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RESEARCH ARTICLE

Remotely-Sensed Derived Built-up Area as an Alternative Indicator in the Study of Thailand's Regional Development

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Abstract Nowadays measuring national and regional development primarily relies on demographic and socio-economic indicators. An indicator in physical dimension e.g., areas of human settlements and their economic uses of lands is usually ignored due to unavailability of data in countries like Thailand. Remotely-sensed derived built-up area was used, for the first time, as a physical indicator for studying Thailand's regional development. Remote sensing - using the decision tree classifier with the combination indices of band ratios, NDVI, MNDWI, and NDBI - and GIS techniques were utilized to estimate the regional proportion of built-up area. The relationships between the percentage of the derived built-up area and the three development indicators - urbanization rate, Gross Regional Product, and Human Achievement Index - were analyzed. Resultantly, the estimate of the 2019 derived built-up area in Thailand was 2.46% with the average accuracy of 84.5%. Regional variation in development levels existed and relationships between the percentage of built-up area and the three development indicators for the regions were strong. However, there was no relationship after excluding the region having the effect of Bangkok. Therefore, remotely-sensed derived built-up area gives new information and is suggested for use for the analysis of Thailand's regional development.

1. Introduction

The existence of uneven regional development in a country remains an important issue for all nations. Thailand, for example, has been considered a great economic and social development success due to continued strong growth and its significant poverty reduction for over the last four decades (World Bank, 2022). However, the growth of the country has predominantly occurred in the region of Bangkok and Vicinities, leaving other regions lagging behind (Lang et al., 2021). Measuring the country's regional development is thus necessary for related government policy decision makers to ensure that the distribution of resources and funds will be allocated to mitigate inequalities and promote development for each region appropriately (Wishlade and Yuill, 1997; Goletsis and Chletsos, 2011). Until now, Thailand's national government has long attempted to develop coherent measurements with the key aim of evaluating the development level of each region. Data and indicators used for the measurement, as in other countries (Fedajey and Nikolic, 2012; Meyer et al., 2016), primarily rely on demographic and socio-economic components.

Currently, there is growing interest in the sustainable regional development (SRD) issue. SRD is a new extended concept of regional development. It is usually defined as the integration of the sustainable development of three dimensions – economic, social, and environmental ones – on the regional level (Jovovic et al., 2017). Its main goal is to find a balance between economic development and environmental degradation within a region. As SRD gives a new perspective, it implies that the methods of measurement and evaluation of the development level of each region need to be adjusted in order that the regional variation in development of a country is truly reflected. While there is still a debate in implementing SRD in practice (Meyer et al., 2016; Jovovic et al., 2017), adding the environmental dimension into the analysis of regional development is a challenging task for regional planners and policy decision makers. In this regard, built-up area is considered as a potential indicator in the environmental dimension for the measurement of regional growth. Built-up area refers to developed areas on the earth's surface, entirely dominated by all man-made structures such as roads, buildings, and bridges. It represents the physical dimension of human settlements and their economic uses of lands (Sabo et al., 2018). Its applications have been used to measure or analyze urban environments and environment quality in a variety of ways, taking into consideration urban density, urban air quality, urban green space, urban heat islands (UHI), and urban climate (Huang et al., 2015; Macarof and Statescu, 2017; Huang et al., 2021; (Mu et al., 2022). Despite its advantages, built-up area has not been used in prior observations of Thailand's regional development due to the high cost and labor intensive nature of conventional approaches such as aerial photography and field surveys.

Satellite remote sensing is a cost-effective solution for land-cover observations. It offers an affordable approach to derive up-to-date and reliable information for a very large area in a relatively short time (Zhang et al., 2014). Mapping urban built-up areas remains a challenge due to the mixed pixel problem (Zhang et al., 2014). Urban and developed land is heterogeneous in nature. An urban pixel always contains a mixture of several objects such as small buildings, trees, open spaces, and roads. A considerable number of techniques have therefore been developed and applied for mapping built-up areas. They can be broadly grouped into two categories. Each category has its own advantages and limitations.

The first category is to classify the input imagery. The pixel-based classification using spectral and/or textual properties (e.g., Liu and Yang, 2013; Zhang et al., 2014; Adam et al., 2016; Hu et al., 2016; Tariq et al., 2021) falls into this category. Until now this approach, particularly the classification of multi-spectral bands of medium resolution imagery (e.g., 15-30 m/pixel) with the supervised classification method, has generally been used for land use/ land cover (LULC) mapping purpose (As-syakur et al., 2012) (Liu and Yang, 2013) (Adam et al., 2016). With this approach, pure pixels containing sole reflectance or textual properties of elements, e.g., lakes or paddy fields, are visibly distinguishable and can be separable from other land cover types. However, in urban areas where the mixed pixels generally occur, this approach tends to produce misclassification, particularly for the mixing of built-up land with other land cover types (Zhang et al., 2014; Hidayati et al., 2018). Improving the classification results due to the mixed pixel problem could be achieved by using high resolution images (e.g., 0.8 m/pixel) (Zhou et al., 2018; Qu et al., 2021) or by incorporating with other techniques in the analysis (Imran et al., 2021; Yin et al., 2021). Besides, in the last few decades, another possible solution which has gained popularity in deriving land use classifications with higher accuracy is the object-based classification technique using high resolution imagery, as seen in the work of (Weih and Riggan, 2010; Estoque et al., 2015; Qu et al., 2021).

The second category is to extract specific properties of the land cover types of interest based on direct segmentation of the image into indices. Until now, a variety of indices have been formulated, modified, and assessed for mapping built-up areas. Overall, these indices are more popular for mapping built-up areas than the first approach due to their ease of use, simplicity, automatic and rapid mapping, and higher accuracy (Zha et al., 2003; Bhatti and Tripathi, 2014). To enhance the extraction of built-up areas, the Normalized Difference Vegetation Index (NDVI) developed by Rouse et al. (1974) has been commonly used for the separation of vegetation from other land cover types (Xue and Su, 2017; Hidayati et al., 2018; Ghazaryan et al., 2021). The Normalized Difference Built-up Index (NDBI) proposed by Zha et al. (2003) was developed by analyzing the spectral response of built-up elements in different bands of the Landsat TM image. Due to its simple mathematical computation and quick mapping, the index has been widely used for automatically mapping urban built-up areas from Landsat TM imagery (Zha et al., 2003; Mwakapuja et al., 2013; Khan et al., 2019; Hidayati et al., 2018). The Normalized Difference Water Index (NDWI) and the Modified Normalized Difference Water Index (MNDWI) formulated by McFeeters (1996) and Xu (2006) respectively, were based on the principle that built-up areas (impervious surfaces) are prone to have a lower moisture or water content than barren areas (pervious surfaces). The indices were reported in many applications to reduce the spectral confusion between built-up and barren areas (Mwakapuja et al., 2013; Hidayati et al., 2018; Ghazaryan et al., 2021). These indices were applied in many areas to test their applicability and accuracy. For example, Hidayati et al (2018) merged several indices - NDBI, NDVI, MNDWI, NDWI, and SAVI (Soil-Adjusted Vegetation Index) - by using four stages: merging of two indices, three indices, four indexes, and five indices to test the accuracy of the built up area extraction in Yogyakarta. The results showed that among several tests, the merging of NDBI and MNDWI produced the highest accuracy of 90.3%. Khan et al (2019) compared the results of the NDBI index and the Built-up Area Extraction Method (BAEM) index through the mapping of built-up areas of Kolkata Megacity in India. The BAEM index, developed by Bhatti and Tripathi (2014), is an amalgamation and integration of Land Surface Temperature (LST), NDVI, and MNDWI. Results of the study showed that those built-up areas derived by the BAEM index had a higher accuracy (89.33%) than achieved by NDBI (83.67%).

