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Statistical Analysis of Solar Radiation in Southern Thailand

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ABSTRACT

The patterns of daily, monthly and seasonal solar irradiance in the three southernmost provinces of Thailand were investigated. Knowledge of these patterns can help predict future patterns of solar radiation falling on the surface of the earth. Daily solar irradiance observations collected from three surface stations in southern Thailand during one and half years were analysed. A natural cubic spline method was applied to describe the seasonal patterns present in the annual time series of the daily observations. The method, together with an optimum number of knots and their proper placement applied to the observations, yielded quite acceptable fits in describing the seasonal pattern of solar radiation observations. A noticeable feature of the models is the bimodal solar radiation pattern. Pattani province recorded a higher mean amount of solar radiation (450.42 Wm^2) relative to the other two provinces. These findings will be essential to stakeholders in the design of solar energy systems since solar irradiance is particularly significant for planning the processes of power plants which convert renewable energy into electricity.

INTRODUCTION

Modelling the patterns of solar irradiance is particularly essential for planning the processes of power plants, which convert renewable energies into electricity. Solar radiation is the major energy source at the Earth's surface, which supports many living organisms (Cheung et al. 2015). Information about the amount of solar radiation falling on a surface of the earth is crucial to engineers and researchers dealing with the design of solar energy systems. Specifically, several modelling techniques for thermal and photovoltaic systems need monthly average daily radiation on a horizontal surface as an input, to forecast the energy production of the system on a monthly basis (Beckman et al. 1977, Ma & Iqbal 1984, Thevenard et al. 2000). The knowledge and understanding of the patterns and variability of the earth's solar irradiance are essential to numerous applications throughout the globe. These fields of applications include solar energy expertise, unindustrialised productivity, terrestrial ecological ecosystem, hydrological systems and climatic applications.

In general, there is a high daily variation of solar radiation at any location throughout the globe. The unit of measurement of the daily solar radiation is Watt per square meter (W/m^2). These daily variations have been mainly attributed to the movement of the earth and the chaotic influence of the troposphere. There is scarcely any efficient way that can accurately be used to estimate the transient solar radiation, but for practical measurement. The measurements performed in most of the official meteorological stations are for the horizontal surface on the timescale of an hour with the unit of MJ/(m^{2}hour), or a day with the unit of MJ/(m^{2}day). These two quantities represent accumulative energy during different time spans instead of transient intensity (Zhang 2017).

Earlier studies in the analysis of solar radiation in Thailand included world distribution of solar radiation (Löf et al. 1966) and global classification of solar radiation (Terjung 1970). The first study was made up of the world map of monthly averages of daily sums of global solar radiation observations which comprised of 1-3 years of solar observations of Thailand. A study by the latter, which was centred on Budyko's Atlas of the Heat Balance of the Earth revealed that Thailand is covered by the global classification of solar radiation climates. These studies failed to give enough detailed account of solar radiation in Thailand (Exell 1975). However, studies such as the solar radiation table of Thailand (Exell & Saricali 1975) and further solar radiation table of Thailand (Exell 1975) gave a comprehensive account of the variability of solar radiation climate of Thailand based on the data from Bangkok, Chiang Mai and some selected areas of Thailand.

Statistical analysis of the fluctuations in solar radiation (Exell 1975) revealed seasonal variation in the radiation observations. Analysis and modelling of solar radiation observation are essential in the design and operation of solar energy application systems. Also, Rayl et al. (2013) revealed that the spatial patterns of solar energy define the cost of execution of the power facilities and its intermittency in time affects the sustainability and the cost-effectiveness of such facilities.

The natural cubic spline is arguably one of the most suitable methods used to describe the patterns of data with high variations. Current application of the natural cubic spline modelling in climate science includes the analysis of annual seasonality extraction and decadal trend in temporal daytime MODIS land surface temperature data in Phuket Thailand (Wongsai et al. 2017). In this study, statistical modelling is used to investigate the pattern of daily solar irradiance in the three southernmost provinces in Thailand.

MATERIALS AND METHODS

Solar radiation data comprise direct and diffusion radiation. The data were collected using an automatic weather station (AWS). AWS collected data for every 5 minutes from local average of 30 seconds of each parameter at each station. Data were sent to a remote website via mobile sim card by communication controller at the station and stored in the database. These data were collected between May 28th, 2013 and February 11th, 2015 (total of 20 months with 624 days).

