



# Prevalence of hypertension in Thailand: Hotspot clustering detected by spatial analysis

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## Abstract

Spatial pattern detection can be a useful tool for understanding the geographical distribution of hypertension (HT). The aim of this study was to apply the technique of local indicators of spatial association statistics to examine the spatial patterns of HT in the 76 provinces of Thailand. Previous studies have demonstrated that socioeconomic status (SES), economic growth, population density and urbanization have effects on the occurrence of disease. Research has suggested that night-time light (NTL) can be used as a proxy for a number of variables, including urbanization, density, economic growth and SES. To date, there has not been any study on spatial patterns of HT and there is no information on how NTL might correlate with HT. Therefore, this study has investigated NTL as a parameter for detection of hotspots of HT in Thailand. It

was found that HT clusters occurred in Bangkok and in metropolitan areas. In addition, significantly low-rate clusters were seen in some provinces in the Northeast and also in southern provinces. These findings should facilitate control and prevention of HT and, therefore, serve as support for researchers, decision-makers, academics and public health officials to propose more sound and effective strategies for the control of HT in Thailand and elsewhere.

## Introduction

Hypertension (HT) is a non-communicable disease with enhanced morbidity and mortality and whose increasing trend worldwide is seen as a global public health challenge. HT is one of the top modifiable risk factors in the field of cardiovascular disease (CVD) (Kayima *et al.*, 2015). In 2025, according to the World Health Organization (WHO), the number of patients in industrialized countries who will have developed HT is estimated at 1.15 billion (WHO, 2015). Moreover, half of those patients will die from ischemic heart disease and stroke where HT is the root cause (MoPH, 2007; Bharati and Ajayi, 2011; WHO, 2015). In Thailand, for instance, it was found that in 2003, 2008 and 2013, the morbidity rate due to HT per 100,000 people was 389.80, 860.53 and 1621.72, respectively, indicating an exponential increase in rate (MoPH, 2015). Many factors are associated with HT, such as age, gender, having a family history of HT, and alcohol consumption (Oliveira *et al.*, 2014; Wei *et al.*, 2015), in addition to overweight/obesity, smoking (Wei *et al.*, 2015), physical inactivity, high dietary salt intake (Chongthawonsatid, 2013), stress (Lwin *et al.*, 2011), education, occupation (Lwin *et al.*, 2011; Wei *et al.*, 2015), economic status, income and social status (Puavilai *et al.*, 2011). These factors are known to contribute to the risk of HT and cerebrovascular disease. In addition, some previous studies also found differences in regional location to be associated with HT (Satipunyaalert, 2014; Wei *et al.*, 2015; Abebe *et al.*, 2015). Residential areas may have influenced health behaviour in terms of lifestyle, social well-being and urbanization (Bharati and Ajayi, 2011). Studies concerning Mae Hong Son Province in Thailand (Satipunyaalert, 2014), Dehui City in Jilin Province in China (Wei *et al.*, 2015) and the Northwest of Ethiopia (Abebe *et al.*, 2015) report a significantly higher tendency for HT in urban areas or cities in contrast to that in rural areas.

Many epidemiological studies indicate that HT occurs in different geographic and metropolitan regions (Satipunyaalert, 2014; Wei *et al.*, 2015; Abebe *et al.*, 2015). Geographic information systems (GIS), together with other instruments used for geographic pattern analysis (George *et al.*, 2013) are important tools for geo-

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graphic analysis. Anselin (1995) has demonstrated the usefulness of applying local indicators of spatial association (LISA) in epidemiological settings. For instance, Rosana Rosseto de Oliveira *et al.* (2012) studied infant mortality in three cities in Paraná state, Brazil using LISA for the analysis of spatial distribution and autocorrelation. Wang *et al.* (2016) analyzed spatial autocorrelation analysis and hotspot analysis of the HIV/AIDS epidemic applying LISA. Night-time light measurements (NTLs) (Mellander *et al.*, 2015; Laohasiriwong *et al.*, 2017) have been used to represent economic growth, population density and urbanization. NTL has also been used in public health and epidemiological studies in recent years, *e.g.*, Laohasiriwong *et al.* (2017) utilized NTL to assess economic growth, urbanization and health care facility coverage. Areas with a prevalence of chronic respiratory disease (CRD) also experience increased light resulting in a correlation with NTL and socioeconomics (Laohasiriwong *et al.*, 2017). NTLs may serve as a new tool for specifying disease hotspots by representing population and industrial growth which typically contribute to epidemics. In urban areas with migration, NTLs can indicate where populations are clustering, through the expansion and increased brightness of the illuminated areas (Henderson *et al.*, 2012). NTLs can also indicate fluctuations in population density, which affect epidemic risk and can therefore replace current methods of outbreak surveillance (Princeton University, 2011).

