Environmental Science and Pollution Research (2021) 28:12056–12066
https://doi.org/10.1007/s11356-020-09157-6

ENVIRONMENTAL AND ENERGY MANAGEMENT

Factors affecting urban electricity consumption: a case study in the Bangkok Metropolitan Area using an integrated approach of earth observation data and data analysis

Can Trong Nguyen [1,2] · Diep Thi Hong Nguyen [2] · Diem Kieu Phan [2]

Received: 21 October 2019 / Accepted: 4 May 2020 / Published online: 15 May 2020

Abstract
Urbanization induces shifts in surface environmental factors, including impervious surface expansion, green space loss, and temperature increase in which the extreme temperature is supposed to significantly raise total electricity consumption (TEC) in urban areas. Applying remote sensing data and data analysis, this study aims to explore relationships between urbanization, surface environmental factors (SEF), and electricity consumption (EC). The relevance of surface temperature and total electricity consumption was also considered. The research found the disturbance of SEF through changes in vegetation index, urban index, and surface temperature. The vegetation was detected to be narrowed while the impervious surface and land surface temperature had the same trend of rising. These tendencies correspond to the urbanization process in the Bangkok Metropolitan Area (BMA). The urbanization process was also detected by extension of customers and electricity consumption, mainly in industrial sectors and household consumption. The number of users in industrial sectors well explained total consumption. Besides, the surface environmental factors jointly contributed to the consumption in the residential sector. Urban expansion assessed by urban index has more contribution to electricity utilization compared to surface temperature. These findings proved that the total consumption originated from the industrial sectors, especially the medium and large scales. These outcomes can serve the electrical business in order to provide adequate and improve service quality.

Keywords Bangkok Metropolitan Area · Electricity consumption · Land surface temperature · Surface environmental factor · Urbanization

Introduction

Bangkok Metropolitan Area (BMA), a geographical zone, includes the capital of Thailand—Bangkok city, where it has been experiencing intense urbanization after being established and overcoming the Second World War (Murakamia et al. 2005; Tsuchiya et al. 2015). The BMA is considered as a magnet of development both in the whole Thailand and Southeast Asia region (Keivani 2010). Additionally, the BMA is contiguous to Eastern Economic Corridor (EEC), a development project launched by the Thailand government to turn three coastal provinces in the east of BMA into a modern metropolis (Tontisirin et al. 2017; Koen et al. 2018). These conditions facilitate the BMA, and so it quickly becomes a densely concentrated center of settlement, industry, commerce, and services. Urbanization process not only turns a city into a hotspot of population concentration and economic growth but also transforms its land use/land cover (LULC) and public appearances. The intensive urbanization induces spatial heterogeneity in urban landscape and disturbance of surface environmental factors (Hassan 2017). The surface environmental disturbances along with local climate, urban geometry, and internal heat sources jointly contribute to urban heat rising (Srivanit et al. 2012; Mohan and Kandya 2015; Fu and Weng 2016).

In Thailand, electricity has become an indispensable energy source for household demands, especially in the urban

Responsible editor: Philippe Garrigues

✉ Can Trong Nguyen
ntcan93@gmail.com

1 Joint Graduate School of Energy and Environment (JGSEE), King Mongkut's University of Technology Thonburi, 126 Pracha Uthit Rd., Bang Mod, Thung Khru, Bangkok 10140, Thailand

2 College of Environment and Natural Resources, Can Tho University, Campus 2, 3/2 Rd., Ninh Kieu District, Can Tho City, Vietnam

areas when traditional fuels (e.g., firewood, honeycomb charcoal, coal, and gas) gradually become strange and even disappear (Pongsapich and Wongsekiarttirat 1994). Electricity consumption in the residential sector has been surging due mainly to convenient-equipment-consumed electricity such as modern kitchen furniture, entertainment devices, and air conditioning systems, although the Thailand government released energy policy to effectively use electricity, save resources, and limit environmental burdens. The general development causes pressure in the electrical business to supply enough for all socioeconomic sectors (Yamtraipat et al. 2006). The recorded figures on total electricity consumption (TEC) of Metropolitan Electricity Authority (MEA) revealed that, although there were a few years with a slight decrease in the total consumption, the general trend was a continuous increase approximately 60% throughout the period from 1998 to 2017. At the end of the period, the year consumption reached the number of 50,700 Gigawatt hours (GWh) (Fig. 1).

Global warming and urban heat island (UHI), urban microclimate phenomena regulated by urbanization, were both verified to affect rising urban temperature and electricity demand in many cities, including Bangkok (Arifwidodo and Chandrasiri 2015; Santamouris et al. 2015). A synthetic impact of tropical climate and UHI exacerbates high temperature in the city than isolated effects. The high temperature in the urban zone was proved to be a principal agent of forcing residential utilization rise (Wangpattarapong et al. 2008). This situation is worse in midsummer when the temperature hits a peak, and dwellers are forced to switch the air conditioning system (Karaman 2019). The thermal factor, therefore, is supposed to increase the total usage in BMA directly. However, this evidence is incomprehensive. Other factors, such as surface environmental factor changes, i.e., urban expansion, and economic growth, also contribute to using electricity somehow.

A screening review using precise keywords of "urbanization" and "electricity consumption" on the Scopus database returned 138 publications within the last 10 years. A skimming through the article titles revealed that most of the studies in these fields are related to three main aspects, including urbanization (22 articles), economic growth (29 articles), and environment (12 articles). However, the study that considered the impacts of environmental changes on electricity consumption is only 2 of 12 studies. Indeed, most studies indicated the positive contribution of urbanization and economic growth to electricity consumption (Al-Bajjali and Shamayleh 2018; Yang et al. 2019; Zhang et al. 2020) in which the residential consumption determined is significantly influenced (Fan et al. 2017; Yang et al. 2019; Liu et al. 2020). With respect to the considered variable, Liu et al. (2020) considered population growth as a social factor. Gross domestic product (GDP) and the structure of the economy were variables regarding the economic aspect. Additionally, water consumption, electricity price, and distance to the power station were also concerns in some studies, and they had a relation with consumption despite low meaning (Ubani 2013; Al-Bajjali and Shamayleh 2018). With multiple linear regression, Ubani (2013) detected the relation of electricity consumption and socioeconomic factors in Nigeria, with $R^2 = 0.992$. The relation between consumption and environmental degradation (i.e., CO_2 emission) was investigated by Shahbaz et al. (2014), while other environmental factors have yet been studied.

