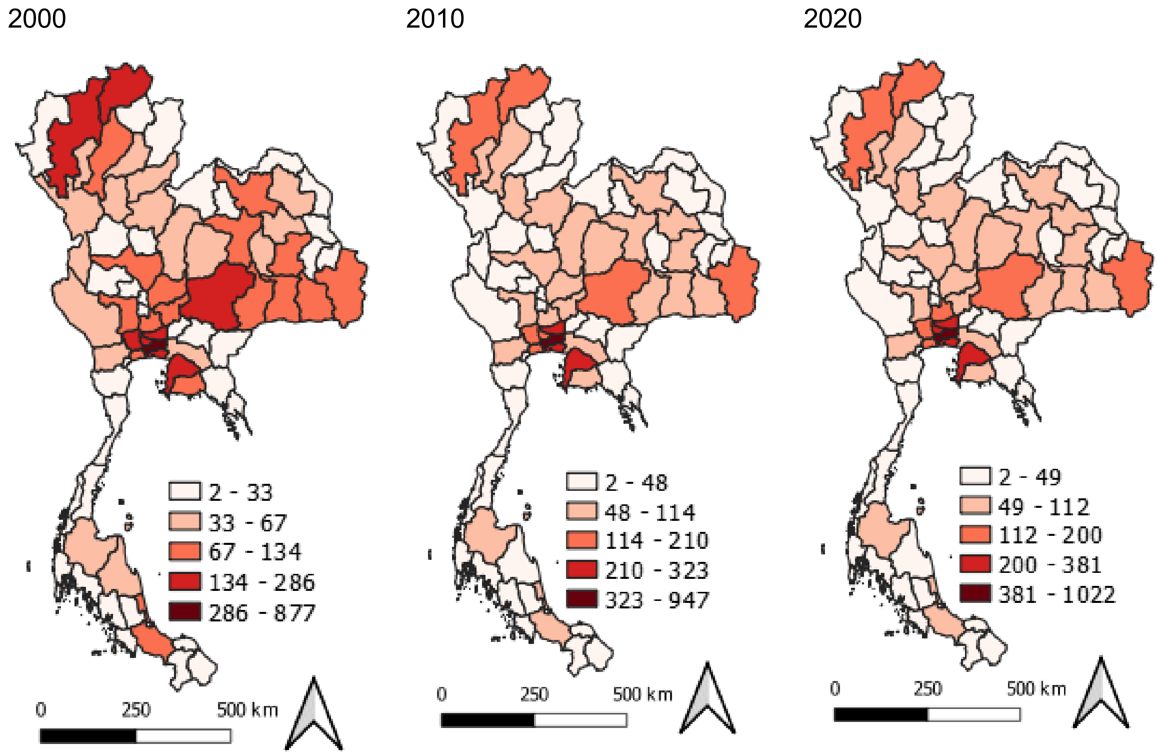
Income Variables

Tradable GPP Per Capita

Following the theoretical construction in the previous section, the tradable GPP includes real GPP of the key sectors as follows: agricultural, industrial (except mining and quarrying), information and communication, financial and insurance, real estate activities, professional, scientific, and technical activities, arts, entertainment and recreation, and other service activities. The real GPP value of these sectors was divided by the population to reflect rising productivity. Figure 4 displays the spatial distribution of the tradable GPP per capita in 2000, 2010, and 2020, suggesting that most economic activities are clustered in the central and eastern regions of Thailand.

Figure 3

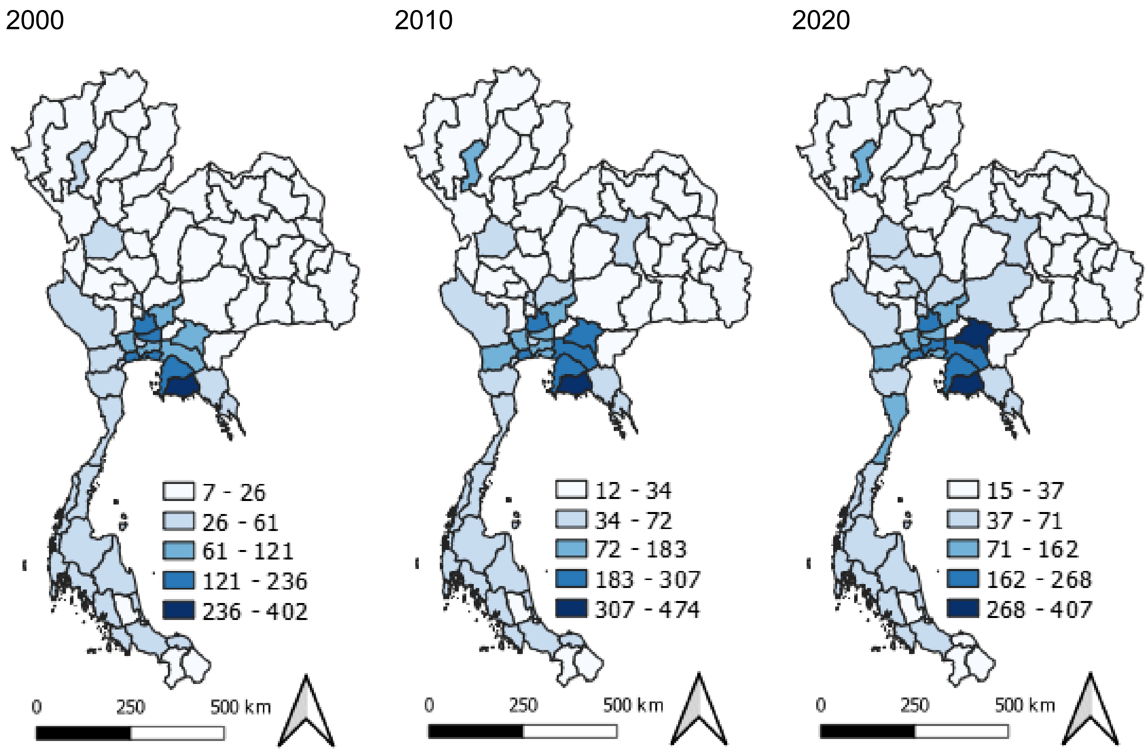
Spatial Distribution of Urban Land Area in Square Kilometers in 2000, 2010, and 2020



Note. The figure was created by the author’s calculation.

Figure 4

Spatial Distribution of Tradable GPP per Capita in 2000, 2010, and 2020



Note. The figure was created by the author’s calculation. The unit is in thousand Baht.

Resource GPP Per Capita

Resource GPP per capita refers to the GPP of the mining and quarrying sector. Again, to derive the per capita value, the real GPP value of the mining and quarrying sector was divided by the population. Figure 5 displays the spatial distribution of the resource GPP per capita in 2000, 2010, and 2020. In contrast to the clustered distribution of tradable GPP, the GPP within the mining and quarrying sector shows a scattered pattern across Thailand.

Environmental Variables

Glaeser et al., (2001) and Duranton (2016) argued that environmental factors could affect city growth in the US and Colombia. To control for this effect, this study includes various measurements of environmental factors, including NDDI, NDVI, NDWI, Land Surface Temperature (at nighttime), and Precipitation (rainfall). The NDDI, NDVI, NDWI, and Temperature data were provided by the Terra MODIS satellite, while Precipitation was obtained from the CHIRPS dataset. All these datasets were processed and downloaded via the Google Earth Engine platform service, as mentioned earlier. The detail of each environmental variable is discussed below.

Normalized Difference Vegetation Index (NDVI)

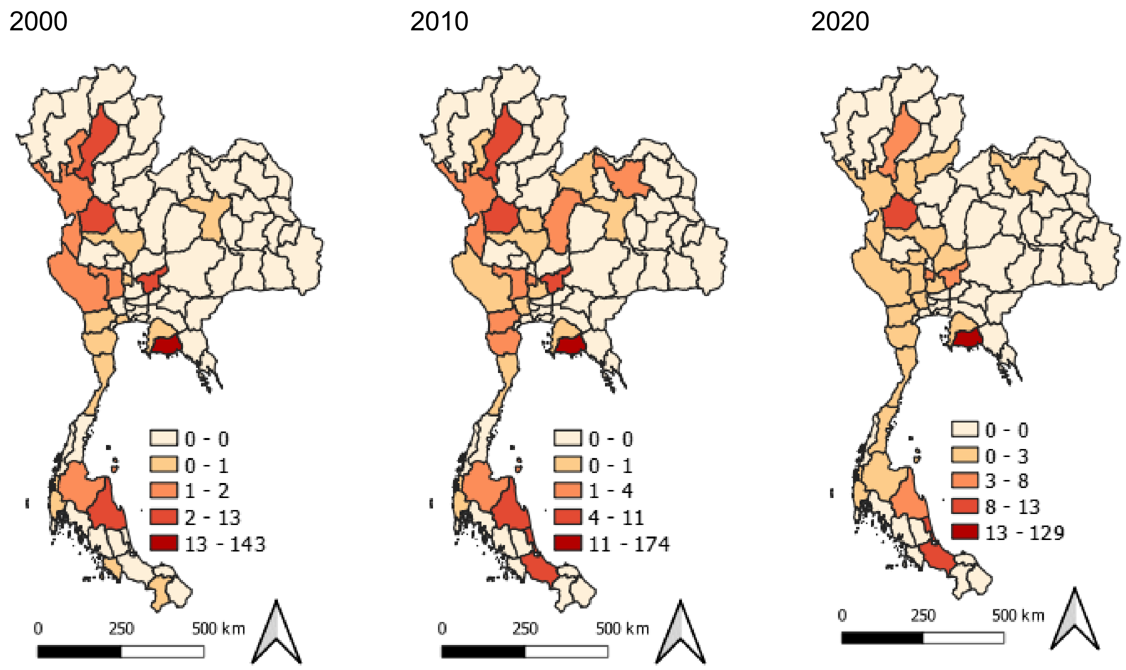
The NDVI plays a crucial role in drought monitoring within ecosystems. NDVI measures dryness based on the changes in chlorophyll content and spongy mesophyll of the vegetation canopy. Those changes determine the greenness of both vegetation and leaves as perceived by humans. The chlorophyll content and spongy mesophyll are reflected via absorption of visible red radiation and NIR radiation, respectively. Red and near-infrared NIR) radiation can be measured via remote sensing using the Terra MODIS and Sentinel-2 satellites. The NDVI could be expressed in a mathematical formula as follows:

$$NDVI = ((NIR - RED))/((NIR + RED)). \qquad (16)$$

The value of NDVI ranges between -1 and 1, where 1 indicates the highest density of vegetation and -1 indicates the lowest density of vegetation. The distributions of NDVI in 2000, 2010, and 2020 are illustrated in Figure 6, suggesting that NDVI is concentrated in the southern regions of Thailand.

