

Development of Empirical Models for Estimating Daily Downward Longwave Radiation Using Meteorological Data in Thailand

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ABSTRACT

This study developed models to estimate daily downward longwave radiation under general sky conditions using meteorological data. The input variables included air temperature, vapor pressure, daily minimum and maximum temperatures, relative humidity, and cloud cover. Data were collected from four meteorological stations, namely Chiang Mai, Ubon Ratchathani, Nakhon Pathom, and Songkhla, during the period from 2018 to 2023. Model development was based on data from 2018 to 2021 using graphical analysis and multiple linear regressions to identify strong relationships and build predictive equations. Seven models were formulated, each using different combinations of meteorological variables. These models were then validated using independent data from 2022–2023. The results showed that downward longwave radiation is largely correlated with meteorological parameters. The developed models provided accurate estimates, closely matching observed radiation values. The root mean square error relative to the mean measured values (RMSE) ranged from 1.7% to 4.4%, and mean bias error relative to the mean measured values (MBE) ranged from -1.4% to 3.9%. The developed model gave a more accurate value of daily longwave radiation. The findings indicate that the proposed models are effective tools for estimating longwave radiation in areas without direct measurements, supporting further research in climate and energy studies.

1. Introduction

Downward Longwave Radiation (DLR) is defined as the thermal infrared radiation emitted by the atmosphere—specifically by greenhouse gases, aerosols, and clouds—towards the Earth's surface. This radiative component typically spans a spectral range from approximately 4 to 100 micrometers. Unlike shortwave solar radiation, which is characterized by high-energy photons originating from the Sun, DLR is a product of terrestrial and atmospheric thermal processes. It is generated when atmospheric constituents absorb longwave radiation emitted by the Earth's surface and subsequently re-emit this energy isotropically, including back towards the surface. The magnitude of this emission is governed by the Stefan–Boltzmann Law, which relates the total energy radiated per unit surface area to the thermodynamic temperature and the emissivity of the atmospheric layer, as expressed in equation (1)

$$L = \varepsilon \sigma T^4 \quad (1)$$

Where L is the emitted radiation (W/m^2), ε is the emissivity (a value between 0 and 1), σ is the Stefan–Boltzmann constant ($5.67 \times 10^{-8} \text{ W/m}^2 \cdot \text{K}^4$), and T is the temperature in Kelvin (K).

The spectral distribution of DLR is highly non-uniform due to the selective absorption and emission properties of atmospheric gases. Major absorption bands include the $15 \mu\text{m}$ CO_2 band and multiple water vapor (H_2O) bands located at wavelengths shorter

than $8 \mu\text{m}$ and longer than $18 \mu\text{m}$. Conversely, the spectral region between 8 and $13 \mu\text{m}$ exhibits relatively low absorption and is known as the Atmospheric Window. This window is critical for the planet's radiative cooling, as it allows a significant portion of surface-emitted longwave radiation to escape directly into space. Consequently, DLR serves as a fundamental component of the Surface Energy Budget and is the primary driver of the greenhouse effect, playing a decisive role in regulating global climate dynamics.

This continuous exchange of longwave radiation between the surface and the atmosphere is a fundamental process that regulates the Earth's energy balance. DLR occurs continuously, both during the daytime and nighttime. Its role becomes particularly important during nighttime and cloudy conditions when incoming solar radiation is limited or absent. Under such conditions, DLR becomes the dominant radiative input to the surface. This process reduces the rate of surface cooling and helps maintain surface temperature stability. For this reason, DLR is often considered one of the most important components controlling nighttime temperature and the thermal behavior of land surfaces. Several atmospheric variables influence the amount of DLR reaching the Earth's surface. These include air temperature, atmospheric water vapor content, cloud cover, and the concentration of greenhouse gases such as carbon dioxide and methane. These variables determine the effective emissivity of the atmosphere, which describes how

