

Article

Energy Consumption Prediction in Vietnam with an Artificial Neural Network-Based Urban Growth Model

Hye-Yeong Lee, Kee Moon Jang  and Youngchul Kim * 

KAIST Urban Design Lab, Department of Civil and Environmental Engineering, KAIST, Daejeon 34141, Korea; leehy305@kaist.ac.kr (H.-Y.L.); keemoonjang@kaist.ac.kr (K.M.J.)

* Correspondence: youngchulkim@kaist.ac.kr; Tel.: +82-42-350-3636

Received: 21 July 2020; Accepted: 17 August 2020; Published: 19 August 2020



Abstract: In developing countries, energy planning is important in the development planning due to high rates of economic growth and energy demand. However, existing approaches of energy prediction, using gross domestic product, hardly demonstrate how much energy specific regions or cities may need in the future. Thus, this study seeks to predict the amount of energy demand by considering urban growth as a crucial factor for investigating where and how much energy is needed. An artificial neural network is used to forecast energy patterns in Vietnam, which is a quickly developing country and seeks to have an adequate energy supply. Urban growth factors, population, and night-time light intensity are collected as an indicator of energy use. The proposed urban-growth model is trained with data of the years 1995, 2000, 2005, and 2010, and predicts the light distribution in 2015. We validated the model by comparing the predicted result with actual light data to display the spatial characteristics of energy-consumption patterns in Vietnam. In particular, the model with urban growth factors estimated energy consumption more closely to the actual consumption. This spatial prediction in Vietnam is expected to help plan geo-locational energy demands.

Keywords: artificial neural network; energy consumption; energy demand; urban growth; night-time satellite light data

1. Introduction

It is important to forecast energy demand, especially in developing countries. The problem with developing countries in the past was that the supply of electric energy was significantly inadequate. The World Bank [1] reported that nearly one billion people worldwide scarcely use electrical energy, and about three billion people still live on inefficient energy sources, such as wood and coal. Most developing countries, such as Ethiopia and India, want to quickly supply energy to people lacking it, since these countries have less access to electricity than do developed countries [1]. For such developing countries, energy-demand forecasting is essential for solving energy poverty.

The situation in Vietnam was not different. In the 1990s, Vietnam had an electrical access of 74.11%, and the situation in rural areas was more severe, at 68.01% [1]. In order to solve this problem, Vietnam's electricity supply has started to increase, based on hydroelectric power generation using the plentiful hydropower resources in Vietnam. As a result, Vietnam now boasts a rural electrification rate of over 98% [2].

Vietnam seems to have solved most of its energy-poverty problems by reaching the same level of electricity accessibility as in advanced countries. However, Vietnam has entered a new phase where energy demand is increasing rapidly. This is partly due to its growth in the industrial and service sectors, which were underdeveloped when the country's economy heavily relied on agriculture. Following this

socio-economic development, Vietnam's GDP rapidly increased, from 6.47 billion USD in 1990 to 223.86 billion USD in 2017, and more than 35% of Vietnam's population currently lives in urban areas [1]. This situation results in an increase in the energy demand in Vietnam. World Group [1] announced that electricity consumption increased by 43.62% over the four years to 2015. Now, Vietnam's concern is with energy distribution, which is necessary to provide energy to the customers efficiently. In other words, it is urgent and critical in Vietnam to have an adequate power supply for the development of cities and growth of the national economy. In this sense, such socio-economic changes in Vietnam need a predictive model for energy supply and demand. Therefore, it is necessary to consider factors related to economic and urban growth in order to estimate future energy consumption in Vietnam.

2. Background

2.1. Approaches in Predicting Energy Demand

The prediction of electrical energy demand has been an important issue in previous studies. Various models that use economic factors have been developed to predict energy demand. Arbex and Perobelli [3] developed an input–output growth model to analyze the effects of economic growth on energy consumption, and Mu et al. [4] developed an input–output table of electricity demand in China based on national economy measures. More recently, data-driven models based on machine learning algorithms have been adopted in order to predict energy demand with a higher level of accuracy. Al-Musaylh et al. [5] complementarily used multivariate adaptive regression spline (MARS), support vector regression (SVR), and autoregressive integrated moving average (ARIMA) models for short-term energy demand forecasting in Queensland, Australia, and Chang [6] revised the back propagation neural network (BPNN) model with the use of latent information (LI) function to be applicable for small-data-set learning in short-term electricity consumption forecasting.

In addition, the Vietnam Energy Outlook Report 2017 [7], provided by the Ministry of Industry and Trade (MOIT), the government agency in Vietnam, shows that Vietnam is forecasting its energy demand by creating three scenarios for GDP growth: Low Scenario, Business-as-usual Scenario (BAU), and High Scenario. The Low Scenario assumes that the region's economy will suffer many difficulties. Conversely, the High Scenario anticipates that there will be very concrete changes in the economy. Finally, the BAU Scenario assumes that the economy will recover globally and supposes an economic status between that of the Low and High Scenarios. The scenarios predict the final energy demand through multiple regression equations between energy demand and GDP. The advantage of this approach is that all three scenarios can predict energy demand, allowing flexibility in setting up energy-supply measures that depend on the economic situation. In addition, long-term prediction is possible, although the predicted value may show a large error.

However, although these economic indicators are important for predicting energy demand, existing models rarely consider the spatial distribution of electrical-energy demand. The amount of energy demand can be obtained only as a numerical value rather than as spatial information. For Vietnam's immediate need for energy supply, it is important to find out where and how much energy is needed. Therefore, this paper focuses on the geographical form of urban growth, in order to find out other spatial factors that affect energy usage. Previous studies have revealed that the form of urban growth can have great influence on the energy-consumption pattern [8]. The growth of cities is also comprehensive information that reflects economic factors, human activity, and social making.

2.2. Approaches in Predicting Urban Growth

The geographical form of urban growth is also important for building an energy-forecasting model in the urban environment. Previous studies sought to develop a numerical model of urban growth to effectively identify urban changes and predict urban growth. The extent of urban growth was defined by applying a mathematical correlation between factors in urban areas (e.g., [9–14]). Urban growth models sought to use urban-relevant elements, including the amount of population growth, consumption of

land, and degree of transportation development, but rarely considered the spatial form of cities [9]. Land-use and land-cover change (LUCC) that explains the topological characteristics of certain areas was also adopted to develop an urban growth model [10], which classified the urban area in terms of land forms, such as temperate mixed forest, plantation, grassland, and urban settlement, and its functions, such as forestry, agriculture, residential, commercial, and industries. For such analysis, Markov matrices were widely used. However, this model describes general tendencies of changes in cities and hardly specifies the changes. Batty [11] developed a model to simulate the spatial interaction between various locations of human activities, called the Land-Use Transportation (LUT) Model, which includes human activities as factors of urban growth. However, the model needs to establish a dataset of human activities, relevant data on which is hard to find in developing countries. Additionally, an urban dynamic process was analyzed to develop a model of urban growth and change. Sudhira et al. [12] sought to measure the potential threats to sustainable development named urban sprawl, and Jat et al. [15] developed this idea to predict the future using Geographic Information System (GIS) and remote sensing. Tayyebi et al. [13] developed an urban growth boundary model (UGBM) that investigated the extent of urban growth as a boundary vector using spatial logistic regression (SLR). Although these studies are a new method for measuring cities, both the extent of urban expansion and the degree of urbanization of that expanded area are not well measured numerically. A two-dimensional lattice of cells that is a cellular automaton (CA) was also adopted to construct a model by representing a site [14]. The SLEUTH model, usually called the Clarke Cellular Automaton Urban Growth Model, was improved from this cellular automaton model for simulating urban growth in advanced cities as in North America, based on abundant geographic information from the United State Geological Survey (USGS) [16]. Thus, previous studies on urban-growth measurement are being actively studied through improved GIS technology and remote sensing.