Figure 5

Spatial Distribution of Resource GPP per Capita in 2000, 2010, and 2020

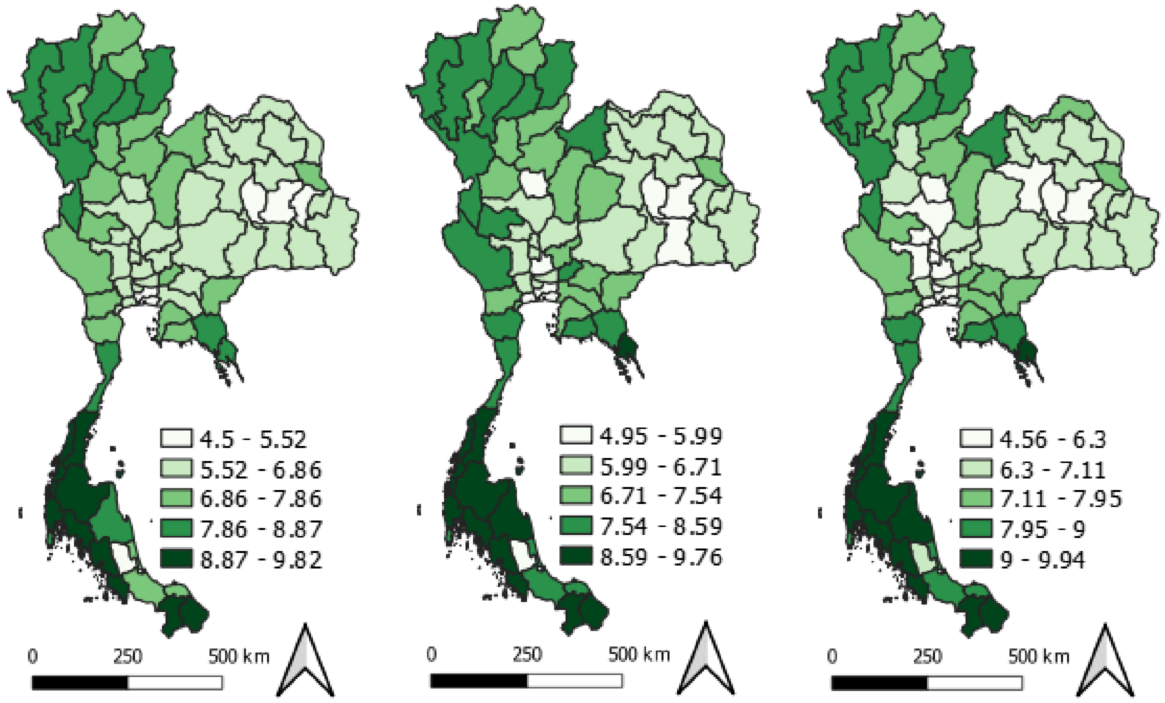


Note. The figure was created by the author's calculation. The unit is in thousand Baht.

Figure 6

Spatial Distribution of NDVI in 2000, 2010, and 2020

2000 2010 2020

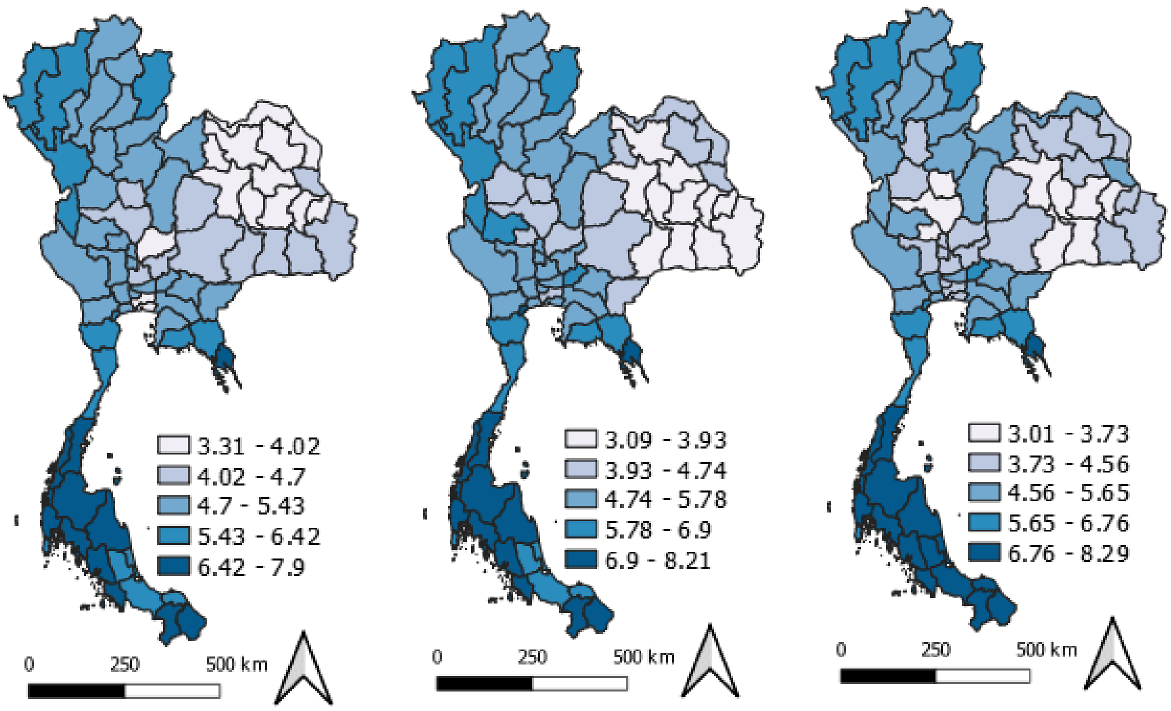


Note. The figure was created by the author's calculation.

Figure 7

Spatial Distribution of NDWI in 2000, 2010, and 2020

2000 2010 2020



Note. The figure was created by the author's calculation.

Normalized Difference Water Index (NDWI)

Based on NDVI, NDWI was used to monitor drought based on the change in both water content and spongy mesophyll. The water content is reflected via absorption of SWIR radiation. The NDWI could be expressed in a mathematical formula as follows:

$$NDWI = ((NIR - SWIR))/((NIR + SWIR)). \quad (17)$$

The value of NDWI ranges between -1 and 1, where a value between 0.2 and 1 indicates the existence of a water surface, and a value between -1 and 0.2 indicates a non-aqueous surface with high humidity. Table 7 displays the spatial distribution of NDWI in 2000, 2010, and 2020, exhibiting patterns comparable to those observed in the spatial distribution of NDVI.

Normalized Difference Drought Index (NDDI)

Following Gu et al., (2007), the NDDI is a combination of NDVI and NDWI geospatial indicators. The NDWI could be expressed in a mathematical formula as follows:

$$NDWI = ((NDVI - NDWI))/((NDVI + NDWI)). \quad (18)$$

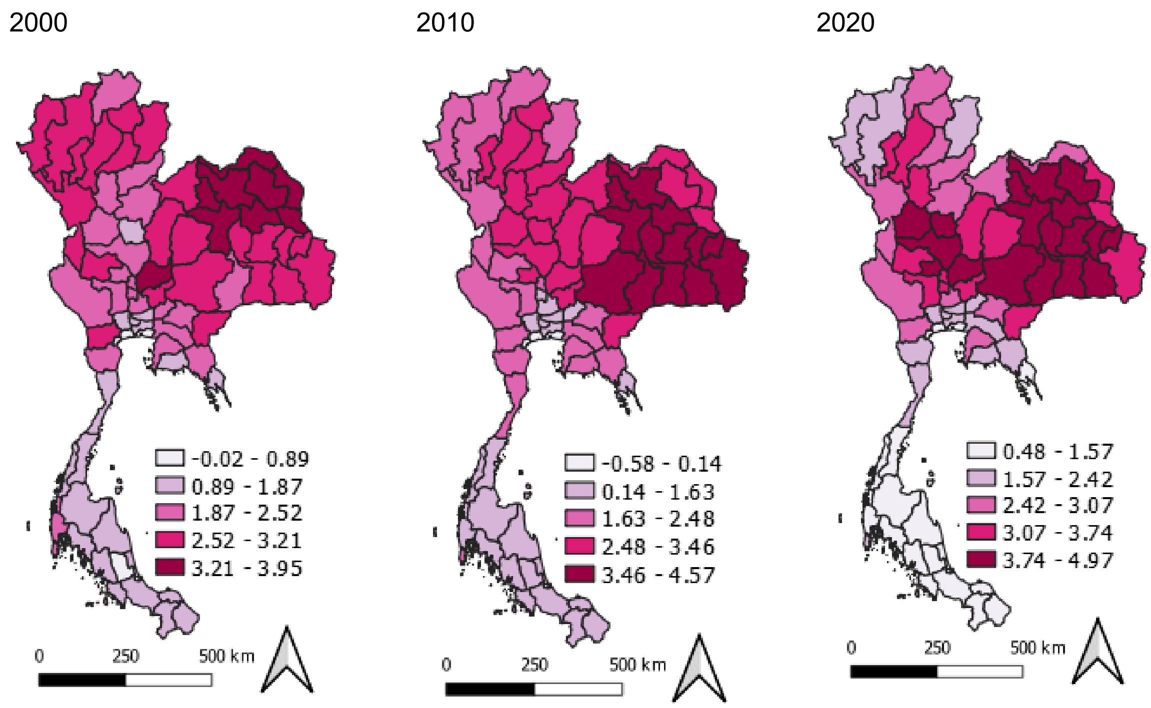
The value of NDDI ranges between -1 and 1, where a value of -1 suggests no drought condition and a value of 1 indicates a severe drought condition. Figure 8 illustrates the spatial distribution of NDDI in 2000, 2010, and 2020. It shows that dryness mostly clusters in northeastern regions.

