P-ISSN 2586-9000
E-ISSN 2586-9027
Homepage : *https://tci-thaijo.org/index.php/SciTechAsia* Science & Technology Asia
Vol.29 No.4 October - December 2024 Page: [168-183]
Original research article

Utilizing Himawari-8/AHI Satellite Data for Accurate Global Solar Radiation Exergy Predictions in Thailand's Climatic Context

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Received 28 December 2023; Received in revised form 11 November 2024
Accepted 19 November 2024; Available online 27 December 2024

ABSTRACT

This study developed and tested a Global Solar Radiation Exergy model using data from the Himawari-8/AHI Satellite, focusing on four key provinces in Thailand: Chiang Mai, Nakhon Pathom, Ubon Ratchathani, and Songkhla. The model's accuracy was evaluated based on R-squared, RMSD, and MBD values. For Chiang Mai, the model demonstrated high precision, with an R-squared value of 0.91, RMSD ranging from 0.90 to 0.91, and MBD between 0.21 and 0.30. In Nakhon Pathom, the model achieved R-squared values between 0.87 and 0.89, RMSD from 0.75 to 0.88, and MBD from 0.60 to 0.79, indicating good accuracy with some variability. The results for Ubon Ratchathani showed R-squared values from 0.78 to 0.79, RMSD between 0.51 and 0.55, and MBD from -0.13 to -0.23, suggesting high accuracy with a tendency to underestimate values. Finally, the model for Songkhla had an R-squared value of 0.81, RMSD ranging from 0.89 to 1.00, and MBD between -0.31 and -0.59, indicating good accuracy with minor variations in estimations. These findings underscore the model's effectiveness in predicting solar energy potential and emphasize the necessity for regional adjustments to enhance precision across diverse geographic settings.

Keywords: Efficiency; Exergy; Solar Energy

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doi: 10.14456/scitechasia.2024.79

1. Introduction

Solar energy, a clean and renewable source, stands at the forefront of addressing global energy challenges and climate change. Despite its rapid growth in adoption and strong support from the scientific community and energy investors, solar energy currently constitutes only a minor fraction of the global energy mix. However, its potential to significantly reduce greenhouse gas emissions and replace fossil fuels is undeniable. Predictions, based on exponential growth trends, suggest that solar energy could potentially meet all of our energy needs by around 2032, although this is subject to various factors such as market saturation and political pressures [1].

The versatility of solar energy is evident in its wide range of applications, from residential power generation to large-scale utility projects, including photovoltaic systems and concentrated solar power plants [2]. Furthermore, the role of solar energy in sustainable and green technologies is highlighted by its use in processes like solar distillation and drying [3], as well as solar pyrolysis reactors for biomass conversion [4].

Solar radiation modeling has evolved significantly, contributing to a deeper understanding of solar energy distribution and its potential applications. This review explores various models and tools developed for solar radiation analysis, highlighting their capabilities and limitations. The Solar Analyst, for example, exemplifies a comprehensive tool that utilizes digital elevation models (DEMs) to calculate insolation maps, taking into account factors like viewshed, surface orientation, and atmospheric conditions. This model adeptly combines the strengths of point-specific and area-based approaches, providing detailed insolation data for various locations [5].

Geographical Information Systems (GIS) have also been instrumental in solar radiation modeling, particularly for complex terrains. GIS models integrate data from both stations and satellites, offering a powerful approach for mapping and interpolating solar radiation data, as outlined in the work under the United Nations Solar and Wind Energy Program [6]. The MARS model, another notable development, has demonstrated its effectiveness in solar radiation forecasting. Researchers have shown the model's superior performance in certain scenarios compared to other techniques like the Kriging method and linear models. These studies underscore the model's capacity to provide reliable solar radiation forecasts based on various atmospheric parameters[7, 8].

In the realm of artificial neural networks, research delves into identifying the optimal combination of inputs for solar radiation modeling. This study identifies key variables that significantly impact solar radiation predictions, offering valuable insights for future modeling endeavors [9]. Clearness indices and climate regimes also shed light on the importance of geographical and temporal factors in solar radiation modeling. This research emphasizes the correlation between clearness indices and diffuse sky ratios, providing a nuanced understanding of solar irradiance variations across different climate regimes [10].

The evaluation of Surface Solar Irradiance (SSI) products from the Advanced Himawari Imager (AHI) on the Himawari-8 satellite, a new-generation geostationary satellite with high spatiotemporal resolution, is a significant aspect of this discussion. Released by the Japan Aerospace Agency (JAXA), these AHI SSI products have shown substantial potential in energy budgets, solar energy, and ecosystem studies. An evaluation using pyranometer measurements from the Chinese Ecosystem Research Network (CERN) at 36 sites in China, from March to December 2016, revealed a strong correlation between the AHI SSI products and ground measurements [11].