efficiently the atmosphere emits longwave radiation. A warmer and more humid atmosphere generally emits more longwave radiation toward the surface. Similarly, the presence of clouds can significantly increase DLR because clouds act as strong emitters of longwave radiation. Therefore, DLR is closely related to the thermodynamic and moisture conditions of the atmosphere. Variations in these atmospheric properties lead to noticeable spatial and temporal differences in DLR, especially in tropical regions where humidity and cloud formation vary strongly throughout the year. DLR is a key component of the surface radiation budget and plays an essential role in determining land surface temperature, weather conditions, and many environmental processes. It directly influences evaporation, plant physiological activity, soil heat storage, and human thermal comfort. In agricultural systems, DLR affects crop growth by controlling surface temperature and evapotranspiration rates. In natural ecosystems, it influences soil moisture retention and biological activity. The importance of DLR is also strongly connected to climate change. As greenhouse gas concentrations increase, the atmosphere becomes more capable of absorbing and re-emitting longwave radiation. This leads to an increase in DLR reaching the surface, which contributes to global warming and modifies regional climate patterns. Understanding DLR is therefore essential for studying the surface energy balance, soil heat flux, evapotranspiration, and nighttime cooling processes. Accurate knowledge of DLR is particularly important in agricultural and hydrological applications. Reliable DLR information improves the estimation of crop water requirements, especially in irrigated areas where evapotranspiration must be carefully controlled. In hydrological studies, DLR contributes to better simulation of soil moisture dynamics, surface runoff, and groundwater recharge. DLR also improves the estimation of land surface temperature, which is an important input for weather forecasting models and climate simulations. In the field of energy planning, DLR data can be used to assess building energy demand, thermal comfort, and the performance of passive cooling systems and renewable energy technologies. For these reasons, reliable DLR data support a wide range of environmental, agricultural, hydrological, and socio-economic applications. Despite its importance, direct measurement of DLR requires specialized instruments such as pyrgeometers or radiometers. These instruments are expensive, require regular maintenance and calibration, and are not always available in remote or developing regions. As a result, many locations around the world do not have continuous and reliable DLR observations. This lack of data creates challenges for researchers and practitioners who need accurate radiation information for modeling and analysis. To address this limitation, researchers have developed empirical and mathematical models to estimate DLR using more accessible meteorological variables such as air temperature, vapor pressure, relative humidity, cloud cover, and wind speed. These data are commonly recorded at standard weather stations. Early empirical models were designed to be simple and easy to apply using only ground-based meteorological data. These models offer important advantages, including ease of use and no requirement for site-specific calibration [1, 2]. A well-known example is the model introduced by Brutsaert [3], which was developed for clear-sky conditions using physical principles. This model estimates atmospheric emissivity based on radiative transfer concepts, making it robust and broadly applicable without local adjustment. Similarly, Prata [4] developed another clear-sky DLR estimation model based on air temperature and vapor pressure. Both models demonstrated strong agreement with measured DLR

values, with high correlation and low estimation error during validation. Further studies have evaluated and compared the performance of various empirical formulas. Josey et al. [5] examined DLR estimation methods over the ocean surface using ship-based observations and found that the formula proposed by Clark et al. [6] provided the best performance. Finch and Best [7] conducted a global assessment of empirical DLR models and reported that the Idso and Jackson [8] model performed well under both clear and cloudy sky conditions due to its versatility and accuracy. Lhomme et al. [9] modified Brutsaert's formula for high-altitude regions such as the Andean Altiplano, which improved frost prediction in complex terrain. These studies confirm that empirical models are valuable tools in regions where direct DLR measurements are not available. With advances in technology, researchers began integrating ground observations with satellite data to improve DLR estimation across large areas with better spatial and temporal resolution. For example, Yang et al. [10] combined ground-based and satellite data to improve DLR estimation over the Tibetan Plateau. Wang and Dickinson [11] investigated global DLR trends using observational records, reanalysis products, and satellite datasets, and discussed their advantages and limitations. Wild et al. [12] pointed out that general circulation models and reanalysis datasets often underestimate DLR, particularly in dry and cold regions, which highlights the need for improved radiation parameterization. Recent studies have introduced more advanced approaches. Pashiardis et al. [13] analyzed longwave radiation in Cyprus and showed that the Idso model remains effective for practical DLR estimation. Chang and Zhang [14] developed new empirical relationships in China aimed at supporting passive cooling system design. Zhu et al. [15] proposed a deep convolutional neural network approach that combines satellite data with ground meteorological data to estimate hourly DLR with higher accuracy than traditional empirical models. Although these advanced methods can provide improved accuracy, they are often complex and depend heavily on high-resolution satellite or reanalysis data. Access to such data may be limited, and the required computational resources can be significant. This can make these methods difficult to apply for routine use, especially in regions with limited data availability or technical capacity. Therefore, there is still a strong need for simple, practical, and reliable empirical models that use only standard meteorological data. Thailand is a tropical country with diverse climatic conditions, including variations in humidity, cloud cover, and temperature throughout the year. These characteristics make DLR estimation both challenging and important. However, continuous DLR measurements are not widely available across the country. Developing empirical models based on commonly measured meteorological variables can provide an effective solution for estimating DLR in areas without radiation instruments.