This study, therefore, is aimed (1) to analyze variations of the surface environmental factors including green cover, impervious surface, and surface temperature over 7 years, at 2010 and 2017; (2) to assess development trend in customers and consumption of electricity business; and (3) to explore main driving forces for rising electricity consumption along with the urbanization, and general development in the BMA.

Materials and research methods

Study area description

Since 1958, the Metropolitan Electricity Authority (MEA), a state-owned enterprise, was established to generate, supply electricity, operate an electrical business, and maintain the electrical usage quality for residents in Bangkok capital, Nonthaburi, and Samut Prakan provinces (MEA 2013). These three administrative provinces were generally named as Bangkok Metropolitan Area (BMA) and divided into 18

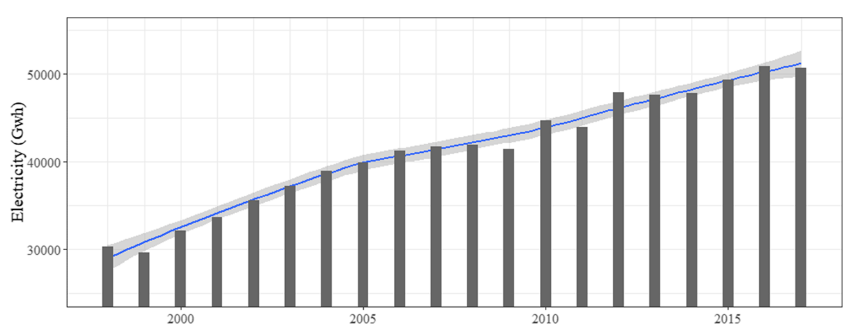

Fig. 1 Total annual electricity consumption (gray columns) and general development trend (smooth line) in the Bangkok Metropolitan Area from 1998 to 2017. Data was aggregated from raw data of MEA

districts corresponding to 18 branch offices for better management (MEA 2016).

The BMA is located in Thailand's central region where it is a hotspot for population and economic magnet (Ostro et al. 1999; Srivanit 2012). The metropolitan covers approximately 3200 km^2 in the delta of Chao Phraya River and spreads out to the Gulf of Thailand in the South (Fig. 2). Located in a tropical monsoon region, regional climate is characterized by long sunshine hours, high humidity, and temperature; the highest air temperature can especially reach over 40 °C in midsummer (Ostro et al. 1999; Ruangwises and Ruangwises 2009; BMA 2017). The high thermal environment in the context of extensive urban areas has forced most residents to turn on air conditioners, so the total consumption often hits the peak in summer (Karaman 2019). That is a remarkable thing in the electrical business in the BMA.

Dataset

Satellite data

In this research, MODIS (Moderate Resolution Imaging Spectroradiometer) products were used to extract monthly SEF in all districts. These products are acquired by Terra satellite, which covers globally from the year 2000 to the present. The data is freely downloaded from NASA's Earth Observing System Data and Information System (EOSDIS). To serve this study, the MODIS data was acquired in 2010 and 2017 corresponding to available electricity data at these 2 years for performing the same scale comparison. The MODIS scene covering Bangkok locates at (27, 07) in Sinusoidal Tile Grid.

The MODIS products that served the study include MOD11B3 and MOD13A3. The products are level 3 version 6, which are aggregated into one monthly composite image by all images collected during a month. MOD11B3 provides average monthly Land Surface Temperature (LST) and emissivity with 5600 m pixel size. This product contains 19 different layers, primarily, it also supplies the aggregated LST estimated by band 31 of the 1-km MOD11_L2 (LP DAAC 2019a), which layer was used in order to detect LST through the study time. Vegetation indices and reflectance bands are the mainly supplied data in MOD13A3 within 11 data layers, in which the NDVI layer, band Near Infrared (NIR), and band Middle Infrared (MIR) were extracted for the research. The MOD13A3 is a product of monthly generating MOD13A2 by an average algorithm. Thus, the spatial resolution of MOD13A3 is equal to MOD13A2, which achieves 1000 m (LP DAAC 2019b).

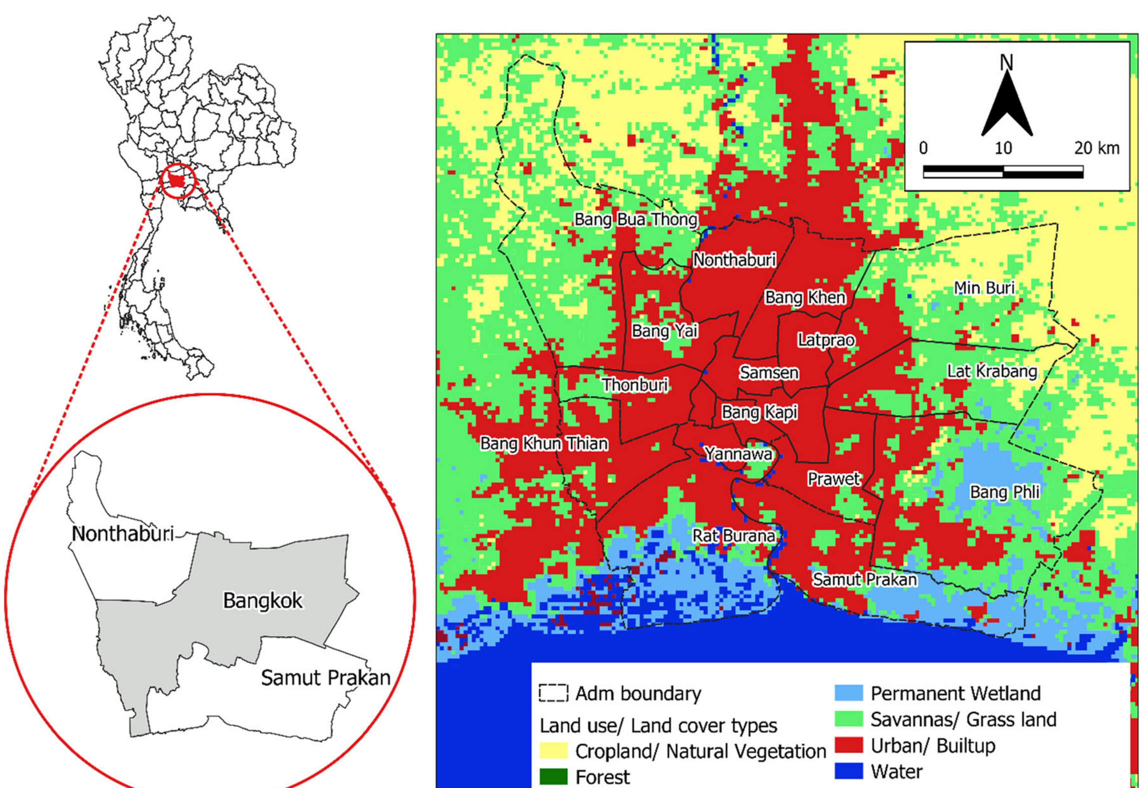

Fig. 2 The Bangkok Metropolitan Area location in central Thailand and component provinces and land cover map in 2017 simulated from MODIS Land Cover product (MCD12Q1)