Despite all efforts, misclassification due to the mixed pixel problem is still the major challenge. All in all, none of the current available methods, techniques, and indices have reported complete separation between built-up areas and barren land. The accuracy in the extraction of built-up areas from satellite imagery still requires improvements. Noted by Khan et al (2019), there has not been a single technique to classify the built-up areas. Integrating the intrinsic aspect of two or more techniques to build a hybrid approach is one solution. Improving the spatial resolution (i.e., high resolution images) as well as the techniques (i.e., the object-based analysis) as previously mentioned may be alternatives to increase the extraction accuracy.

Up to now, the applications of remotely-sensed derived built-up areas have been extensive, particularly in the studies of urban extent, urban expansion, and urban population (World Bank Group, 2015; Al-Bilbisi, 2019; Ghazaryan et al., 2021). Another recent dimension is to apply derived built-up areas for socio-economic studies. In these studies, the relationships between built-up areas and socio-economic indicators were investigated for different purposes in different scales of study – city, provincial, regional, or national levels (e.g., Ma & Xu, 2010; Ma et al., 2012; Propastin & Kappas, 2012; Wang et al., 2012; Li et al., 2013; Yue et al., 2014; Faisal & Shaker, 2014; Faisal et al., 2016; Chen et al., 2020).

At the city level, for example, Ma and Xu (2010) conducted research in Guangzhou in China with three main goals. They aimed 1) to monitor the urban expansion of the built-up area of the city over the period of 23 years lasting from 1979 to 2002, 2) to model its urban expansion, and 3) to analyze the driving forces for urban expansion by investigating the relationships between the extracted built-up area of the city and three indicators – Gross Domestic Product (GDP), total population, and urban resident income and urban traffic of the city map. The results showed that 1) Guangzhou was extended by about 4.5 times from the year 1979 to 2002, 2) the model of urban expansion in Guangzhou is characterized by radial expansion centered on the old town, which takes the form of expansion in rings and along major traffic routes, and 3) the built-up area of Guangzhou is highly correlated with GDP ($R2 = 0.99$), total population ($R2 = 0.98$), urban resident income ($R2 = 0.98$), and urban traffic of the city ($R2 = 0.96$), which are considered the dominating driving factors for expansion of the urban built-up area of Guangzhou. Another research study, Faisal et al. (2016), aimed to predict the GDP of seven major cities in Canada between 2005 and 2010 by using remotely-sensed derived built-up area. Their work investigated the relationship between the extracted built-up area and three socio-economic parameters – the real GDP, total population, and total employment. These parameters, provided by Canada's national housing agency (Canada's Mortgage and Housing Corporation (CMHC)), were chosen because they are currently used by federal/municipal authorities to measure the economic growth of the city and country. The results showed that the built-up area of the seven cities is highly correlated with the real GDP ($R2 = 0.80$), total population ($R2 = 0.82$), and total employment ($R2 = 0.83$). Their findings suggest that these results can be used as a generic indicator for targeting a specific real GDP with respect to the planned industrial areas for any new city development and regional planning.

In an example of regional study, the research work of Li et al. (2013) aimed to investigate the potential of nighttime light (NTL) imagery in modeling a regional economy in China, with a comparative analysis between two NTL sensors – the DMSP-OLS and the NPP-VIIRS. The research was based on the concept that artificial nighttime light can reflect the use of public lighting and commercial lighting, which are strongly associated with the state of the economy. In the study, linear regression was used to investigate the relationship between built-up areas (through satellite nighttime light) and Gross Regional Product (GRP). The results showed that GRP was highly correlated with both NTL sensors, but the high correlation with NPP-VIIRS imagery (R2 values of 0.94 with the county GRP) was greater than that of DMSP-OLS/F18 imagery (R2 values of 0.85 with the county GRP). The finding provides an alternative to model the global and regional economy at very low cost by using NTL imagery, especially in the regions where economic census data are difficult to access. In another research study, Chen et al. (2020) proposed a method for analyzing regional economic situations using remotely-sensed images to extract land use and land cover change (LUCC) information. The approach was tested and validated with experiments in Zhoushan City in China. The research investigated the ability of LUCC information to estimate economic indices. The LUCC information was extracted from Landsat images, taking the area of construction land as the explanatory variable after correlation analysis. Eleven economic indices, including GDP, value-added of primary industry (VPI), fixed assets investment (FAI), total tourist income (TTI), and gross industrial output value (GIOV), etc. were incorporated. The results showed that the economic statistical index is the most sensitive to the construction land area with the average correlation coefficient of 0.949. The results also prove that LUCC information could be used as an explanatory indicator for estimating economic development at the regional level.

Regarding these past research, the role of remotely-sensed derived built-up area data is obvious. It provides timely and up-to-date information, reflecting urban extent and urban expansion. All studies also show that built-up areas and socio-economic activities are closely related. Built-up area can reflect the role of socio-economic indicators (e.g., GDP, the measurement of urban residents' income) as driving factors for urban expansion (Ma and Xu, 2010). It can be used to predict GRP (Li et al., 2013) and real GDP (Faisal et al., 2016), and can be incorporated with other socio-economic indicators for the analysis and modelling of regional economic development (Chen et al., 2020). Therefore, built-up area is a direct reflection of economic activity. Since the monitoring of socio-economic activities is very important for understanding regional economic development levels and policymaking, built-up area is thus considered very useful information for the municipal authorities and helps facilitate regional development and planning. These exemplified studies also imply that built-up area is a potential indicator for the regional study.

With inspiration from the above applications, this study aims to investigate and assess the relationships between the percentage of built-up area and the development indicators of three dimensions – demographic (urbanization rate), economic (Gross Regional Product), and social (Human Achievement Index) indicators. These three dimensions were chosen because they are currently used by Thai government – the Office of the National Economic and Social Development Council (NESDC) – to evaluate the level of development of the country. The analysis was conducted based on the availability of multi-source data in 2019. Satellite remote sensing and GIS techniques were utilized to extract and estimate the regional proportion of built-up area of the whole country. The output of remotely-sensed derived built-up area is reported and proposed in this study as an alternative indicator, adding in the physical dimension to allow deeper exploration of regional variation in development.