This study aims to develop simple and reliable empirical models for estimating daily downward longwave radiation in Thailand using only standard meteorological data that are readily available from weather stations. Data from four representative stations will be used, including Chiang Mai, Ubon Ratchathani, Nakhon Pathom, and Songkhla. These stations cover different climatic regions of Thailand and represent a wide range of atmospheric conditions typical of tropical environments. The objective is to provide a practical estimation tool for regions lacking DLR measurements and to contribute to improved radiation estimation for applications in climate, agriculture, hydrology, and environmental research in tropical regions.

2. Research area and data

2.1 Research area

The focus of this study is Thailand, a tropical nation situated between latitudes 5°N to 21°N and longitudes 97°E to 106°E, which possesses a wide range of diverse climatic conditions. To investigate the statistical characteristics of downward longwave radiation (DLR) and develop robust mathematical estimation models, measurement instruments were strategically installed at four representative locations across the country. These sites include the Northern Meteorological Center in Chiang Mai (CM: 18.77°N, 98.96°E), the Ubon Ratchathani Meteorological Station (UB: 15.24°N, 105.02°E), the Nakhon Pathom Meteorological Station (NP: 14.01°N, 99.96°E), and the Southern-east Coast Meteorological Center in Songkhla (SK: 7.41°N, 100.62°E). The DLR data collected from these stations serve as the primary basis for analyzing regional variations and validating the performance of the proposed models. The geographical distribution and specific coordinates of these measurement sites are further illustrated in Fig. 1.

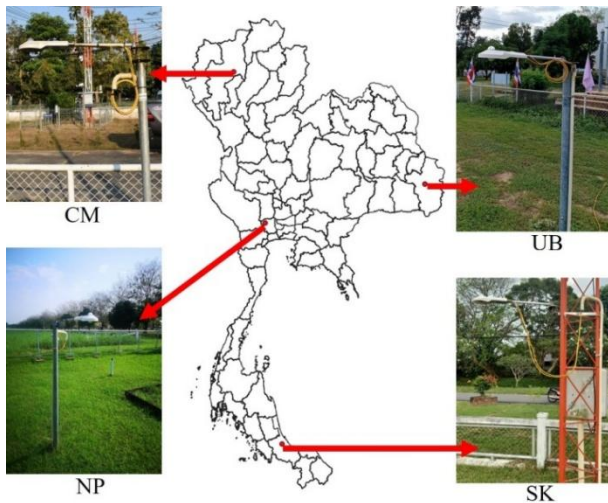


Fig. 1 The CNR4 net radiometer at four stations in Thailand.

The installed instrument is the CNR4 net radiometer, which consists of five sensors: two pyranometers, two pyrgeometers, and one temperature sensor. An example of the instrument is shown in Fig. 2.

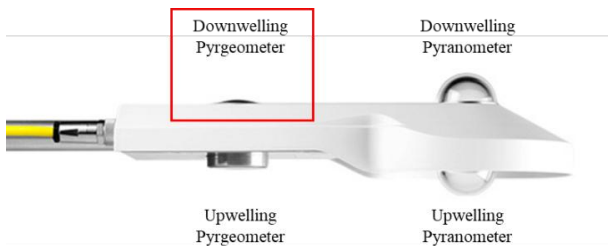


Fig. 2 The CNR4 net radiometer.