Electricity consumption data

The electrical database was provided by the Metropolitan Electricity Authority. The database includes monthly sold electricity and total customers in the 18 districts. The amounts of total electricity consumption and consumers were categorized into seven sectors, including resident, small industry, medium industry, large industry, specific sectors, government, and total consumption. The number of customers implies the development of economy and urbanization (in social aspect) regarding the number of customers in industry and resident, respectively.

Methodology

The research was divided into three core work packages, including extraction of the SEF, analysis of economic growth, and exploration of correlation among variables and the total electricity consumption increase. The detailed framework describing data sources, analysis methods, and research outputs is shown in a flowchart below in Fig. 3.

MODIS preprocessing and remotely sensed base index retrieval

Dataset of MOD11B3 and MOD13A3 was simultaneously downloaded from the EOSDIS website using Cygwin software (NASA EOSDIS 2019). Subsequently, a set of preprocessing steps was automatically implemented by MODIStsp package on R language (Busetto et al. 2019). The preprocessing tasks consist of coordinate system correction, spatial subset, resolution resampling, scale applying, and layer extraction. Referenced projection is Universal Transverse Mercator (UTM) applying ellipsoid of WGS84 on zone 47 Northern, corresponding to the Thailand location.

The daytime-aggregated LST layer was extracted from MOD11B3, representing the thermal features. The Normalized Difference Vegetation Index (NDVI) layer in MOD13A3 was extracted to illustrate green space features. The NDVI layer was calculated using a ratio equation described by Tucker (1979), which is the ratio between a visible reflectance band of Red (620–670 nm) and NIR (Near Infrared, 841–876 nm). Although the MOD13A3 provides multiple vegetation indices, the product also gives four reflectance bands, including Red (620–670 nm), Blue (459–479 nm), NIR (Near Infrared, 841–876 nm), and MIR (Middle Infrared, 2105–2155 nm) (LAADS DAAC 2019). Thus, this research calculated the Normalized Difference Built-up Index (NDBI) using Eq. (1) on NIR and MIR bands. The NDBI index was applied to highlight urban surfaces such as built-up, road, pavement, and impervious surfaces (Zha et al. 2003; Bhatti and Tripathi 2014).

$$\mathrm{NDBI} = \frac{\mathrm{MIR}-\mathrm{NIR}}{\mathrm{MIR}+\mathrm{NIR}} \tag{1}$$

where MIR is middle-infrared wavelength ($\mu = 2105$–

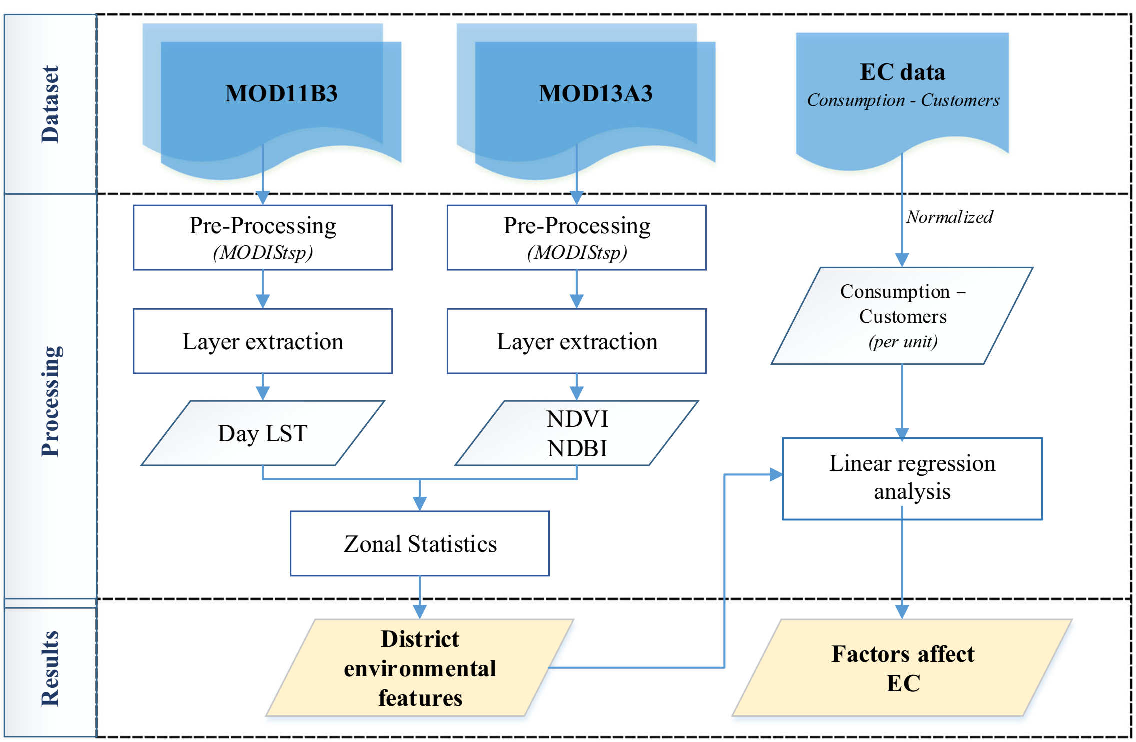

Fig. 3 A framework of methodology in this study

2155 nm), NIR is near-infrared wavelength ($\mu = 841$–876 nm).

Zonal statistics of surface environmental factors

Surface environmental factors (SEF) considered in the study were temperature, vegetation, and urban surfaces that were represented by LST, NDVI, and NDBI, respectively. These indicators are a monthly combination, and every single district consists of many pixels corresponding to specific values. The discrete pixels in each district were calculated as a single average number using Zonal statistics for multiband (ZSM) plugin (Silvani 2019). The ZSM synthesizes average values for all districts and months of the year in each index. Then, heatmap with cluster grouping was drawn based on the mean value of the SEF for better visualization.