2. Literature Review

In their paper titled ”A Data-Driven Approach for On-line Gas Turbine Combustion Monitoring using Classification Models,” Allegorico and Mantini [7] employed logistic regression and an artificial neural network to recognize anomaly patterns leading to combustion issues. They also integrated a physics-based algorithm into their study for comparison. Their findings revealed that machine learning models, particularly logistic regression, outperformed their counterparts, demonstrating the potential of these models in detecting combustion anomalies. However, their focus on combustion monitoring alone rather than on broader efficiency metrics and their analysis under specific turbine conditions limits the generalizability of their approach

Jihad and Tahiri [8], in their work ”Forecasting the Heating and Cooling Load of Residential Buildings by Using a Machine Learning Algorithm ’Gradient Descent,’” predicted the energy requirements of residential buildings in the Agadir region of Morocco. They achieved remarkable accuracy rates of 98.7% and 97.6% for prediction and test data, respectively, using gradient boosting. This high performance influenced our choice of the algorithm for our research. However, their study focused solely on residential buildings, which differ significantly in efficiency and operational dynamics from industrial power plants, thereby limiting the direct applicability of their findings to Combined Cycle Power Plants (CCPPs).

Elfaki and Ahmed [9] utilized artificial neural network (ANN)-based regression models with a four-input dataset to predict the electrical output power of a combined cycle power plant. Their research highlighted the stochastic behaviour of the regression model and concluded that increasing the dataset size led to improved predictions and enhanced the reliability of the ANN model. Yet, with only four input variables, their model potentially missed additional factors relevant to more complex energy systems like CCPPs.

Kaya, Tufecki, and Gurgen [10] conducted an experiment using a six-year dataset, incorporating temperature, humidity, pressure, and exhaust vacuum as inputs. They formed both local and global predictive models using various techniques, including conventional multivariate regression, additive regression, k-NN, feedforward ANN, and K-Means clustering. Their findings illustrated that even basic regression tools such as K-NN could forecast net yield with an average relative error of less than 1%, underscoring the potential for improved performance with the incorporation of more advanced tools and comprehensive pre-processing. This finding highlighted the potential for improved performance with advanced tools and thorough pre-processing. However, their study did not explore ensemble methods that could capture complex interactions between variables.

Siddqui et al. [11] estimated power production by a Combined Cycle Power Plant (CCPP) on an hourly basis using machine learning algorithms. They evaluated five models, including K-Nearest Neighbors, Linear Regression, Gradient-Boosted Decision Trees, Artificial Neural Network, and Deep Neural Network, with the Gradient-Boosted Decision Trees yielding the most favorable results. Their work underscores the need to evaluate multiple models to achieve optimal accuracy; however, it concentrated only on power prediction without exploring efficiency or other operational metrics

Similarly, Alketbi et al. [12] employed four machine learning methods–Multiple Linear Regression, K-Nearest Neighbors, Multilayer Perceptron, and Random Forest Regression-on four input variables. Their experiments demonstrated that Random Forest Regression produced the most promising outcomes. While effective, their approach used a limited number of input variables, possibly overlooking additional significant operational factors for power plants.

In reviewing previous studies, we noted that regression methods were commonly used but with limited input variables, often missing critical aspects of CCPP efficiency. This prompted us to expand our experiments to include not only key environmental factors but also a range of internal components. Additionally, we employed advanced machine learning techniques, such as gradient boosting, adaptive boosting, and bagging ensembles, alongside various regression methods to identify the most effective model. By incorporating a broader set of variables and sophisticated techniques, our study aims to offer a more accurate and comprehensive approach to efficiency estimation.

Estimating Surface Solar Irradiance (SSI) from the AHI on the Himawari-8 satellite is vital for solar energy implementation, weather and climate modeling, and ecological and agricultural studies. The employed model retrieves properties of clouds, aerosols, and surface albedo to accurately calculate global, direct, and diffuse SSI components. Its success hinges on calibration against in-situ measurements across Australia, factoring in elements like water vapor, often overlooked in physics-based methods. Validated over three years using data from 11 Australian sites, the model has proved effective in various conditions, exhibiting low biases and error rates. Once calibrated, it operates independently, using only geostationary satellite inputs, demonstrating the feasibility of deploying the model globally with minimal ground data [12].

For estimating Global Horizontal Irradiance (GHI), four machine learning algorithms and their ensemble, using Himawari-8 data as the sole input, have been employed. These models have shown impressive accuracy, with results outperforming the official Himawari-8 shortwave radiance product. However, variations in model effectiveness under different weather conditions, particularly under overcast skies, highlight the need for further refinement. Despite these challenges, this approach shows promise for near-real-time GHI estimation [13].