Land Surface Temperature

The land surface temperature is measured both during the daytime and nighttime via remote sensing by the Terra MODIS satellite. The increasing temperature could lead to a decline in economic productivity, especially in developing countries (Burke et al., 2015). Nevertheless, land surface temperature at nighttime was selected as an explanatory variable in this study because higher nighttime temperatures have been found to negatively affect not only crop yield but also office productivity in the Netherlands (Daanen et al., 2013; Mohammed & Tarpley, 2011). The spatial distributions of nighttime land surface temperature in 2000, 2010, and 2020 are shown in Figure 9.

Figure 8

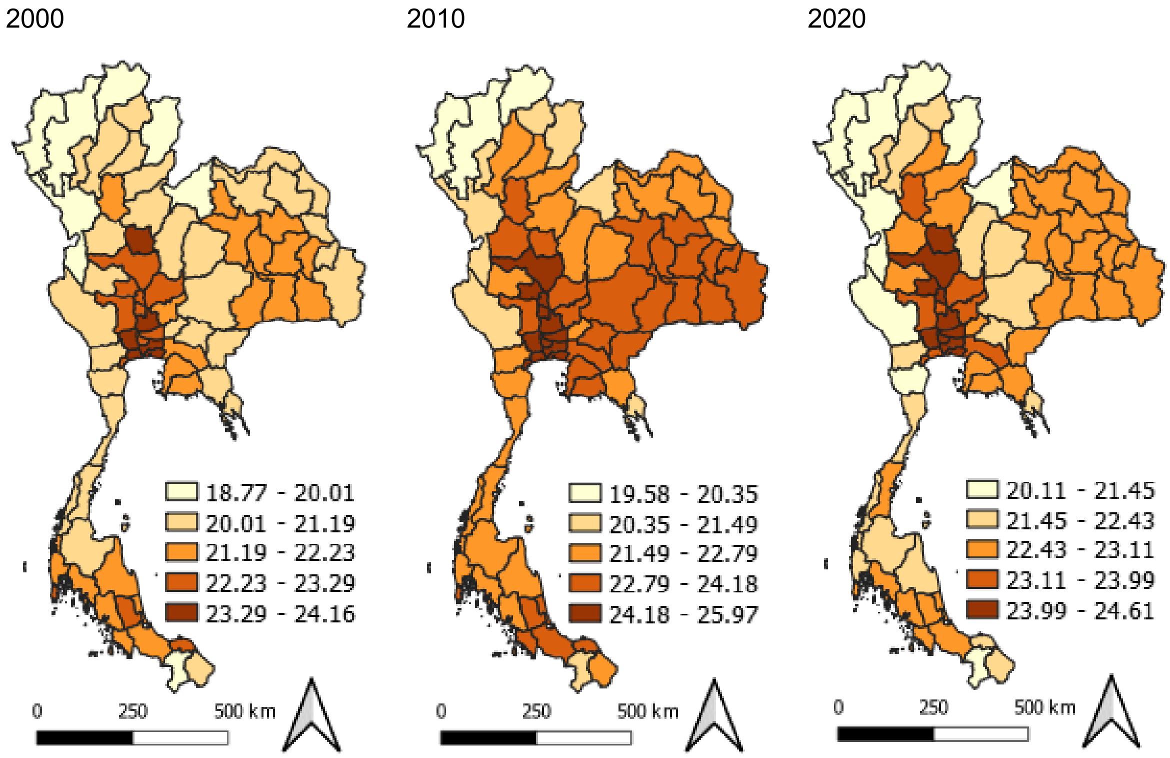
Spatial Distribution of NDDI in 2000, 2010, and 2020



Note. The figure was created by the author's calculation.

Figure 9

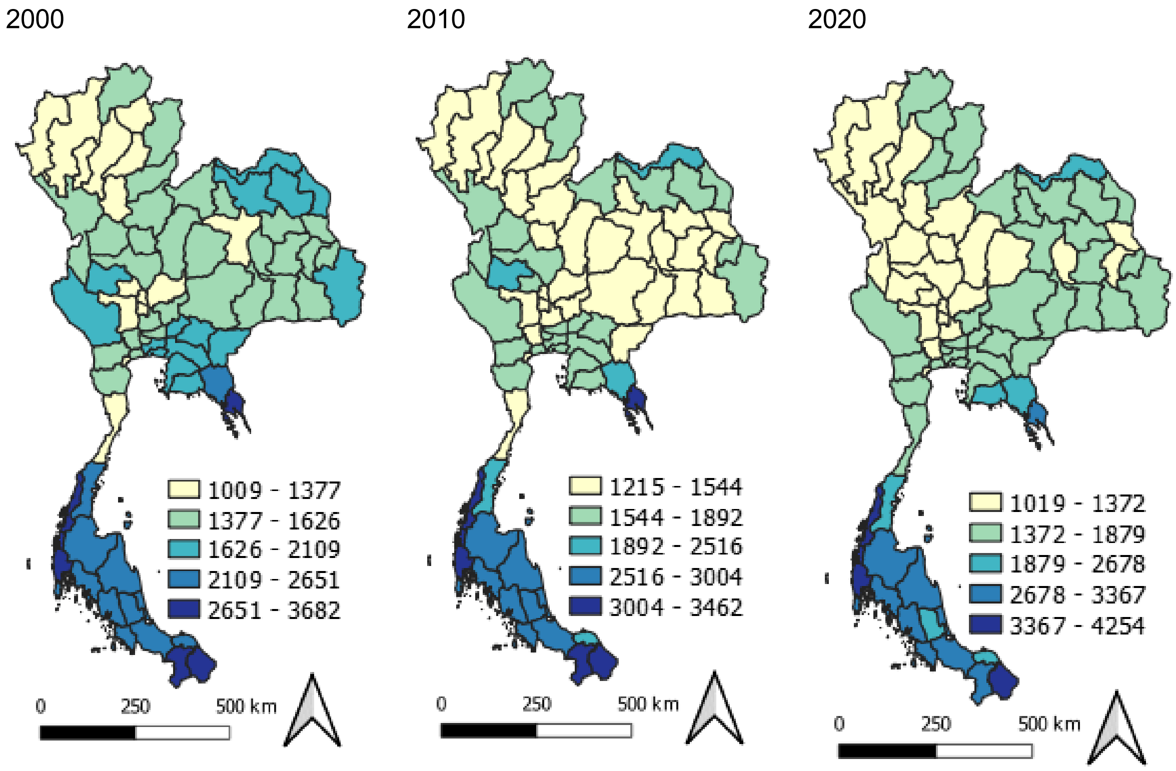
Spatial Distribution of Land Surface Temperature (At Nighttime) in Celsius in 2000, 2010, and 2020



Note. The figure was created by the author's calculation.

Figure 10

Spatial Distribution of Annual Precipitation in Millimeters in 2000, 2010, and 2020



Note. The figure was created by the author's calculation.

Precipitation

The precipitation data are obtained from the Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) dataset. The CHIRPS dataset is a collection of both remote sensing data from satellites and ground station data. This technique cross-checks the accuracy of precipitation data from satellite and ground stations.

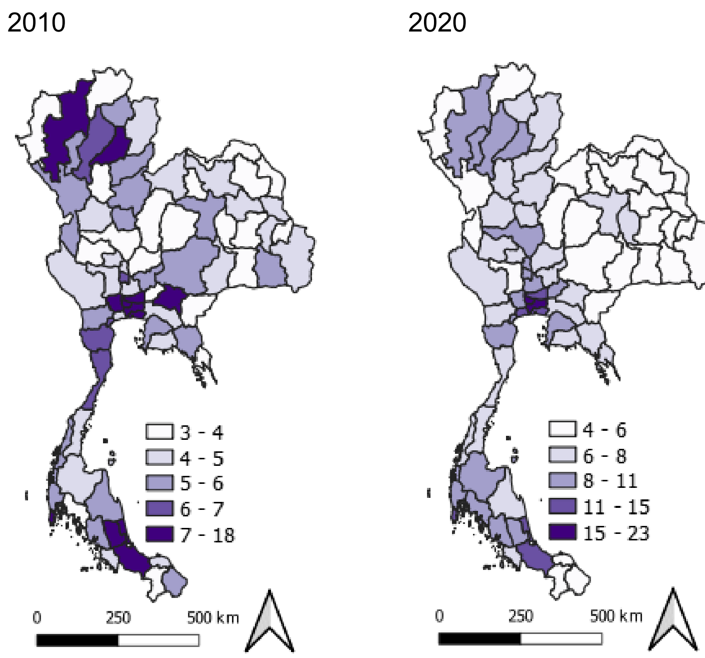
Variations in precipitation could affect agricultural productivity in non-irrigated areas or trigger conflict in many developing countries that inherited extractive institutions (Amare et al., 2018; Miguel et al., 2004). Although environmental factors are often thought to be exogenous or, at worst, irrelevant, it could still be argued that the environment plays some vital role in determining urban growth. For example, the availability of water was found to positively affect long-run city growth in Columbia (Duranton, 2016). As roughly 31 percent of workers in Thailand were employed in the agricultural sector (World Bank, 2021), environmental factors such as availability of water and amount of rainfall (all of which are captured by satellite) could affect the tradable sector productivity and subsequent urban growth. Figure 10 displays the Spatial distribution of annual precipitation in 2000, 2010, and 2020.

Share of Workers with Higher Education

Various well-known studies of literature often consider human capital as a main driver of city growth, especially in developed countries (Glaeser et al., 2004; Glaeser et al., 1995; Simon & Nardinelli, 2002). Higher wages and positive local amenities were often associated with higher levels of human capital in cities (Moretti, 2004; Shapiro, 2006), which subsequently attracted workers into cities. Thus, a share of workers with higher education was used to control the effect of human capital on city growth. Similar to previous figures, the spatial distribution of the share of workers with higher education, expressed as a percentage, was mapped and displayed in Figure 11. However, since data on the share of workers with higher education in 2000 is not available, Figure 11 only shows the share of workers with higher education in 2010 and 2020. The main data used in the regression models were briefly summarized in Table 1.

Figure 11

Spatial Distribution of Share of Workers with Higher Education in 2010 and 2020



Note. The figure was created by the author’s calculation.

Table 1

Summary of Data

Variable type	Description	Unit	Source
Dependent variable	Urban land area	Square kilometer	MODIS
Income variables	1. Tradable GPP per capita 2. Resource GPP per capita	Million Baht per population	NESDC
Environmental variables	1. NDDI 2. NDVI 3. NDWI	-1 to 1	MODIS
	4. Land surface temperature (at nighttime)	Celsius	MODIS
	5. Precipitation	Millimeter of rain per year	CHIRPS
Socio-economic variable	1. Share of worker with higher education	Percent of total workforce	LFS

Note. This table was created from the author's compilation.