Thailand is a tropical area, located in the heart of the mainland Southeast Asia between latitudes 5o 37¢ N to 20o 27¢ N and longitudes 97 o 22¢ E to 105 o 37¢ E. It covers an approximate area of 513,000 square kilometers (Figure 1). The country nowadays comprises 76 provinces plus Bangkok. In 2019 when the analysis of the study was carried out, Thailand 's total population was approximately 69 million and the urbanization rate was 35% (NSO, 2020). Economically, the country had a GDP of 50,187 billion Baht (or about US$ 724 billion) (NESDC, 2021). According to the social development measure, Thailand's Human Achievement Index (HAI) was 0.62 out of 1.00 (NESDC, 2019) while the HDI was scored 0.78 (UNDP, 2020). The HAI was developed by Thailand's Office of the National Economic and Social Development Council (NESDC). The index is a social measure which is like that of the HDI developed by the United Nations, but HAI has more measurement details adopted to best fit to the data available in Thailand.

2. The Methods

Datasets

Dataset in the study includes three types of data – Landsat 8 satellite images, a provincial boundary GIS layer, and socio-economic data.

A total of 38 scenes of Landsat 8 OLI satellite images between path 126 - 132 and row 46 - 56 covering the whole country in 2019 were downloaded from the United States

Geological Survey (USGS) Earth Explorer. All scenes were in the Universal Transverse Mercator (UTM) coordinate system with zone 48 North and WGS84 datum. A provincial boundary GIS layer data is available in shape file format, acquired from the Department of Transportation, Thailand. Demographic and socio-economic data (Table 1) are available in the text-based format, provided by the Office of the National Economic and Social Development Council (NESDC) and National Statistical Office (NSO). Nowadays these data have been analyzed and used to measure the development of the country at the regional level.

Methodology

The methodological flow of this research (Figure 2) is summarized into two main processes – remote sensing and GIS.

Remote sensing process

The satellite remote sensing process for built-up area extraction was carried out by using ENVI 5.2 software. Firstly, all Landsat 8 images were pre-processed by the atmospheric correction method to eliminate the influence of atmospheric scattering. The 38 reflectance images were thus created. Secondly, the investigation of bio-physical characteristics of land cover types was performed. Fine level classes for image classification (Table 2) were assigned to help better understand the bio-physical characteristics of land cover types. Training samples or 'Region of Interest' (ROI) of eighth image scenes were chosen as the training sites of the study. Selection of these scenes was intended to cover the differentiation of physical characteristics – topography and climate - of the whole country. The exemplified graph in Figure 3 compares the observed values of the built-up class by using different measurement techniques derived from the same training samples of the eight selected scenes. The finding was that spectral reflectance of bands, band ratios, and automated built-up indices - NDVI, NDBI, MNDWI – were potentially used for the separation between the designated land cover classes in the study site. Spectral reflectance alone could be used to separate cloud from other land cover types. Some band ratios (e.g., the ratio of Blue/SWIR band), to some degree, was able to separate built-up area from bare area. Amongst the tested indices applied to Landsat 8 images, the NDVI index (Eq. 1) worked well in separation of vegetation and other land cover types. The NDBI index (Eq. 2) was used in separating built-up area/bare land from other land cover types. The MNDWI index (Eq. 3) improved basically the separation of built-up area and bare land in most areas.

$$NDVI = \frac{NIR-R}{NIR+R} \quad \text{................Eq. 1}$$

where NIR = near infrared band (Band 5 of Landsat 8 image), R = red band (Band 4 of Landsat 8 image)

$$NDBI = \frac{SWIR\_1-NIR}{SWIR\_1+NIR} \quad \text{............Eq.2}$$

where SWIR_1 = short wave infrared band (Band 6 of Landsat 8 image), NIR = near infrared band (Band 5 of Landsat 8 image)

$$MNDWI = \frac{G-SWIR\_1}{G+SWIR\_1} \quad \text{.............Eq.3}$$

where G = green band (Band 3 of Landsat 8 image), SWIR_1 = short wave infrared band (Band 6 of Landsat 8 image)

Thirdly, images of the 9 land cover classes (Class Level 1) were classified by using the supervised classification technique of decision tree classifier. Decision tree classifier has been evidenced in many remote sensing research to facilitate the extraction of a huge amount of information

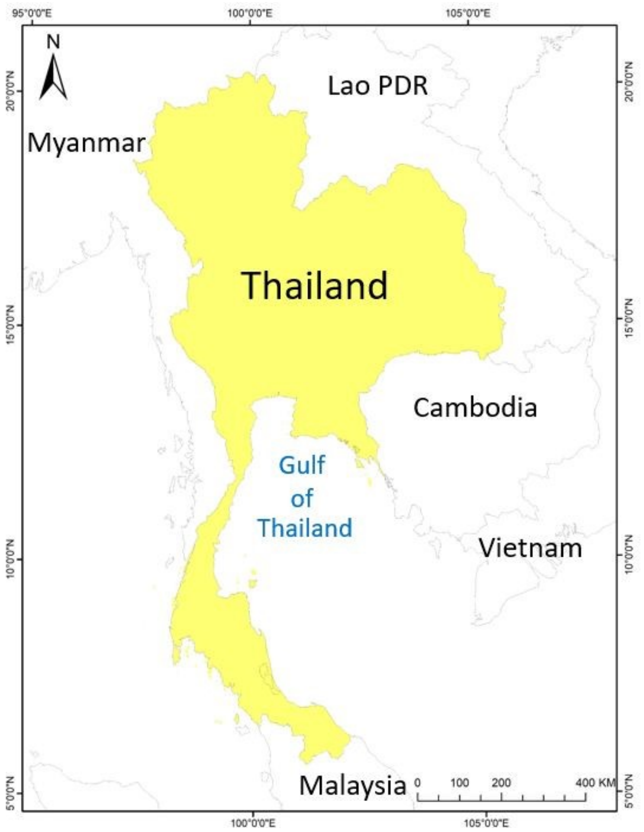


Figure 1. Thailand and neighboring countries

Table 1. Demographic and Socio-economic Data Used in The Study

Types of indicators	Data	Year of data compilation	Source
1. Demo-graphic	Urbaniza-tion rate	2019	Population Cen-sus (NSO, 2020)
2. Economic	Gross Re-gional Prod-uct (GRP)	2019	Report (NESDC, 2021)
3. Social	Human Achieve-ment Index (HAI)[1]	2019	Report (NESDC, 2019b)

Remark : [1] HAI, developed by NESDC, is a social indicator. The score ranges from 0 – 1, ranging from the lowest to the highest. HAI comprises 6 key indicators. They comprise : 1) well-being of Thai people and society, 2) national competitiveness, economic growth, and income distribution, 3) development of human capital, 4) social equality and equity, 5) sustainability of national biodiversity, environmental quality, and natural resources, and 6) government efficiency and better access to public services.

from images by using simple and flexible computing and give higher classification accuracies when compared to some classification techniques (Lu and Weng, 2006; Suarez-Rubio et al., 2012; Sharma et al., 2013). The technique is also considered the most suitable one to integrate many types of data - spectral and non-spectral data - during image classification (Pooja et al., 2011). Decision tree is multistage classifications hierarchically constructed by using a series of (binary) decision rules, based on knowledge of the spectral properties of each class, to place pixels into land cover classes (Tso and Mather, 2016). The 9-class classification image created by the decision tree classification technique was then combined into the 5-class classification image (Class Level 2).