Because energy usage is a consequence of the economy and other factors, we want to create a model that predicts energy needs through urban growth. That is, we will include the forms of urban growth for predicting energy consumption in Vietnam in order to investigate how urban change affects energy demand. Accordingly, we attempt to combine these advanced urban-growth models with energy-consumption prediction.

3. Methods

To predict energy demand, we sought to develop a new method in a comprehensive way. In particular, the main research question was how urban change affects energy demand. It was divided into three parts. How can we identify the spatial distribution of electrical energy consumption? How can energy consumption be predicted with an urban growth pattern? What factors are used as inputs and outputs of the model?

3.1. How Can We Identify the Spatial Distribution of Electrical Energy Consumption?

We intended to study how urban growth factors affect energy demand, so we used the spatial indicator of urban change, which refers to data per pixel obtained by dividing the entire site area into a constant grid shape. Therefore, the predicted energy demand as output should have been secured as spatial data. However, it was difficult to directly obtain the spatial distribution of energy use, because Geographic Information System (GIS) data is not constructed well in developing countries such as Vietnam [17], whereas many developed countries have been promoting national strategic development projects through the GIS. Furthermore, in order to find the exact spatial distribution of energy consumption, it was necessary to find not only the locations of all buildings in Vietnam, but also the energy used by each building. However, obtaining such data was so complicated that it was hardly possible. Therefore, we needed data that could replace building information data.

Among alternatives, this study focused on night-time satellite data. Since the National Oceanic and Atmosphere Administration (NOAA) collected the night-time satellite data, various studies have been carried out based on its application. Existing studies have shown that night-time satellite

data can be used as two types of indicators: economic and electrification related. In economic terms, it was shown that night-time satellite data and economic activity have a strong correlation with GDP [18], and a map of calibrated poverty levels was drawn by being combined with other geographic information [19]. However, this study assumed that night-time satellite data could indicate energy-consumption patterns. Previous studies asserted that night-time light output can be used to classify electrified villages and distant areas accurately. Above all, there is a linear relation between DMSP (Defense Meteorological Satellite Program) night-time light data and electrical-power consumption [20], and the spatial characteristics of energy-power consumption have a pattern similar to that of night-time satellite data [21]. In addition, such data provides a spatial distribution of the energy consumption within a grid pattern and is available to anyone through NOAA. For these reasons, we assumed that the night-time light image was an indicator of the energy-consumption pattern. Based on this assumption, we estimated energy demand by predicting future light data in this study.

Night-time satellite light data, which is used as an indicator of energy consumption in this study, is among the remote sensing data given by the Defense Meteorological Satellite Program-Operational Line Scan System (DMSP-OLS). The two OLS sensors detect visible/near-infrared (0.4 to 1.1 μm) and thermal infrared (10.5 to 12.6 μm) wavebands with a resolution of 30×30 arc-seconds, giving about a 1×1 km resolution. This night-time light data has been generated as a form of 'stable light image' per year, which excludes sunlight, glare, moonlight, auroras, and observation with clouds. Therefore, it contains the predicted brightness from cities, towns, and other sites with persistent lighting, including gas flares. The brightness of each grid is recorded with a digital number (DN) ranging from 0 to 63 in a relative 6-bit scale. Accordingly, this digital number was used as a prediction output in this study, and the data from 1995 to 2010 is shown in Figure 1.

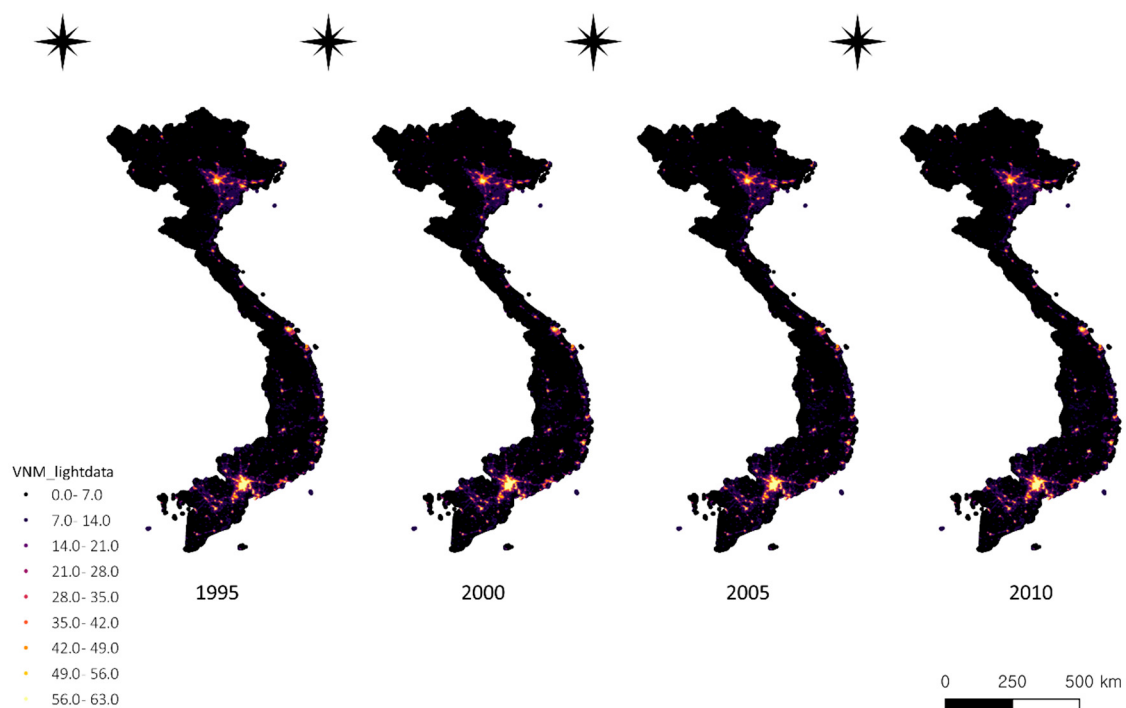


Figure 1. Vietnamese night-time light pattern from 1995 to 2010.

3.2. How Can Energy Consumption Be Predicted by an Urban Growth Pattern?

To successfully predict energy consumption from an urban growth pattern, two requirements need to be considered. First, the prediction model should be able to predict the site attribute, since night-time satellite data exists as grid information. Second, the model should include various urban growth factors to conform with the aim of this research. In order to meet these two conditions, we selected an Artificial Neural Network (ANN) as a method to establish a model that can predict future night-time satellite

data. According to previous research, ANN overcomes the limitations of existing models, which have a limited number of rules and extremely high time consumption, and can show the relationship between current site attributes and potential future urban growth (Maithani, 2009). In addition, ANN has the advantage of applying various kinds of data regardless of its distribution [22]. Thus, the ability to predict changes in urban growth through site attribute data with various types of distribution satisfied the requirements of this study.

The most basic element in ANN is a neuron. Each neuron is located in a different layer and inputs a factor to produce the desired data [23]. The ANN architecture represents the arrangement of neurons in each layer and the connections between them [22]. A feed-forward multilayer perception of ANN architecture consists of three layers: an input layer, a hidden layer, and an output layer. The input layer is determined by the input data source, and the number of hidden neurons is found out by trial and error [24]. Thus, the neurons in each layer in the ANN architecture were assigned to have adequate weights and bias from training.

3.3. What Factors Are Used as Inputs and Output of the Model?

As mentioned in the previous section, ANN trains several inputs to one output to analyze the network between them; so the composition of the input data plays a very important role. In order to consider the effect of urban-change factors on energy-consumption patterns and conduct precise data analysis, we assumed that predicted night-time satellite data was defined as a function of three main factors: urban growth, population, and night-time light satellite data.

