Estimation of Hourly Near Infrared Radiation Using Artificial Neural Network and Performance Comparison with the Semi-Empirical Model at Nakhon Pathom Province

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Abstract

In this research, methods for estimating near infrared radiation (NIR: 0.695-2.8 micron) at Silpakorn University, Nakhon Pathom province (13.82°N, 100.04°E) have been developed using an artificial neural network (ANN) and a semi-empirical model. The input data of these models consist of aerosol optical depth (AOD) and precipitable water (W) measured by a Sunphotometer, and clearness index (k_t) obtained from ratio of measured incident solar radiation to calculated extraterrestrial solar radiation. The ANN and semi-empirical models were formulated using the collected data at Nakhon Pathom station for the period of 2009-2015. Then, the results obtained from these models were tested and validated against the measured data at the station during a two-year-period (2016-2017). The comparison results show that the near infrared radiation obtained from the ANN and semi-empirical models are in reasonable agreement with the measurement. The root mean square difference (RMSD) are 6.08% and 4.47%, and the mean bias difference (MBD) are 4.91% and 3.02% for the ANN and semi-empirical models, respectively.

Keywords: near infrared radiation, artificial neural network, semi-empirical model, Nakhon Pathom

Introduction

In general, the incident solar radiation on the Earth's surface has a spectrum range of 0.3-3.0 micron which can be classified as ultraviolet radiation (0.28-0.4 micron), visible light (0.4-0.7 micron) and near infrared radiation (NIR, 0.695-2.8 micron). The NIR band contributes about 52% of total energy from the sun (Petty, 2004). The NIR that passes through the earth's atmosphere helps to maintain the energy balance. It also affects the cloud formation and air temperature (Iqbal, 1983). Therefore, the NIR is important for monitoring global climate change (Escobed, Gome, Oliverira, & Soares, 2009).

In addition, in biomass production, deterministic plant growth simulation models are usually employed for the prediction of the production (Lokupitiya et al., 2009; Morel et al., 2014) and these models usually require information on both visible and NIR parts of the solar spectrum.

Due to the measurement of NIR is very limited, many scientists have attempted to develop models and methods for estimating NIR but they are rather complex methods and regional limited (Jacovides, Tymvios, Boland, & Tsitouri, 2015; Escobed, Gome, Oliverira, & Soares, 2011). For example, Escobed et al. (2011) developed a model for calculating NIR from ratio but the model can be used in limited area. Therefore, the objective of this work is to propose a simple method to calculate hourly NIR at Silpakorn University, Nakhon Pathom province (13.82°N, 100.04°E). The proposed method used an artificial neural networks (ANN) techniques and a semi empirical model with require input parameters that influence the NIR. These two methods can be applied to estimate hourly NIR in many regions.

Methods and Materials

Measurement and data

In this work, the hourly NIR was calculated from artificial neural networks techniques and semi-empirical model. The data used in this work consist of aerosol optical depth, precipitable water and clearness index which the details are described below.

Aerosol optical depth (AOD) and precipitable water (W) are important parameters for calculating the hourly NIR as they can attenuate the radiation. The data of AOD and W were obtained from a sunphotometer installed at Silpakorn University (Figure 1a).

Figure 1 a) Sunphotometer and b) Pyranometer installed on the roof top of the Science building at Silpakorn University

The sunphotometer measures the selected direct spectral radiation. The data are then transferred to Aerosol Robotic Network (AERONET) of NASA in order to generate the AOD and W. Generally, the values of AOD are in the range of 0.1-0.7 and W are in the range of 1.0-6.5 cm for Nakhon Pathom during the study period (Figure 2). The error bars represent standard deviation (S.D.) which can be calculated by equation (1) (Cumming, Fidler, & Vaux, 2007):

$$\mathrm{S.D.}=\sqrt{\frac{\sum_{i=1}^{n}(x_i-\bar{x})^2}{(n-1)}} \tag{1}$$

where x_i is each value of the data set where i=1,2,3,...,n, $\bar{x}$ is the mean value of the data set and n is the number of data points in the data set.