Fourthly, confusion matrix was used for accuracy assessment. The technique is commonly used for assessing the classification accuracy by comparing the results of classification against the reference data obtained from the field survey or high-spatial resolution images (Congalton and Green, 2009). For each scene, the comparison between the 5-class classification image and high-spatial resolution satellite images available in Google Earth Pro was made over the area by means of random sampling method. The minimum accuracy assessment of built-up class in this study was set at 70%, otherwise threshold values in those scenes were readjusted and image re-classification in the previous step was performed until reached its determined minimum accuracy value. In this regard, the accuracy assessment of the built-up class of all 38 scenes yielded on average an accuracy of 84.50%. Accuracy details are given in Table 3. A few scenes, however, had much less accuracy than others (approximately 70%). Misclassification in these few scenes was typically occurred in mountainous and coastal areas because these scenes were frequently covered with mixed clouds and fogs. Another problematic area was the bare lands in mountains which were exposed to strong sunlight. These areas usually had the observed values in all measured techniques quite the same as those of the built-up class on the flat areas. Finally, for each scene the 5-class classification image was combined into 2 classes – built-up

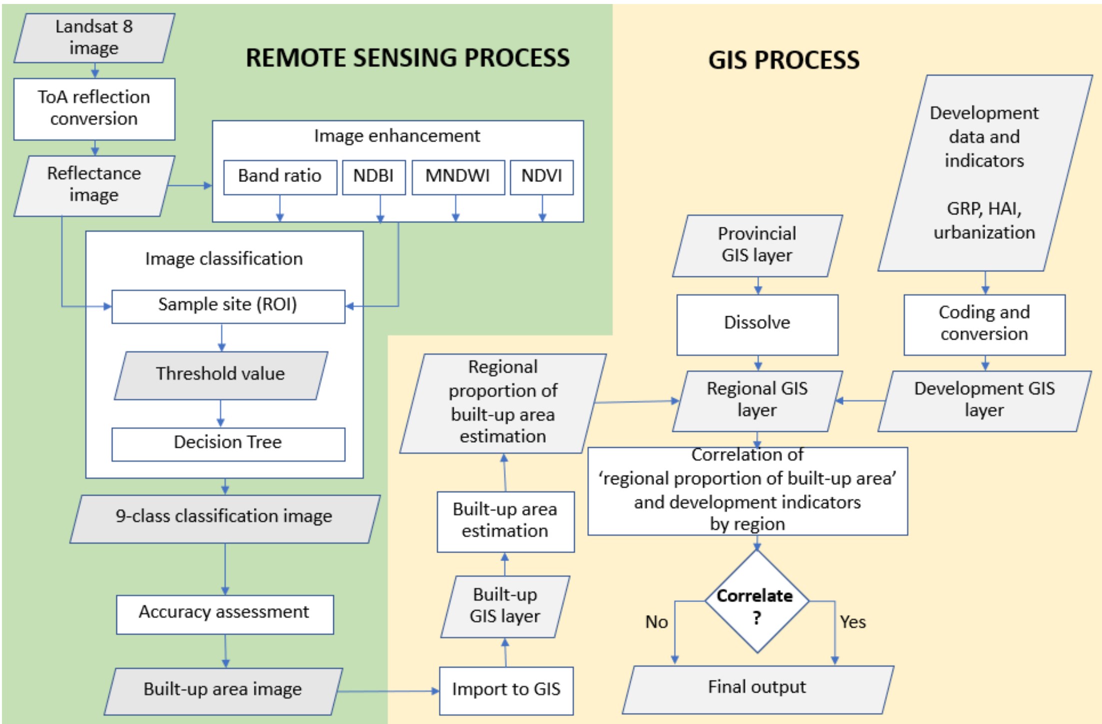


Figure 2. The Overall Workflow

Table 2. Land cover nomenclature classes

Class Level 1 (9 classes)	Class Level 2 (5 classes)	Class Level 3 (2 classes)
1. Built-up	1. Built-up	1. Built-up
2. Bare land	2. Bare land	
3. Dense vegetation	3. Vegetation	
4. Sparse vegetation		
5. Water	4. Water	2. Non-built-up
6. Mixed water (e.g., water mixed with other land cover types)		
7. Cloud	5. Cloud	
8. Mixed cloud / Sparse cloud / Fog / Smog		
9. Shadow (cloud shadow)		

and non-built-up area, so-called “Built-up area” image (Class Level 3). Extraction of built-up area for the entire country was thus complete. The final step was to mosaic all 38 built-up area images together and import it to the GIS environment.

GIS process

Handling GIS data was performed using ArcGIS 10.7.1 software. Firstly, the provincial records in the provincial layer data were dissolved into the regional layer data (Figure 4). Secondly, the derived built-up area image was clipped by the region. Then, the built-up area was extracted. Its regional proportion, or the percentage of built-up area per region, was calculated. Thirdly, the demographic and socio-economic data was incorporated in the GIS environment. These data were coded and transformed to be used as GIS layer, so called “development” layer. The layer comprises urbanization rate, GRP, and HAI. Finally, for each region the built-up area was correlated with these development indicators to reveal the relationship. The scatterplot was utilized to depict the relationship between the percentage of built-up area and these indicators. The linear regression analysis and the coefficient of determination (R2), similar to the statistical techniques used in the previous works (Ma and Xu, 2010; Li et al., 2013; Faisal and Shaker, 2014; Faisal et al., 2016), were built to analyze the relationship between any of these two indicators. R2 values scale from 0.0 to 1.0. By following the previous studies’ criteria, in this study the correlation is considered high (R2 0.8), moderate (0.5 > R2 < 0.8), and low (R2 0. 5) respectively.

4. Results and Discussion

Result

Results of the study, the derived built-up area and its regional proportion as well as the relationships between the percentage of built-up area and the development indicators, are reported.

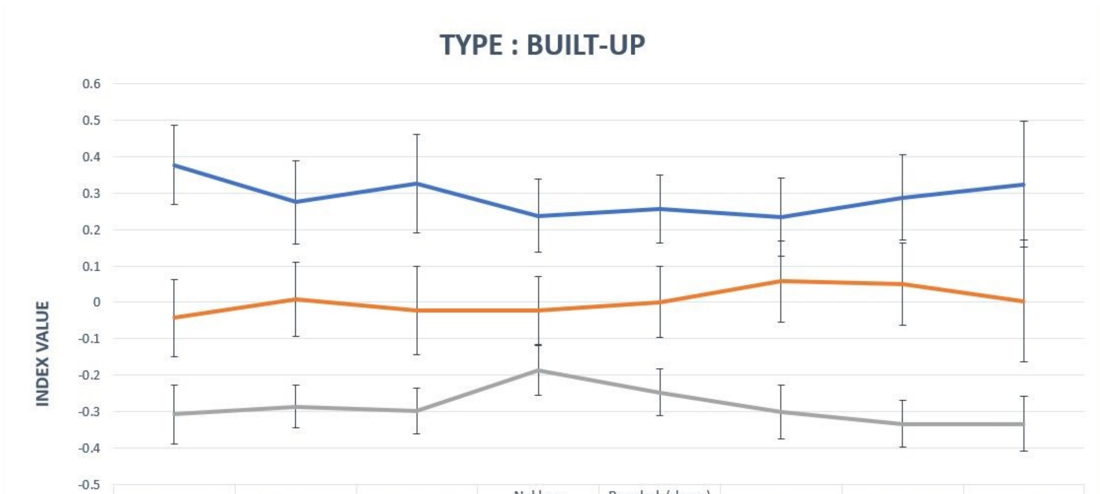
Built-up area and its regional proportion