3.3.1. Urban Growth Factor

Vietnam is located on the eastern shore of the Indochinese Peninsula in Southeast Asia and stretches approximately 1650 km from north to south. Laos and Cambodia are across the border to the west, China to the north, and coastal areas to the east and south. Vietnam has mountains in the north and a highland region in the central part of the country. In particular, it has an unusual terrain with two main deltas from the Hong and Mekong rivers. Considering the huge influence of landscape topography on the residential use of land [25], these geographical characteristics of Vietnam are expected to have a great influence on the formation of cities. Therefore, we selected the distance to the water area and the elevation as representative characteristics of topography and city blooming. GTOPO30, which is a global digital elevation model (DEM) developed by the U.S. Geological Survey's Center for Earth Resources Observation and Science, was used as the elevation information in this research. The data was constructed as a raster topographic information with a horizontal grid spacing of 30 arc seconds, as shown in Figure 2. In addition, the distance from each pixel to the nearest water area shown in Figure 3 (i.e., lake, river, small water flow, etc.) was calculated in QGIS software. Therefore, all pixels contained both elevation and the distance to the nearest water. Finally, we attempted to add spatial extensibility of the terrain into the model to better use topographic information. The composition of surrounding cells within a certain area has a neighborhood effect on the central cell, influencing its characteristics [26]. Thus, gradients of elevation of each pixel towards east, west, south, north, southwest, southeast, northwest, and northeast were added using QGIS. Particularly, in this study, the gradient to the border of Vietnam was set as infinite, because of the prediction rule that the higher the gradient, the lower the spatial scalability and eventually the urban growth. This "preset to infinite" indicates that urban expansion in that direction is impossible. Since this topographical information assumed that there is no change and had virtually no annual data, this study did not include time-dependent changes. Therefore, urban growth factors included elevation, distance to water area, and gradients of elevation in eight directions, i.e., east, west, south, north, southwest, southeast, northwest, and northeast.

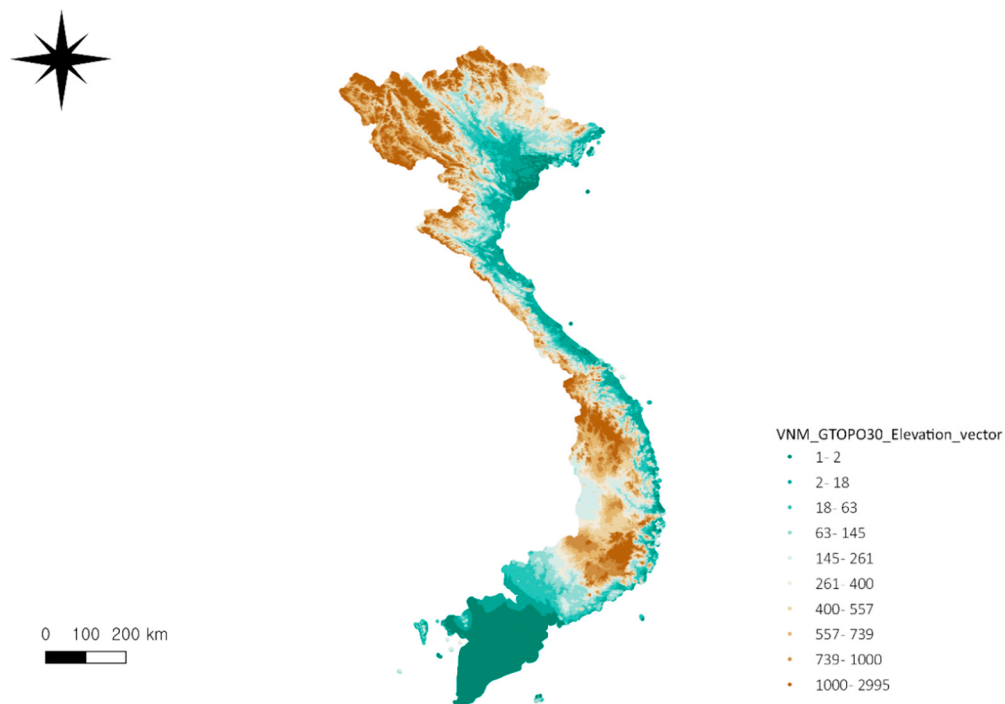


Figure 2. GTOPO30 elevation data of Vietnam from the U.S. Geological Survey's Center for Earth Resources Observation and Science.

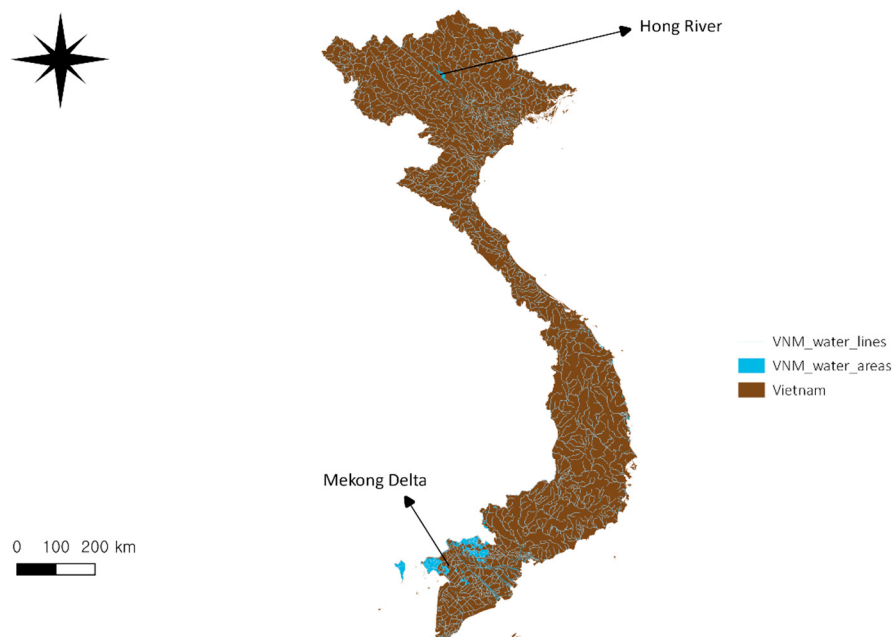


Figure 3. Vietnamese River and water flows.

3.3.2. Population

Although the topographic aspects of Vietnam were considered in the previous section, this section highlights human activity in Vietnam. Human activity has been involved in shaping cities and revitalizing the economy, so it is expected to affect energy usage. In fact, there is also a tendency to see DMSP night-time light data as a result of human activity [20]. Therefore, this study suggested that an increase in population resulting from people gathering in a certain location would lead to the formation of cities and economic development, and eventually have a great influence on the consumption of electrical energy. The population data of 1995, 2000, 2005, and 2010 were used. The population of each

cell was calibrated by the US Department of Energy, Oak Ridge National Laboratory, system known as LandScan, which does a survey of population data. LandScan measured the population of the area where people were staying for a short period of time [19]. Hence, its data was optimized to indicate the residence of humans. An example of the LandScan population data is depicted in Figure 4.

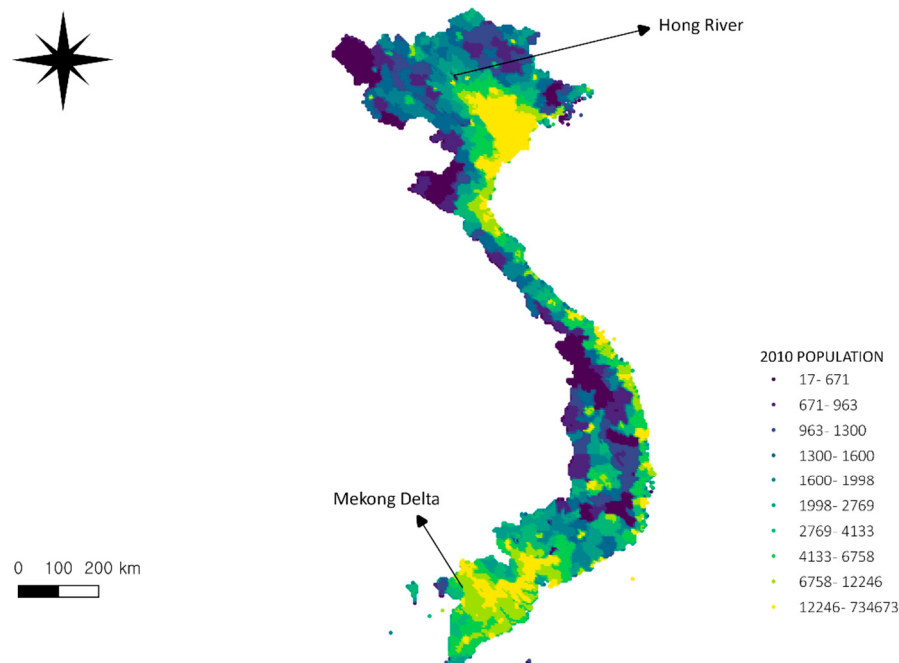


Figure 4. LandScan population data for 2010 in Vietnam.