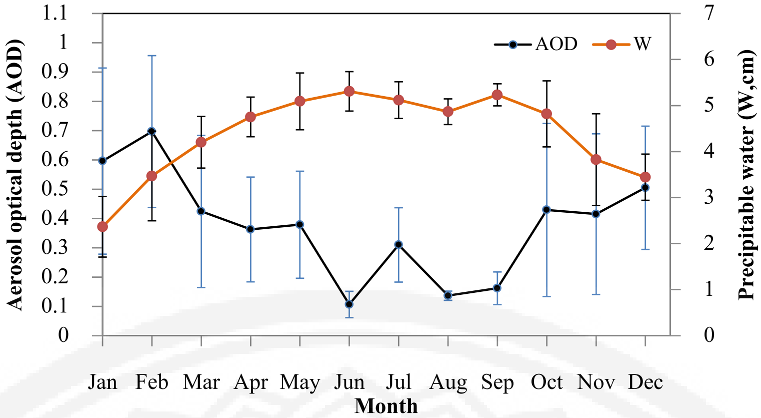

Figure 2 Variation of the aerosol optical depth and the precipitable water obtained from the sunphotometer at Nakhon Pathom in 2009

The clearness index represents the amount of the atmosphere especially the clouds, which obtained from ratio of incident surface solar radiation to extraterrestrial solar radiation. It can be obtained as follows:

$$k_t = \frac{I}{I_0} \tag{2}$$

where k_t is the clearness index, I is incident surface solar radiation in a broadband wavelength (MJ/m^2-hr) and I_0 is extraterrestrial solar radiation (MJ/m^2-hr).

The incident solar radiation in a broadband wavelength (0.3-3.0 micron) were measured by a pyranometer (Kipp&Zonen, model CMP11) at the station (Figure 1b).

The extraterrestrial solar radiation can be calculated as follows (Iqbal, 2006):

$$I_0 = I_{sc} E_0 \cos\theta_z \tag{3}$$

where I_{sc} is solar constant (4.917 MJ/m^2-hr) (Lang, 2006), E_0 is eccentricity correction factor of the Earth (-) and and θ_z is solar zenith angle (degree).

The eccentricity correction factor of the Earth can be calculated as follows (Duffie & Beckman, 1991):

$$E_0 = 1 + 0.033\cos\left[\frac{2\pi d_n}{365}\right] \tag{4}$$

where d_n is julian day.

The solar zenith angle which depends on latitude (ϕ), declination (δ) and hour angle (ω) can be calculated from the following equation (Iqbal, 2006):

$$\cos\theta_Z = \sin\phi\sin\delta + \cos\phi\cos\delta\cos\omega \tag{5}$$

The hourly NIR was measured by a Precision Spectral Pyranometer (Eppley, model PSP) with the RG695 filter (Figure 3a) allowing only the radiation covering the range of 0.695-2.8 micron passing through the detector. This instrument is also installed at Silpakorn University (Figure 3a).

The voltage signals from the pyranometer and precision spectral pyranometer were recorded by a multi-channel datalogger (Yokogawa, model DX2000) every ten minute. These data were converted to broadband solar radiation and NIR by using their sensitivity values. The 10-minute data were then averaged to hourly and then used for formulating and model validation.