The classification results of the study are demonstrated as a graph showing the percentage of built-up area for each region and a map showing the built-up area image overlaid with the regions in Figure 5 and Figure 6 respectively. The derived built-up area in 2019 was 12,695 sq. km from the total of 515,876 sq. km. In equivalence, built-up area in the country amounts to 2.46% of the total. Thailand, mainly divided by the NESDC based on its geographical and socio-economic development conditions, comprises seven regions. These include (1) Bangkok and Vicinities, (2) the Central region, (3) the North region, (4) the Northeast region, (5) the East region, (6) the South region, and (7) the West region. A brief description of the regions (Encyclopædia Britannica, 2022) and the regional variation in percentage of built-up area (Figure 5) is given.

Bangkok and Vicinities and the Central region are predominantly a lowland area, primarily drained by the Chao Phraya River. The region of Bangkok and Vicinities – Samut Prakan, Pathum Thani, Samut Sakhon, Nakhon Pathom, and Nonthaburi – is separated from the Central region as the area is notable for the concentration of commercial, industrial, and transport activities. Economic growth of the region has taken place more rapidly than elsewhere and has attracted people from other parts of the country. Nowadays, this region remains the predominant urban center in the country. Based on the classification results, Bangkok and Vicinities has the highest percentage of built-up area (29.49% of the total region).

The Central region, dominated by its fertile floodplain and wet-rice cultivation, is currently one of the most productive agricultural regions in the country. The Central region also has the second-highest percentage of built-up area (7.07% of the total).

The North region, sharing borders with Myanmar, is predominantly a mountainous area while the middle and southern parts are predominantly plains. Surrounded by several mountain ranges, the region is cooler than other parts of the country and is popular to visit in December and January. The North has almost the smallest percentage of built-up area (1.89% of the total).



	Chiang Mai	Khon Kaen	Ayutthaya	Nakhon Ratchasrima	Bangkok (down) / Chonburi	Phuket	Surat Thani	Songkhla
NDVI	0.376308	0.274167	0.326362	0.237233	0.256801	0.233892	0.288049	0.324288
NDBI	-0.04282	0.008619	-0.02181	-0.021682	0.00106	0.057348	0.048799	0.003787
MNDWI	-0.30683	-0.286038	-0.297642	-0.187055	-0.247064	-0.299986	-0.3332221	-0.333045

Figure 3. Comparison of the average index values (NDVI, NDBI, MNDWI) of built-up class (mean and S.D.) derived from the training samples of the 8 selected scenes

The Northeast region is characterized by the Khorat plateau. Farming is poor in this region due to its arid land and long dry season. The Mekong River flows past much of the northern and eastern edge of the region. The region has a built-up area amounting to 2.41% of the total.

The East region extends to the border of the northeastern plateau to the north, and the Gulf of Thailand to the south. This region is where the Eastern Seaboard Development Program (ESB) is located. Today, the ESB has been developed to become the most important port and industrial area of Thailand and it attracts large numbers of migrants. While fruit and tourism in this region are popular among Thais, the main contribution to GRP of this region comes from the industrial sector. The region is ranked third in terms of built-up area (2.46% of the total).

The South region consists of a peninsula with a mountainous spine and sandy coastline. This region is well-known as a tourist destination, and its income is derived mainly from the tourism and service sectors. However, the region has the lowest percentage of built-up area (0.45% of the total) compared to other regions.

The West region, consisting mostly of green mountainous ranges along the Myanmar border, is lightly populated. The region comprised the smallest built-up area (1.66% of the total).

Based on the spatial observation (Figure 6), the concentration and distribution of the built-up area can clearly be detected. The distribution patterns varied across regions. The concentration of built-up pixels was at its greatest for Bangkok and Vicinities. The density generally declined across the Central region in the north-south direction. Another high concentration area is detected in the North where Chiang Mai – one of the top tourist cities of Thailand – is located. In the Central region and the Northeast, built-up pixels were generally in a random dispersion pattern. In the East, the built-up pixels were located mainly in the provinces along the coastline, whereas built-up pixels were hardly seen at all in the South. In the West, the built-up pixels were found to be dispersed mainly in the provinces close to the Central region.

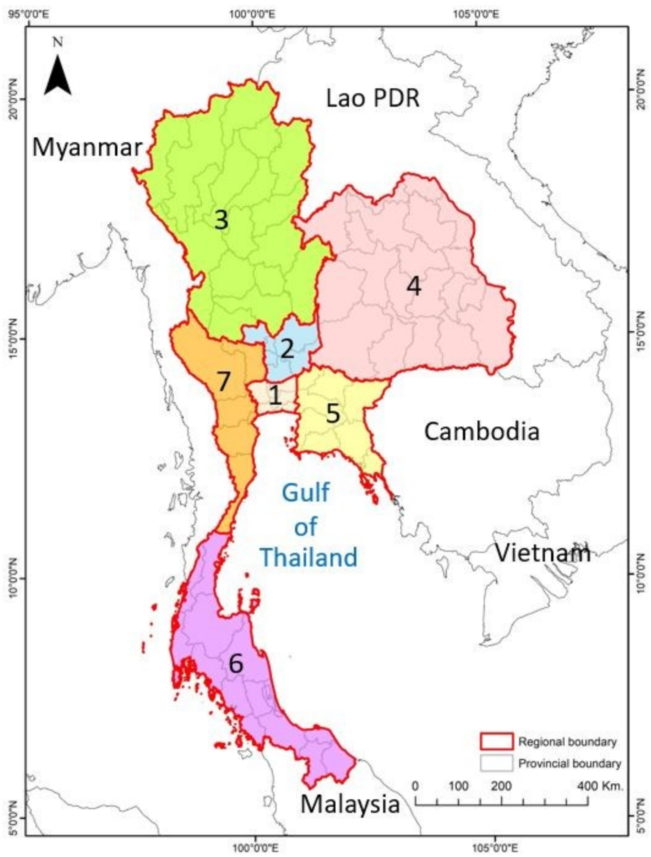


Figure 4. The NESDC's regions, namely (1) the Bangkok and Vicinities, (2) the Central, (3) the North, (4) the Northeast, (5) the East, (6) the South, and (7) the West

Some considerations according to the regional variation in distribution patterns should be mentioned. The factors influencing the distribution patterns across regions, such as topographical conditions, transportation, socio-economic activities, distribution of infrastructural facilities and social amenities, are diverse. The causes of their distribution are questionable and further analysis is required to explain these distribution patterns. Further, the effects of some distribution patterns such as the over-concentration of economic and/or industrial activities in some locations in a region are the main concern for urban and regional planners, particularly in terms of energy consumption or air pollution issues. In this regard, there are explicit advantages of remotely-sensed derived built-up area evaluation, which can give useful information both in terms of quantity and spatial domain. Built-up area information and its distribution patterns can be useful in several applications in regional study. Results of the study thus imply that built-up area can serve as an indicator in the physical and/or environmental dimension for the measurement of regional development.