RESULTS

Descriptive Statistics

Table 2 presents the mean and standard deviation of each variable for the years 2000, 2010, and 2020. The average urban land area steadily increased from 71 square kilometers in 2000 to 82.85 square kilometers in 2020. Similarly, the real tradable GPP per capita remarkably rose from 44,643 Baht a year to 66,663 Baht a year during the same period. But the change of real resource GPP per capita depicted more fluctuation.

Compared to economic variables, the mean values of environmental factors were relatively stable but still showed some noticeable trends. The mean of NDDI and NDVI slightly increased during the past two decades, while NDWI and precipitation increased in 2010 but decreased in 2020. The temperature at night became warmer as the average land surface temperature at night increased by 1.24 degrees Celsius over 20 years. The NDDI, NDWI, and precipitation exhibited a significant change in standard deviation, indicating higher variability.

The level of human capital in Thailand has significantly progressed, as the share of workers with college degrees rose from 3.67 percent of the total workforce in 2002 to 8.12 percent in 2020, indicating increased accessibility to tertiary education.

Regression Results

The effect of increased productivity in tradable sectors on urban land expansion was evaluated using Eqs. 12, 13, and 14. Since each environmental factor was estimated separately (as mentioned earlier), each regression contains four specifications, labeled M1, M2, M3, and M4, respectively. Table 3 shows the results of non-spatial panel regression. The results suggest that the lagged value of GPP per capita has a significant and positive effect on urban growth, which is consistent with the derived theory that the productivity of tradable sectors leads to urbanization. The resource GPP per capita, although positive, remains insignificant in all four specifications. These results are not surprising, as resource income has been dominated by industrial income since the implementation of the first national economic and social development plan in the 1950s, which aligns well with proposition 2.

Table 2

Descriptive Statistics of Variables in the Regression

Variables	2000	2010	2020
Urban land area	71.34 (110.32)	75.83 (120.34)	82.85 (133.36)
Real tradable GPP per capita	44,643.82 (63624.52)	61,675.62 (81362.05)	66,663.8 (77187.77)
Real resource GPP per capita	2,719.98 (16439.98)	3,465.806 (20017.47)	2,792.972 (14807.39)
Sum of NDDI	2.34 (0.80)	2.35 (1.13)	2.78 (1.14)
Sum of NDVI	7.21 (1.22)	7.29 (1.18)	7.52 (1.23)
Sum of NDWI	5.18 (1.12)	5.48 (1.31)	5.28 (1.43)
Sum of precipitation	1,792.48 (594.05)	1,848.25 (590.00)	1,787.07 (741.31)
Land surface temperature at night	21.49 (1.22)	22.93 (1.35)	22.73 (0.98)
Share of worker with college degree	3.67 (2.23)	5.81 (2.45)	8.12 (3.38)

Note. Standard deviations are in parentheses.

Table 3

Results of Non-Spatial Panel Regression

Dependent: Urban land area	M1	M2	M3	M4
Real tradable GPP per capita (at t-10)	0.05*** (2.91)	0.06*** (3.36)	0.05*** (3.04)	0.05*** (2.96)
Real resource GPP per capita (at t-10)	0.145 (1.22)	0.154 (1.29)	0.146 (1.23)	0.01 (0.85)
NDDI (at t-10)	-2.15*** (-2.71)			
NDVI (at t-10)		0.27 (0.26)		
NDWI (at t-10)			1.57** (2.01)	
Precipitation (at t-10)				0.01*** (5.08)
Average land surface temperature at night (at t-10)	0.72* (1.65)	0.40 (0.95)	0.59 (1.35)	0.39 (0.93)

Table 3 (Continued)

Dependent: Urban land area	M1	M2	M3	M4
Share of workers with a college degree (at t-10)	61.80*** (3.24)	66.45*** (3.48)	62.73*** (3.28)	46.49** (2.43)
Constant	62.01*** (6.60)	61.53*** (4.74)	51.45*** (4.57)	57.11*** (6.12)
Observation	684	684	684	684
Within R-squared	0.0659	0.0547	0.0608	0.0933
Between R-squared	0.1477	0.1426	0.1066	0.0833
Overall R-squared	0.1450	0.1401	0.1046	0.0802

Note. T-statistics are reported in parentheses. * p<0.05, ** p<0.01, *** p<0.001.

Environmental variables were found to have a significant impact on urban land expansion. Specifically, NDDI, a drought measurement, negatively impacted urban land growth, whereas NDWI and precipitation had a positive effect on urban land growth. Nevertheless, the impact of land surface temperature at night on urban land was less robust, showing a significant impact (at a much wider confidence interval) only in the M1 specification. Similar to the productivity of tradable sectors, regressions suggest that the level of human capital has a significant impact on urban land expansion in all specifications.

In addition to the standard non-spatial panel regression, this study employed spatial panel regression techniques that explicitly control for spatial autocorrelation, which could potentially arise due to the data being collected in geographical units. Spatial autocorrelation was illustrated by calculating a bivariate Local Moran's I statistic. The results of Moran's I statistics were shown in the Appendix. The application of spatial panel regression techniques controlled both spatial autocorrelation and unobserved provincial characteristics, making the results more robust.

The results of the spatial lag panel and spatial error regression were presented in Tables 4 and 5, respectively. The signs and significance levels of each variable in Tables 4 and 5 are consistent with the result presented in Table 3. According to Table 4, tradable GPP per capita has a significant effect on urban growth, while resource income has no meaningful effect. The impact of natural factors on urban growth could be attributed to the same set of climate variables, and the impact of human capital on urban growth was also found to be significant.

Nevertheless, the rho and lambda coefficients depicted in Tables 4 and 5 provide some meaningful discussion, as expected in the methodology section. Specifically, the rho coefficient is statistically significant in all specifications of Table 4, while the rho coefficient (presented in Table 5) is not. The results suggest that spatial spillover operates through a change in the dependent variable or through a change in the error term. In other words, urban land growth in a particular province spills over to its neighbor in a predictable way.

In addition to the non-spatial and spatial panel regressions, Table 6 displays the estimated results of the dynamic panel-data regression. The regression confirms an inertia effect of urban land expansion, meaning that past urban land expansion has influenced current urban land expansion. The dynamic expectations of workers influenced urban land expansion in Thailand. Notably, the real urban tradable GPP per capita and share of workers with college degrees remain significant but with much lower estimated coefficient values. The environmental factors are insignificant in the dynamic panel model, except for average nighttime land surface temperatures, which were found to negatively affect urban land expansion.

Table 4

Results of Spatial Lag Panel Regression

Dependent: Urban land area	M5	M6	M7	M8
Real tradable GPP per capita (at t-10)	0.05*** (2.7)	0.05*** (3.22)	0.05*** (2.94)	0.05*** (2.87)
Real resource GPP per capita (at t-10)	0.15 (1.31)	0.15 (1.38)	0.15 (1.32)	0.10 (0.92)
NDDI (at t-10)	-2.01*** (-2.69)			
NDVI (at t-10)		0.03 (0.02)		
NDWI (at t-10)			1.36* (1.85)	
Precipitation (at t-10)				0.01*** (5.18)
Average land surface temperature at night (at t-10)	0.69* (1.68)	0.38 (0.95)	0.55 (1.35)	0.38 (0.97)
Share of workers with a college degree (at t-10)	52.73*** (2.86)	56.07*** (3.04)	53.90*** (2.92)	39.41** (2.14)
rho	0.10** (1.99)	0.12** (2.23)	0.10** (1.96)	0.09* (1.66)
Observation	684	684	684	684
AIC	4032.5	4039.8	4036.3	4013.3
BIC	4064.2	4071.4	4068	4045
Within R-squared	0.08	0.07	0.07	0.10
Between R-squared	0.13	0.13	0.10	0.07
Overall R-squared	0.13	0.13	0.09	0.07

Note. T-statistics are reported in parentheses. * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Table 5

Results of Spatial Error Panel Regression

Dependent: Urban land area	**M9**	**M10**	**M11**	**M12**
Real urban tradable GPP per capita (at t-10)	0.05*** (2.84)	0.05*** (3.17)	0.05*** (3.00)	0.05*** (2.93)
Real resource GPP per capita (at t-10)	0.15 (1.31)	0.16 (1.39)	0.15 (1.32)	0.10 (0.93)
NDDI (at t-10)	-2.14*** -(2.85)			
NDVI (at t-10)		0.17 (0.16)		
NDWI (at t-10)			1.55** (2.08)	
Precipitation (at t-10)				0.005*** (5.39)
Average land surface temperature at night (at t-10)	0.72* (1.74)	0.40 (0.98)	0.58 (1.42)	0.39 (0.98)
Share of workers with a college degree (at t-10)	59.97*** (3.14)	62.66*** (3.23)	61.33*** (3.22)	44.69** (2.39)
lambda	0.0185 (0.29)	0.0377 (0.58)	0.0148 (0.23)	0.0224 (0.37)
Observation	684	684	684	684
AIC	4036.3	4044.3	4040.1	4015.9
BIC	4068	4075.9	4071.7	4047.6
Within R-squared	0.07	0.05	0.06	0.09
Between R-squared	0.15	0.14	0.10	0.08
Overall R-squared	0.14	0.14	0.10	0.08

Note. T-statistics are reported in parentheses. * p<0.05, ** p<0.01, *** p<0.001.

Table 6

Results of Dynamic Panel Regression

Dependent: Urban land area	**M13**	**M14**	**M15**	**M16**
Urban land area (at t-1)[2]	1.10*** (230.89)	1.11*** (233.41)	1.11*** (230.77)	1.10*** (224.29)
Real urban tradable GPP per capita (at t-10)	0.01*** (3.60)	0.01*** (.370)	0.01*** (.364)	0.01*** (3.56)
Real resource GPP per capita (at t-10)	-0.003 (-0.16)	-0.004 (-0.16)	-0.004 (-0.15)	-0.007 (-0.29)
NDDI (at t-10)	0.004 (0.04)			
NDVI (at t-10)		-0.12 (-0.99)		
NDWI (at t-10)			-0.03 (-0.32)	
Precipitation (at t-10)				0.0002 (1.58)
Average land surface temperature at nighttime (at t-10)	-0.19*** (-4.21)	-0.19*** (-4.54)	-0.19*** (-4.38)	-0.19*** (-4.44)
Share of workers with a college degree (at t-10)	4.32* (1.77)	4.14* (1.69)	4.32* (1.77)	4.30* (1.76)
Constant	-4.32*** (-4.44)	-3.37** (-2.47)	-4.11*** (-3.52)	-4.45*** (-4.55)
Observation	532	532	532	532

Note. Z-statistics are reported in parentheses. * p<0.05, ** p<0.01, *** p<0.001.