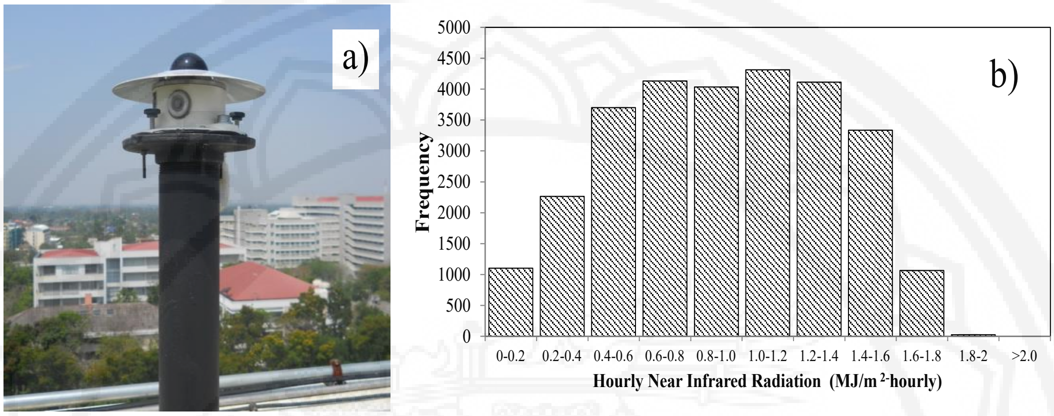

Figure 3 a) The Precision Spectral Pyranometer (Eppley, model PSP) with the filter (RG 695) installed at the roof top of a building at Silpakorn University and b) Histogram of hourly NIR at Silpakorn University from 2009-2017

From Figure 3b, it is a histogram of hourly NIR showing that the most of intensity of hourly NIR at Silpakorn University are in range 0.4-1.6 MJ/m^2-hr. The maximum value is 1.96 MJ/m^2-hr in summer and the minimum value is 0.05 MJ/m^2-hr in rainy season.

The hourly data of NIR, broadband solar radiation, AOD, W, k_t and θ_z were collected from 2009 to 2017 (9 years). Then it was separated into two groups. The first group was used for model development; 2009-2015 containing 9,348 data points and the second group was used for model validation; 2016-2017 including 2,184 data points.

ANN modeling of near infrared radiation

In this work, the artificial neural networks technique was used for calculating the hourly NIR. The software of ANN was developed by the University of Waikato, New Zealand, called WEKA. The ANN model is a mathematic program which works like human brain. The ANN model consists of input layer, hidden layer and output layer. The multilayer perceptron with back-propagation algorithm was used for ANN training.

To obtain the NIR by using the ANN, in the first step, the ANN model was designed with four layers shown in Figure 4.

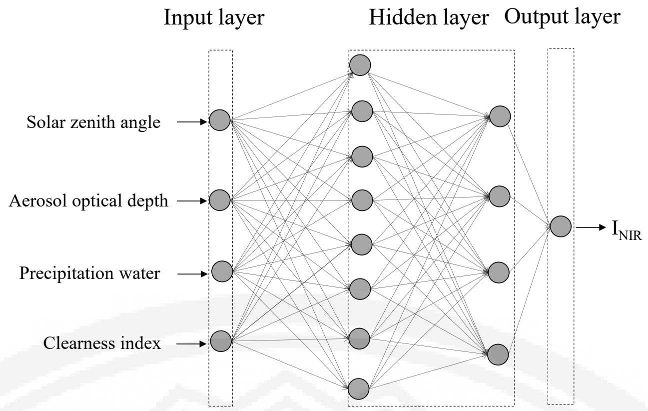

Figure 4 The structure of the ANN model to predict hourly NIR

There are one input layer, two hidden layers and one output layer. The input layer consists of the parameters affecting hourly NIR. These parameters are aerosol optical depth, precipitable water, clearness index and solar zenith angle. First hidden layer consists of eight neurons and the second hidden layer has four neurons. Each neuron has two functions that are summation function and activation function (Yusuf, Mustafa, & Emrah, 2017).

In the second step, the ANN was trained by using input data during the year 2009-2015. In this step, the back-propagation algorithm was used for ANN training (Figure 5), the data was trained and the weight value was changed with the reverse training process until the ANN model can provide the best result.