In Thailand, the government has used various tools to assess HT. However, spatial clustering of the disease, particularly at the national level, has rarely been applied to investigate characteristics of HT clusters in terms of geography. In addition, there has been limited use of socioeconomic status (SES) indicators, especially NTLs, in the epidemiology of HT. The aims of this study were to examine the spatial clustering of HT in Thailand and to clarify if there is a correlation between NTLs and HT. The findings should provide data to support interventions in specific high-rate areas. Academics, researchers, decision makers and public health personnel will be able to use the results to develop new strategies for HT control and prevention at the regional level.

## Materials and Methods

### Study area

Thailand is an upper-middle-income country in Southeast Asia with a population of approximately 68 million as of 2017. The latitude and longitude coordinates are 15.8700° N, 100.9925° E. The capital and largest city is Bangkok. Thailand shares a total of 4863 km of border with neighbouring countries, *i.e.*, Myanmar and Laos to the North, the Gulf of Thailand and Malaysia to the South, Laos and Cambodia to the East, and the Andaman Sea and the southern extremity of Myanmar to the West (Figure 1). With the addition of a new province, Bung Kan, in 2011, Thailand is divided into 76 provinces (Figure 1).

### Data sources

This study used data from the National Socioeconomics Survey (NSS), a cross-sectional study conducted by the National Statistical Office (NSO) in 2005, 2006 and 2007. It represents the latest nationwide surveys incorporating detailed questionnaires regarding health status and chronic diseases. The surveys used stratified two-stage random sampling, firstly selecting provinces

and then selecting blocks/villages. In this way, a nationally representative sample was selected to respond to a structured questionnaire for all 76 provinces in Thailand. There were 76 strata altogether and each stratum was divided into two parts according to the type of local administration, namely, municipal and non-municipal areas. Selection of primary sampling, *i.e.*, the selection of blocks/villages, was performed separately and independently in each part by using a probability proportional to the total number of households in that block or village. In the second step, the selection of secondary sampling units, *i.e.*, private households, was based on using a systematic method in each type of local administration (details of this sampling are available at [http://web.nso.go.th/survey/house\\_seco/meth.pdf](http://web.nso.go.th/survey/house_seco/meth.pdf)). The questionnaires collected information under seven categories consisting of education, health care, employment, income, finances, migration and attitudes/opinions. The outcome, defined as having HT diagnosed previously by a physician, was based on a blood pressure reading of 140/90 mmHg or higher and with the individual being continuously treated for HT. A total of 16,306, 16,539 and 16,488 participants, who met the inclusion criteria of Thai nationality and being aged 15 years or over, were included in the analysis for each year. The NTL data for Thailand used in this study were extracted from the global stable lights imagery of 2005-2007 collected by the Operational Linescan System (OLS) sensor onboard satellites