Data normalization and linear regression analysis

The electricity consumption database is not similar to the environmental indices, which represents the usage and number of users in the entire district. Nevertheless, the total area of the counties is varied from district to district. Thus, to perform a peer group comparison, the electricity consumption and the number of users were standardized in the same measurement scale of kWh per km^2 and customers per km^2, respectively.

Subsequently, monthly variables of each district, including dependent variables (i.e., the normalized consumption in each sector) and independent variables (i.e., environmental indices, the normalized customer in each sector), were analyzed using simple linear regression and multiple linear regression. Simple regression illustrates a single effect, while multiple regression is expected to reveal cooperative impacts. The regressions were evaluated by the regression coefficient, R square (R^2). R square value is in the range of [0:+ 1]. The magnitude of R square presents the meaning of regression, e.g., the approaching one (1) value informs more significantly meaningful regression (Zou et al. 2003).

Results and discussions

Disturbance of surface environmental factors

Variation of surface environmental factors in the city was assessed through monitoring the shift in the value of NDVI, NDBI, and LST from 2010 and 2017. LST indicates changes of surface thermal environment, while NDVI and NDBI reveal variation of surface properties through changes of vegetated coverage and impervious surface expansion.

In general, green spaces in 2017 were declined compared to the year 2010, and the annual mean NDVI value decreased from 0.42 in 2010 to 0.41 in 2017. The built-up areas and impervious pavements typically replaced the green spaces. Conversely, the NDBI value speedily increased by the difference between annual mean values was 0.04. The urban surfaces are impervious, and water cannot infiltrate into the soil and evaporate into the atmosphere for cooling as a natural process often takes place on natural surfaces covered with vegetation (Lu and Weng 2006). Vegetation loss and paved surfaces propitiously contribute to elevate the thermal environment in urban areas (US EPA 2008). Observed data indeed revealed that LST slightly climbed from 34.45 to 34.47 °C. There was an increase of 0.02 °C over 7 years, in other words, it was only ~ 0.003 °C per year. This trend is not significantly different, but it shows a consistent trend with conversions of green and impervious covers. LST is broadly demonstrated that it negatively correlated with green cover areas and vice versa for impermeable surfaces.

The NDVI reveals not only potential vegetation types but also the vegetated greenness and proportion. The negative value range is non-vegetated surfaces (e.g., water, barren), while the approaching + 1.0 values represent dense vegetation (Tucker 1979; Burgan and Hartford 1993). The NDBI and NDVI values had a negative linear correlation, the correlation coefficient between these two land cover types, in this case, achieved a high correlation with $r = 0.82$ (Richard 1990; Mukaka 2012; Sun et al. 2012; Malik et al. 2019). The NDVI values throughout the districts reach positive values, while NDBI values occupy corresponding negative values (Fig. 4-a). Based on these two land cover features, BMA districts were clustered into two main groups corresponding to spatial patterns. Urban districts with high urban index and low vegetation index (NDVI < 0.3) were namely Lat Krabang, Bang Kapi, Bang Khen, Nonthaburi, Wat Liap, Yannawa, and Khlong Toei. On the contrary, the rest of the districts that held both low NDBI and high NDVI (NDVI > 0.5) were isolated as countryside districts (Fig. 4-a).

Surface temperature has a profoundly positive relationship with NDBI, while the temperature has a low correlation with NDVI with an inverse relation (Zhang et al. 2009; Sun et al. 2012; Rasul et al. 2015). Similarly, this study found statistically significant correlations ($P = 0.001$, $r = 0.53$ for NDBI, and $r = -0.35$ for NDVI). The districts distributed to two spatial patterns are relatively similar to NDVI-NDBI patterns. Districts with high surface temperature were these urban districts grouped by NDVI-NDBI and supplemented four moderate-high temperatures, including Prawet, Thonburi, Bang Khun Thian, and Bang Yai. The low-temperature countryside districts are where mean temperature did not exceed 33 °C during the observed period (Fig. 4-b).

The urbanization with SEF disturbance was convinced by variation of the indices of NDVI, NDBI, and LST. The urban index was detected increasing in almost all districts, while the vegetation index decreased correspondingly. The slowly urbanized counties were Min Buri, Bang Bua Thong,