The geographic sites where the daily surface solar radiation observations were collected for the study are shown in Fig. 1. The annual daily average solar radiation observations from May 28th, 2013 to February 11th, 2015 was computed for each of the provinces and thus each province was made up of 365 solar observations. The natural cubic spline model was then applied to the 365 daily solar radiation observations in each of the provinces to determine the patterns (Fig. 1).

The cubic spline function: Spline functions are defined as piecewise polynomials of degree *n*. The pieces join in the so-called knots and satisfy continuity conditions for the function itself and the first *n-1* derivatives. Therefore, a spline function of degree *n* is a continuous function having *n-1* continuous derivatives (Wold 1974). The natural cubic spline model reduces the integral of the squared second derivative over the interval between knots, and it makes possible linear extrapolation outside the knots. The natural cubic spline can be defined mathematically as:

$$s(t) = a + bt + \sum_{k=1}^{p-2} c_k \left[(t - t_k)_+^3 - \frac{(t_p - t_k)}{(t_p - t_{p-1})} (t - t_{p-1})^3 + \frac{(t_{p-1} - t_k)}{(t_p - t_{p-1})} (t - t_p)_+^3 \right] \quad ...(1)$$

Where, p is the number of knots, $t_1 < t_2 < t_3 < ... < t_p$ are indicated time knots and $(t - t_k)_+$ is $t - t_k$ when $t > t_k$ and 0 elsewhere, a, b and c_k are the parameters to be estimated. An investigation by (Wold 1974) revealed that an advantage in the model fitting analysis using natural cubic spline, in particular, is that it provides appropriate results with no loss of information and no bias due to simplification of the model when observation is fitted into curves.

Deciding on the optimum required knots of the model: In general, finding the optimum required number and the position of knot to obtain a well-fitting spline curve is essential in spline modelling. Conversely, (Wold 1974) revealed some technique in the selection process and is centered on the ways of adding knots in intervals, where the residuals display trends as indicated by serial correlation. These amount of knots indicate the number of linear parts of the model. The higher the number of knots in the model the smoother the model. However, more parameters will be estimated if a large number of knots are applied. A consistent pattern of data requires fewer knots in the modelling process whereas, high variation in the data requires a large number of knots to be applied (Jamrozik et al. 2010).

There are two main methods used in the optimum number of knots and their positions of placement determination. Primarily, the first method depends on try and error. In that, a considerable number of knots could be placed in cases where there are high variations in the data and fewer knots when the data are quite consistent. Conversely, Wahba (1990) emphasised that few knots must be placed to make sure that at least the spline model has four to five points per interval. Contrary to the liberty of the researcher to choose the knots, the second technique is the automatic approach. In this method, the optimum number of knots are chosen directly by the data. This method would use an iterative algorithm for the free knot spline (Hou 1978). Choosing a considerable number of knots gives larger values of the adjusted r-square with low cross-validated error, but placing more than 10 knots does not have any positive influence of their models (Wongsai et al. 2017). Selecting knots greater than 10 decreased the smoothness and introduced high variations in the model.

RESULTS AND DISCUSSION

Preliminary analysis of the daily solar observation is

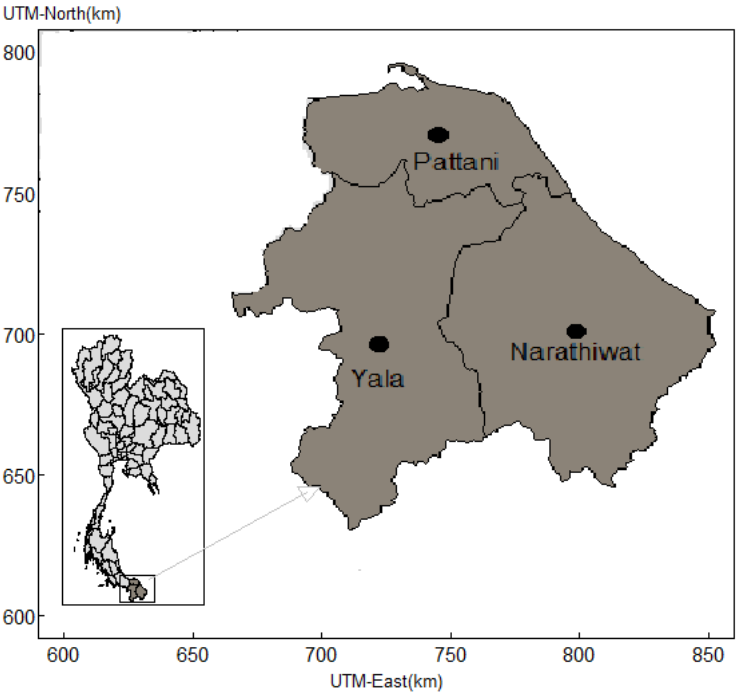

Fig 1: The map showing all the provinces of Thailand and the location of the study area. The black points indicate the station where the solar observations were collected.