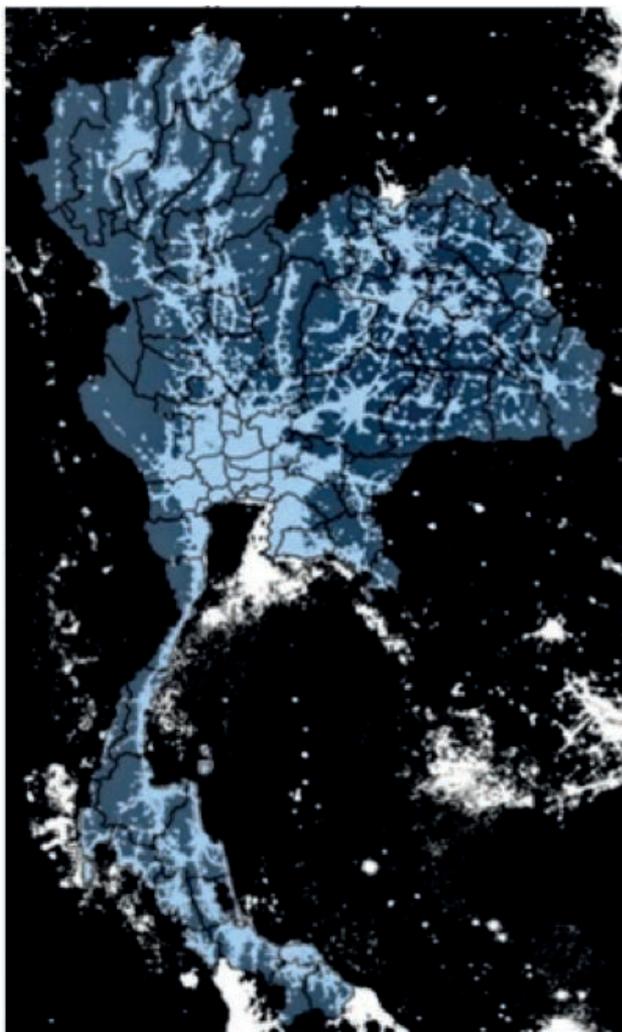
Figure 1. Map of Thailand and its provinces.

F15 (F152005, F152006 and F152007) and F16 (F162005, F162006 and F162007) of the Defence Meteorological Satellite Program (DMSP), USA (Figure 2).

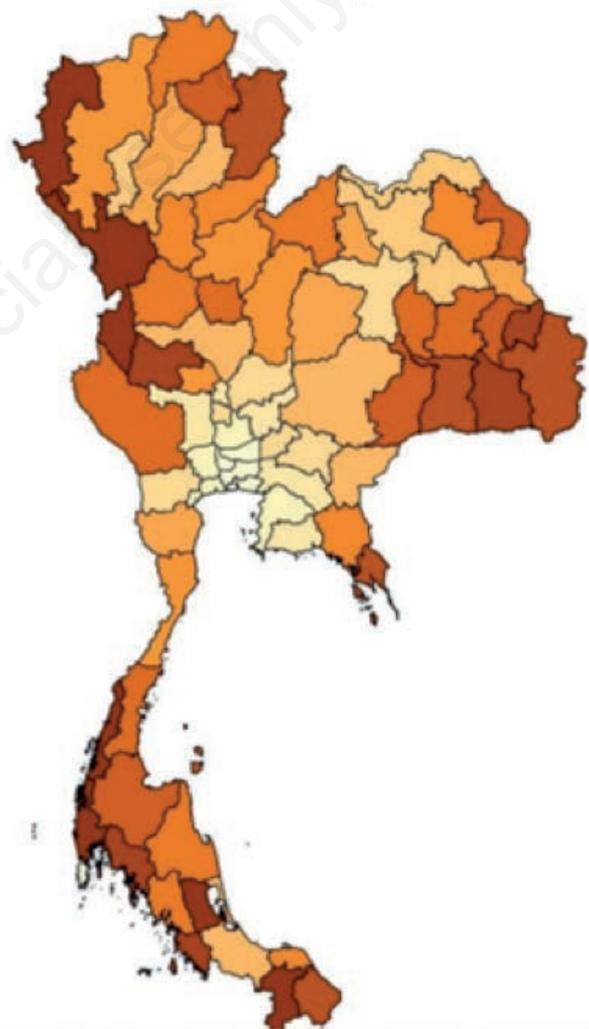
### Spatial pattern detection

The detection of HT spatial patterns was based on localized detection of prevalent spatial patterns. For exploratory spatial data analysis we used the open GIS software Quantum GIS (QGIS) introduced by Steiniger and Hunter (2013), together with GeoDa (<https://geodacenter.github.io>) to determine measures of spatial autocorrelation analysis (Anselin, 2006), and Stata version 10.0 (Stata Corp, College Station, TX, USA) to calculate the prevalence of HT, and for correlation analysis. The prevalence of HT for each province was calculated as the total number of HT participants in