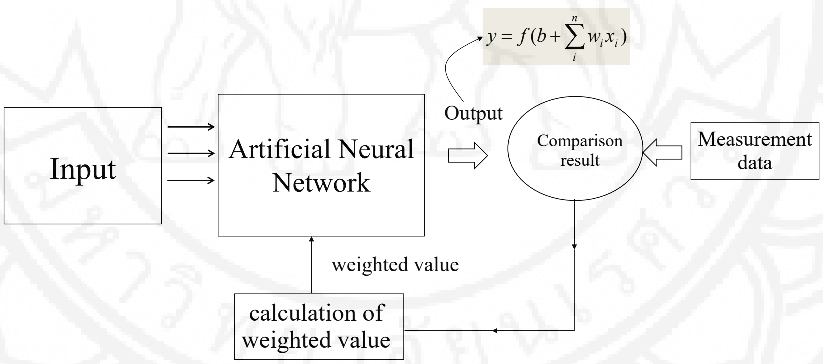

Figure 5 The back-propagation algorithm

The result was then transferred to the activation function. The output from the ANN can be written in the equation (6) as follows (Hagan, Demuth, & Beale, 1996):

$$y = f(b + \sum_{i}^{n} w_i x_i) \qquad (6)$$

where y is output data, x is input data, w is weighted value, b is bias value and n is number of the data.

Finally, the hourly NIR was calculated by using the ANN algorithm and then validated against the data at the same station for the period of two years (2016-2017).

Semi-empirical model

The semi-empirical model for calculating hourly NIR has been developed using atmospheric parameters. NIR passing through the atmosphere is attenuated by parameters of the atmosphere such as aerosol, water vapor and clouds. The most of NIR is attenuated by water vapor in the atmosphere. In addition, the hourly NIR also depends on the position of the sun. Therefore, in this work, the input data consist of aerosol optical depth (AOD), precipitable water (W), clearness index (k_t) representing the amount of clouds, solar zenith angle (θ_z) and eccentricity correction factor of the earth (E_0), which the details are already described in earlier section.

The NIR was exponentially depended with water vapor and aerosol, and linearly depended with cloud. Therefore, the correlation between the radiation and the atmosphere parameters can be written in the semi-empirical equation as follows:

$$I_{NIR} = a_0 I_0 E_0 (\cos\theta_z)^{a_1} \{\exp(a_2 w + a_3 AOD)\} (a_4 k_t - 1) \qquad (7)$$

where I_{NIR} is hourly near infrared radiation (MJ/m^2-hr), I_0 is extraterrestrial solar radiation (MJ/m^2-hr) and a_0, a_1, a_2, a_3 and a_4 are empirical constants.

The empirical constants in equation (7) were estimated by using a nonlinear regression technique (Seber & Wild, 1989). The values of the empirical constants and their related statistics are shown in Table 1.

Table 1 The empirical constants and t- statistic

Empirical constant	**value**	**t-statistic**
a_0	0.01382	5.519
a_1	0.01523	3.308
a_2	-0.0123	-16.049
a_3	0.04171	14.688
a_4	37.5536	6.137

From Table 1, the t-statistic values are all greater than 2 that is meant all empirical constants are significant at 95% (Dougherty, 2002). Therefore, the constant values are suitable for predictability of the NIR in equation (7) for Nakhon Pathom region.

Modeling performance criteria

In this work, the model performance was evaluated using standard statistical criteria consist of the square of correlation coefficient (R^2), the root mean square difference (RMSD) and mean bias difference (MBD):

$$RMSD = \frac{\sqrt{\dfrac{\sum_{i=1}^{N}(I_{NIR,model} - I_{NIR,meas})^2}{N}}}{\dfrac{\sum_{i=1}^{N} I_{NIR,meas}}{N}} \times 100\% \qquad (8)$$

$$\mathrm{MBD} = \frac{\dfrac{\sum_{i=1}^{N}(I_{NIR,model} - I_{NIR,meas})}{N}}{\dfrac{\sum_{i=1}^{N} I_{NIR,meas}}{N}} \times 100\% \tag{9}$$

where $I_{NIR,model}$ is hourly near infrared radiation calculating from each model (MJ/m^2-hr), $I_{NIR,meas}$ is hourly near infrared radiation from measurement (MJ/m^2-hr) and N is number of data.