3.3.3. Present Night-Time Light Satellite Data and Its Slope toward North, South, East, West

Finally, we tried to obtain more sophisticated future light data values by inputting night-time light data. We used time-series data to improve predictability of light data. All data from 1995 to 2010 and the variation over time was used for prediction. By the neighborhood effect, the light data of the center grid would have been affected by the surrounding data, so the spatial extensibility was also a matter of concern. It was also obtained by calculating gradients in the center, east, west, north, southeast, southwest, northeast, and northwest using QGIS in the same way as for elevation.

3.4. Implementation of ANN

3.4.1. Data Preparation

In this study, a raster image of Vietnam in a 2.5×2.5 km resolution unit was converted to a point vector layer, consisting of approximately 40,000 pixels with input data corresponding to each position. Likewise, the night-time light satellite data, which was selected as output data, was entered in the same way, with values ranging from 0 to 63. This study built two Tests in order to compare the effect of urban growth. For Test 1, data was modified into all the above types of input, except for topographic information, in 1995, 2000, and 2005 to perform time forecasting; the total number of neurons in the input layer was 42, as represented in Table 1. For Test 2, only the annual light data from 1995 to 2010, including its gradients and change over time, was used in the input; in total, 29 neurons were used, as summarized in Table 2.

Table 1. The Artificial Neural Network (ANN) architecture composition of Test 1 for Training.

Input, Output	Factor	Detailed Type of Neuron	Position of Neuron in Layer
Input	Urban Growth factor	Elevation	1
		The distance to the water area	2
		Gradients of elevation in 8 directions	3~10
	Population	Population for 1995, 2000, 2005	11~13
	Night-time Satellite Light	Night-time light data for 1995, 2000, 2005	14~16
		Gradients of light data in 8 directions for 1995, 2000, 2005	17~40
		Change of light data over time from 1995 to 2000 and one from 2000 to 2005)	41~42
Output	Night-time Satellite Light	Night-time light data for 2010	1

Table 2. The ANN architecture composition of Test 2 for Training.

Input, Output.	Factor	Detailed Type of Neuron	Position of Neuron in Layer
Input	Night-time Satellite Light	Night-time light data for 1995, 2000, 2005	1~3
		Gradients of light data in 8 directions for 1995, 2000, 2005	4~27
		Change of light data over time from 1995 to 2000 and one from 2000 to 2005)	28~29
Output	Night-time Satellite Light	Night-time light data for 2010	1

3.4.2. Generating Network

This study used the feed-forward net function of Matlab Neural Network Toolbox, which created a multilayer feed-forward network to implement ANN. A feed-forward network consists of input, hidden, and output layers that are connected to each other. The first data enters the input layer and connects with each subsequent neuron in the hidden layer. This multilayer feed-forward network had 10 neurons within one hidden layer, since it was a shallow network. Finally, mapping to the output generated the new multilayer network. The first network was built and initiated manually to conduct this process.

3.4.3. Training Network and Testing

Network training is the process of discovering the relationship between the input neurons initially provided and the final output neurons. The network is prepared for starting training after finishing initiation of network weights and bias. These weights and bias are tuned during training to optimize performance, which is defined by the network performance function, mean square error (MSE). MSE is the average squared error between the network output and the targeted output. Therefore, there are some optimization algorithms using either the gradient of the network performance or the Jacobian of the network errors for the weights. This optimization method to calculate the gradient and the Jacobian is called the back-propagation algorithm. Matlab offers various back-propagation algorithms that perform backward computations through the network: Levenberg–Marquardt, Bayesian Regularization, Scaled Conjugate Gradient, Gradient Descent, Quasi-newton, Resilient Back-propagation, and so on. For this study, we used the Levenberg–Marquardt algorithm, which has the fastest convergence for training (Maithani, 2009). As mentioned earlier, the ANN architecture for training was composed as in Tables 1 and 2. The feed-forward network divided the total of 401,839 points for Vietnam into three parts: Training, Validation, and Testing samples. Of all the samples, 70% were used for training, and 15% each for validation and Testing. Training samples were used for tuning according to the

resulting errors during training. Validation samples were applied for network generalization to end training when this generalization stopped improving. Testing samples were independently used to test network performance during and after training. Figure 5 shows the performance plot of Test 1 versus the iteration number. If the MSE value reached the minimum, the iteration was stopped. Finally, this training process would generate the network containing each weight and bias.

The next step was the Testing process. Tables 3 and 4 show the architecture of ANN for Testing. The crucial point was that the data after five years was in the same position in the ANN architecture. In addition, since the final predicted 2015 light data should have been the output through the Testing process, no data should have been put into the output neuron. Therefore, if we re-entered the input data after 5 years based on the calculated network, we could get a new predicted output.

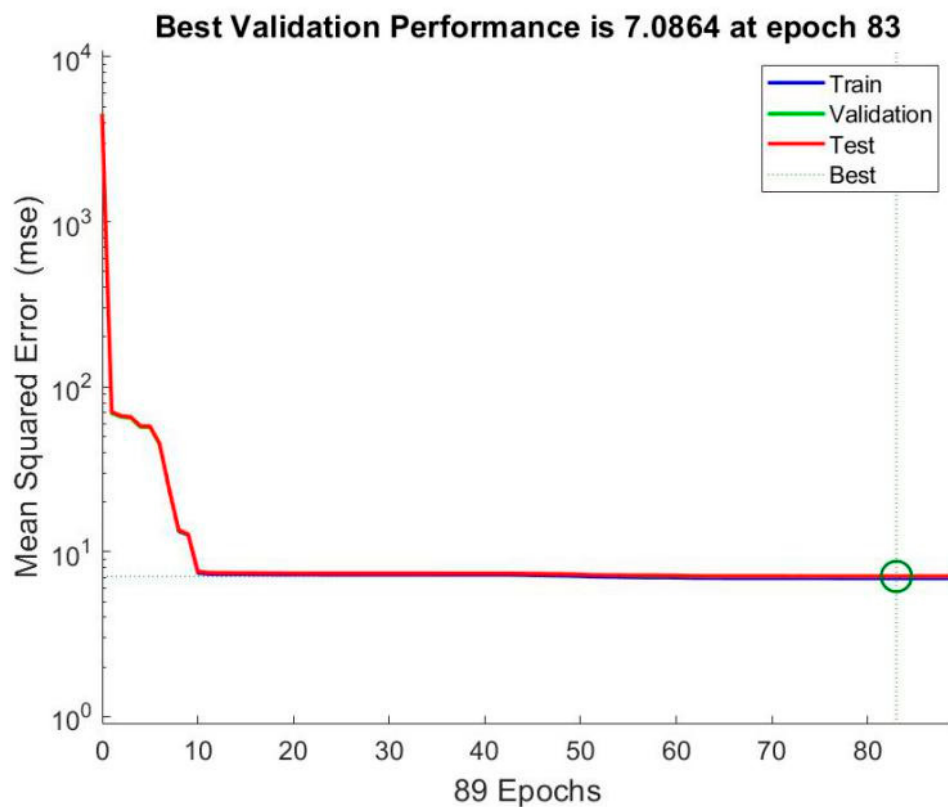


Figure 5. Performance for Test 1 of the Artificial Neural Network.

Table 3. The ANN architecture composition of Test 1 for Testing.