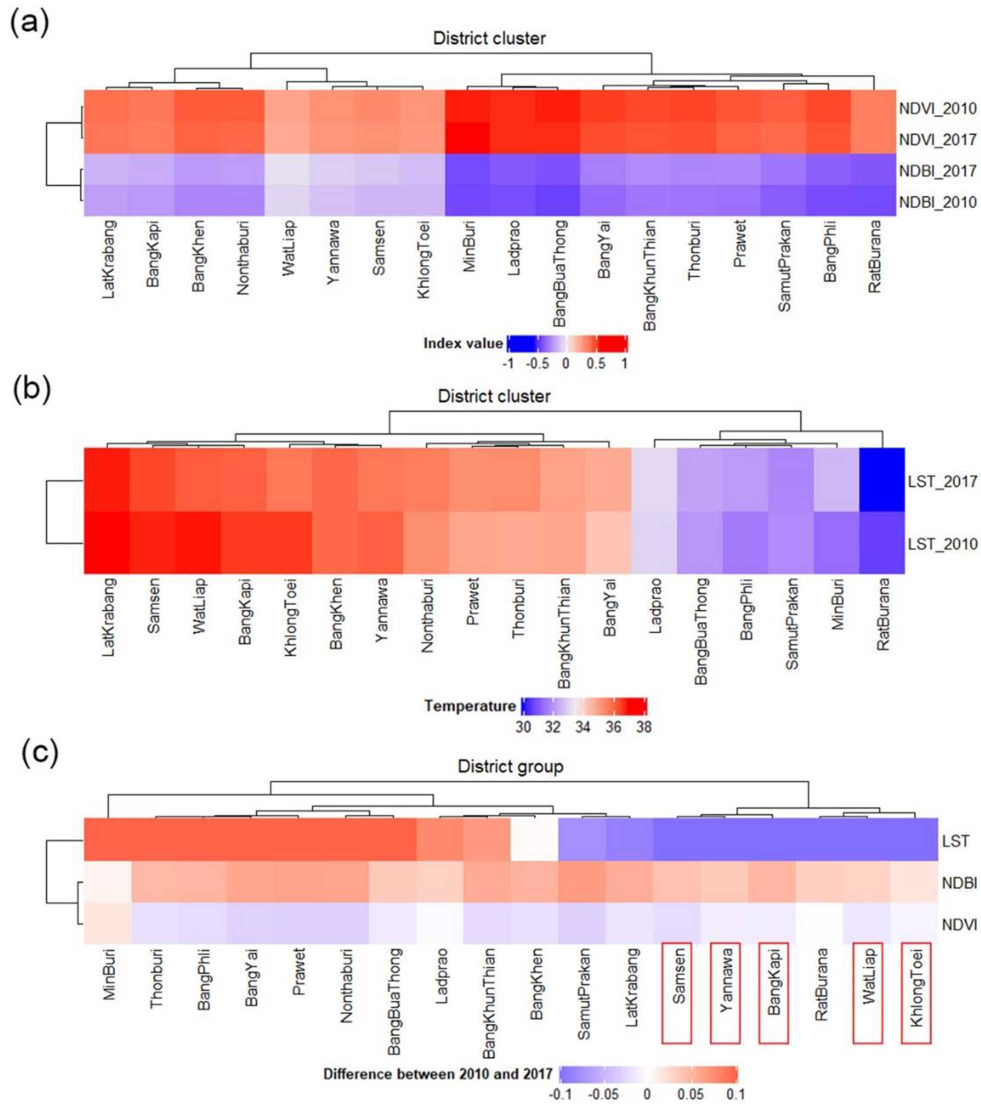

Fig. 4 Heatmap illustrates clusters and values of annual NDVI and NDBI (**a**), annual LST (**b**), and the difference between 2017 and 2010 on LST, NDBI, and NDVI (**c**)

Latprao, Rat Burana, Wat Liap, and Khong Toei, where there was a slight shift in urban and vegetation index. Based on the differences of SEF, the districts were considered as two primary groups, the high- and low-urbanized districts. The central counties (e.g., Samsen, Yannawa, Bang Kapi, Rat Burana, Wat Liap, Khlong Toei) typically had dense urban density, and so these places gradually expanded. In contrast, the remaining countryside counties exposed rapid urbanization (Fig. 4-c). The entire BMA surface temperature is obviously expected to rise owing to the mentioned urbanization and its relations with NDVI-NDBI. However, the LST only increased in the high-urbanized districts, i.e., countryside districts. The growth derives from the thermal contribution of expanded built-up areas. In explicitly, the additional heat from urban expansion in the inner city is less than amount in the suburban areas, since the urban districts have low urbanization rate. Moreover, the decline of LST occurred with the integration of a low urbanized rate and a climate phenomenon called weak La-Nina (WL) in 2017 (GGWS 2020). In La-Nina year, temperature will be colder than average temperature, and it will be warmer in El-Nino year (e.g., 2010: Moderate El-Nino). Min Buri was a curious county when both NDVI, NDBI, and LST increased in 2017. Min Buri is covered by the large area of cropland (as seen in land cover map in Fig. 2, "Study area description") (LDD 2012); the area significantly contributes to both vegetation index and LST during crop peak times and bare soil after harvesting, as a temporal heat absorption.

The variations of these SEF were not statistically significant in both the whole BMA and separated districts through the mean testing of two independent samples using the *t* test analysis. However, the slight changes in mean values of NDVI, NDBI, and LST obviously revealed the urbanization trend and formation of urban microclimate at BMA through the observation times.

Growth trends in electricity customers and consumption

Table 1 shows customer structure and shared proportion of usage in electricity subsectors. Regarding customer structure in the electricity business, residential client was the primary consumer who always accounted for three fourths to four-fifths of the total customers. The next sector was small industry with 23.2% and 19.2% in 2010 and 2017, respectively. Medium industry and large industry always accounted for less than 1% of customers. Large industry dominated only 0.1% of clients, but consumption in this sector was always the highest contributor, around 30%. The residential sector was the second highest consumer sector, which achieved the number of 21.6% and 23% in 2010 and 2017, respectively. Small and medium industries were the next main contributors to the total consumption.

In 2017, there were 7.95 million new users in all subsectors, in which 97.3% of the new users was in resident. Similarly, total consumption increased by 5549 million kilowatt-hours, with 41.9% in household demand and 36.4% for large industry. These raises revealed the urbanization trend in BMA in both demography and economic aspects. In terms of geographical aspect, urbanization is a spatial expansion of urban surfaces (Weng and Lu 2008), while demographers are interested in urban populations, including natural growth and immigrants. The urbanization in this research was considered as a rise of the resident users when the denizens increased and had an integrated need for both housing and electrical usage for their daily purposes.

The progression in the electrical business also proved the urbanization process and economic development in the BMA. The increase of household clients indirectly revealed population growth and housing development through their essential needs. The number of industrial customers represents economic development. Virtually all firms in BMA were reported to be small and medium-sized enterprises (World Bank Thailand 2016), which was proved by the growth of customers in small and medium industries. The principal industries in the BMA listed as automobile and automotive parts, electrical appliances and components, cement, auto manufacturing, heavy and light industries, plastic, textiles and garments, and so on. Moreover, the service sector (e.g., retail and tourism) is a potential branch and prioritized for development.

Table 1 Percentage of consumption and customer by sector (unit: percent)

Division	Year	res	sma	med	lar	spe	gov
Customers	2010	75.3	23.2	0.8	0.1	0.1	0.5
	2017	79.9	19.2	0.7	0.1	0.1	0.01
Consumption	2010	21.6	19.5	16.0	30.5	7.8	4.7
	2017	23.0	19.0	17.2	31.5	8.6	0.7

*Note: res = resident; sma = small industry; med = medium industry; lar = large industry; spe = specific sectors; gov = government

Dynamics affecting electricity consumption

Descriptive statistics

Table 2 presents descriptive statistics for the primary variables for discovering factors affecting electricity consumption, adopting regression analysis. The variables are divided into three clusters, which are customers and consumption in electricity subsectors, and environment variables. In general, the resident was a primary sector with customers fluctuated between 214 and 3803 users. Other sectors have negligible users. Especially, some districts have no users in the large industry, specific sectors, and government. However, consumption in residents was often in the range of 48 to 1557 million kilowatt-hours, which was smaller than the amount of industrial purposes. Consumption in industrial sectors always exceeded 2000 million kilowatt-hours, especially, the large industry even reached 5623 million kilowatt-hours. Concerning the environmental factors, districts had NDVI and NDBI range of 0.2–0.65, and −0.56–0.01, respectively. Surface temperature was remarkably different from district to district, with the temperature gap (or urban heat island intensity) up to 3.03 °C.