As shown in Fig. 2, data was collected from a downward longwave radiation sensor. The signal from the sensor was recorded as electrical potential in millivolts, with measurements taken every second. These data were automatically recorded using a YOKOGAWA FX1012 data logger and later converted into radiation values using equation (2).

$$DLR = \frac{V}{C} + \sigma T^4 \quad (2)$$

Where DLR is the downward longwave radiation in watts per square meter (W/m^2), V is the electrical potential obtained from the sensor in millivolts (mV), C is the sensitivity of the instrument in microvolts per watt per square meter ($\mu V/W/m^2$), and T is the temperature measured by the TC100 sensor, expressed in Kelvin (K).

2.2 Data

Since the primary objective of this study is to analyze the spatio-temporal variation of downward longwave radiation across representative regions of Thailand and to evaluate the robustness of the proposed estimation models, the selection of input parameters was meticulously carried out based on established physical principles and previous literature. The chosen atmospheric variables—namely daily mean air temperature (T_{mean}), vapor pressure (e_a), daily minimum and maximum temperatures (T_{min} and T_{max}), relative humidity (RH), and cloud cover (C)—represent the key drivers of the longwave radiative transfer process. While temperature dictates the emissive power of the atmosphere according to the Stefan-Boltzmann law, vapor pressure and relative humidity serve as proxies for water vapor content, which is the dominant greenhouse gas responsible for atmospheric opacity in the infrared spectrum. Additionally, the inclusion of cloud cover accounts for the significant enhancement of DLR under non-clear sky conditions. To ensure the reliability of the model development and testing, a comprehensive daily dataset spanning six years (2018–2023) was compiled. This period was selected to capture inter-annual variability and diverse seasonal patterns. The data were sourced from four high-standard meteorological stations equipped with specialized radiometers, ensuring that the ground-truth measurements used for validation meet the necessary scientific rigor.

2.2.1 Air temperature and Relative humidity

To measure air temperature and humidity, a standard set of meteorological instruments used worldwide is applied. This equipment is called a Stevenson Screen or a thermometer shelter. It includes the following instruments: 1) Wet and dry bulb psychrometer: This device measures the difference between the wet bulb and dry bulb temperatures using two thermometers. One is a dry-bulb thermometer that measures the air temperature, while the other is a wet-bulb thermometer (with a cloth covering the bulb). As the water evaporates from the wet cloth, the temperature drops. This temperature difference is then used to calculate the relative humidity (RH). 2) Maximum thermometer: This thermometer is filled with mercury and is used to measure the daily maximum temperature. It is a glass tube with a narrow constriction near the bulb. When the temperature rises, mercury expands and passes the constriction. When the temperature falls, the mercury contracts, but the mercury column stays in place at the highest point, allowing the maximum temperature to be ready. The thermometer is installed horizontally inside the Stevenson screen, with the bulb end slightly higher (about 5 degrees) than the other end to prevent mercury from flowing back. 3) Minimum thermometer: This instrument is used to record the daily minimum temperature. It contains alcohol and a small black glass index inside a glass tube. The temperature range is typically from -10 to 50 degrees Celsius. The index moves with alcohol as the temperature drops. When the temperature rises again, the alcohol increases, but the index remains in place, indicating the lowest temperature. This thermometer is also installed horizontally in the Stevenson Screen, with the bulb end slightly lower (about 3 degrees) to help the index move easily when the temperature decreases. These instruments are shown in Fig. 3.