Results and Discussion

ANN and Semi-empirical model

To investigate the performance of the algorithm, the ANN algorithm and semi-empirical model were used to calculate hourly NIR at Silpakorn University during a two - year - period (2016 - 2017). As these data were not involved in the formulation of the model, they were an independent data set. The hourly NIR calculated from the ANN algorithm, semi-empirical model and the ground-based measurement data were compared. The comparison results are shown in Figure 6a for the ANN model and Figure 6b for the semi-empirical model.

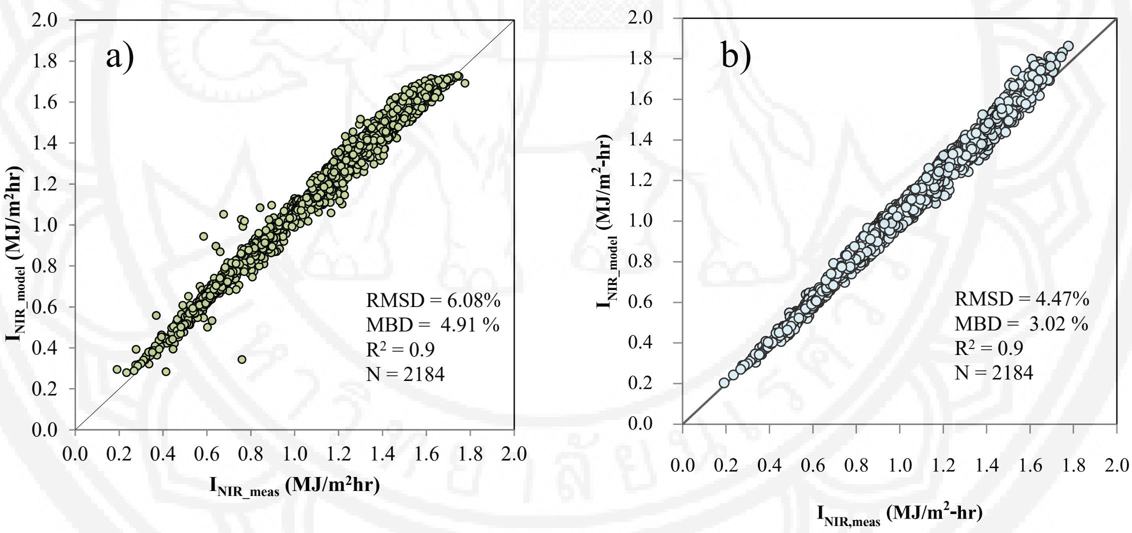

Figure 6 a) Hourly near infrared radiation using the ANN model (I_{NIR_model}) versus the measurement values (I_{NIR_meas}) and b) Hourly near infrared radiation using the semi-empirical model (I_{NIR_model}) versus the measurement values (I_{NIR_meas})

From Figure 6a, the result shows that hourly NIR from the ANN model and that from ground-based measurement at Silpakorn University are in good agreement, with the discrepancy in terms of the root mean square difference (RMSD) of 6.08% and mean bias difference (MBD) of 4.91%. The case of the semi-empirical model (Figure 6b) gives the RMSD of 4.47% and MBD of 3.02%. From the results, both models give overestimation of hourly NIR which may resulting from some parameters that are not accounted in the models i.e. ozone. The results also show that the semi-empirical model predicted hourly NIR slightly better than the ANN model. This may be because the semi-empirical model products from the direct relationship between the NIR and the input parameters while the ANN model is fixed algorithm. However, both models introduced in this work are simple methods and the results are comparable with other models (Escobed et al., 2009; Escobed et al., 2011).

In order to compare the diurnal and seasonal variations of NIR from these two models with the ground-based measurement, the hourly NIR from semi-empirical model, ANN model and measurement were additionally calculated to daily data.