Relationships between the percentage of built-up area and the development indicators

Although the built-up area and its regional proportion (Figure 5 and Figure 6) can reveal their variations in regions, relationships between the percentage of built-up area and the three development indicators gave more interesting results. According to the regions, the three development indicators (urbanization rate, GRP, HAI) generally have a positive correlation with the percentage of built-up area in different degrees (Figure 7 - 9). The highest correlation (R2) was with urbanization rate (0.88), followed by that of GRP (0.85), and HAI (0.66) respectively. In other words, the higher the percentage of built-up area results in a higher the urbanization rate, a higher the GRP, and a higher the HAI. The results thus indicate that the regional proportion of built-up area can be used to predict urbanization rate, GRP and HAI.

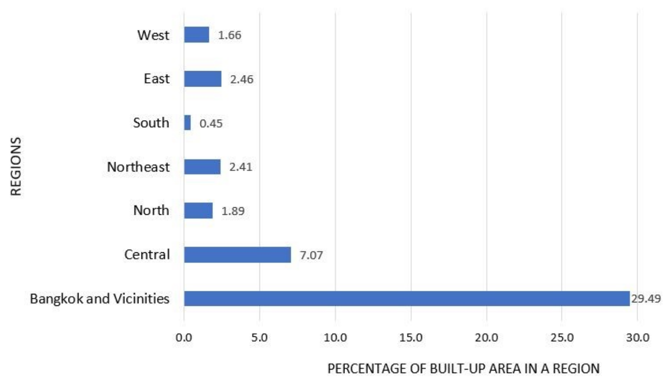


Figure 5. Percentage of built-up area in regions in 2019

Despite the positive relationships mentioned above, outliers in Figure 7 - 9 which were mainly contributed by the Bangkok and Vicinities were questionable and led to further investigation. Additional analysis was done to observe the effect of Bangkok which was included in the Bangkok and Vicinities. The Bangkok and Vicinities was thus eliminated from the analysis for further investigation. The correlations between the percentage of built-up area and the three development indicators were re-examined. Results show that there was no relationship between the percentage of built-up area and any of the three indicators after excluding the Bangkok and Vicinities (Figure 10 - 12). Compared with the previous analysis (Figure 7 - 9), the R2 between the percentage of built-up area and urbanization rate reduced sharply from 0.88 to 0.04. The R2 between the percentage of built-up area and GRP reduced steeply from 0.85 to 0.04. As well the R2 between the percentage of built-up area and HAI noticeably reduced from 0.66 to 0.16. The results thus indicate that inclusion and exclusion of the Bangkok and Vicinities had a considerable impact on the regions. Assessment of the study is discussed in the next section.

Discussion

Thailand’s national motto of “Security, Prosperity and Sustainability” is currently the country’s vision stipulated in the National Strategy (2018 – 2037) (NESDC, 2019a). In pursuit of sustainability, the National Strategy focuses on creation of a balance between economy, environment, and quality of life for future generations. The sustainability strategy has been applied to all development aspects including the sustainable regional development (SRD). With

Table 3. Classification accuracies of the 38 Landsat scenes

Landsat Scene no.	Path	Row	Built-up Accuracy (%)	Commission Error (%)	Omission Error (%)
1	126	49	82.41	9.19	17.59
2	126	50	85.34	2.83	14.66
3	127	48	85.07	11.68	14.93
4	127	49	86.52	0.96	13.48
5	127	50	85.85	0.00	14.15
6	127	52	85.21	9.96	25.09
7	127	56	89.02	1.18	10.98
8	128	47	72.05	0.92	27.95
9	128	48	79.81	35.68	20.19
10	128	49	83.61	21.01	16.39
11	128	50	81.24	20.62	18.76
12	128	51	88.16	36.26	11.84
13	128	55	78.53	11.90	21.47
14	128	56	94.31	14.62	5.69
15	129	47	73.89	36.23	26.11
16	129	48	75.21	22.56	24.79
17	129	49	83.06	41.49	16.94
18	129	50	84.49	20.00	15.51
19	129	51	81.50	15.06	18.50
20	129	52	81.48	2.75	18.52
21	129	53	85.20	3.28	14.8
22	129	54	84.80	4.01	15.20
23	129	55	82.12	2.58	17.88
24	130	46	92.12	55.61	7.88
25	130	47	88.74	64.75	11.26
26	130	48	87.28	7.10	12.72
27	130	49	85.16	76.04	14.84
28	130	50	85.36	71.97	14.64
29	130	51	81.57	34.42	18.43
30	130	52	92.53	17.47	7.47
31	130	53	89.85	30.40	10.15
32	130	54	89.44	2.89	10.56
33	131	46	89.28	12.24	10.72
34	131	47	72.87	13.48	27.13
35	131	48	81.55	8.80	18.45
36	131	49	92.87	4.17	7.13
37	131	50	89.16	48.14	10.84
38	132	47	80.14	11.94	19.86

an aim to implement SRD in practice, each region requires management to balance the effects of increasing economic growth, improved social welfare and quality of life, an increasing urban population (urbanization), the appropriate expansion of urbanized areas, energy efficiency, and so forth. To monitor and measure the success of SRD, indicators of economic, social, demographic, and physical and/or environmental dimensions are necessary, and their interactions and relationships should be observed. In the present study, remotely-sensed derived built-up area is the focus of an approach which captures up-to-date human settlement data and observes the effects of the associated economic activities across the global surface.