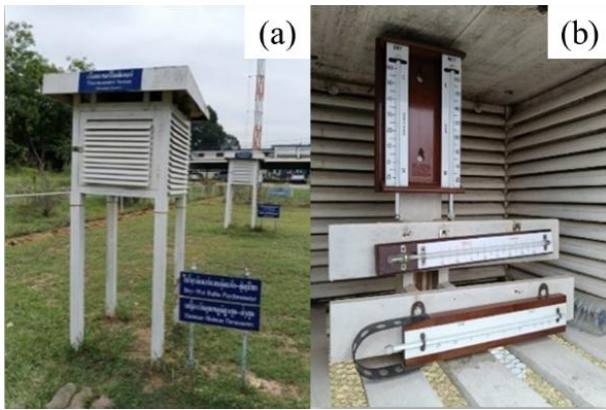


Fig. 3 Instruments of air temperature and relative humidity: (a) Stevenson Screen or a thermometer shelter. (b) Wet and dry bulb psychrometer (Upper) and maximum-minimum thermometer (Under).

2.2.2 Cloud cover

Cloud cover is measured by visual observation, which is a basic meteorological method. It involves observing the sky with the naked eye to estimate the amount, type, and height of clouds. Although modern technologies such as ceilometers and satellites are available to support this process, visual observation still plays an important role especially in areas without instruments or for training purposes to build a deeper understanding of atmospheric conditions. Cloud amount is measured in parts, which divides the sky into 10 equal parts. Observers report how many parts of the sky are covered by clouds using a scale from 0 to 10. If there are no clouds, it is reported as 0; if half the sky is covered, it is 5; and if the sky is completely covered, it is reported as 10. Cloud types are classified by their height levels: high-level, mid-level, low-level, and vertically developed clouds. Examples include Cirrus, Altostratus, Stratus, and Cumulonimbus. These cloud types are important for weather forecasting and understanding weather phenomena in each area. Furthermore, researchers have discovered that low-level clouds with a thickness exceeding 300 meters exhibit emissivity levels nearly identical to those of a blackbody. This finding allows for downward radiation to be estimated using a function based on the precipitable water content beneath the cloud base. When this model was tested against actual station data in Brazil, it delivered highly accurate results, showing an average error margin of only 4.6%. Such precision proves that incorporating cloud characteristics as a key variable makes this model both effective and exceptionally well-suited for tropical and subtropical regions, where atmospheric conditions are similar worldwide [16].

2.2.3 Vapor pressure

In atmospheric physics, vapor pressure is defined as the partial pressure exerted by water vapor in the air when it is in thermodynamic equilibrium with liquid water or ice. It serves as an indicator of the amount of water vapor present in the atmosphere at a specific time. In meteorology, vapor pressure is generally classified into two principal types. The first is actual vapor pressure (e_a), representing the true partial pressure of water vapor in the air, which can be calculated using equation (3). The second is saturation vapor pressure (e_s), referring to the maximum vapor pressure that the air can hold at a given temperature, calculable by equation (4) [17]. When the actual vapor pressure equals the saturation vapor pressure, the air reaches saturation, leading to condensation processes that may produce clouds, fog, or precipitation. The key distinction lies in the fact that actual vapor pressure is dependent on the existing quantity of water

vapor in the air, whereas saturation vapor pressure is primarily determined by temperature and is independent of the actual water vapor content. An additional related parameter is the vapor pressure deficit (VPD), defined as the difference between saturation and actual vapor pressure, which is widely used to assess plant transpiration and water requirements. Vapor pressure is a fundamental variable in various atmospheric and environmental applications, including the calculation of relative humidity, weather forecasting, evaluation of precipitation and fog potential, assessment of ecosystem water balance, estimation of agricultural evapotranspiration, and analysis of human thermal comfort. Furthermore, it is frequently incorporated into climate models and extreme weather early warning systems [18-20], highlighting its significance in atmospheric science and environmental research.

$$e_a = \frac{RH}{100} \times e_s(T) \quad (3)$$

$$e_s(T) = 0.6108 \times \exp\left(\frac{17.27T}{T + 237.3}\right) \quad (4)$$

Where e_s represents the saturation vapor pressure (hPa), T is the air temperature ($^{\circ}\text{C}$), 0.6108 is the saturation vapor pressure of water at 0°C (hPa), e_a is the actual vapor pressure (hPa), and RH is the relative humidity.