Input, Output	Factor	Detailed Type of Neuron	Position of Neuron in Layer
Input	Urban Growth factor	Elevation	1
		The distance to the water area	2
		Gradients of elevation in 8 directions	3~10
	Population	Population for 2000, 2005, 2010	11~13
		Night-time light data for 2000, 2005, 2010	14~16
	Night-time Satellite Light	Gradients of light data in 8 directions for 2000, 2005, 2010	17~40
		Change of light data over time from 2000 to 2005 and one from 2005 to 2010	41~42

Table 4. The ANN architecture composition of Test 2 for Testing.

Input, Output	Factor	Detailed Type of Neuron	Position of Neuron in Layer
Input	Night-time Satellite Light	Night-time light data for 2000, 2005, 2010	1~3
		Gradients of light data in 8 directions for 2000, 2005, 2010	4~27
		Change of light data over time from 2000 to 2005 and one from 2005 to 2010	28~29

4. Result

Figures 6 and 7 show the regression results between output, which is a result of prediction, and target, which is a value for training; a linear relation is identified through the R value close to 1. Because the R value is mostly 0.95 in the results of Tests 1 and 2, we conclude that each training process is perfect. Therefore, since network training in both Tests has good results with small errors, we will focus more on the differences between the two Tests.

Figure 8 shows the results of Test 1, which predicted 2015 light data by applying both urban growth factors and satellite light data, whereas Figure 9 shows the result of Test 2, which predicted 2015 light data by applying only satellite light data. According to the spatial distribution and the changes in night light, the result of Test 1 shows that the areas of bright light are expanding around the Hanoi and Ho Chi Minh city centers. The result of Test 2 shows a distribution pattern similar to the result of Test 1. However, the bright areas are more widely dispersed in Test 2. Likewise, the total DN value of Vietnam in 2015 is 3,136,156, which is larger than that of result 1.

Figure 10a shows the amount of electricity used by administrative districts in the Test 1 and Test 2 results and Figure 10b shows the population of each administrative district. According to Figure 10a, more energy is consumed mainly in areas such as Hanoi, Ho Chi Minh, Dong Nai, Long An, and Gia Lai. Test 2 shows larger consumption than Test 1 in almost all cities, because the total DN value of Test 2 was larger than that of Test 1. Hanoi and Ho Chi Minh, the most well-known cities in Vietnam, show larger consumption predictions. The number of people in each city in Figure 10b and the energy usage measured in Tests 1 and 2 in Figure 10a seem to have a similar pattern. According to Figure 10c, which shows electricity consumption per capita of each city, while Tay Ninh, Long An, Gai Lai, Bin Thuan, and Dac Lac demonstrate relatively large consumption per capita, Dac Lac demonstrates an exceptionally large consumption of electricity per capita. Those cities would be necessary to develop a careful planning for energy consumption of electricity.

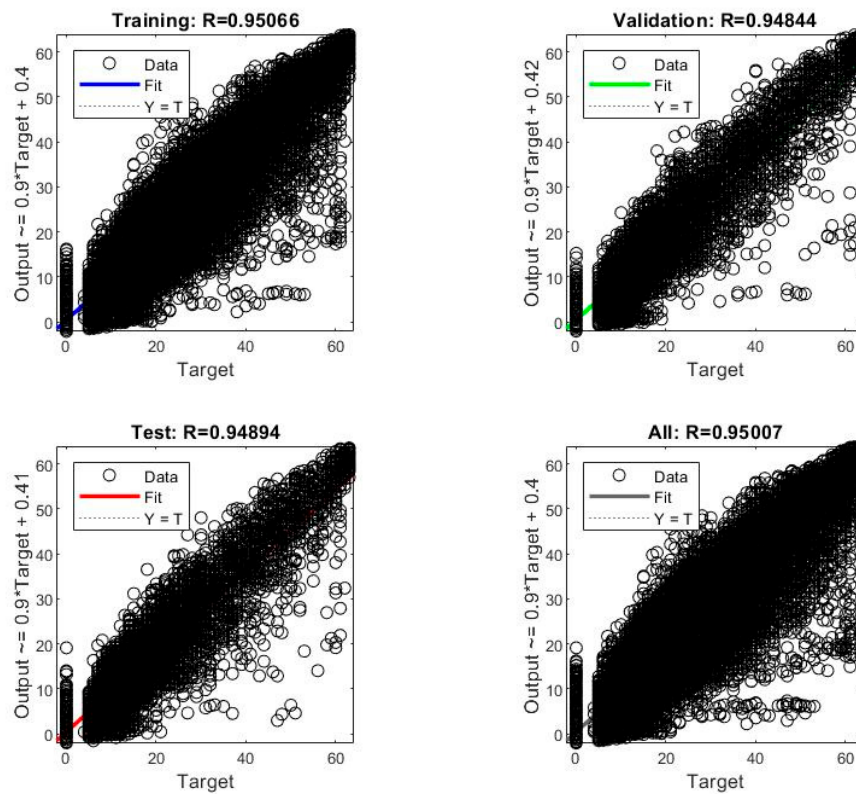


Figure 6. Regression between output and target of Test 1.

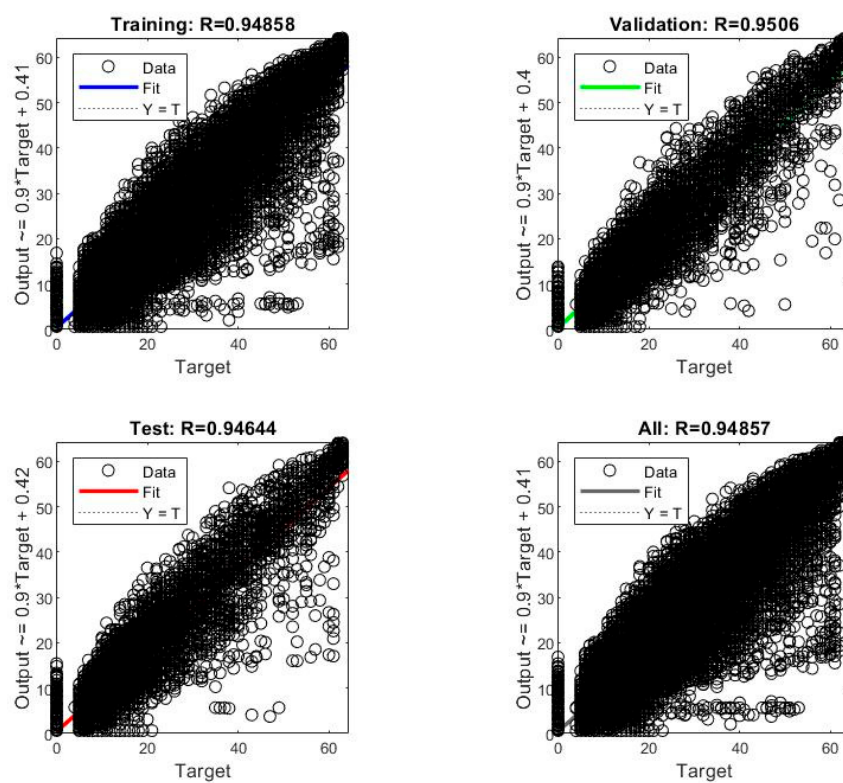


Figure 7. Regression between output and target of Test 2.