A statistical model for computing global spectral solar irradiance across Thailand under various sky conditions is also noteworthy. It integrates clear-sky global spectral irradiance with a cloud modification function, utilizing data from four regional stations. This model, validated with ground-measured spectral data from 2017 to 2021, uses sky images and Himawari-8 derived cloud indices. Its close alignment with actual measurements, evidenced by a root mean square difference of 9.48%, emphasizes its accuracy and importance for solar energy research in Thailand, especially in leveraging advanced satellite data like Himawari-8 [14].

The Himawari-8 satellite's advanced geostationary capabilities have been crucial in solar radiation modeling, particularly in Asia. Its ability to precisely track solar irradiance at sub-hourly intervals is essential for accurately assessing SSI and understanding atmospheric dynamics. The satellite's extensive coverage over diverse Asian climatic zones makes it invaluable for regional solar studies. In Thailand, Himawari-8's capabilities are especially beneficial in addressing tropical climate challenges for solar energy forecasting, offering a reliable data source for enhanced solar radiation modeling.

Exergy, a pivotal property in thermodynamics, is defined as the maximum useful work achievable when a system reaches equilibrium with its environment. This concept encompasses the state of both the system and its environment, factoring in the irreversibilities that occur in thermodynamic processes. These irreversibilities, which lead to entropy generation, contribute to the destruction of exergy, thereby limiting the potential useful work [15]. Exergy analysis, which considers these irreversibilities, has become essential in assessing and determining the limits of work achievable in various thermodynamic processes. In renewable energy, this analysis is particularly vital, as it's used to evaluate the performance and efficiency of innovative systems such as photovoltaic/thermal (PV/T) systems [16-19], and hydrogen production systems [20-23].

Exergy constitutes a critical element in the scholarly examination of solar energy systems, wherein the exergy of solar radiation emerges as a fundamental determinant of the system's overall exergy, encapsulating aspects such as thermal and electrical exergy. The model proposed, predicated upon ambient temperature parameters, has made a significant contribution to the field, particularly in the context of thermodynamic analysis of incident solar radiation [24]. This conceptual advancement has galvanized the academic community, prompting researchers to develop predictive models for solar radiation exergy. These models, which incorporate the Angstrom-Prescott solar radiation paradigm, have been applied with notable success in diverse geographic contexts, especially relevant to studies focusing on variables such as sunshine duration and day length [25-27]. Furthermore, the researcher introduces a nuanced concept of spatial solar exergy display, effectively building upon the foundational framework established by the total solar radiation model [28]. A novel dynamic roll bond PVT collector system under real-world conditions highlights key advancements in solar, thermal, and electrical modeling, offering improved exergy analysis for PVT panels over extended periods [29]. A new CPC and PTC-based CPV/T-STEG hybrid system is proposed, incorporating a steady-state coupled model validated through 3-D simulations. The study reveals improvements in electrical and thermal performance, with a detailed analysis of the impact of critical parameters such as solar concentration and flow rate on system efficiency [30].

Utilizing data from the Himawari-8 satellite to develop global solar radiation exergy models provides significant advantages for solar energy research and applications. Himawari-8's capability to provide spatiotemporal information with higher resolution than other models allows researchers to analyze solar radiation exergy more precisely, reflecting the efficiency of solar radiation conversion into usable energy. Therefore, this research aims to create a global solar radiation exergy model specifically for Thailand, utilizing data from the Himawari-8 satellite. This model has the potential to assist in estimating global solar radiation exergy under various environmental conditions in Thailand. The research will enhance our understanding of solar energy utilization at the local and regional levels and develop new methods for efficient solar energy use in Thailand. This, in turn, will positively impact energy planning and sustainable development within the country, leading to a more informed and efficient utilization of solar energy resources.

3. Methodology

3.1 Solar radiation model

The solar radiation model employs a satellite-based methodology, as proposed by Hay and Hanson [31]. In this model, the coefficients a, and b have been empirically determined.

$$\frac{H}{H_0} = a_b \alpha_p. \tag{3.1}$$

The monthly average daily extraterrestrial solar radiation on the horizontal surface, denoted as Ho, can be calculated using the following equation [32].