3. Methodology and results

This section presents a systematic analysis of downward longwave radiation in Thailand and the subsequent development of mathematical estimation models. The study focuses on characterizing DLR behavior under all-sky conditions, encompassing both clear-sky and cloudy-sky situations by integrating key atmospheric constituents and cloud cover data into the analytical framework. The dataset therefore includes the full range of atmospheric conditions observed during the study period, ensuring that the resulting models are applicable to realistic environmental conditions in tropical regions. The methodology is structured into four primary phases: first, an analysis of monthly daily DLR averages from 2018 to 2023; second, an investigation into the correlation between daily DLR and various meteorological variables; third, the formulation of mathematical models for DLR estimation; and finally, a rigorous evaluation of model performance using standard statistical metrics. This comprehensive approach ensures that the developed models are robust and applicable to the country's diverse tropical climates.

3.1 Analysis of downward longwave radiation monthly averages daily (2018–2023)

Downward longwave radiation data were collected using a CNR4 net radiometer, which continuously measures incoming and outgoing radiation components at the Earth's surface. The instrument recorded electrical signals at one-second intervals throughout the observation period. These raw signals do not directly represent radiation values, so they were converted into physical radiation units using the calibration relationship provided in Equation (2). This conversion step is essential to ensure that the recorded electrical output accurately reflects the actual longwave radiation received at the surface. After conversion, the one-second radiation data produced a very large dataset. To make the data more suitable for analysis and interpretation, the one-second values were first aggregated into hourly averages. This step helped reduce short-term fluctuations caused by momentary atmospheric changes while still preserving the general radiation trend within each hour. The hourly averages were then used to calculate daily totals of downward longwave radiation.