Regression analysis

Foremost, the effects of customer numbers in consumption were examined through simple linear regressions. The regression between the sum of customers and total consumption is medium-meaningful with $R^2 = 0.65$. More specifically, the high-meaningful regressions belong to the number of users in the industrial sectors (i.e., small-medium-large industry), with $R^2 > 0.85$, especially, large industry has $R^2 = 0.94$ (Table 3).

Subsequently, the environmental factors were tested in turn through single and multiple regression. The regression coefficients are shown in Fig. 5, which revealed both isolated and resonant effects on electricity consumption. Overall, the individual factors lowlier influence on sector's consumption and total usage. Among these three elements, NDBI and LST positively affected consumption and vice versa for NDVI. However, coefficients from simple regressions on NDBI were more significant than NDVI and LST, which means NDBI notably led to consumption rising. The contribution of LST was negligible because of $R^2 < 0.2$ in almost all sectors except for the residents ($R^2 = 0.38$). This impact was considered as a result of urbanization when green spaces were narrowed and dominated by urban landscapes. The multiple regressions

Table 2 Descriptive statistics on main variables, including customers and electricity consumption in different sectors, and environmental variables (NDVI, NDBI, LST). Consumption is in the unit of × 1000 kWh/km^2

Group	Variables	Minimum	Mean	Maximum	Standard deviation
Customer	Resident	214	1596	3803	1042
	Small industry	31	431	2229	544
	Medium industry	1	15	66	17
	Large industry	0	1	8	2
	Specific sector	0	3	14	4
	Government	0	5	62	12
	Total customer	253	2052	5335	2052
Consumption	Resident	48	609	1557	434
	Small industry	31	524	2619	625
	Medium industry	40	453	2365	469
	Large industry	47	845	5623	1062
	Specific sector	0	224	2658	498
	Government	0	70	778	159
	Total consumption	209	2726	14,141	2885
Environment	LST	21.44	34.44	41.26	3.03
	NDVI	0.20	0.41	0.65	0.10
	NDBI	− 0.56	− 0.28	0.01	0.13

explained better electricity usage, but these regressions were limited at medium meaningful, with $R^2 < 0.8$. The total consumption ($R^2 = 0.58$), medium industry ($R^2 = 0.60$), small industry ($R^2 = 0.66$), and resident utilization ($R^2 = 0.78$) were the most adequately described by the three variables linear regression.

These two regression analyses revealed that the electricity utilization was more influenced by user growth, which significantly induced the consumption in industrial sectors. Meanwhile, the environmental conversions led to a substantial increase in usage for residential and small industry purposes. The impacts of environmental disturbances on consumption were greater with integrated contributions. Besides, the consumption in the government sector was hard to explain by both the user number and surface environment.

Discussion

Monthly MODIS data is a composite product in which affected pixels by cloud were masked out and calculated by mean algorithm. Thus, the products hardly achieve high accuracy like using higher resolution data (e.g., Landsat), especially for surface temperature. Surface temperature is a sensitive data that is relatively affected by complex weather conditions in tropical climate. The indices of NDVI and NDBI are not quite suitable for observing urban expansion since NDVI and NDBI depend on absorb and reflectance radiation daytime in different weather conditions. Within the study, however, the spatial data is a target in order to extract the surface environmental factors in the whole BMA districts, which official meteorological data cannot adequately cover. In further research, the area of urban and vegetation on medium/high resolution will be potential data for quantitatively measuring urban expansion. Data frequency is one of the limitations when using medium-/high-resolution imagery, but users can consider it based on purposes.

Green space loss, urban expansion, surface temperature increase, growth of resident users, and industrial users generally represent different urbanization aspects, while urbanization is obviously a primary dynamic of the growth of electricity business. The total electricity consumption is mostly

Table 3 Regression coefficients (R^2) from simple linear regression between customer numbers in each electricity subsector and total electricity consumption. The regressions are statistically meaningful, with p value lower than the level of 0.01

	cus.res	cus.sma	cus.med	cus.lar	cus.spe	cus. gov	cus.total
Consumption	0.52	0.66	0.88	0.94	0.85	0.21	0.65

*Note: cus.res = Customer in resident; cus.sma = Customer in small industry; cus.med = Customer in medium industry; cus.lar = Customer in large industry; cus.spe = Customer in specific sectors; cus.gov = Customer in government; cus.total = total of customers in all sectors

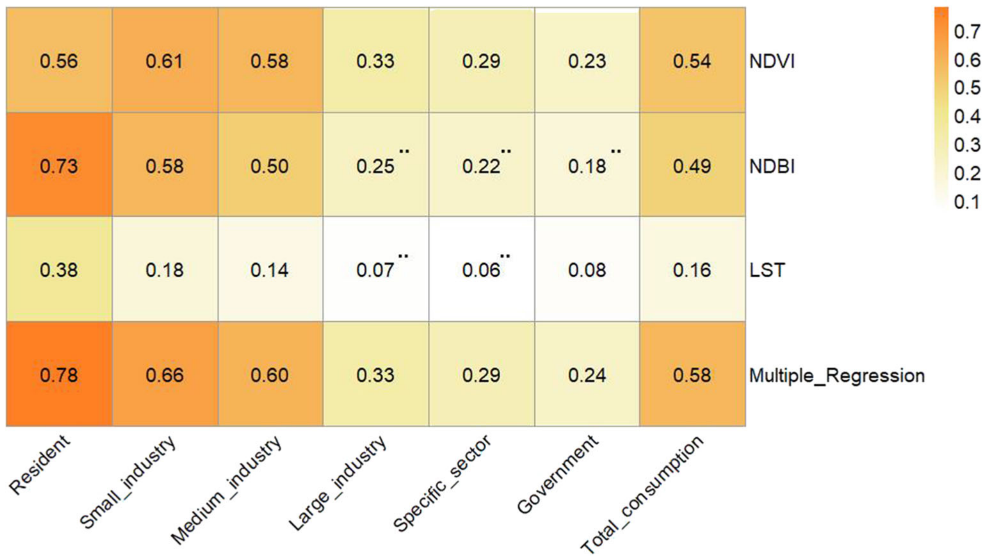

Fig. 5 Regression coefficients (R^2) from simple linear regression between NDVI, NDBI, LST, and electricity consumption by different fields; and the last row is from multiple linear regression between three environmental factors and consumption. Darker cell represents a higher R^2 value. All regressions are statistically meaningful, with p value lower than the level of 0.01 except variable with (¨) symbol is not significant in multiple regression

devoted by the economic factors (i.e., industrial sectors) more than the shifts in the surface environment. This research proved the temperature innocent in increasing the total consumption. Nevertheless, there is a sufficient basis to include the impacts of surface temperature in exaggerating electricity in the residential sector, while the significant contribution to the total energy comes from the industries. These relationships between energy consumption with socioeconomic factors and surface environment meaningfully support the electrical business. Further, the electrical business can better understand their leading clients and establish a development scenario based on the factors such as urban expansion, green loss, and population prediction, and so, the electrical business can predict the amount of necessary electricity and effectively supply the energy for sectors in the region.