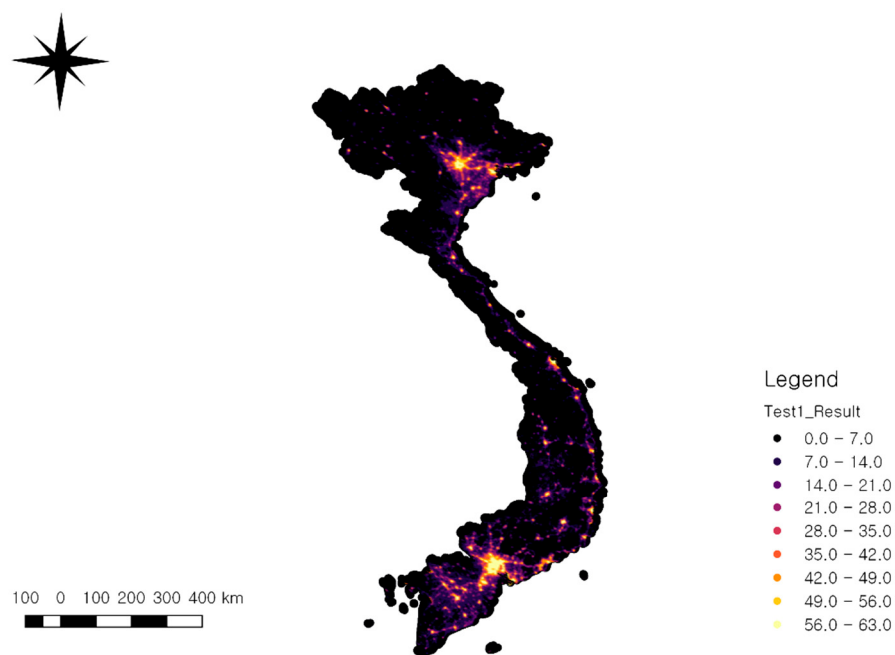


Figure 8. The result of Test 1.

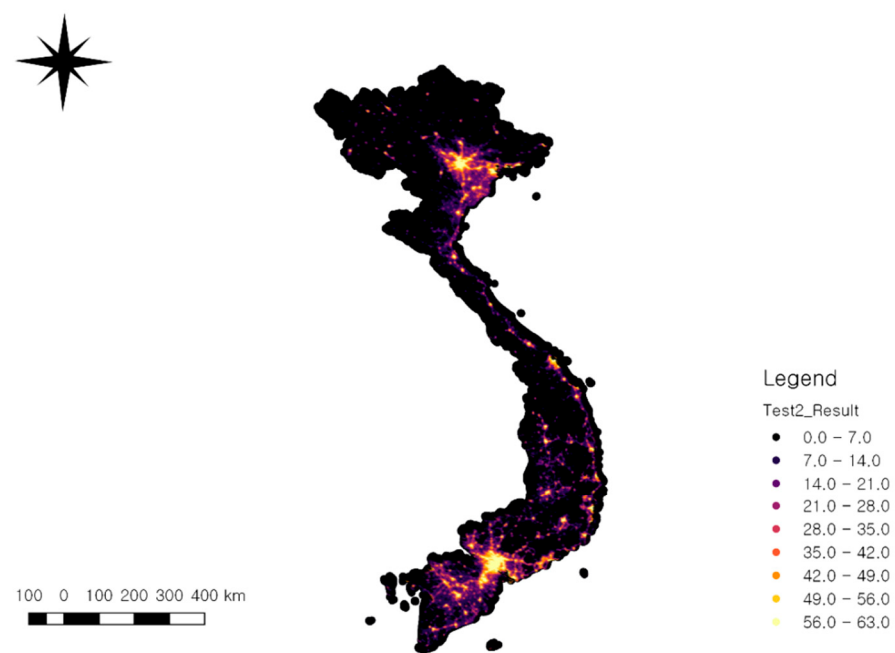


Figure 9. The result of Test 2.

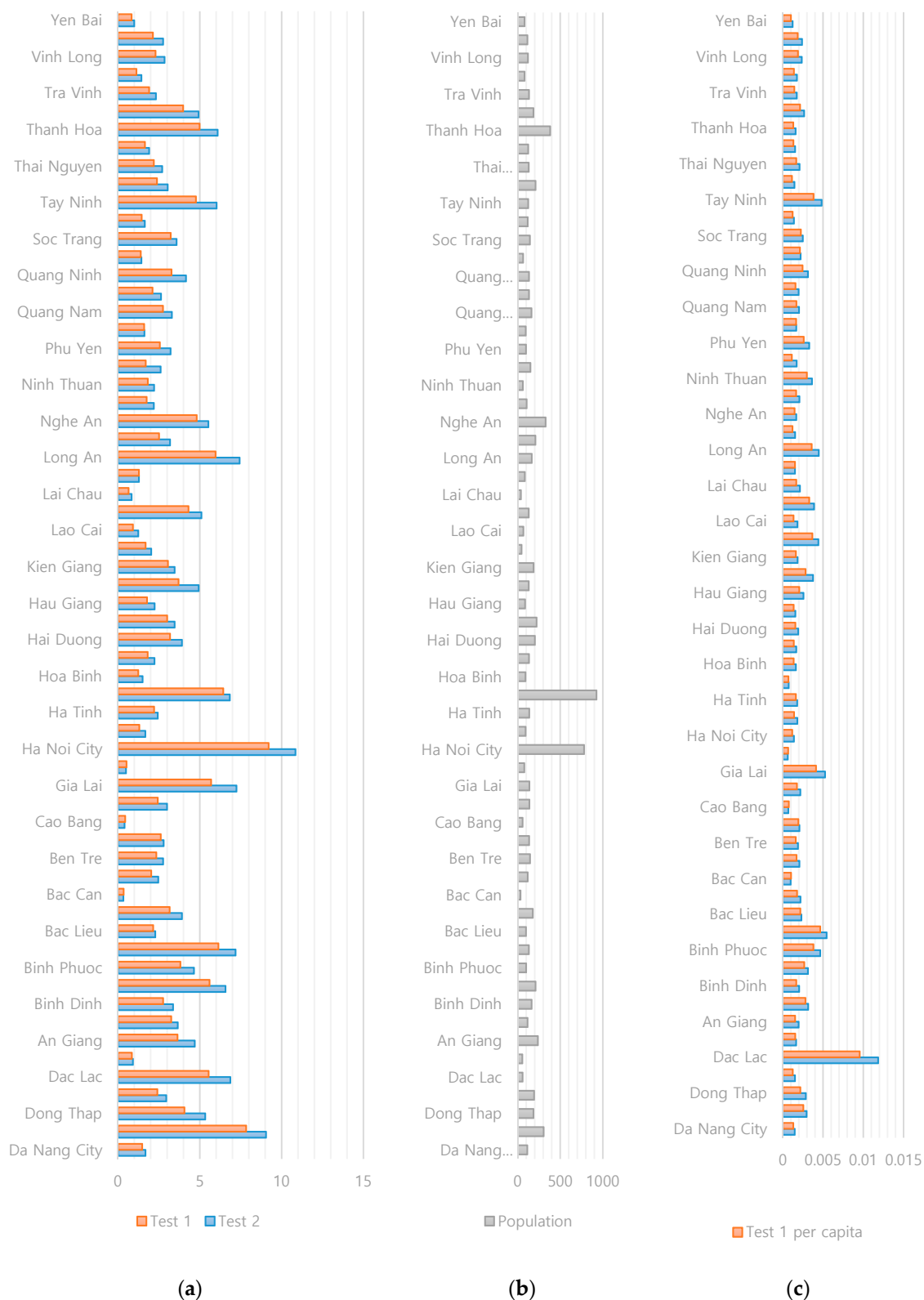


Figure 10. Electricity Consumption of Each Vietnam City. (a) Electricity consumption of each Vietnam city (kW). (b) Population (ten thousand people). (c) Electricity consumption of each Vietnam city per capita.

5. Discussion

The final aim of this study is prediction of electricity consumption for year 2015. We conducted a regression analysis between night-time light data and electricity consumption by assuming a linear relation between them, using the relationship between the actual total energy use over time and the actual total digital number (DN) in order to find the linear relationship between the two, whereas previous studies have found a linear relationship according to administrative locations. The reason for grasping the relationship between total annual energy demand and the digital number is to predict the future demand through the obtained trend line formula. Electricity consumption (in kW) as used in this regression analysis is defined as total annual electricity generation plus imports minus exports.