that province (the numerator) divided by the total number of participants in that province (denominator). Thus, the spatial distribution of the prevalence of HT could be visualized. To conduct a spatial autocorrelation analysis on the spatial distribution, the geographic patterns and clusters were measured using LISA (Anselin, 1995). The province-level layers of polygons and points were matched to the prevalence of HT. The spatial distribution of the prevalence of HT was obtained from the province-level polygon map, which included the latitudes and longitudes for each province. The calculated prevalence of HT was further visualized with province-level layers on the polygon map and labelled with the administrative code for each province. Exploratory spatial pattern analysis was also used to determine the distribution patterns for the prevalence of HT for each year of data.



Source: DMSP/OLS data and authors computed



Source: Authors' computation  
Note: Bright color indicates the high magnitude of nighttime light index

Figure 2. Raw data for night-time light from Defence Meteorological Satellite Program/Operational Linescan System (DMSP/OLS).

## Statistical approach

### Local indications of spatial autocorrelation

Anselin (1995) made a significant advance within areal analysis by defining a class of LISA as a tool for exploratory spatial data analysis. In the present study, LISA was used to analyze the spatial distribution, and the GeoDa program was used to reveal the prevalence of HT. In addition, the QGIS program was used to prepare data before input into the GeoDa program. The initial data, where HT was prevalent in the province locations, were combined with the NTL data. The results from QGIS were saved as a shape file. Univariate spatial pattern analysis used HT clusters analysis, and bivariate spatial pattern analysis used HT clusters with NTL data analysis. The shape file data were then entered into the GeoDa program for spatial distribution analysis. The weighting matrix with  $k$ -nearest neighbours was 3 and the significance level ( $P$ -value) of 0.05 was chosen. The results generated a Moran's  $I$  index (Anselin, 1995; Anselin *et al.*, 2006) and a coloured map. The value of the local Moran's  $I$  ranges from +1 (indicating high-high or low-low clusters) through 0 (indicating random pattern) to -1 (indicating high-low or low-high outliers) (Barrell J and Grant J, 2013; Wang *et al.*, 2016). The maps were represented by a five-colour scheme, with high-high assigned as red (hotspot), low-low as blue (coldspot), low-high as light blue, high-low as pink and random patterns shown as white (Anselin, 2003).

In this study, the local Moran's  $I$  index was used for cluster feature analysis. There were five possible results when computed by LISA: high-high, low-low, low-high and high-low were significant areas and one area (random pattern) was not significant. Hotspots were deemed to have a high prevalence of HT, whereas coldspots denoted low prevalence. Mixtures of high and low scores in neighbouring areas were considered as spatial outliers. The meanings of the parameters in both equations were the same as those described for the local Moran's  $I$  formula. In addition, we considered NTL for bivariate spatial pattern analysis, which may be important for local spatial pattern detection of the HT prevalence. A Pearson's correlation was run to assess the relationship between NTL and the prevalence of HT in all provinces.