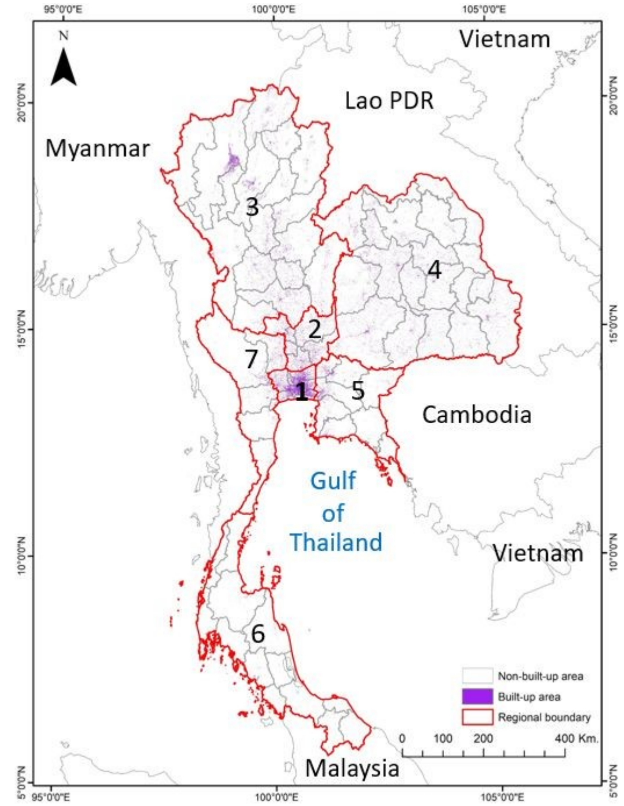
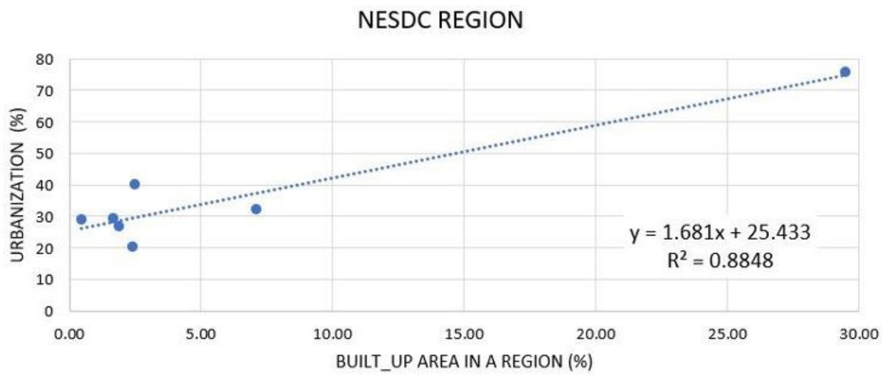


Figure 6. Built-up area image overlaid with regions, namely (1) Bangkok and Vicinities, (2) the Central, (3) the North, (4) the Northeast, (5) the East, (6) the South and (7) the West

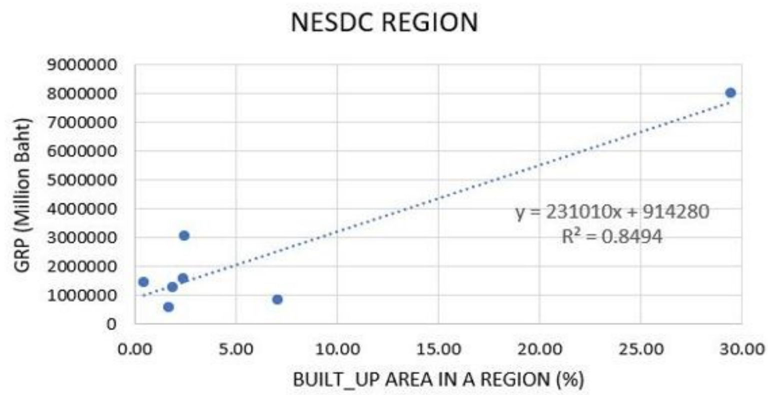
The strengths of this study are as follows. 1) This study created the remotely-sensed derived built-up area, serving as a missing-data indicator to monitor Thailand's regional development in the spatial domain. 2) This study provided the relationship measurement of the above four dimensions - demographic (urbanization rate), economic (GRP), social (HAI), and physical (derived built-up area). In this regard, the present study differs from other works in that the previous works measured only the relationships between one or two dimensions e.g. the research of (Spiezia, 2003; Ma and Xu, 2010; Fedajey and Nikolic, 2012; Li et al., 2013; Faisal and Shaker, 2014; Yue et al., 2014; Faisal et al., 2016). Therefore, this study is considered a pioneer work, proposing the four dimensions for Thailand's regional study.

Assessment of the present study was through the investigation of the regional variation (Figure 5 and Figure 6) and the correlation (R2) results between the percentage of derived built-up area and the development indicators (Figure 7 - 12). The main point is that inclusion and exclusion of the Bangkok and Vicinities had a considerable impact on the analysis as it made the correlation results (Figure 7 - 12) largely differ as summarized in Table 4. The finding is unique to Thailand which is, in my opinion, affected by the effect of Bangkok's urban primacy. Bangkok has long been considered as a primate city - being two or more times the population of the second-largest city in a country (Lang et



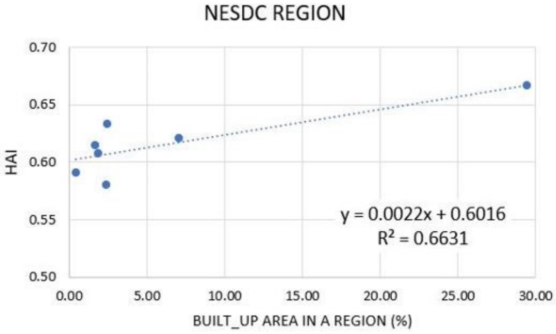
	NESDC region	Built-up area (%)	Urbanization rate (%)
1	Bangkok and Vicinity	29.49	76.05
2	Upper Central	7.07	32.33
3	North	1.89	27.09
4	Northeast	2.41	20.28
5	South	0.45	28.99
6	East	2.46	40.26
7	West	1.66	29.43

Figure 7. Percentage of Built-up Area Versus Urbanization Rate



No.	NESDC sub-regions	Built-up area (%)	GRP (Million Baht)
1	Bangkok and Vicinity	29.49	8,025,935
2	Upper Central	7.07	861,896
3	North	1.89	1,299,834
4	Northeast	2.41	1,596,094
5	South	0.45	1,473,623
6	East	2.46	3,042,916
7	West	1.66	597,788

Figure 8. Percentage of built-up area versus GRP



No.	NESDC sub-regions	Built-up area (%)	HAI
1	Bangkok and Vicinity	29.49	0.67
2	Upper Central	7.07	0.62
3	North	1.89	0.61
4	Northeast	2.41	0.58
5	South	0.45	0.59
6	East	2.46	0.63
7	West	1.66	0.61

Figure 9. Percentage of built-up area versus HAI

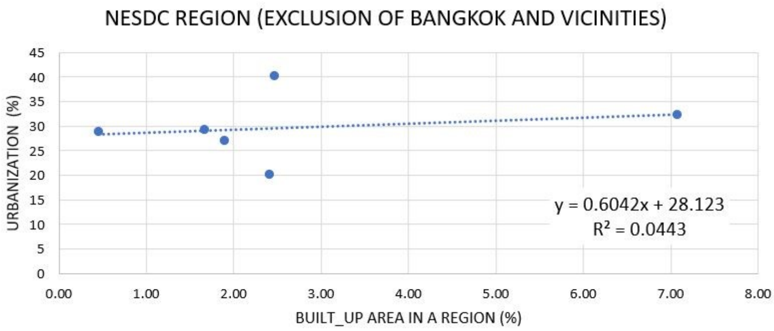


Figure 10. Percentage of built-up area versus urbanization rate (exclusion of the Bangkok and Vicinities)