The solar constant, Gsc, is 1367 W/m^2.

$$H_0 = \frac{(24 \times 3600 G_{sc} E_0)}{\pi} [\cos\varphi \cos\delta \sin W_s + \frac{\pi W_s}{180} \sin\varphi \sin\delta]. \tag{3.2}$$

The correction factor for the variation of the Earth-Sun distance (E_0) and declination can be determined using equations derived from Duffie and Beckman [32] and Cooper [33], respectively. The order of days in a year is represented by d_n, ranging from 1 on January 1 to 365 on December 31. For the purpose of Eqs. (3.3)-(3.4) February is considered to have 28 days. Eq. (3.5) involves the sun hour angle (W_s), while the latitude of the measuring station is denoted as φ.

$$E_0 = 1 + 0.033 \cos(\frac{2\pi d_n}{365}), \tag{3.3}$$

$$\delta = 23.45 \sin[\frac{360}{365}(d_n + 284)], \tag{3.4}$$

$$W_s = \cos^{-1}[-\tan(\delta)\tan(\varphi)]. \tag{3.5}$$

3.2 Exergy of global solar radiation model

Global solar radiation exergy can be represented in terms of maximum conversion efficiency and incident solar radiation [34].

$$H_{exergy} = \Psi \cdot H. \tag{3.6}$$

The equation can be reformed by dividing it by Ho to obtain the ratio of total radiation to extraterrestrial radiation, as shown in Eq. (3.7).

The parameters for the model that will be constructed will be discussed in the next section.

$$\frac{H_{exergy}}{H_0} = \Psi(T_0) \cdot \frac{H}{H_0}. \tag{3.7}$$

The solar radiation exergy efficiency, represented by Ψ, is determined by the solar temperature T_s, which is approximately 6,000 K, and the average daily ambient temperature for each month, T_0 [35].

$$\Psi = 1 + \frac{1}{3}\left(\frac{T_0}{T_s}\right)^4 - \frac{4}{3}\frac{T_0}{T_s}. \tag{3.8}$$

From Eqs. (3.1) and (3.6), we can develop a model using empirical equations for this study. A notable feature of this model is that it requires only a single input parameter, which is the actual planetary albedo (α_p), to calculate the solar radiation exergy. There's no need for the global solar radiation or the solar radiation exergy efficiency.

$$\frac{H_{exergy}}{H_0} = \Psi(T_0) \cdot \frac{H}{H_0}.$$

$$= \quad \Psi(T_0) \cdot f(a, b, \alpha_p),$$

$$\frac{H_{exergy}}{H_0} = f(a, b, \alpha_p). \qquad (3.9)$$

3.3 Research case studies

Experimental data for this study were sourced from two main origins. First, the monthly average daily global solar radiation data were obtained from measurement stations within the solar energy research laboratory network at the Faculty of Science, Silpakorn University [36]. Second, the average daily and monthly ambient temperatures were collected from the Thai Meteorological Department database [37], and the actual planetary albedo was observed from the VIS band of the Himawari-8/Advanced Himawari Imager (AHI) at the Meteorological Satellite Center of JMA [38]. The primary objective of this research is to investigate the solar exergy potential in four strategically distributed capital provinces of Thailand: Chiang Mai, Nakhon Pathom, Songkhla, and Ubon Ratchathani. These stations are located in the northern, central, southern, and northeastern regions of Thailand, respectively, and offer geographic diversity in terms of latitude, as indicated in Table 1. The locations of these four provinces are illustrated in Fig. 1. Data from 2015 to 2016 were utilized for modeling Global Solar Radiation Exergy, and the models were subsequently tested using data from 2017.

Table 1. Information about the provinces considered in the study.

Location	Latitude	Longitude
Chiang Mai	18.78° N	98.88° E
Nakhon Pathom	13.82° N	100.04° E
Ubon Ratchathani	15.25° N	105.87° E
Songkhla	7.20° N	100.60° E

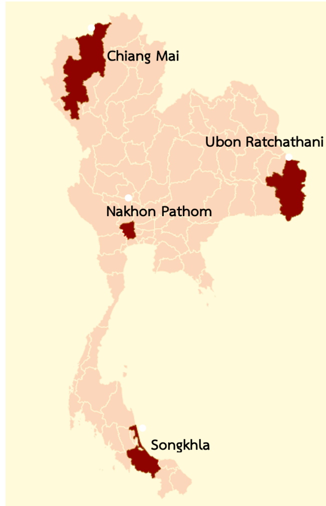

Fig. 1. Map of Thailand indicating the locations of the four stations.

4. Results and Discussion

An analysis of the average daily total solar radiation per month from 2015 to 2017 at stations in Chiang Mai, Nakhon Pathom, Songkhla, and Ubon Ratchathani helps us understand the variability in solar radiation levels in Thailand over the years. This information is beneficial for efficient solar energy planning. These data will be used to create models predicting solar energy potential, taking into account the environmental temperatures in Thailand. This information is crucial for developing strategies for utilizing solar energy in the future, both within Thailand and in neighboring countries in Southeast Asia. The details from Fig. 2 are as follows:

- The Chiang Mai station, located in the northern region of Thailand, reveals significant seasonal variability in solar exergy potential. Throughout the year, the average monthly solar radiation reaches its zenith in May with a peak value of 21.48 MJ/m^2, accompanied by the year's highest