Discrepancies between the amount of electricity and the consumption or exported amount are considered to be transmission and distribution losses. On the other hand, the annual total digital number was collected by NOAA from 1995 to 2013, and Figure 11 shows collected electricity-consumption data from 1995 to 2013 from the World Indicator and the annual total Digital Number. Additionally, Figure 12 shows the electricity consumption for the total number of DN. From this relation, we can get the linear trendline

$$y = 7.40 \times 10^{-5}x - 15.6869395 \quad (1)$$

with $R^2 = 0.8292894$. An R^2 value close to 1 implies that the relationship between the two datasets over time further stabilizes the linearity.

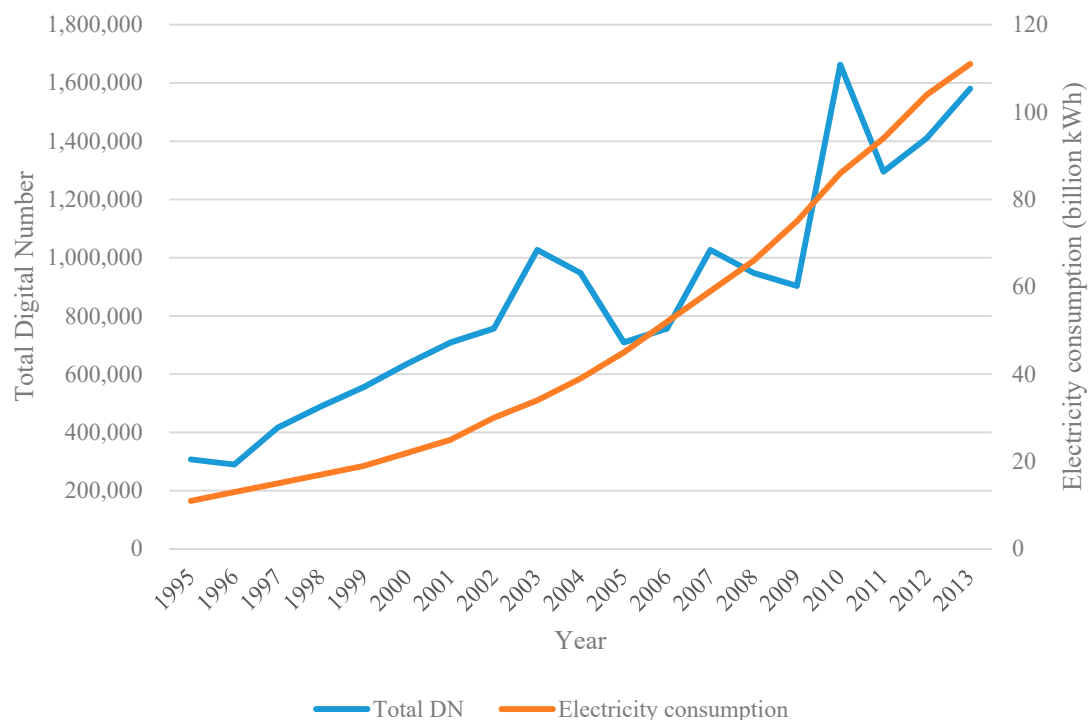


Figure 11. Annual Electricity Consumption (billion kWh) in Vietnam.

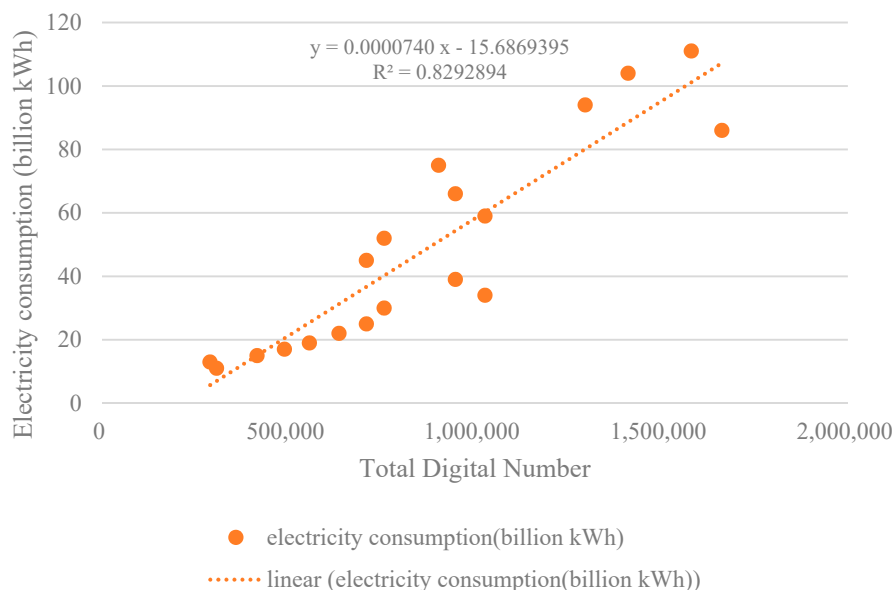


Figure 12. The relation between Electricity Consumption (billion kWh) and the total Digital Number (no unit) of Vietnam from 1995 to 2013.

Through the regression analysis, this study assigns the total number of digital numbers in Test 1 and Test 2 to this formula. Test 1 is the predicted night-time satellite data for 2015 applying both urban growth factors and light data, and Test 2 applies only satellite light data. Therefore, Table 5 shows that the result of Test 1 predicts 180.12 billion kWh of electricity consumption in 2015, and the result of Test 2 predicts 216.39 billion kWh of electricity consumption in 2015. Both estimates are higher than the actual electricity consumption for 2015, which is 135 billion kWh. We can deduce why the results are not exactly the same as the actual data from Figure 12. This situation is likely to be influenced by the higher total DN value in 2010. The average annual growth rate of DN is 12.08%, whereas the rate of increase from 2009 to 2010 was 84.13%. Since we did not use a large number of time steps during training, this exaggerated data would have a significant effect on regression, which is a limitation of this research. However, comparing this with actual energy consumption, it is also noted that Test 1 using urban factors produced an estimation closer to the real values than did Test 2, using only light data, as shown in Table 4. Accordingly, we found that it is effective to combine night light data, population, and urban factors for forecasting energy consumption.

Table 5. Expected energy consumption and error in 2015.

Results 1 and 2	Total DN	Expected Energy Consumption	% Error with (Actual Data = 135 kWh)
Result 1	2,646,002	180.1172 billion kWh	33.42015
Result 2	3,136,156	216.3886 billion kWh	60.28786

Since night-time light data is information for more precise prediction, we expected a test containing time-series light data to make better predictions. However, a prediction based on urban factors provided more accurate information, even though Test 1 was measured with only two time steps for a five-year period, because of having limited data, and Test 2 reported all of the annual data for the ten-year period. In fact, ANN has been used to derive future output by inserting time-sequenced data, but it requires at least several tens to hundreds of time steps for more accurate prediction. In Vietnam, however, there is little annual data available, and the electricity supply has rapidly increased since the 1990s. Therefore, there are limitations to prediction methods like Test 2. The fact that more accurate data is obtained when urban growth factors are added to night-time light information is an important result, showing the possibility of energy-demand prediction through considering urban growth.

6. Conclusions

This study is significant in that it proposed a model that reflects the characteristics of Vietnam, which has a different form of urban development and economic growth from that of developed countries. The results show that the urban growth factor is an argument that can more effectively measure electrical-energy demand. In addition, we used satellite data provided from developed countries in the prediction model, making it helpful for developing countries whose topographic information is not sufficiently constructed yet. This is also effective when considering the urban growth factor and the specific geographical conditions and characteristics of Vietnam. The essential advantage of this model over existing models is that the spatial distribution of energy demand can be predicted. Therefore, this will be a very useful resource in developing countries where energy demand is rising rapidly and needs to be supplied quickly.