Conclusions

This research demonstrated the disturbance of surface environmental factors. Increasing urban index and surface temperature and reducing vegetation index simultaneously revealed a general tendency of urbanization in BMA over 7 years from 2010 to 2017. The economic development was figured out through the growth of customers and consumption in different sectors. The residential sector was the most substantial increase in both customers and shared consumption, and large industry was the second-largest increase in consumption. The consumption was detected that it is more sufficiently contributed by industrial users. The environmental surface factors efficiently explained electricity consumption in small industry, medium industry, and significantly for the residential sector except large industry and specific sector. These two sectors could not even be interpreted by the urban index, the most meaningful contributor to the consumption among the surface environmental factors. Besides, the research also affirmed that surface temperature only strongly affected consumption in the residential sector, and this impact was relatively low for the rest sectors. The study proved the relationships between total consumption and urbanization-related factors. Understanding these relations is meaningful for the electricity business in forecasting future demand and provides adequate avoidance of power shortages.

Acknowledgments This study is a part of the first author's research in his intern scholarship at KMUTT Geospatial Engineering and Innovation Center (KGEO), Faculty of Science, King Mongkut's University of Technology Thonburi, Thailand. We especially thank the kind support and suggestions of Dr. Pariwate Varnakovida and MSc. Sanwit Iabchoon (KGEO) during this research. We extend our gratitude to the Metropolitan Electricity Authority, Thailand for their primary data support. Finally, we would also like to thank the National Aeronautics and Space Administration (NASA) for the MODIS dataset used throughout this research.

References

Al-Bajjali SK, Shamayleh AY (2018) Estimating the determinants of electricity consumption in Jordan. Energy 147:1311–1320. https://doi.org/10.1016/j.energy.2018.01.010

Arifwidodo S, Chandrasiri O (2015) Urban Heat Island and household energy consumption in Bangkok, Thailand. In: 2015 International Conference on Alternative Energy in Developing Countries and Emerging Economies. Elsevier B.V., pp 189–194

Bhatti SS, Tripathi NK (2014) Built-up area extraction using Landsat 8 OLI imagery. GIScience Remote Sens 51:445–467. https://doi.org/10.1080/15481603.2014.939539

BMA (2017) Bangkok profile. In: Bangkok Metrop. Adm. http://www.bangkok.go.th/main/page.php?&340&l=en. Accessed 11 Jan 2018

Burgan RE, Hartford RA (1993) Monitoring vegetation greenness with satellite data, Ogden