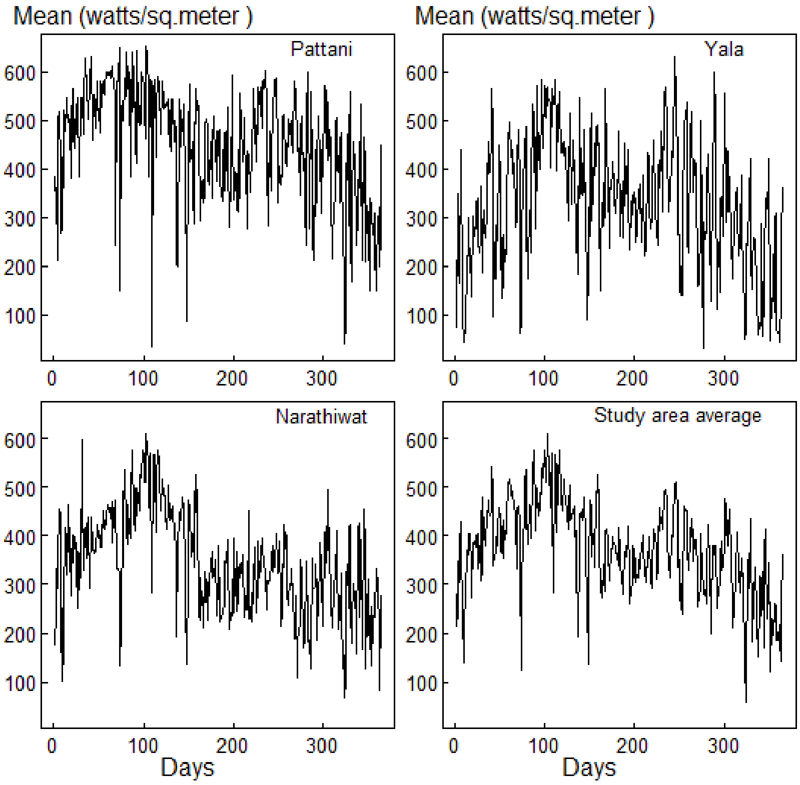

Fig. 2: The daily average solar radiation.

Table 1: Summary statistics of the daily solar radiation observations.

Station	Longitude	Latitude	Solar radiation (W/m^2)				CV (%)
			Minimum	Mean	Median	Maximum	
Pattani	101.32	6.43	35.25	450.42	473.83	651.13	26
Narathiwat	101.83	6.76	67.75	343.80	339.93	609.45	31
Yala	101.28	6.54	30.83	328.78	337.88	629.64	40
Overall mean	-	-	57.07	374.30	379.00	609.40	26

presented in Table 1. Pattani received the highest mean daily solar radiation of 450.42 Wm^{-2} followed by Narathiwat with a daily mean of 343.80 Wm^{-2}. The lowest daily mean of 328.78 Wm^{-2} was observed in Yala.

Analysis of the percentage coefficient of variation (CV) revealed high variations in the daily solar observations in Yala (40%) relative to Narathiwat (31%) and Pattani (26%). The high observed CV in Yala implies that the solar observations are more consistent in Pattani and Narathiwat relative to Yala.

Fig. 2 shows the time series observations of the daily solar radiation. It clearly displays that the radiation distribution patterns of the three provinces have a bimodal feature. Fig. 3 shows the 5-day average of the observed daily solar radiation for each province. It revealed some seasonal pattern with the bimodal features. In Pattani, the daily solar radiation increases sharply from January and attain the first peak in March. It then reduces gradually to June and increases again and attains the second peak in August, while it increases sharply from January until the first peak is observed between March and April in Yala. It then reduces sharply until August when it increases again to the second peak in August. Daily solar radiation in Narathiwat also increases sharply from January and attain the first peak in March. It then decreases gradually until June, where it increases steadily again until the second peak is attained in October. Low levels of solar radiations are evident in most of the study areas between October and December, and this may be due to the onset of the northeast monsoon season which brings a considerable amount of rains to the east coast of southern Thailand. In general, the average daily solar radiation in Pattani and Yala were relatively higher than the overall mean solar radiation observed in the study area.