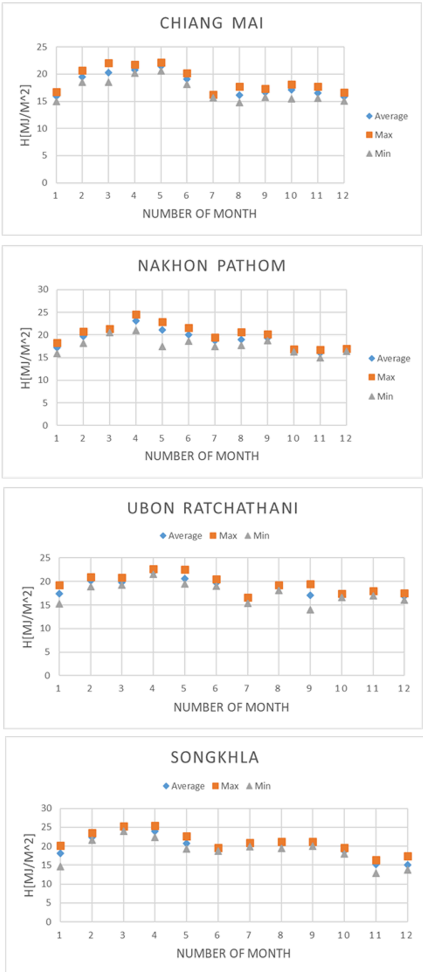

Fig. 2. Average daily total solar radiation per month from 2015 to 2017.

recorded figure of 22.14 MJ/m^2. This peak is indicative of the intense solar influx during the dry, pre-monsoon summer period. Conversely, the lowest average radiation is observed in July, at the heart of the rainy season, with an average of 15.91 MJ/m^2, and the absolute minimum is recorded in August at 14.77 MJ/m^2, likely due to increased cloud cover associated with monsoonal patterns. This oscillation between the summer highs and the wet season lows underscores the influence of Thailand's tropical climate on solar radiation levels. Such data are crucial for optimizing the design and implementation of solar energy systems by ensuring that seasonal fluctuations are accounted for in energy projections and infrastructure planning. With clear trends of higher radiation levels during the hot, dry season, and a decrease during the rainy and cooler months, these insights can inform more efficient, climate-conscious applications of solar technology in the region.

- Nakhon Pathom station, reflecting the climate dynamics of central Thailand, shows insightful variations in solar radiation throughout the year. The average monthly solar radiation values peak in April, reaching a high of 23.17 MJ/m^2, which aligns with the transition toward the hot season when solar insolation is at its strongest. This period is pivotal for solar energy harvesting, suggesting the potential for maximizing solar energy capture. After the peak, there is a significant decrease during the rainy season, with July's average dipping to 18.79 MJ/m^2, and the station's minimum value recorded at 17.46 MJ/m^2, reflecting the reduced solar radiation due to cloud cover and precipitation. The data also show a recovery in solar radiation post-monsoon, with values climbing back up in August to an average of 19.03 MJ/m^2. The variation from a maximum of 24.48 MJ/m^2 in the hot dry season to a minimum of 14.93 MJ/m^2 toward the end of the rainy season in November illustrates the robust seasonal impact on solar potential. These fluctuations highlight the need to incorporate seasonal trends into the planning and operation of solar energy systems, ensuring they are equipped to manage the changes in solar radiation and maintain efficiency throughout the year.

- In southern Thailand, the Songkhla station's detailed solar radiation measurements capture the profound variability that is crucial for optimizing solar energy systems. March is notable with an average solar radiation of 24.53 MJ/m^2, showcasing the area's maximum solar harvesting potential in a month characterized by long periods of sunshine and clear skies. In stark contrast, December's average plummets to 15.05 MJ/m^2, reflecting the reduced solar capacity during the northeast monsoon, which brings shorter days and increased cloudiness. Even within individual months, such as April, the variation is substantial, with solar radiation peaking at 25.43 MJ/m^2 and dropping to a minimum of 22.29 MJ/m^2, underscoring the need for a solar energy infrastructure that can adapt to not only seasonal but also daily changes in solar irradiance.

- In Ubon Ratchathani, a northeastern province of Thailand, the solar radiation data reveals pronounced seasonal variation affecting solar energy potential. The average solar radiation peaks in April at 22.02 MJ/m^2, coinciding with the region's hot, dry season– ideal conditions for solar harvesting. However, the average dips to its lowest in July at 16.11 MJ/m^2, reflecting the influence of the monsoon with increased cloudiness. The data shows a notable disparity within the year, with the highest solar radiation reaching 22.62 MJ/m^2 in April and the lowest at 13.98 MJ/m^2 in September, indicating the need for solar energy systems to be resilient and adaptable to these significant shifts. Solar systems in Ubon Ratchathani must be designed to optimize energy capture during peak radiation and to operate efficiently through the less predictable rainy season, ensuring a stable year-round energy supply.