Although the signs and significance levels of each variable are remarkably similar across model specifications, the estimated coefficients of the spatial panel regression are smaller than those of the non-spatial regression. An explanation and discussion of estimated results are provided below.

These results lead to six insights. First, the productivity of urban tradable sectors positively affected urban land expansion in Thailand, as predicted by Proposition 2, which is consistent with previous literature (Bai et al., 2012; Deng et al., 2008; Gao et al., 2015; Li et al., 2018; Liu & Feng, 2016). The econometric results from the non-spatial panel regression, spatial lag panel regression, and spatial error panel regression show that the coefficient of the key variable—real tradable GPP per capita (at t–10)—ranges from 0.05 to 0.06. This implies that a 100,000 Baht increase in real tradable GPP per capita is associated with an increase of 5 to 6 square kilometers of urban land over the following 10 years, reflecting the growing demand for urban land as income rises.

However, when dynamic expectations of workers and the inertia effect of urban land expansion are controlled for, the coefficient of the key variable increases from 0.05 to 1.10. This suggests that the impact of income growth on urban land expansion is significantly larger when accounting

[2] It is worth noting that the coefficients of lagged dependent variable in M13-M16 models are slightly above 1. Empirically, it describes the characteristic of data and does not damage interpretation of the regression model since the objective of the study focuses on short-term effect of economic and environmental factors on urbanization in contrast to long-term ones.

for these dynamic effects. In other words, a 100,000 Baht increase in real tradable GPP per capita would lead to an increase of 11 square kilometers of urban land over the following 10 years. The result from dynamic panel regression is our preferred model, as it mitigates potential biases arising from estimation. Therefore, it is estimated that a 100,000 Baht increase in real tradable GPP per capita would lead to an increase in future urban land demand of 11 square kilometers.

However, the coefficient values of revenue from natural resources, though positive, are statistically insignificant in all specifications, contradicting the prediction of Proposition 1. These results suggest that rising productivity from urban tradable sectors drove urban land expansion in Thailand by allowing workers to efficiently meet their subsistence food consumption, increasing their surplus income, and demand for products from the urban sector. However, the increased revenue from natural resources did not affect urban expansion in Thailand.

Resource revenue represents only a small share of total real GDP—less than 3 percent—compared to revenue from urban tradable sectors, and this share is expected to continue declining. Moreover, only six provinces have a significant proportion of resource GPP relative to their tradable GPP, with values exceeding 10 percent. Therefore, resource GPP generates limited spillover effects and consequently does not contribute significantly to capital accumulation and urbanization.

However, this does not imply that resource-driven urbanization is impossible. For such urbanization to occur, natural resources must constitute a significant source of national revenue. Highly urbanized, resource-exporting countries—such as Angola and Nigeria (oil), Botswana and Liberia (diamonds and gold), Zambia (copper), and the Ivory Coast (cocoa)—primarily rely on resource exports as a key source of national income. In contrast, Thailand relies mainly on manufactured goods exports as its primary source of income. Therefore, urbanization in Thailand is more likely to be driven by income from industrialization rather than from resource-based revenues.

Second, according to the results from standard panel regression, spatial lag, and spatial error regression, the natural factor was still relevant in predicting urban land expansion in Thailand. The estimated results indicate that higher water availability has a significant influence on urban land growth prediction, suggesting that favorable natural factors play a role in urbanization. As documented in Jhearmaneechotechai (2015), a higher amount of water may lead to higher yields and productivity in agricultural activities, generating higher income and demand for products and services from urban sectors. A hospitable environment might prevent workers from leaving the area and induce population growth. However, the coefficients of environmental factors became insignificant in the dynamic regression, implying that when urban growth's autocorrelation was considered, water availability was no longer relevant to urbanization. The effects of water availability were, therefore, at best, indirect.

Third, the substantial impact of human capital on urban land expansion in Thailand suggests that higher education has positive externalities on urban growth. A higher share of workers with higher wages could attract more workers to cities, leading to their growth. A higher number of college workers was associated with higher wages and amenities that come with higher education, such as a university, a park, a theatre, or high-paying jobs. This migration led to cities growing and encouraged agglomeration externalities, a process that promoted further migration through higher wages.

Fourth, the urban land expansion of the province in Thailand had a positive impact on the urban land expansion of its neighboring provinces in a predictable manner.

Fifth, it was found that controlling for spatial autocorrelation lowered estimated coefficients. A possible explanation is that the standard non-spatial regression may not be able to control for some omitted variables that drove urban growth but were captured through spatial regression. In other words, the impacts of estimated coefficients on urban growth were attenuated by spatial autocorrelation in the regression model.

Sixth, dynamic expectations of workers affect the tempo of urban land expansion in Thailand. Workers observed actual urban land expansion in a particular province and decided to move there in the next period. The previous urban land expansion was also found to have a strong impact on current urban land expansion.

Policy Recommendations

Recent insights yield numerous crucial policy recommendations to foster sustainable urbanization in Thailand. The gross provincial product (GPP) per capita of the urban tradable sector and human capital induce urban land expansion; however, worker expectations and environmental considerations also affect these patterns.

Policies must prioritize the generation of a polycentric urban framework and transform perceptions of regional growth potential, transitioning Thailand from its existing monocentric paradigm. These policies should aim to augment urban land while promoting equitable economic development and reducing socio-economic disparities between urban and rural regions. Effective decentralization relies on multiple factors, including enhancing institutional capacity for urban planning, securing funding for infrastructure and education, and sustaining

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- Enhancing regional universities and vocational institutions.
- Implementing urban development hubs in high-potential regional cities through public and private investment.
- Restructuring budgetary transfers to enhance the authority of local governments.
- Enhancing connectivity and digital infrastructure across various areas.

These policies should aim to augment urban land while promoting equitable economic development and reducing socio-economic disparities between urban and rural regions.

Limitations

This study provides new insights into the relationship between economic development and urban land expansion in Thailand; however, several limitations should be addressed based on the current literature.

First, future research should relax the simplified assumptions of homogeneous labor and perfect labor mobility, which are often employed in theoretical models. Empirical evidence strongly contradicts these premises. Future studies could consider factors such as labor heterogeneity, migration costs, market frictions, and constraints in the informal labor market. By integrating these real-world complexities, future research can develop more accurate and policy-relevant models that better capture the nuanced dynamics of labor markets and spatial economic development.

Second, institutional, political, and cultural elements are ignored due to data constraints. As suggested by Seto et al. (2012), modern urban growth is influenced by numerous factors that are challenging to thoroughly assess on a global scale, including foreign capital flows, the informal economy, land-use regulations, and overall transportation costs. In addition, Buldan (2024) identifies the case of amenity migration in Türkiye driven by lifestyle choices. Alternatively, some policy schemes may intentionally promote migration and urban transformation (Prasittisopin et al., 2024). Hence, future studies should incorporate these features into their analytical frameworks.

Third, the rural-urban distinction used in the model is overly simplistic. Peri-urban areas, as discussed in studies by Allen (2003), Narain (2009), Douglas (2006), and Lerner and Eakin (2011), are indeed dynamic transitional zones that feature complex interactions between urban and rural systems. These studies collectively challenge the traditional rural-urban divide and advocate for a new approach that recognizes the integrated, adaptive, and participatory governance frameworks present at peri-urban interfaces.

Fourth, a significant concern is the potential for reverse causality. Urbanization can influence key factors such as temperature, vegetation, and water supply, potentially leading to endogeneity issues. In particular, income growth and urban development may occur simultaneously, making it challenging to interpret the causal relationships accurately.

Fifth, migrant flows are not directly monitored. While the study employs urban land change as a proxy, actual demographic movement is unmeasured, limiting insights into how labor mobility contributes to urban expansion.

Sixth, the use of provinces as spatial units may hide intra-provincial variance. More detailed, sub-provincial statistics would provide a more accurate reflection of localized urban dynamics and spatial variability.

Subsequent research must tackle these concerns by employing more granular spatial units, amalgamating institutional and migration data, and utilizing causal identification methodologies such as instrumental variables or natural experiments. These measures would enhance the robustness and significance of forthcoming findings.

CONCLUSION

This study provides a comprehensive and empirically grounded assessment of urban land expansion in Thailand, using satellite-derived urban land cover data and province-level economic indicators from 2000 to 2020. By integrating geospatial data with econometric modeling, we have offered a novel perspective on the determinants of urban growth in a rapidly developing Southeast Asian country. The study's key contribution lies in evaluating how income growth, particularly in urban tradable sectors, drives urban land expansion, while also considering the roles of environmental conditions and human capital.

Essentially, the study applies a theoretical model that enables a simulation of rural versus urban dynamics, capturing the mechanisms by which labor shifts from agricultural to industrial and service sectors in response to rising productivity. The results show that income from tradable sectors significantly predicts urban expansion, while resource revenues do not. Moreover, urban growth exhibits spatial spillover effects and dynamic inertia, with prior urban land expansion and workers' expectations contributing to future urban growth.

In sum, this paper demonstrates the potential of using satellite-based geospatial data in combination with economic modeling to understand spatial development processes. The findings provide policy-relevant insights for promoting balanced regional development, reducing spatial inequality, and planning for sustainable urban growth in Thailand.