Fig. 4 shows the patterns of the solar radiation data as revealed by the cubic spline model for all the study areas. In the placing and selecting the optimum number of knots for each of the fitted curves in the study area, a compromise was drawn between the number of knots and the value of the adjusted r-square values. A random number of knots were placed, and the number that improves the fitted cubic spline curve with the highest adjusted r-square values was selected.

In this study, the optimum number of knots varied from 6-9 in the study areas. In Pattani, nine knots were seen to be the best in modelling the solar patterns, while six knots were observed in Yala to be the optimum number of knots. The model in Narathiwat required seven optimum knots while the study area average required six optimum knots in fitting the model. The suitability of the model was examined using the adjusted r-squared values. These observed adjusted r-squared values from the models were 0.22, 0.40,0.45 and 0.53 in Pattani, Yala, Narathiwat and the overall study area average respectively. The adjusted r-square values of greater than 0.5 revealed that the fitted cubic spline models explain over 50% of the variations in the solar radiation observations, while values of below 0.5 reveal that the models describe less than 50% of the variations in the data.

The fitted models revealed low adjusted r-square values. The low adjusted r-square values observed, do not imply that the cubic spline models do not fit the data very well. However, the low adjusted r-square values observed may be as a result of high variations in climatic data due to other physical processes, which are not under the scope of the model. Analysis and closer look at the singular models from the various areas indicate that the timing of variations has been modelled quite well. However, the levels of the variations are considerably smaller than the observed data. A similar observable feature is a dip in the curve and the bimodal solar radiation patterns which are evident in all the models.

The evident dip in the models from all the three areas of the study due to the reduction in the daily solar radiation between May and June could be a result of the influence of the onset of the southwest monsoon, which brings a significant amount of rainfall to the study area. Besides, the arrival of the Inter-Tropical Convergence Zone (ITCZ), which arrives in May, and the tropical cyclones may also bring a considerable amount of rainfall during this period in the south of Thailand. A study by Cheung et al. (2015) has revealed that rainfall amount is approximately proportional to the amount of cloud. Rainfall amount is also related to the amount of cloud, therefore, a more considerable amount of cloud cover may absorb the more substantial part of the

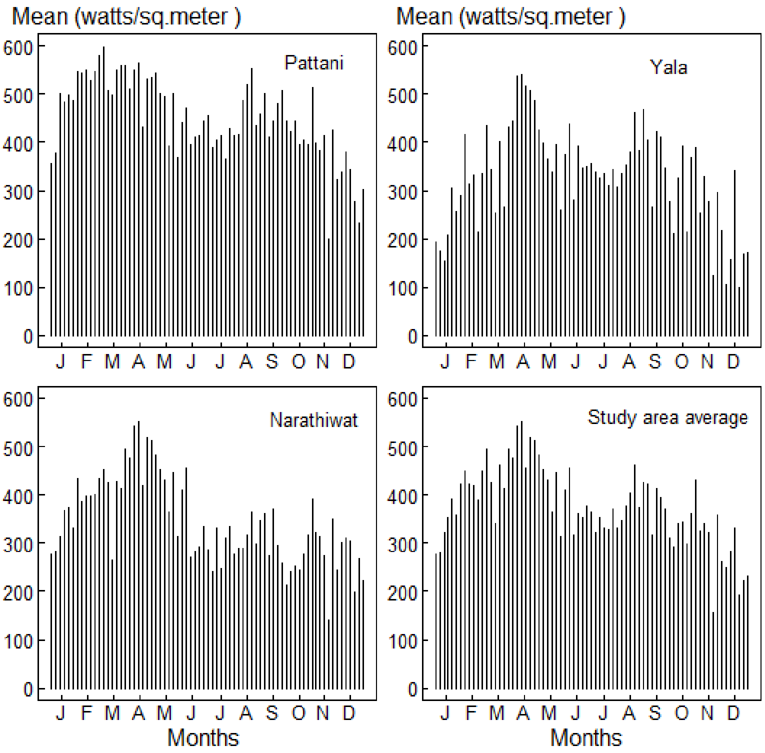

Fig. 3: Monthly patterns based on the estimated 5-day mean solar radiation. The vertical bars show the 5-day mean within a particular month.