## Results

### Correlations between night-time light and hypertension

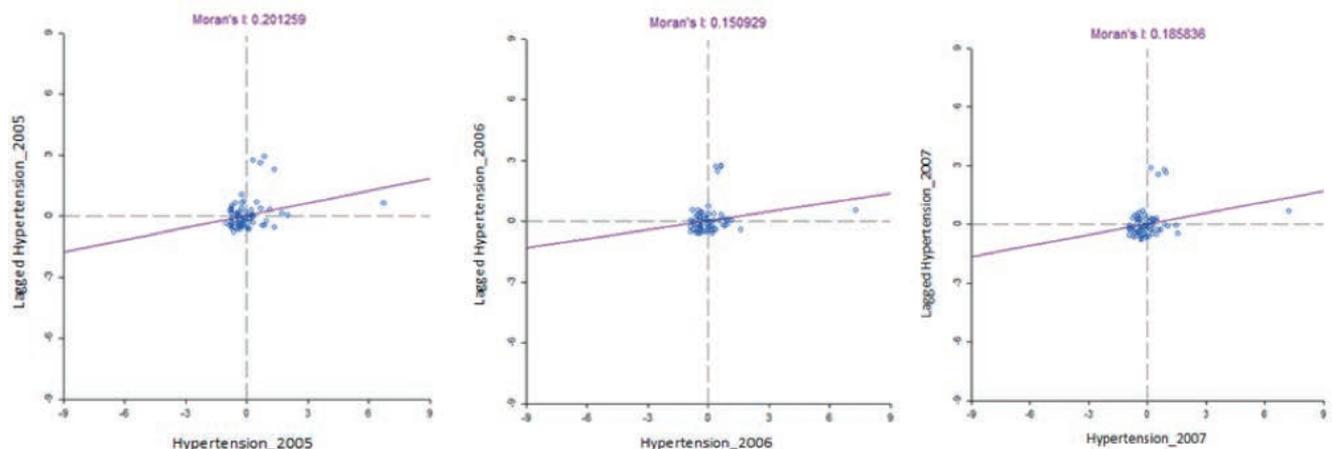
The provincial Pearson's correlation studies of NTL and HT prevalence showed moderate positive correlations in 2005 (0.533; 95% CI: 0.346–0.679;  $P < 0.001$ ), 2006 (0.510; 95% CI: 0.318–0.661;  $P < 0.001$ ) and 2007 (0.490; 95% CI: 0.294–0.646;  $P < 0.001$ ), as indicated by the similar Pearson's correlation values in the three years (Table 1).

### Local spatial patterns

The spatial pattern technique indicated that the results were similar in all three years. The results showed that clusters of HT occurred in Bangkok and other metropolitan areas. In addition, significant low-rate clusters were noted in some provinces in the northeast and in southern regional provinces. The univariate Moran's  $I$  scatter for annualized prevalence of HT in 2005, 2006 and 2007 showed a slight positive spatial autocorrelation, the Moran's  $I$  values being 0.201, 0.151 and 0.186, respectively; moreover, the values were significant (0.05 significance level), which indicated clustering. Moreover, there were hotspots (high-high) in Bangkok and in the adjoining provinces of Nakhon Pathom, Nonthaburi, Pathum Thani and Samut Prakan for all three years, while coldspot (low-low) clusters were located in some provinces in the north-eastern and southern regions (Figures 3 and 4).

**Table 1. The correlation between night-time light and hypertension for 2005, 2006 and 2007.**

Year	Correlation level	95% CI	P-value
2005	0.533	0.346-0.679	<0.001
2006	0.510	0.318-0.661	<0.001
2007	0.490	0.294-0.646	<0.001



**Figure 3. Moran's  $I$  scatter plot matrix (univariate) for prevalence of hypertension for 2005-2007.**

The results showed a significant correlation between NTL and HT. This would suggest that NTL in areas with high population densities can be used to define the spatial extent of development of HT. The results indicated a positive spatial autocorrelation, the Moran's *I* values for 2005, 2006 and 2007 being significant at the 0.05 significance level with values of 0.488, 0.473 and 0.499,

respectively. For all three years, the identified hotspot clusters were located in the Bangkok and metropolitan areas of Nakhon Pathom, Nonthaburi, Pathum Thani and Samut Prakan, while coldspot clusters occurred in some provinces in the northeastern and southern regions; these findings (Figures 5 and 6) are similar to the results for univariate analysis (Figure 4).