In Figure 7, the hourly values of NIR from the three data sets were plotted against time to investigate the diurnal variation. The result shows that the diurnal variations from these datasets are similar. From the figure, the NIR presented a variation from 0.57 – 1.55 MJ/m^2-hr. The maximum of the NIR can also be interpreted as the amplitude of the diurnal evolution (1.55 MJ/m^2- hr). In case of the seasonal variation (Figure 8), the variations of NIR from the semi-empirical model, the ANN model and the measurement also show similar pattern. The maximum value is 11.76 MJ/m^2-hr in summer and the minimum value is 8.18 MJ/m^2-hr in rainy season.

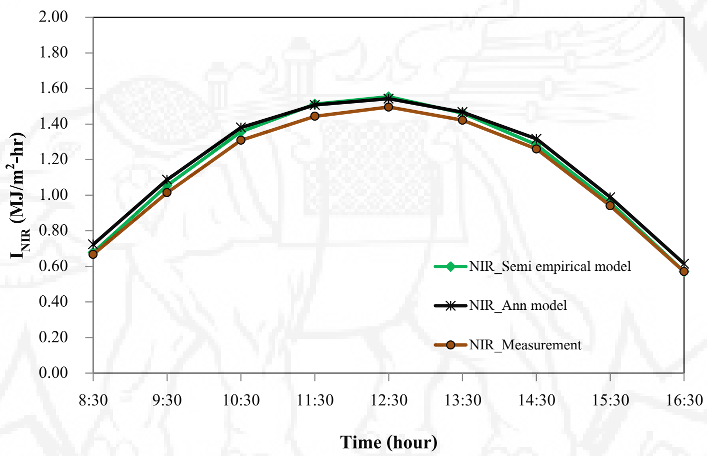

Figure 7 Diurnal variation of NIR (I_{NIR}) from the semi-empirical model, the ANN model and the ground-based measurement at Silpakorn University from 2009-2017

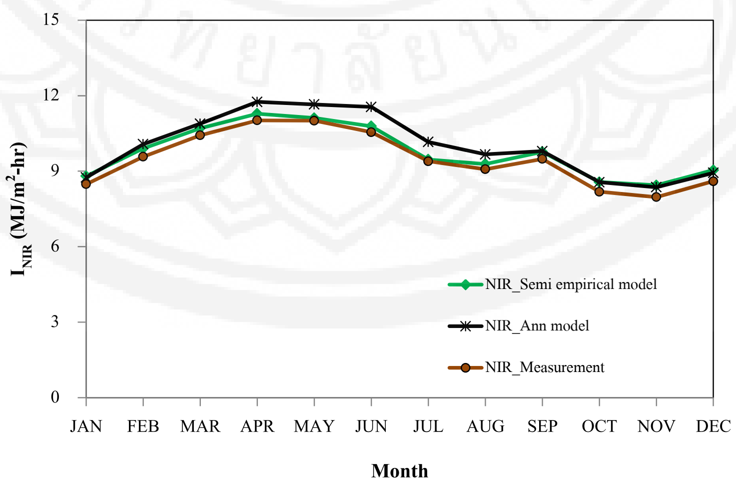

Figure 8 Seasonal variation of NIR from the semi-empirical model, the ANN model and the ground-based measurement at Silpakorn University from 2009-2017

Conclusion

In this work, we have developed the ANN and semi-empirical models for calculating the hourly near infrared radiation from atmospheric parameters at Silpakorn University. The input data used in these methods consist of aerosol optical depth, precipitable water, clearness index, solar zenith angle and eccentricity correction factor of the earth. For the validation of the model, the hourly near infrared radiation obtained from the ANN and semi-empirical models were reasonable agreed with those from ground-based measurement, with the root mean square difference (RMSD) of 6.08% and 4.47%, and the mean bias difference (MBD) of 4.91% and 3.02% for the ANN and semi-empirical models, respectively. Therefore, these two methods can be used to estimate hourly near infrared radiation in Nakhon Pathom and other regions having similar environment. These models may be applied for other regions with different environments by modifying the constant values of the semi-empirical model and weight values in the ANN model.

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