DISCLOSURES AND ACKNOWLEDGMENTS

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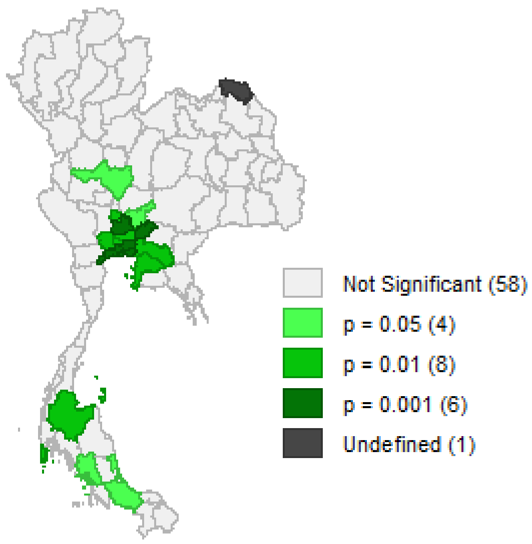
APPENDIX

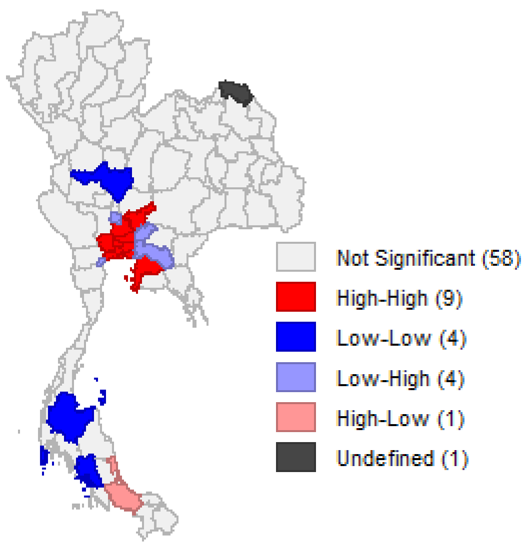
Figure A1

Results of Univariate Local Moran's I of Urban Area in 2020

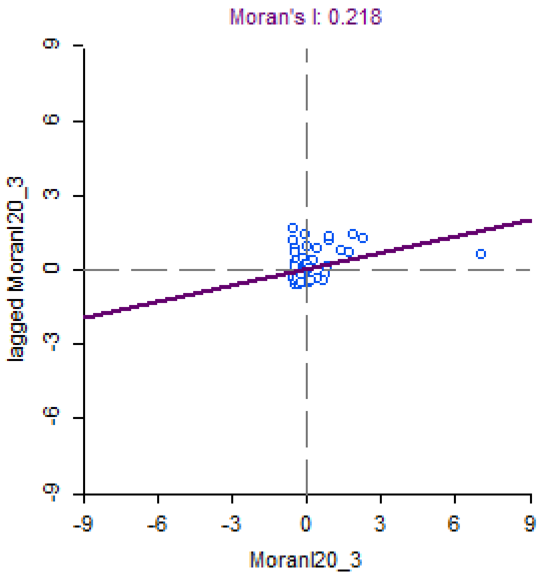
Panel A



Panel B



Panel C

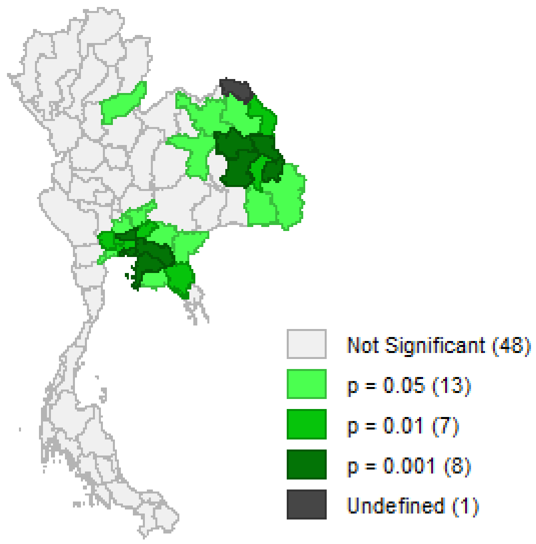


Note. Panel A: Significant Map. Panel B: Cluster Map. Panel C: Moran Scatter Plot

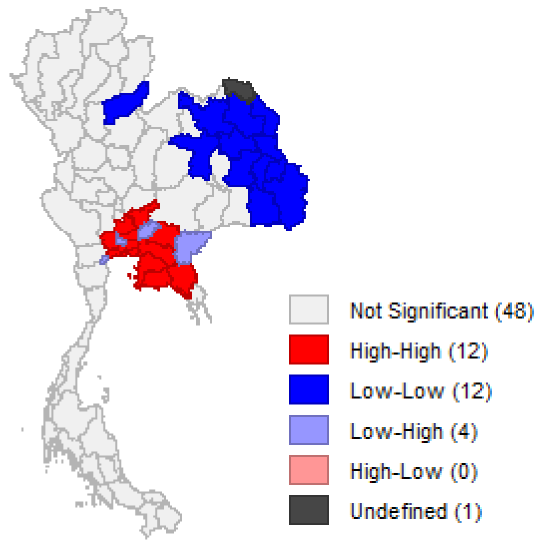
Figure A2

Results of Univariate Local Moran's I of Tradable GPP Per Capita in 2010

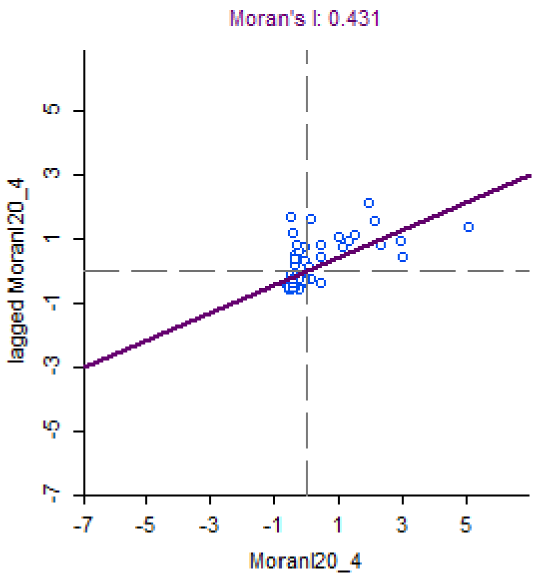
Panel A



Panel B



Panel C

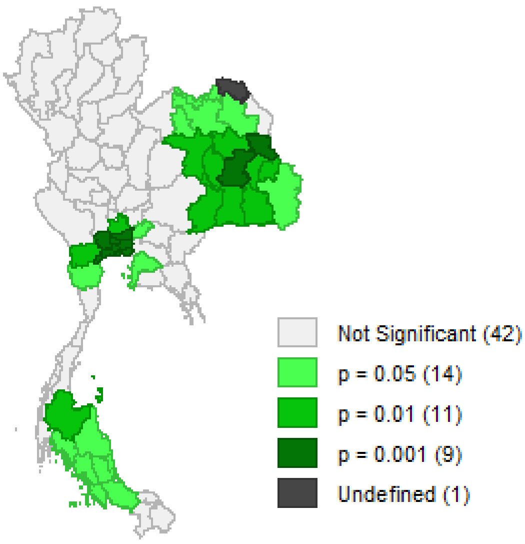


Note. Panel A: Significant Map. Panel B: Cluster Map. Panel C: Moran Scatter Plot

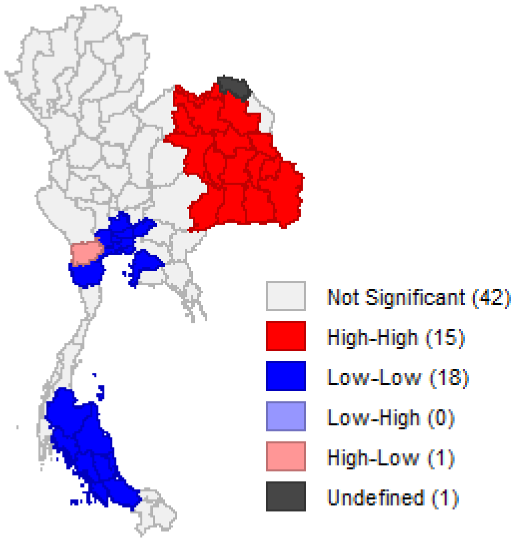
Figure A3

Results of Univariate Local Moran's I of NDDI in 2010

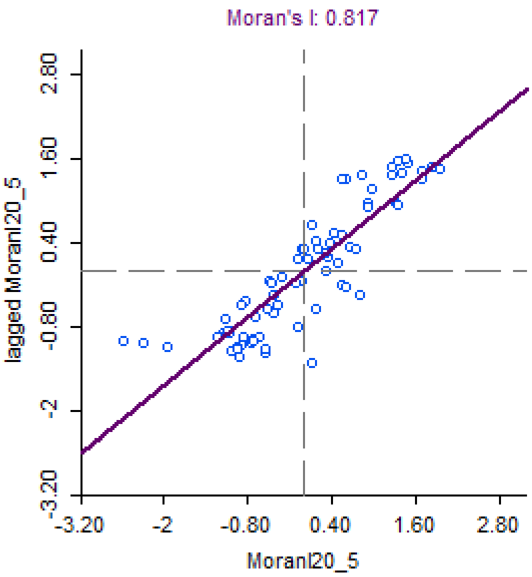
Panel A



Panel B



Panel C

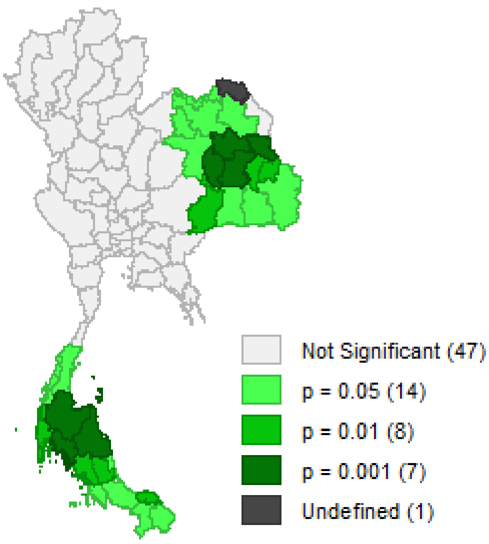


Note. Panel A: Significant Map. Panel B: Cluster Map. Panel C: Moran Scatter Plot