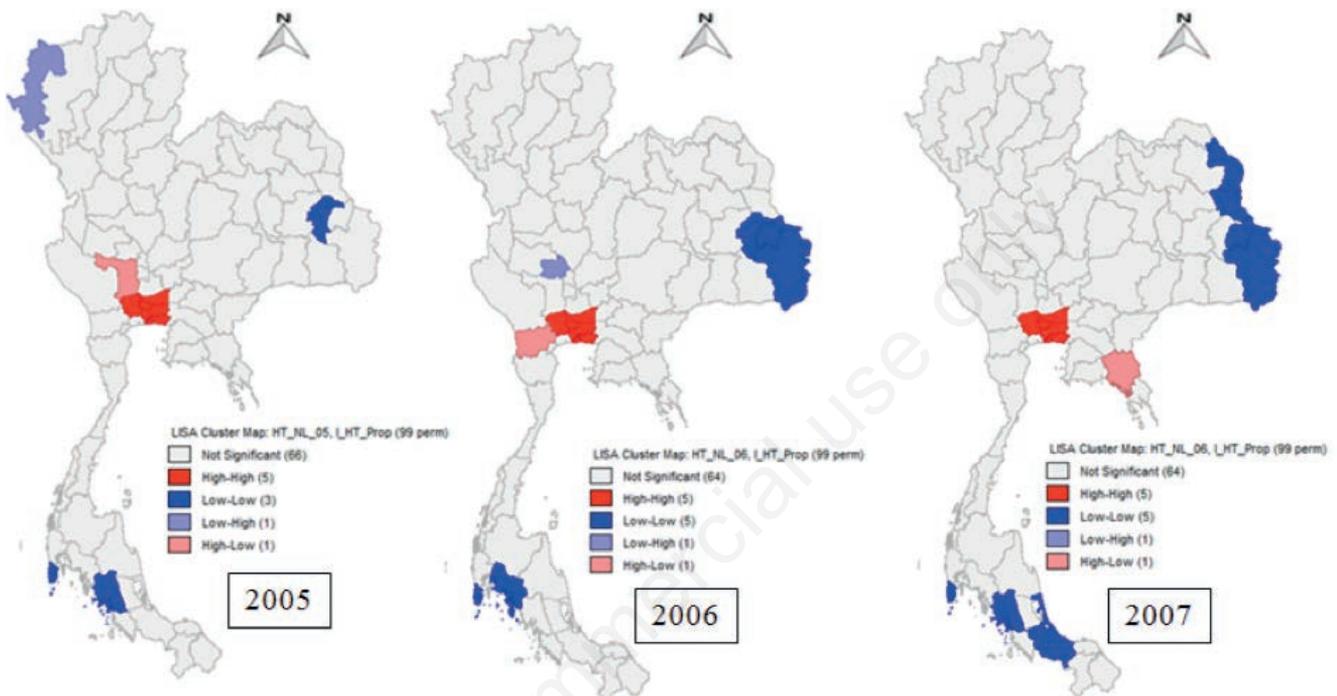


Figure 4. LISA (univariate) map for prevalence of hypertension for 2005-2007.

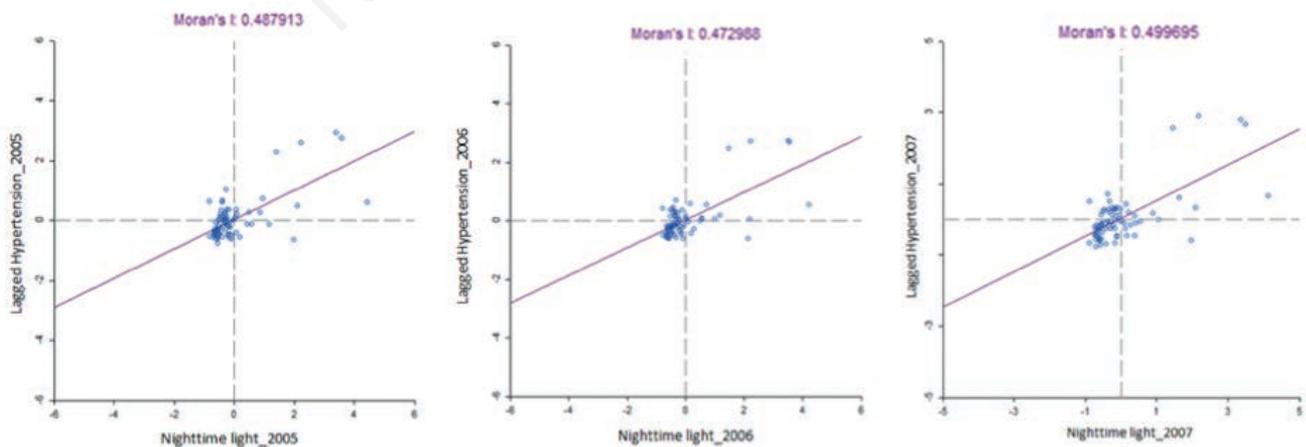


Figure 5. Moran's *I* scatter plot matrix (Bivariate: night-time light and hypertension) for prevalence of hypertension for 2005, 2006 and 2007.