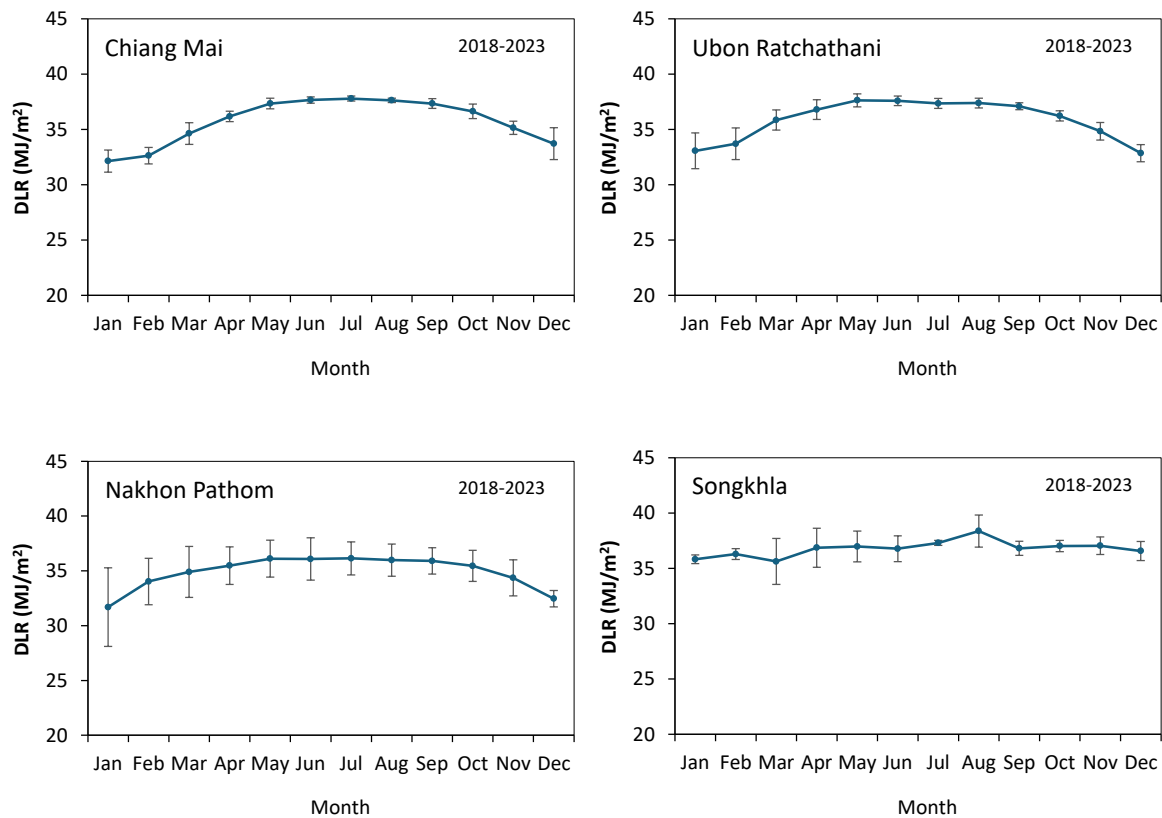


Fig. 4 Monthly averages daily downward longwave radiation at the four stations.

These daily totals were subsequently converted into units of megajoules per square meter to provide a more practical representation of the total daily energy received at the surface. Following the calculation of daily values, the data were further processed to determine monthly averages. All daily downward longwave radiation values within the same month were averaged to produce a representative monthly mean. This approach reduces the effect of unusual daily conditions and provides a clearer picture of the typical radiation behavior for each month. To analyze long-term patterns, the monthly averages were calculated for each month over a six-year period from 2018 to 2023. For example, all daily averages recorded in January for each year were averaged together to obtain a long-term January mean. The same procedure was applied to February, March, and the remaining months until December. This method allowed the study to capture consistent monthly characteristics while minimizing the influence of short-term variations or extreme events in individual years. Finally, the processed results were presented as long-term monthly average daily downward longwave radiation graphs for each station. These graphs clearly illustrate the typical annual variation of downward longwave radiation at each location and allow comparison between stations. An example of these results is shown in Fig. 4, which summarizes the long-term monthly radiation patterns observed during the study period.

At the Chiang Mai station, the monthly average daily downward longwave radiation showed a clear seasonal pattern throughout the year. The values gradually increased from the beginning of the year and continued rising until reaching their highest levels around May and June. After this peak period, the radiation values remained relatively stable during the middle of the year before gradually decreasing toward the end of the year. This pattern corresponds well with the seasonal climate of northern Thailand, where the hot season occurs in the middle of the year and is followed by a cooler period toward the end of the year.

The increase in radiation during the hot season can be explained by higher air temperature and greater atmospheric moisture, which enhance the atmospheric emissivity and lead to higher longwave radiation reaching the surface.

The Ubon Ratchathani station displayed a pattern very similar to that observed in Chiang Mai. The radiation values increased steadily from January to June, remained nearly constant during the mid-year months, and then decreased gradually during the later part of the year. Although the overall trend was the same, the radiation values at Ubon Ratchathani were slightly lower than those recorded at Chiang Mai throughout the year. This similarity in pattern reflects the comparable seasonal characteristics between the northeastern and northern regions of Thailand, where temperature and humidity rise during the hot season and decrease during the cooler months, directly affecting the amount of downward longwave radiation.

At the Nakhon Pathom station, the variation pattern was also consistent with that observed at Chiang Mai. The monthly average radiation started at approximately 33 MJ/m² in January and increased to nearly 35 MJ/m² during the period from April to June. After reaching this peak, the values remained relatively stable for several months before decreasing toward the end of the year. This behavior reflects the hot summer climate typical of the central region of Thailand, where high temperatures and significant moisture in the atmosphere during the middle of the year contribute to higher longwave radiation levels. The gradual decrease toward the end of the year corresponds to the transition into cooler and drier conditions.

In contrast, the Songkhla station showed a noticeably different pattern compared to the other three stations. The radiation values at this station remained relatively stable throughout the entire year, mostly within the range of 35 to 38 MJ/m². There was only a slight increase observed during the period from July to September. This

stability indicates the strong influence of the southern coastal climate, which is characterized by consistently high humidity, frequent rainfall, and less seasonal variation in temperature. These conditions help maintain a relatively constant level of atmospheric emissivity, resulting in small fluctuations in downward longwave radiation across different months.