Our study began with the calculation of the monthly average daily global solar radiation, which entailed averaging the solar radiation data for each month across the full data period. For instance, the Nakhon Pathom station's data for April was averaged from the measurements taken between April 2015 and April 2016, yielding the monthly average daily global solar radiation for that month. This value was then normalized by dividing it by the monthly average daily extraterrestrial solar radiation for April. This methodology was consistently applied across all twelve months of the year. We also computed the actual planetary albedo by averaging relevant measurements over the same timespan.

The computation of the solar radiation exergy efficiency was based on the monthly average daily ambient temperature which was derived from the mean of daily temperatures for the month and a solar temperature of 6,000K, as stated in Eq. (3.8). We further processed these values using a linear regression fitting method aligned with Eq. (3.9) within a Python environment. The primary function of this study was to estimate the parameters *a*′ and ’*b*,’ which are indicative of the influence of solar radiation exergy efficiency and actual planetary albedo on our model (Fig. 3). The linear regression technique was instrumental in delineating the complex interplay between these variables.

5. Results and Discussion

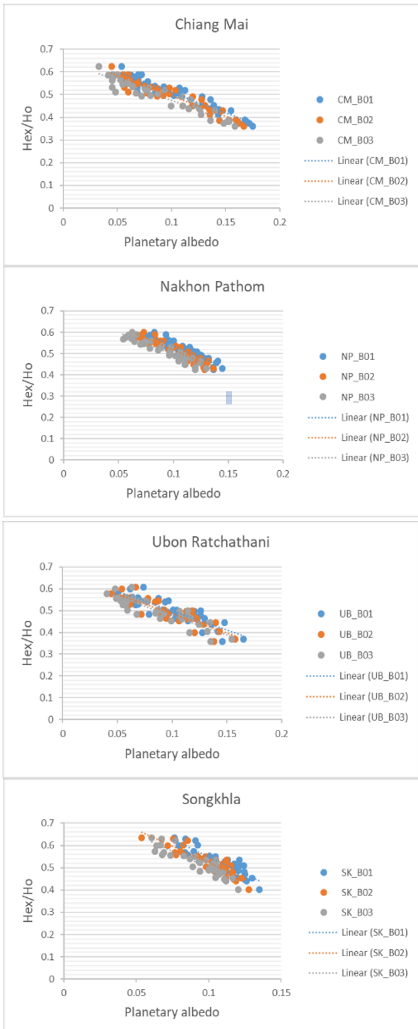

Fig. 3. The relationship between the solar radiation exergy per extraterrestrial solar radiation(H_ex/H_0) and the actual planetary albedo (α_p) .

The regression constants for the various stations across Thailand were ascertained as seen in Table 2. For Chiang Mai, the constants a' ranged from 0.65 to 0.69, and b' from -1.75 to -1.82, with an R-squared value of 0.91 across all three bands. Nakhon Pathom showed a' values from 0.70 to 0.76, b' values from -2.05 to -2.26, and R-squared values between 0.87 and 0.89. Ubon Ratchathani's a' ranged from 0.65 to 0.68, b' from -1.75 to -1.78, and R-squared values of approximately 0.78 to 0.79. Songkhla's a' values were significantly higher, ranging from 0.79 to 0.86, and b' values from -2.95 to -3.14, with an R-squared value consistently at 0.81.

Table 2. Regression constants for Thailand station.

Site Area	Model	a'	b'	R^2
Chiang Mai	B01	0.69	-1.82	0.91
	B02	0.67	-1.8	0.91
	B03	0.65	-1.75	0.91
Nakhon Pathom	B01	0.76	-2.26	0.87
	B02	0.74	-2.21	0.87
	B03	0.7	-2.05	0.89
Ubon Ratchathani	B01	0.68	-1.77	0.78
	B02	0.66	-1.78	0.79
	B03	0.65	-1.75	0.79
Songkhla	B01	0.86	-3.14	0.81
	B02	0.82	-2.96	0.81
	B03	0.79	-2.95	0.81

The regression analysis across different bands and locations revealed distinct patterns. The R-squared values indicate a strong correlation between the measured and predicted values of solar radiation exergy efficiency, especially for the Chiang Mai station across all bands. This suggests that the models are well-fitted for this region and that the solar radiation exergy efficiency is highly predictable based on the parameters a' and b'.