Busetto L, Ranghetti L, Wasser L, Hanson J (2019) A tool for automating download and preprocessing of MODIS land products data (MODIStsp)
Fan JL, Zhang YJ, Wang B (2017) The impact of urbanization on residential energy consumption in China: an aggregated and disaggregated analysis. Renew Sust Energ Rev 75:220–233. https://doi.org/10.1016/j.rser.2016.10.066
Fu P, Weng Q (2016) A time series analysis of urbanization induced land use and land cover change and its impact on land surface temperature with Landsat imagery. Remote Sens Environ 175:205–214. https://doi.org/10.1016/j.rse.2015.12.040
GGWS El Niño and La Niña years and intensities. In: Golden Gate Weather Serv https://ggweather.com/enso/oni.htm. Accessed 16 Feb 2020
Hassan MM (2017) Monitoring land use/land cover change, urban growth dynamics and landscape pattern analysis in five fastest urbanized cities in Bangladesh. Remote Sens Appl Soc Environ 7:69–83. https://doi.org/10.1016/j.rsase.2017.07.001
Karaman B (2019) Bangkok's electricity consumption hits new record high. In: Thail. Bus. News. https://www.thailand-business-news.com/environment/72026-bangkoks-electricity-consumption-hits-new-record-high.html. Accessed 3 Jun 2019
Keivani R (2010) A review of the main challenges to urban sustainability. Int J Urban Sustain Dev 1:5–16. https://doi.org/10.1080/19463131003704213
Koen V, Asada H, Rizwan M, Rahuman H (2018) Boosting productivity and living standards in Thailand. OECD Econ Dep Work Pap. https://doi.org/10.1787/e525c875-en
LAADS DAAC (2019) Terra & Aqua Moderate Resolution Imaging Spectroradiometer (MODIS). In: Level-1 Atmos. Arch. Distrib. Syst. Distrib. Act. Arch. Cent. https://ladsweb.modaps.eosdis.nasa.gov/missions-and-measurements/modis/. Accessed 18 May 2019
LDD (2012) Land use map in central plain of Thailand 2010–2012. In: L. Dev. Dep. http://www.ldd.go.th/ldd_en/en-US/map/map-details/land-use-in-the-central-region/1/. Accessed 15 Feb 2020
Liu X, Sun T, Feng Q, Zhang D (2020) Dynamic nonlinear influence of urbanization on China's electricity consumption: evidence from dynamic economic growth threshold effect. Energy 196:117187. https://doi.org/10.1016/j.energy.2020.117187
LP DAAC Terra Land Surface Temperature/Emissivity Monthly L3 Global 6 km SIN Grid. In: L. Process. Distrib. Act. Arch. Cent. https://lpdaac.usgs.gov/products/mod11b3v006/. Accessed 18 May 2019a
LP DAAC Terra Vegetation Indices Monthly L3 Global 1 km SIN Grid. In: L. Process. Distrib. Act. Arch. Cent. https://lpdaac.usgs.gov/products/mod13a3v006/. Accessed 18 May 2019b
Lu D, Weng Q (2006) Use of impervious surface in urban land-use classification. Remote Sens Environ 102:146–160. https://doi.org/10.1016/j.rse.2006.02.010
Malik MS, Shukla JP, Mishra S (2019) Relationship of LST, NDBI and NDVI using landsat-8 data in Kandaihimmat watershed, Hoshangabad, India. Indian J Geo Marine Sci 48:25–31
MEA (2013) Annual Report 2013. "Leveraging for tomorrow." Bangkok metropolis
MEA (2016) Sustainability report 2016. Move forward to Smart Metro. Bangkok metropolis
Mohan M, Kandya A (2015) Impact of urbanization and land-use/land-cover change on diurnal temperature range: a case study of tropical urban airshed of India using remote sensing data. Sci Total Environ 506–507:453–465. https://doi.org/10.1016/j.scitotenv.2014.11.006
Mukaka MM (2012) A guide to appropriate use of correlation coefficient in medical research. Malawi Med J 24:69–71. https://doi.org/10.1016/j.cmpb.2016.01.020
Murakamia A, Zain AM, Takeuchi K et al (2005) Trends in urbanization and patterns of land use in the Asian mega cities Jakarta, Bangkok, and Metro Manila. Landsc Urban Plan 70:251–259. https://doi.org/10.1016/j.landurbplan.2003.10.021
NASA EOSDIS How To: Use the download access script. In: Earth Data Wiki. https://wiki.earthdata.nasa.gov/display/EDSC/How+To%3A+Use+the+Download+Access+Script. Accessed 18 May 2019
Ostro B, Chestnut L, Vichit-Vadakan N, Laixuthai A (1999) The impact of particulate matter on daily mortality in Bangkok, Thailand. J Air Waste Manage Assoc 49:100–107. https://doi.org/10.1080/10473289.1999.10463875
Pongsapich A, Wongsekiarttirat W (1994) Urban household energy consumption in Thailand. Energy 19:509–516
Rasul A, Balzter H, Smith C (2015) Spatial variation of the daytime surface urban cool island during the dry season in Erbil, Iraqi Kurdistan, from Landsat 8. Urban Clim 14:176–186. https://doi.org/10.1016/j.uclim.2015.09.001
Richard T (1990) Interpretation of the correlation coefficient: a basic review. J Diagnostic Med Sonogr 6:35–39. https://doi.org/10.1177/875647939000600106
Ruangwises S, Ruangwises N (2009) Occurrence of aflatoxin M1 in pasteurized milk of the School Milk Project in Thailand. J Food Prot 72:1761–1763. https://doi.org/10.4315/0362-028X-72.8.1761
Santamouris M, Cartalis C, Synnefa A, Kolokotsa D (2015) On the impact of urban Heat Island and global warming on the power demand and electricity consumption of buildings–a review. Energy Build 98:119–124. https://doi.org/10.1016/j.enbuild.2014.09.052
Shahbaz M, Sbia R, Hamdi H, Ozturk I (2014) Economic growth, electricity consumption, urbanization and environmental degradation relationship in United Arab Emirates. Ecol Indic 45:622–631. https://doi.org/10.1016/j.ecolind.2014.05.022
Silvani D (2019) Zonal statistics for multiband raster
Srivanit M (2012) Assessing the impact of urbanization on urban thermal environment: a case study of Bangkok metropolitan. Int J Appl Sci Technol 2:243–256
Srivanit M, Hokao K, Phonekeo V (2012) Assessing the impact of urbanization on urban thermal environment: a case study of Bangkok metropolitan. Int J Appl Sci Technol 2:243–256
Sun Q, Wu Z, Tan J (2012) The relationship between land surface temperature and land use/land cover in Guangzhou, China. Environ Earth Sci 65:1687–1694
Tontisirin N, Phoomikiattisak D, Anantsuksomsri S (2017) Land use change in the eastern economic corridor of Thailand: an application of cellular automata-Makov Model. In: The 54th Annual Meeting of the Japan Section of the RSAI. pp 1–7
Tsuchiya K, Hara Y, Thaitakoo D (2015) Linking food and land systems for sustainable peri-urban agriculture in Bangkok Metropolitan Region. Landsc Urban Plan 143:192–204. https://doi.org/10.1016/j.landurbplan.2015.07.008
Tucker CJ (1979) Red and photographic infrared linear combinations for monitoring vegetation. Remote Sens Environ 8:127–150. https://doi.org/10.1016/0034-4257(79)90013-0
Ubani O (2013) Determinants of the dynamics of electricity consumption in Nigeria. OPEC Energy Rev 37:149–161. https://doi.org/10.1111/opec.12004
US EPA (2008) Urban heat island basics. In: Reducing urban heat islands: compendium of strategies. Washington, DC: U.S. Environmental Protection Agency
Wangpattarapong K, Maneewan S, Ketjoy N, Rakwichian W (2008) The impacts of climatic and economic factors on residential electricity consumption of Bangkok Metropolis. Energy Build 40:1419–1425. https://doi.org/10.1016/j.enbuild.2008.01.006
Weng Q, Lu D (2008) A sub-pixel analysis of urbanization effect on land surface temperature and its interplay with impervious surface and vegetation coverage in Indianapolis, United States. Int J Appl Earth Obs Geoinf 10:68–83. https://doi.org/10.1016/j.jag.2007.05.002

World Bank Thailand (2016) Getting back on track: reviving growth and securing prosperity for all. Thailand Systematic Country Diagnostic. World Bank Group, Washington

Yamtraipat N, Khedari J, Hirunlabh J, Kunchornrat J (2006) Assessment of Thailand indoor set-point impact on energy consumption and environment. Energy Policy 34:765–770. https://doi.org/10.1016/j.enpol.2004.07.009

Yang Y, Liu J, Lin Y, Li Q (2019) The impact of urbanization on China's residential energy consumption. Elsevier B.V

Zha Y, Gao J, Ni S (2003) Use of normalized difference built-up index in automatically mapping urban areas from TM imagery. Int J Remote Sens 24:583–594. https://doi.org/10.1080/01431160304987

Zhang Y, Odeh IOA, Han C (2009) Bi-temporal characterization of land surface temperature in relation to impervious surface area, NDVI and NDBI, using a sub-pixel image analysis. Int J Appl Earth Obs Geoinf 11:256–264. https://doi.org/10.1016/j.jag.2009.03.001

Zhang M, Zhang K, Hu W, Zhu B, Wang P, Wei YM (2020) Exploring the climatic impacts on residential electricity consumption in Jiangsu, China. Energy Policy 140:111398. https://doi.org/10.1016/j.enpol.2020.111398

Zou KH, Tuncali K, Silverman SG (2003) Statistical concepts series: correlation and simple linear regression. Radiology 227:617–622. https://doi.org/10.1148/radiol.2273011499