In general, as seen in Figures 3-6, the LISA statistical results concurred with Bangkok and metropolitan areas having the greatest clustering of HT.

## Discussion

A correlation between NTL and the prevalence of HT was established in this study. The findings showed significant correlation between NTL and HT at the province level. The NTL data may represent differences in factors such as geography, economic growth, urbanization, and healthcare facilities. Such correlations may be used to assess economic growth in the provinces as proposed by Mellander *et al.* (2015). In this study, the geographical disparities indicated differences in individual and socioeconomic factors, including population density, urbanization, residential area per capita and human behavior or lifestyle; and these factors were found to be determinants in the spatial dynamics of HT in Thailand as discussed by Satipunyaalert (2014). The relationship of the NTL data to population size was similar to that of the HT data, a fact that could indicate NTL representing factors affected differently, such as various environmental determinants of illness or health problems given the disparities in socioeconomic status, social determinants and lifestyle mentioned by other authors (Puavilai *et al.*, 2011; Wei *et al.*, 2015; Lwin *et al.*, 2015). The recent use of NTL for the analysis or estimation of spatial inequalities has highlighted

many health problems which were found to be dependent on spatial differences or spatial inequalities (Chaiwat, 2016). The present study is also consistent with the findings of Bharti *et al.* (2011) and after the correlation has been confirmed at the provincial level throughout Thailand, it is suggested that remote sensing focused on NTL may be used in public health studies. The NTL data would represent factors such as population density, urban areas, economic status and social environment, risk factors already implicated in health and disease problems for the area (Bharati and Ajayi, 2011).

The NTL data represented population size in the areas investigated and this coincided with highly significant hotspots for HT. Comparison of the three maps in each year yielded similar findings in terms of the location of HT hotspots on each map. The findings indicated that both the univariate and the bivariate methods detected high incidences of HT in Bangkok and the metropolitan areas. At the same time, low rates of HT were indicated in some provinces in the north-eastern and southern regions of Thailand. The LISA analysis established five major cities (Bangkok, Nakhon Pathom, Nonthaburi, Pathum Thani and Samut Prakan) as being at the core of the high-rate cluster. LISA proved effective in spatial pattern analysis in that high-rate and low-rate HT regions were accurately classified. Although there could be additional factors controlling the prevalence of HT in these five cities compared to other metropolitan regions, the hotspot areas did experience dynamic changes in urban populations and in the concentration of industries. The identification of hotspots specifies priority areas for