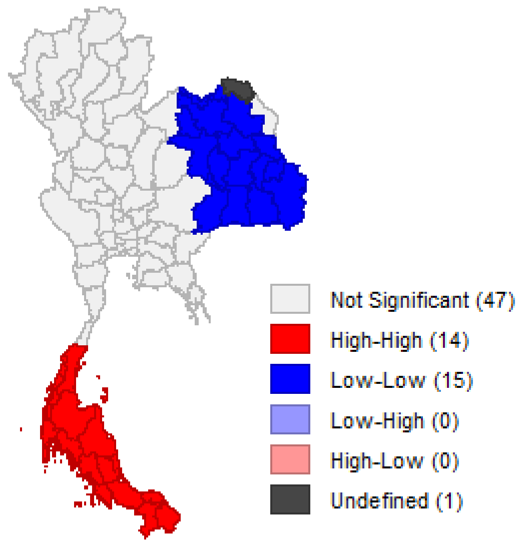
Figure A4

Results of Univariate Local Moran's I of NDWI in 2010

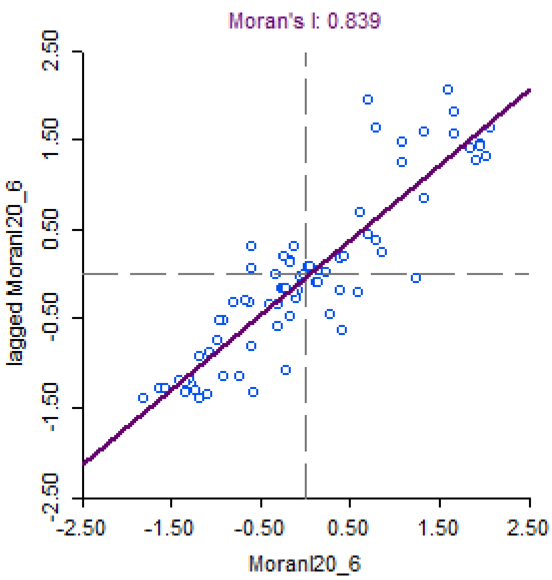
Panel A



Panel B



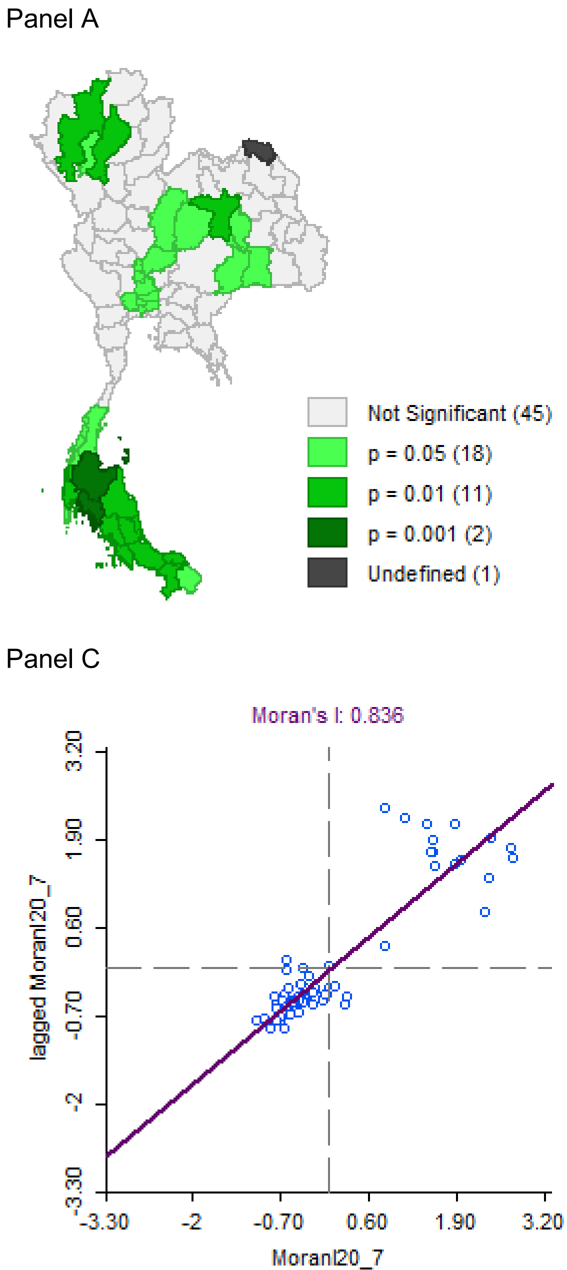
Panel C



Note. Panel A: Significant Map. Panel B: Cluster Map. Panel C: Moran Scatter Plot

Figure A5

Results of Univariate Local Moran's I of Precipitation in 2010



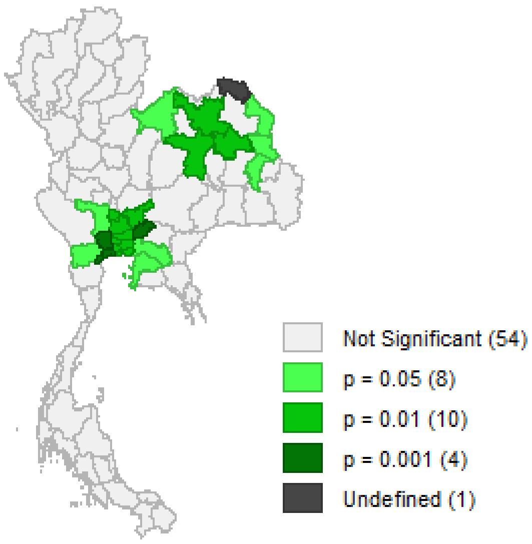
Note. Panel A: Significant Map. Panel B: Cluster Map. Panel C: Moran Scatter Plot

Figure A6

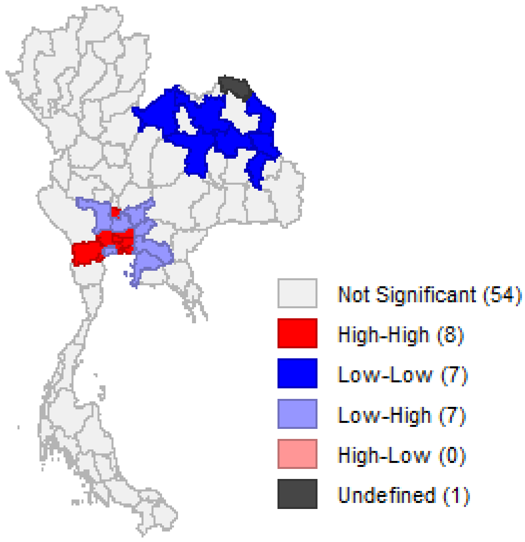
Results of Univariate Local Moran's I of the Share of Workers with Higher Education in 2010

Note. Panel A: Significant Map. Panel B: Cluster Map. Panel C: Moran Scatter Plot

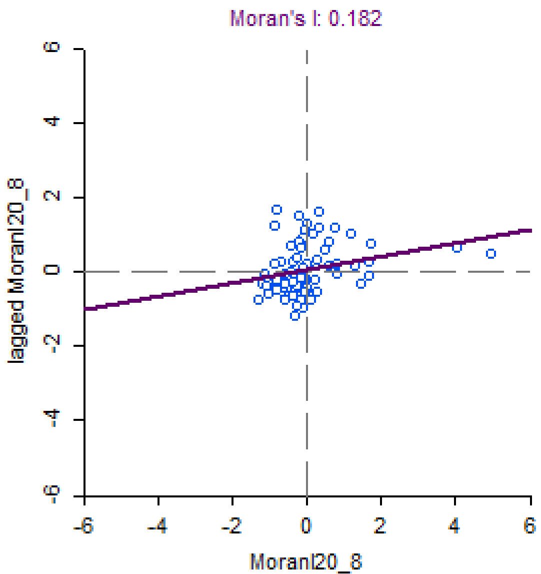
Panel A



Panel B



Panel C

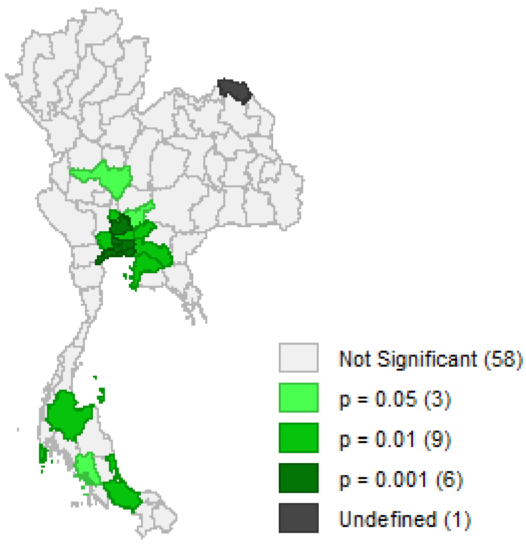


Note. Panel A: Significant Map. Panel B: Cluster Map. Panel C: Moran Scatter Plot

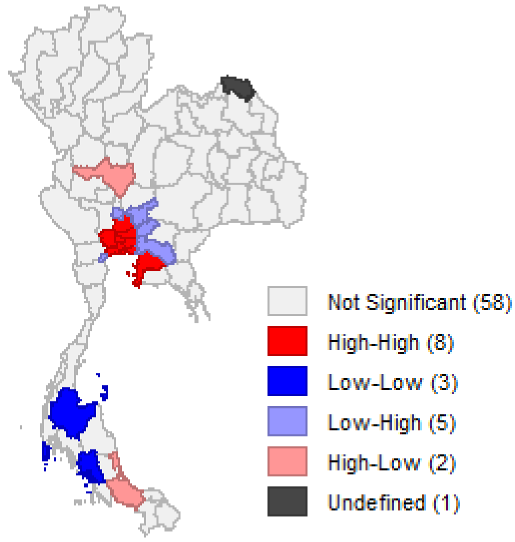
Figure A7

Results of Univariate Local Moran's I of Non-spatial Panel Regression (M1)'s Residual in 2020

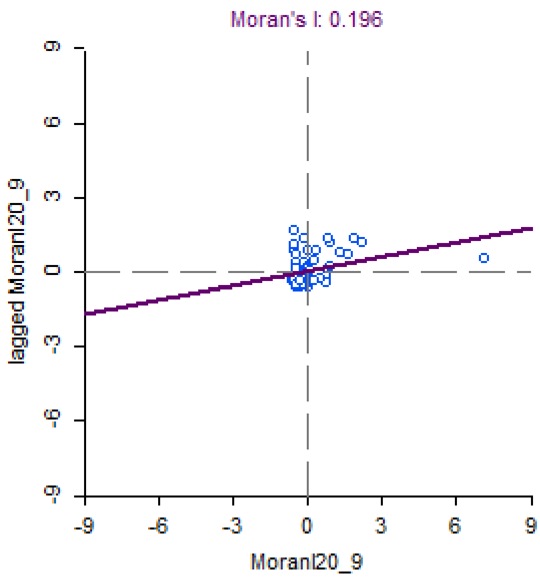
Panel A



Panel B



Panel C

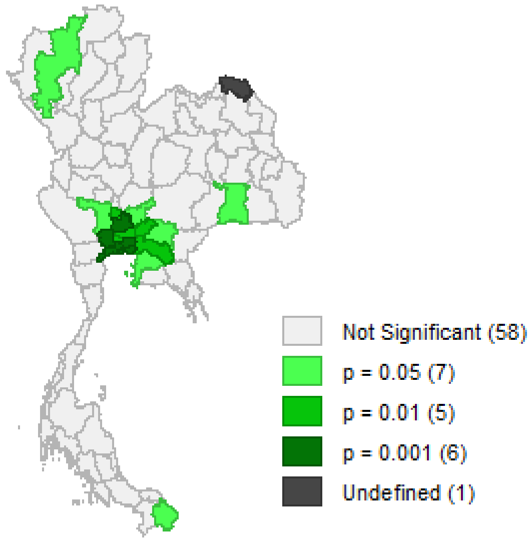


Note. Panel A: Significant Map. Panel B: Cluster Map. Panel C: Moran Scatter Plot