The variation in the constants a' and b' between the different locations and bands reflects the unique solar radiation profiles and atmospheric conditions at each site. For example, the higher a' values in Songkhla could be attributed to its coastal environment, which may affect the atmospheric clarity and, consequently, the solar radiation received. The b' values, which are negative across all models, indicate an inverse relationship with the solar radiation exergy efficiency. The magnitude of these values points to the sensitivity of the exergy efficiency to changes in the albedo and the intensity of solar radiation. The differences in R-squared values among the sites suggest that certain regions like Chiang Mai have more consistent solar radiation patterns compared to others like Ubon Ratchathani. This could be due to a variety of factors, including geographical position, local climate, and seasonal weather variations.

Overall, the regression constants and R-squared values obtained from our models provide a robust framework for predicting solar radiation exergy efficiency in Thailand. The insights gained from this study can be utilized to optimize the design and operation of solar energy systems, ensuring they are tailored to the specific solar profiles of each location.

Furthermore, the distinct patterns observed in the VIS bands of the Himawari-8/AHI data underline the importance of considering spectral differences in solar radiation for more precise energy forecasts.

For the four study sites, the main findings are as follows from the data presented in Tables 3 and the differences between observed and predicted values illustrated in Fig. 4 for seven station.

The model testing using 2017 data for the assessment of solar radiation exergy efficiency yielded statistical indicators, as shown in Table 3. This testing aimed to evaluate the predictive strength of the models defined by the regression constants from Table 2 for various stations in Thailand. The models were based on the VIS bands of the Himawari-8/Advanced Himawari Imager (AHI) for three different wavelengths: the blue band (B01) at 0.46 µm, the green band (B02) at 0.51 µm, and the red band (B03) at 0.64 μm.

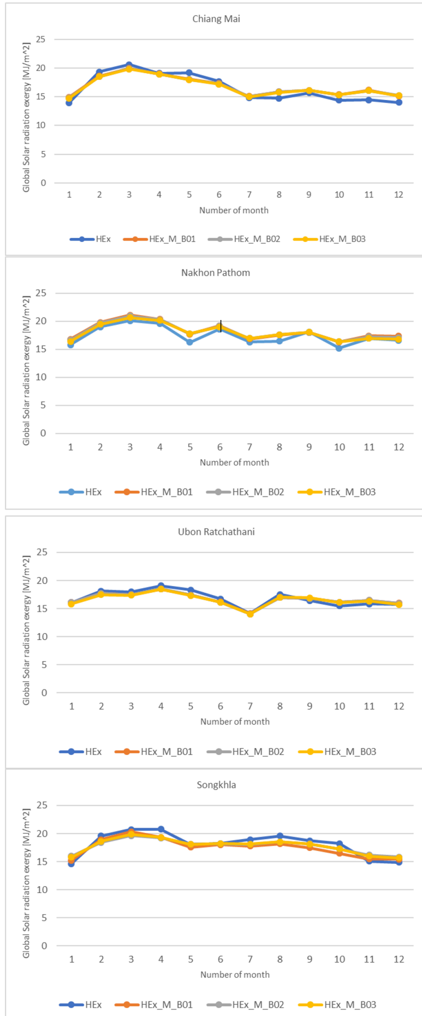

Fig. 4. Calculation and forecast values of Global Solar radiation exergy of stations in Thailand.

For Chiang Mai, the models demonstrated relatively low root mean square deviations (RMSD) ranging from 0.90 to 0.91,

Table 3. Statistical indicators of Global Solar radiation exergy model for stations.

Site Area	Model	RMSD	RMSD(%)	MBD	MBD(%)
Chiang Mai	B01	0.91	5.5	0.3	1.83
	B02	0.9	5.47	0.27	1.61
	B03	0.9	5.42	0.21	1.3
Nakhon Pathom	B01	0.88	5.05	0.79	4.54
	B02	0.84	4.84	0.74	4.25
	B03	0.75	4.33	0.6	3.47
Ubon Ratchathani	B01	0.51	3.05	-0.13	-0.77
	B02	0.51	3.06	-0.14	-0.84
	B03	0.55	3.28	-0.23	-1.36
Songkhla	B01	0.98	5.38	-0.59	-3.27
	B02	1	5.52	-0.31	-1.73
	B03	0.89	4.9	-0.31	-1.69

and RMSD percentages between 5.42% to 5.50%, indicating close agreement with the observed values. The mean bias deviation (MBD) for Chiang Mai was positive across all bands, suggesting a slight overestimation of the solar radiation exergy by the models.

In Nakhon Pathom, the RMSD values varied from 0.75 to 0.88 with RMSD percentages from 4.33% to 5.05%, which were lower than those for Chiang Mai, implying a more accurate model prediction for this area. However, the MBD was notably higher, especially in B01, indicating a more substantial overestimation in solar radiation exergy.

Ubon Ratchathani showed the lowest RMSD values among all sites, ranging from 0.51 to 0.55, with corresponding RMSD percentages from 3.05% to 3.28%, reflecting the highest model accuracy. Interestingly, the MBD values were negative, which means the models tended to underestimate the solar radiation exergy for this site.