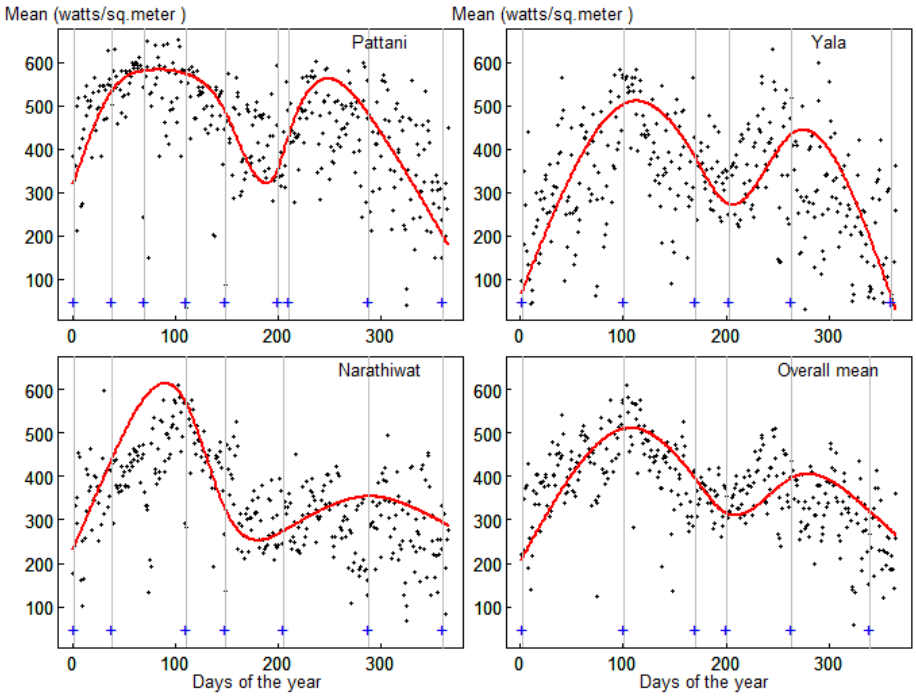

Fig. 4: The fitted cubic spline model to the solar radiation data. The red curve shows the fitted spline model while the grey points revealed the observed solar data. The symbol + shows the knots of the curves and where they are placed.

solar radiation falling on the surface of the earth. Exell (2000) reported that the effects of the cloud on the solar radiation expected at the Earth's surface are complex. If there is a cloud between the sun and the point of observation, then the beam of solar radiation is lessened. Diffusal of solar radiation, diversely, may be greater or less in the presence of cloud than under a clear sky, depending on the type and amount of the cloud.

The decreasing daily solar radiation in the study area from September to December could also be as a result of the onset of the northeast monsoon, which conveys a great amount of rainfall in the east coast of Southern Thailand, particularly during October to November. Particularly, November is the wettest month of the study area. A significant amount of rainfall during this period may be as a result of a large amount of the cloud cover which may also absorb a large percentage of the solar radiation that reaches the surface of the earth. The high uniform peak revealed by the spline model in Pattani during February to April may be due to frequent clear days in the dry season, which is consistent with the result of Exell (1975) in a similar study in Thailand and study in the United States of America by Bennett (1967).

CONCLUSIONS

In-depth understanding of the variability patterns of daily solar irradiance time series observations is vital for the control of solar energy. Appropriate methods for the modelling of climate data particularly solar radiance has been presented. The patterns of the solar irradiance in the southernmost of Thailand were modelled using a natural cubic spline method. The developed models from the observational data fit the data quite well in describing the seasonal patterns and the bimodal patterns of solar radiation in the southernmost of Thailand.

This information on the patterns on the daily solar radiations modelled by the cubic spline functions are vital in climate studies. An exceptional feature of this method is that it can model time series observations very well even in cases of a considerable amount of consecutive missing observations without the imputation of the missing observations. This method could be explored in the modelling of other climate variables such as rainfall, wind speed and *in situ* temperature observations and will be essential even in the determination of long-term variability patterns of solar irradiance and its real applications.

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