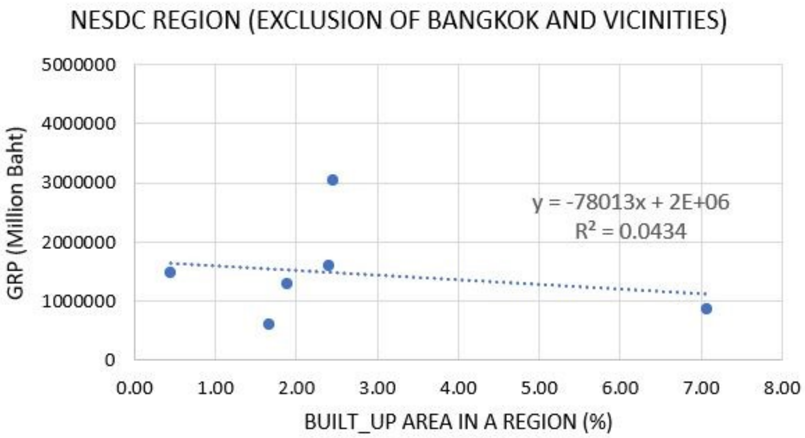


Figure 11. Percentage of built-up area versus GRP (exclusion of the Bangkok and Vicinities)

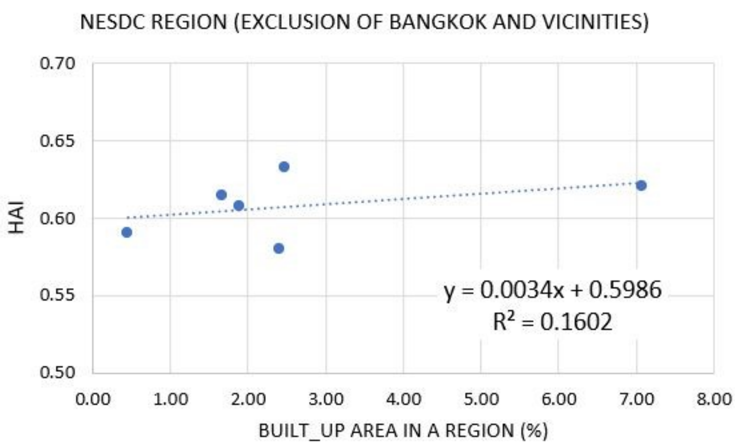


Figure 12. Percentage of built-up area versus HAI (exclusion of the Bangkok and Vicinities)

al., 2021). It has a 100% urbanization rate, has a primacy rate today of about 5 times compared with the next largest cities of the country, and had the highest (34%) share of the overall GPP (Gross Provincial Product) in 2019 according to the latest NSO and NESDC report (NSO, 2020; NESDC, 2021).

While several studies researched Bangkok's primate city in different aspects (Ayal, 1992; Murayama et al., 2017; Lang et al., 2021), the merit of the built-up area in this study is that it can reveal new information - the comparative analysis of inclusion and exclusion of the effect of Bangkok - which had not existed in the prior observation of Thailand's regional study. In this regard, the "strong correlation" results based on inclusion of Bangkok and Vicinities (Table 4) imply that built-up area is a direct reflection of economic activity and urbanization. In other words, the economic growth of a region and/or the increase in the urbanization of a region result in the expansion of urban area in a region. The evidence of this finding could be explained by observing the urban expansion of Bangkok to its vicinity and regional cities, so-called the Extended Bangkok Metropolitan Region (EBMR) or Bangkok's Mega-Urban Region. However, the "no correlation" results based on exclusion of Bangkok and Vicinities (Table 4) give a new perspective to the role of built -up area in that the economic growth of a region and/or the increase in the urbanization of a region may or may not involve with the expansion of urban area in a region. This finding is opposite to the evidence given by the past research works (e.g., Y. Ma and Xu, 2010; Ma et al., 2012; Propastin and Kappas, 2012; Wang et al., 2012; Li et al., 2013; Faisal and Shaker, 2014; Yue et al., 2014; Kamil Faisal et al., 2016; Chen et al., 2020).

Noticeably, these past research studies were conducted in countries having different urban hierarchical system compared to that of Thailand such as China (having several super-cities) and Canada (having the city hierarchies of rank-size rule distribution). In my opinion, the "no correlation" information is noteworthy as it can truly reflect the uneven regional development in Thailand. Therefore, excluding the effect of Bangkok's urban primacy creates new information and awareness, which otherwise would result in misinterpretation and misleading conclusion. Further implication is that our understanding of how to use remotely-sensed derived built-up area information is still limited. Further research should be carried out to reveal the relationships with respect to other parameters such as employment, incomes, CO_2 emission etc. A study at provincial level can potentially reveal new information. Moreover, since the effect of Bangkok is uncovered, replication of the analysis for other countries, particularly those experiencing the effect of urban primacy, is another direction for further work.

All in all, what is acquired from the analysis from both dimensions (inclusion and exclusion of the effect of Bangkok) of relationships is that this study can demonstrate the regional proportion of built-up areas both in terms of quantity and spatial domain as well as its relationships to the existing development indicators. It can also offer other directions of work that can be conducted based on the distribution patterns of built-up areas in a region or across regions, e.g., the analysis study of factors influencing their distribution patterns, the study of environmental impacts (i.e., air pollution issue) due to over-concentration of built-up areas in a region. Therefore, this study can reveal informative information which is beneficial to the regional analysis. Despite that only a limited number of regions for investigating the relationships were used, a large part of the regional variation is satisfactorily explained.

5. Conclusion

Recently, Thailand's national strategy (2018 – 2037) has applied the sustainability concept to all development aspects including the sustainable regional development (SRD). With an aim to monitor and measure the success of SRD, indicators of economic, social, demographic, and physical and/or environmental dimensions are necessary, and their interactions and relationships should be observed. In this study, remotely-sensed derived built-up area is applied for the first time as a physical indicator, adding in the spatial dimension for the study of regional development of Thailand. Satellite remote sensing and GIS techniques were utilized to extract and estimate the regional proportion of built-up area of the whole country in 2019. Relationships between the regional proportion of built-up area and the three development indicators (urbanization rate, Gross Regional Product, and Human Achievement Index) were analyzed through the linear regression analysis and the coefficient of determination (R2). The findings are as follows. 1) Estimate of built-up area of the total country from Landsat 8 images was 2.46% with the average accuracy of 84.50%. 2) The built-up area and its regional proportion can reveal regional variation of the country. 3) The relationships between the percentage of built-up area and the three development indicators for regions were relatively strong. However, there was no relationship after excluding the region having the effect of Bangkok. The findings suggest that remotely-sensed derived built-up area has the advantage of providing efficient and accuracy spatial data for various research purposes in regional study and policy-

Table 4. Comparison of the correlation (R2) results between the derived built-up area and different types of development indicators, obtained from author's study

Research studies	Development indicators		
	GRP	Urb	HAI
Before excluding Bangkok and Vicinities	0.85	0.88	0.66
After excluding Bangkok and Vicinities	0.04	0.04	0.16

Remark : [1] GRP refers to Gross Regional Product
[2] Urb refers to Urbanization rate
[3] HAI refers to Human Achievement Index

decision makers should consider using remotely-sensed derived built-up area information as an input indicator for the regional study.

Acknowledgement

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