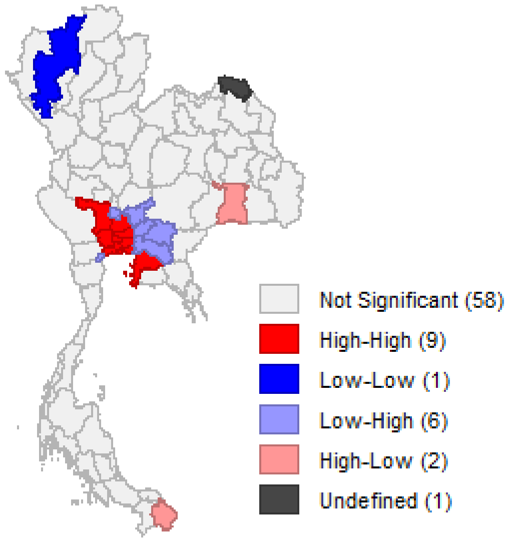
Figure A8

Results of Univariate Local Moran's I of Spatial Lag Panel Regression (M5) 's Residual in 2020

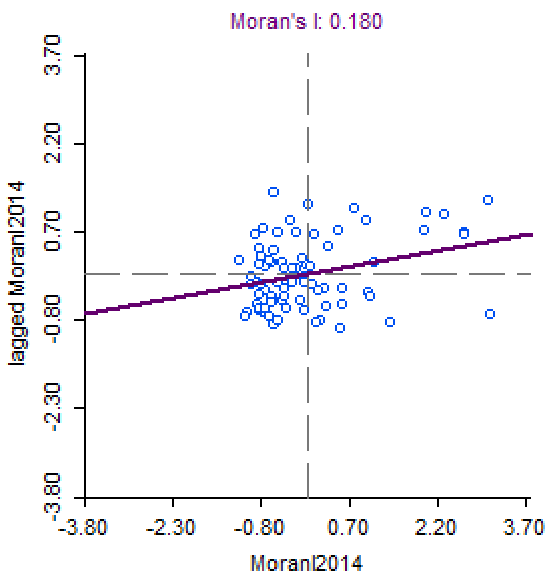
Panel A



Panel B



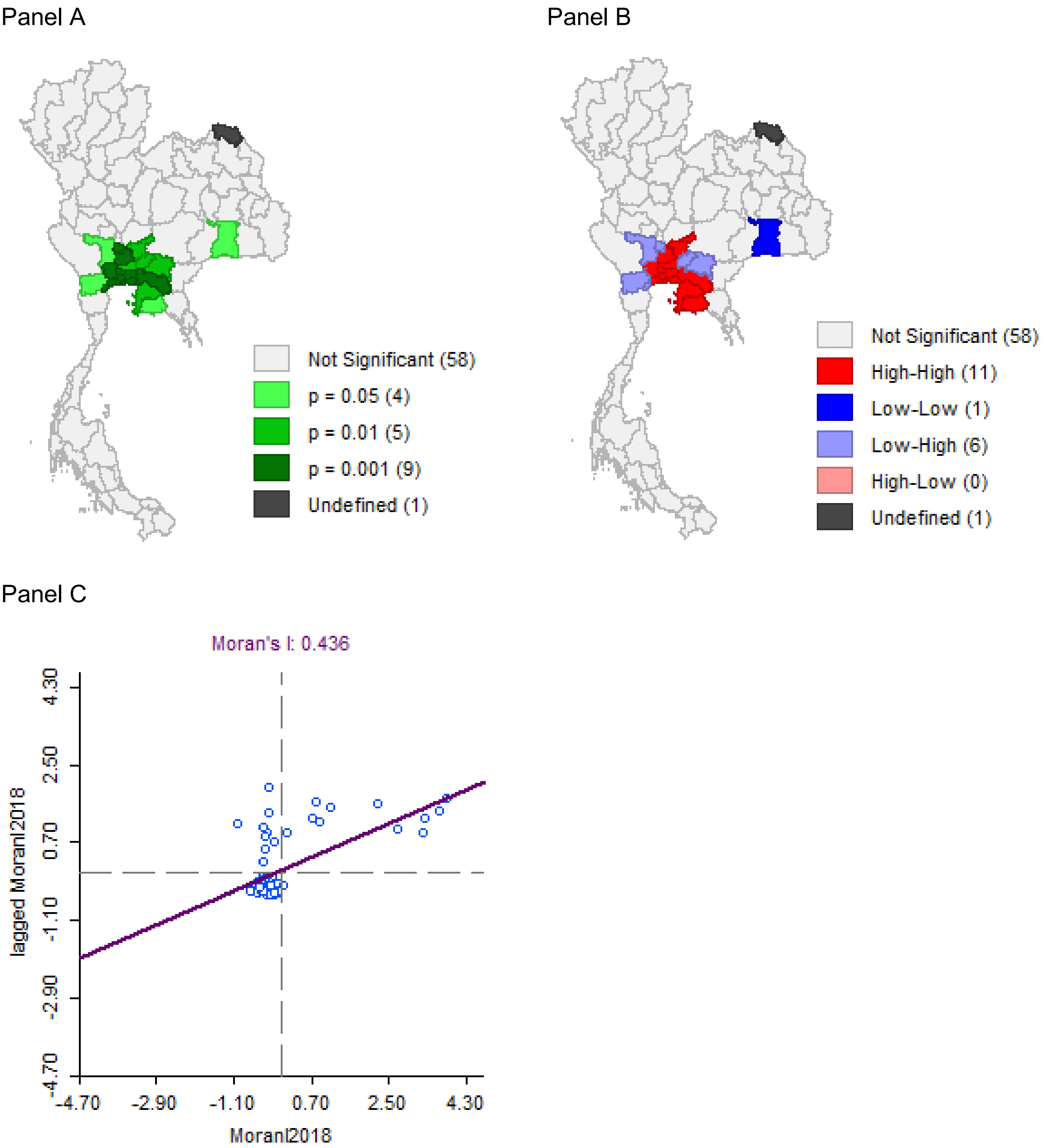
Panel C



Note. Panel A: Significant Map. Panel B: Cluster Map. Panel C: Moran Scatter Plot

Figure A9

Results of Univariate Local Moran's I of Spatial Error Panel Regression (M9)'s Residual in 2020

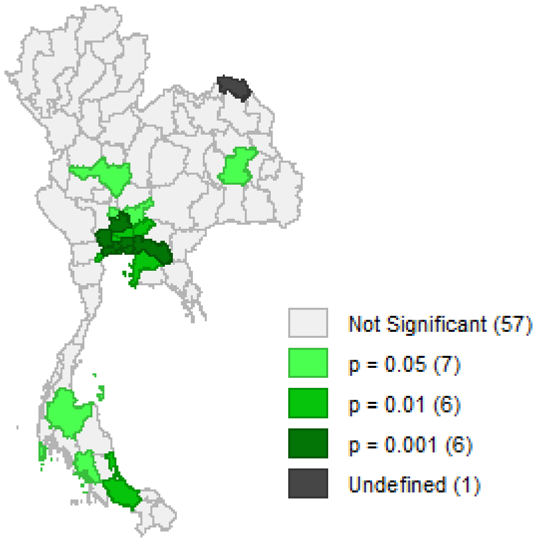


Note. Panel A: Significant Map. Panel B: Cluster Map. Panel C: Moran Scatter Plot

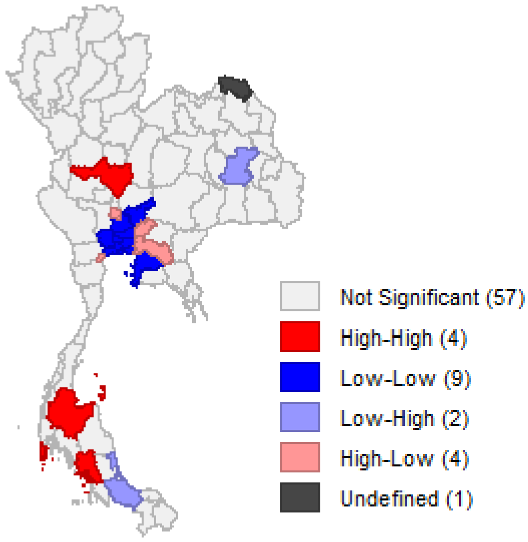
Figure A10

Results of Univariate Local Moran's I of Dynamic Panel Regression (M13) s Residual in 2020

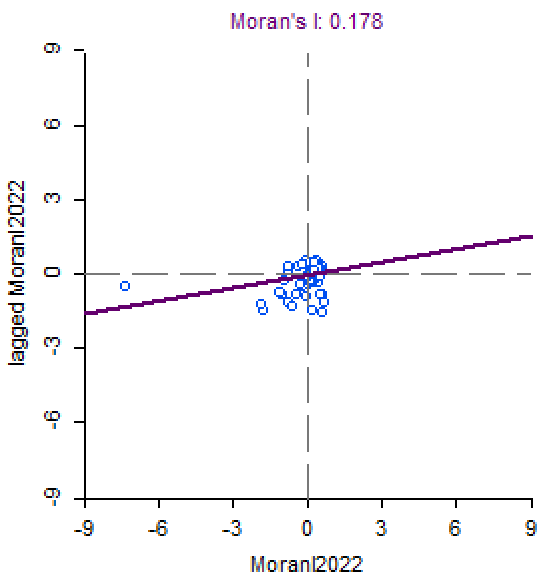
Panel A



Panel B



Panel C



Note. Panel A: Significant Map. Panel B: Cluster Map. Panel C: Moran Scatter Plot