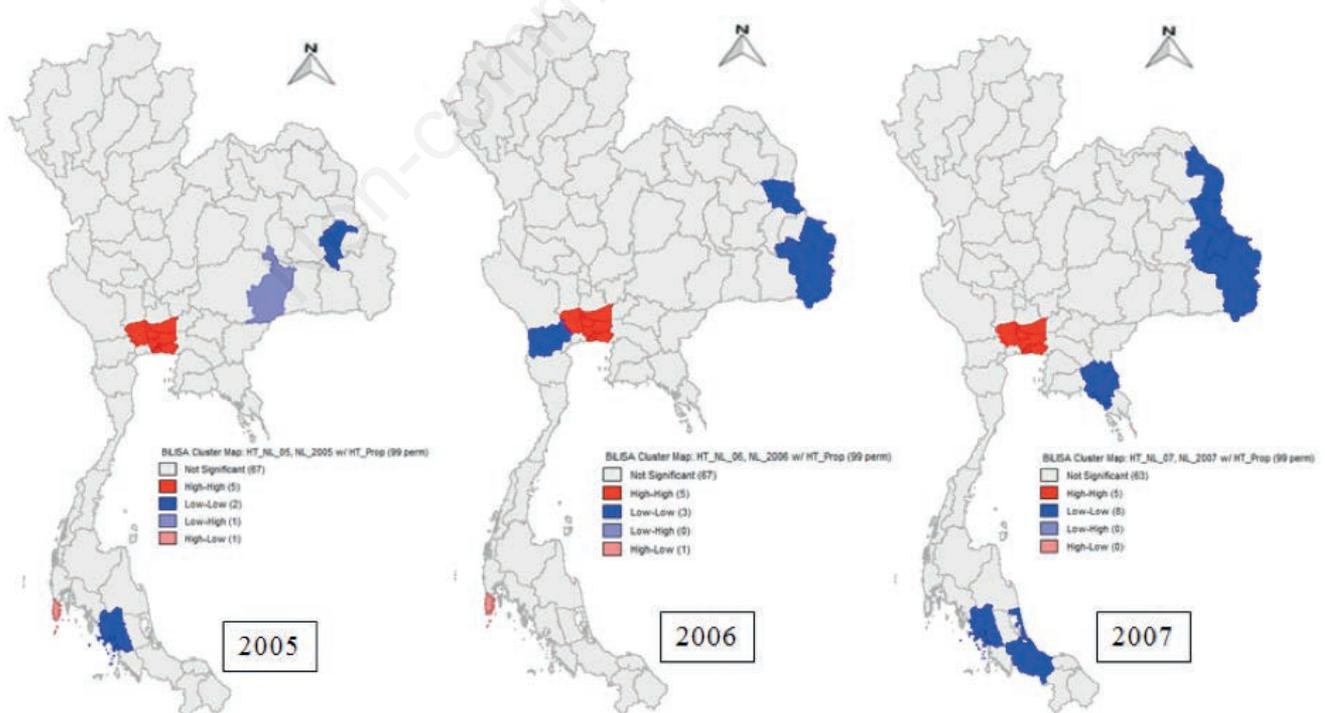


Figure 6. LISA (Bivariate: night-time light and hypertension) map for prevalence of hypertension for 2005-2007.



HT control and prevention supporting local health centres in their administration of health promotion and prevention measures appropriate to the lifestyles of people in the community. The findings therefore indicate that the application of multiple GIS methods is an effective approach for identifying clusters of HT prevalence at the province level. Moreover, no single technique was considered the best; the most appropriate technique(s) for spatial cluster analysis should be selected because each approach has its advantages and disadvantages (Sasson *et al.*, 2012).

The results show that the prevalence of HT was highest in Bangkok and the metropolitan areas. It is well known that the environment can influence health. Many people who have lived previously in other regions of Thailand have migrated to the cities for work, thus increasing urbanization and industrialization. The social environment affects the lifestyle, which represents an important risk factors for HT (Bharati and Ajayi, 2011); other factors are lack of physical activity (Chongthawonsatid, 2013), alcohol consumption (Oliveira *et al.*, 2014; Wei *et al.*, 2015), stress (Lwin *et al.*, 2011), and socioeconomic disparities such as level of education, occupation, and income (Wei *et al.*, 2015; Lwin *et al.*, 2011; Puavilai *et al.*, 2011). In contrast, the north-eastern and southern regions differ from the metropolitan areas as these regions have a more rural environment and retain a richer and more traditional culture. Most of the population work in the agricultural sector, engage in more outdoor activity, and spend much less time travelling to work. Given these circumstances, the prevalence of HT is low.

## Conclusions

The LISA statistic can be used in spatial pattern analysis to examine the prevalence of disease related to clusters. LISA can also identify the focus of high- and low-incidence clusters of HT. Spatial analysis is particularly appropriate for recognizing clusters of HT because HT is associated with environmental factors, such as location, *e.g.*, urban or rural area, social environment and lifestyle. The hotspot regions of HT display significant spatial risk factors for socioeconomic disparity, such as the level of monthly household income, education and geographic location, all of which may be represented by NTL. The findings showed significant correlation between NTL and HT at the provincial level. These findings can be used in health policy and planning by public health personnel and the health delivery service. With respect to the hotspot areas, the health and human development sectors should be given priority in terms of proactive strategies and actions which should include health promotion and HT prevention, proactive case reporting and prompt treatment and rehabilitation for those individuals suffering from HT and its complications. Using the map as a guide to specify risk factors in the regions could contribute to more efficient preventive and control programs for HT with relevance to the social environmental context.

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