However, this study includes some limitations. First, it is difficult to predict long-term demand after another five years. The Digital number can change as satellites change, which can affect predicted values. In fact, the satellite systems that provide the data used in this study also provided data from 1992 to 2013, and it were then measured by other satellites, so there may be a risk of subsequent estimates. Second, regression analysis based on national DN data does not provide good predictions for local characteristics of energy consumption. In other words, it is difficult to consider regional differences due to the regression analysis through the full annual DN of Vietnam. Last, for difficulties in acquiring data of actual electrical energy consumption in individual cities of Vietnam, the validity of the prediction model suggested in this study remains to be tested. Therefore, future studies are suggested to advance prediction models for a long-term growth, such as forecasting with GDP in a variety of scenarios, and using other factors for more precise predictions of energy consumption. Economic growth and energy demands would be helpful to be compared with prediction models. Additionally, building information data would be helpful to identify the relationship between buildings and energy consumption in specific locations. By exploring built forms, it might be helpful to specify energy consumption in a certain area.

Author Contributions: Conceptualization, H.-Y.L. and Y.K.; methodology, H.-Y.L., K.M.J. and Y.K.; software, H.-Y.L.; validation, H.-Y.L., K.M.J. and Y.K.; writing—original draft preparation, H.-Y.L.; writing—review and editing, K.M.J. and Y.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (NRF-2018R1D1A1B07046164), by the National Research Foundation of Korea (NRF) Grant funded by the Ministry of Science and ICT for convergent research in Education-research Integration through Simulation On the Net (EDISON) (NRF-2017M3C1A6075020), and by the Korea Ministry of Land, Infrastructure and Transport (MOLIT) as the [Innovative Talent Education Program for Smart City].

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

References

1. World Development Indicators, Databank, World Bank Group. Available online: <https://databank.worldbank.org/source/world-development-indicators> (accessed on 29 November 2018).
2. Vietnam Electricity. Vietnam Electricity Annual Report. 2017. Available online: <http://www.evn.com.vn> (accessed on 8 July 2018).
3. Arbex, M.; Perobelli, F.S. Slow meets Leontief: Economic growth and energy consumption. *Energy Econ.* **2010**, *32*, 43–53. [CrossRef]
4. Mu, T.; Xia, Q.; Kang, C. Input-output table of electricity demand and its application. *Energy* **2010**, *35*, 326–331. [CrossRef]
5. Al-Musaylh, M.S.; Deo, R.C.; Adamowski, J.F.; Li, Y. Short-term electricity demand forecasting with MARS, SVR and ARIMA models using aggregated demand data in Queensland, Australia. *Adv. Eng. Inform.* **2018**, *35*, 1–16. [CrossRef]

6. Chang, C.J.; Lin, J.Y.; Chang, M.J. Extended modeling procedure based on the projected sample for forecasting short-term electricity consumption. *Adv. Eng. Inform.* **2016**, *30*, 211–217. [\[CrossRef\]](#)
7. Vietnam Ministry of Industry and Trade. Vietnam Energy Outlook Report. 2017. Available online: https://ens.dk/sites/ens.dk/files/Globalcooperation/Official_docs/Vietnam/vietnam-energy-outlook-report-2017-eng.pdf (accessed on 27 June 2018).
8. Permana, A.S.; Perera, R.; Kumar, S. Understanding energy consumption pattern of households in different urban development forms: A comparative study in Bandung City, Indonesia. *Energy Policy* **2008**, *36*, 4287–4297. [\[CrossRef\]](#)
9. Duranton, G.; Turner, M.A. Urban growth and transportation. *Rev. Econ. Stud.* **2012**, *79*, 1407–1440. [\[CrossRef\]](#)
10. López, E.; Bocco, G.; Mendoza, M.; Duhau, E. Predicting land-cover and land-use change in the urban fringe: A case in Morelia city, Mexico. *Landsc. Urban Plan.* **2001**, *55*, 271–285. [\[CrossRef\]](#)
11. Batty, M. Urban modeling. In *International Encyclopedia of Human Geography*; Thrift, N., Kitchin, R., Eds.; Elsevier: Oxford, UK, 2009; pp. 51–58.
12. Sudhira, H.S.; Ramachandra, T.V.; Jagadish, K.S. Urban sprawl: Metrics, dynamics and modeling using GIS. *Int. J. Appl. Earth Obs. Geoinf.* **2004**, *5*, 29–39. [\[CrossRef\]](#)
13. Tayyebi, A.; Perry, P.C.; Tayyebi, A.H. Predicting the expansion of an urban boundary using spatial logistic regression and hybrid raster–vector routines with remote sensing and GIS. *Int. J. Geogr. Inf. Sci.* **2014**, *28*, 639–659. [\[CrossRef\]](#)
14. Clarke, K.C.; Gaydos, L.J. Loose-coupling a cellular automation model and GIS: Long-term urban growth prediction for San Francisco and Washington/Baltimore. *Int. J. Geogr. Inf. Sci.* **1998**, *12*, 699–714. [\[CrossRef\]](#)
15. Jat, M.K.; Garg, P.K.; Khare, D. Monitoring and modeling of urban sprawl using remote sensing and GIS techniques. *Int. J. Appl. Earth Obs. Geoinf.* **2008**, *10*, 26–43. [\[CrossRef\]](#)
16. Silva, E.A.; Clarke, K.C. Calibration of the SLEUTH urban growth model for Lisbon and Porto, Portugal. *Comput. Environ. Urban Syst.* **2002**, *26*, 525–552. [\[CrossRef\]](#)
17. Taleai, M.; Mansourian, A.; Sharifi, A. Surveying general prospects and challenges of GIS implementation in developing countries: A SWOT-AHP approach. *J. Geogr. Syst.* **2009**, *11*, 291–310. [\[CrossRef\]](#)
18. Elvidge, C.D.; Baugh, K.E.; Kihn, E.A.; Kroehl, H.W.; Davis, E.R.; Davis, C.W. Relation between satellite observed visible-near infrared emissions, population, economic activity, and electric power consumption. *Int. J. Remote Sens.* **1997**, *18*, 1373–1379. [\[CrossRef\]](#)
19. Elvidge, C.D.; Sutton, P.C.; Ghosh, T.; Tuttle, B.T.; Baugh, K.E.; Bhaduri, B.; Bright, E. A global poverty map derived from satellite data. *Comput. Geosci.* **2009**, *35*, 1652–1660. [\[CrossRef\]](#)
20. Amaral, S.; Camara, G.; Monteiro, A.M.V.; Quintanilha, J.A.; Elvidge, C.D. Estimating population and energy consumption in Brazilian Amazonia using DMSP night-time satellite data. *Comput. Environ. Urban. Syst.* **2005**, *29*, 179–195. [\[CrossRef\]](#)
21. Chand, T.K.; Badarinath, K.V.S.; Elvidge, C.D.; Tuttle, B.T. Spatial characterization of electrical power consumption patterns over India using temporal DMSP-OLS night-time satellite data. *Int. J. Remote Sens.* **2009**, *30*, 647–661. [\[CrossRef\]](#)
22. Maithani, S. A neural network based urban growth model of an Indian city. *J. Indian Soc. Remote Sens.* **2009**, *37*, 363–376. [\[CrossRef\]](#)
23. Atkinson, P.M.; Tatnall, A.R. Introduction neural networks in remote sensing. *Int. J. Remote Sens.* **1997**, *18*, 699–709. [\[CrossRef\]](#)
24. Kavzoglu, T.; Mather, P.M. The use of back propagation artificial neural networks in land cover classification. *Int. J. Remote Sens.* **2003**, *24*, 4097–4938. [\[CrossRef\]](#)
25. Pijanowski, B.C.; Brown, D.; Shellito, B.A.; Manik, G. Using neural networks and GIS to forecast land use changes: A land transformation model. *Comput. Environ. Urban Syst.* **2002**, *26*, 553–575. [\[CrossRef\]](#)
26. Pijanowski, B.C.; Pithadia, S.; Shellito, B.A.; Alexandridis, K. Calibrating a neural network-based urban change model for two metropolitan areas of the Upper Midwest of the United States. *Int. J. Geogr. Inf. Sci.* **2005**, *19*, 197–215. [\[CrossRef\]](#)