Songkhla's models yielded the highest RMSD values, from 0.89 to 1.00, with RMSD percentages between 4.90% and 5.52%. The MBD for Songkhla was negative across all models, with a substantial deviation in B01, indicating a consistent underestimation of solar radiation exergy.

The statistical analysis of the solar radiation exergy models for the year 2017 reveals a consistent pattern of model performance across different regions of Thailand. Chiang Mai's models showed a slight overestimation bias but maintained a good fit as indicated by the low RMSD values. The trend of overestimation could be due to the models' sensitivity to certain climatic parameters that might be more pronounced in the northern region.

Nakhon Pathom's results, while demonstrating a more accurate RMSD, also showed an overestimation trend, albeit at a higher bias compared to Chiang Mai. This could reflect a regional specificity that might not have been fully captured by the model's parameters.

Ubon Ratchathani's negative MBD values suggest that the models may need further refinement to account for local atmospheric or environmental conditions leading to an underestimation of the solar radiation exergy. The low RMSD values, however, suggest that the models are on the right track and, with adjustments, could potentially offer highly accurate predictions.

Songkhla's models, despite having the highest RMSD, indicate a need for model adjustment to account for the underestimation of solar radiation exergy. The coastal climate's variability, including factors such as aerosol content and cloud cover, may be influencing the accuracy of the models.

Overall, the statistical indicators suggest that while the models are robust, regional adjustments are necessary to enhance accuracy. The positive and negative biases in MBD highlight that the model parameters are sensitive to local environmental conditions, which must be carefully considered in model calibration. The study underscores the importance of localized model validation and the potential need for regional-specific calibration to ensure the models' efficacy in predicting solar radiation exergy with high precisio.

6. Conclusion

This study successfully developed and evaluated a model for predicting global solar radiation exergy using data from the Himawari-8/AHI satellite, specifically applied to four key provinces in Thailand. The findings provide valuable insights into the accuracy and adaptability of solar radiation exergy models under diverse climatic conditions. The major results of this investigation are as follows:

- The developed model demonstrated high accuracy with R-squared values ranging from 0.78 to 0.91, showing reliability in predicting solar radiation exergy across different regions.
- The Root Mean Square Deviation (RMSD) values varied between 0.51 and 1.00, indicating the model's close agreement with observed data. The Mean Bias Deviation (MBD) ranged from -0.59 to 0.79, showcasing slight regional overestimations or underestimations that highlight the need for adjustments.
- The use of actual planetary albedo as a primary input provided a novel and effective approach for estimating solar radiation exergy, minimizing the need for ground-based radiation data.
- This model is suitable for regional energy planning and development, providing a pathway for the creation of national-level solar exergy maps, which can guide the more efficient utilization of solar energy across both urban and rural areas.
- The study underscores the importance of further refining models to better handle local climatic factors, such as cloud cover and aerosol content, to enhance prediction accuracy.

Acknowledgements

The authors would like to express gratitude to the Thailand Science Research and Innovation Fundamental Fund (Contract no. TUFF41/2566) and the National Research Council of Thailand (NRCT) (Contract no. N42A650197) for their generous financial support of this study. Additionally, thanks are extended to the Solar Energy Research Laboratory, Department of Physics, Faculty of Science, Silpakorn University, for providing the solar radiation data crucial to this research. We also appreciate the Thai Meteorological Department for supplying the air temperature data, which played a vital role in our analysis.

Table 4. Nomenclature

H_{exergy}	Global solar radiation exergy (MJ/m^2)
E_{ex}	Exergy of solar radiation (MJ/m^2)
Ψ	Solar radiation exergy efficiency
G_{sc}	Solar constant (1367 W/m^2)
H_0	Monthly average daily extraterrestrial solar radiation (MJ/m^2)
H	Global solar radiation (MJ/m^2)
E_0	Correction factor for the variation of the Earth-Sun distance
α_p	The actual planetary albedo
T_s	Solar temperature (6000 K)
T_0	The average daily ambient temperature for each month (°C)
a, b	Empirical constants in regression analysis (dimensionless)
ϕ	Latitude of the measuring station (degrees)
ω_s	Sun hour angle at sunset (degrees)
δ	Solar declination (degrees)
d_n	Day number in the year, from 1 on January 1 to 365 on December 31
B01	Blue band of the Himawari-8/AHI
B02	Green band of the Himawari-8/AHI
B03	Red band of the Himawari-8/AHI
R^2	Coefficient of determination
RMSD	Root Mean Square Deviation (MJ/m^2)
RMSD (%)	Percentage of Root Mean Square Deviation (%)
MBD	Mean Bias Deviation (MJ/m^2)
MBD (%)	Percentage of Mean Bias Deviation (%)

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