When comparing all four stations together, it becomes clear that Chiang Mai, Ubon Ratchathani, and Nakhon Pathom exhibit distinct seasonal variations in downward longwave radiation, closely related to the changes in temperature and humidity associated with Thailand's hot and cool seasons. In contrast, Songkhla presents the most stable and least variable pattern throughout the year due to the persistent humid and maritime climate of southern Thailand. This comparison highlights how regional climatic characteristics influence the temporal behavior of downward longwave radiation at different locations.

3.2 Correlation between meteorological variables and DLR

In addition to analyzing the long-term monthly variation of daily DLR, this study collected meteorological data from four observation stations: the Northern Meteorological Center, Chiang Mai Province (CM); Ubon Ratchathani Meteorological Station, Sawang Wirawong District, Ubon Ratchathani Province (UB); Nakhon Pathom Meteorological Station, Nakhon Pathom Province (NP); and the Southern-east Coast Meteorological Center, Songkhla Province (SK). The data used in this study are daily records from 2018 to 2023 (2018–2021 for model development and 2022–2023 for model performance evaluation), including the following main meteorological variables: daily mean air temperature (T_{mean}), daily maximum temperature (T_{max}), daily minimum temperature (T_{min}), relative humidity (RH), cloud cover (C), and vapor pressure (e_a).

These variables were analyzed for their relationship with DLR using scatter plots, where the meteorological variables are shown on the x-axis and DLR on the y-axis. The analysis was performed for all four stations, and the results are presented in the following Fig. 5-8.

The analysis of the relationship between meteorological variables and downward longwave radiation (DLR) at Chiang Mai station ($N = 1,156$) reveals that minimum temperature (T_{min}) exhibits the strongest correlation ($R^2 = 0.90$), as it best reflects the radiative

properties of the atmosphere during nighttime in the absence of solar shortwave interference. The second most influential variable is actual vapor pressure (e_a , $R^2 = 0.78$), which follows a power function relationship with DLR, consistent with the role of water vapor as the dominant greenhouse gas governing longwave emission as described by Brutsaert's empirical framework. Mean temperature (T_{mean} , $R^2 = 0.52$) and cloud cover (C, $R^2 = 0.49$) show moderate correlations, while relative humidity (RH, $R^2 = 0.16$) and maximum temperature (T_{max} , $R^2 = 0.06$) demonstrate weak associations — RH being limited by its temperature-dependent nature and T_{max} being strongly driven by daytime solar heating rather than atmospheric longwave properties. These findings suggest that T_{min} and e_a are the most physically meaningful and statistically reliable predictors for developing an empirical model to estimate DLR at the CM site.

The analysis of the relationship between meteorological variables and downward longwave radiation (DLR) at Ubon Ratchathani station ($N = 1,213$) reveals a pattern broadly consistent with Chiang Mai, though with notable differences in the strength of individual predictors. Minimum temperature (T_{min}) again emerges as the strongest linear predictor ($R^2 = 0.86$), followed closely by actual vapor pressure (e_a , $R^2 = 0.84$) with a power function relationship ($\text{DLR} = 156.38 \cdot e_a^{0.30}$), where the exponent is slightly higher than that observed at Chiang Mai (0.26), possibly reflecting the more humid continental climate of the northeastern region. Mean temperature (T_{mean} , $R^2 = 0.58$) performs moderately, while cloud cover (C, $R^2 = 0.31$) and relative humidity (RH, $R^2 = 0.23$) show weaker associations compared to Chiang Mai, and maximum temperature (T_{max} , $R^2 = 0.11$) remains a poor predictor consistent with the previous station. Notably, at Ubon Ratchathani the gap between T_{min} and e_a is much narrower ($R^2 = 0.86$ vs. 0.84) compared to Chiang Mai ($R^2 = 0.90$ vs. 0.78), suggesting that vapor pressure plays a comparably important role at this station and that both variables should be considered as co-primary predictors in any empirical DLR model developed for this site.

The analysis of the relationship between meteorological variables and downward longwave radiation (DLR) at Nakhon Pathom meteorological station, Kamphaeng Saen district ($N = 1,286$), located within Kasetsart University's Kamphaeng Saen campus surrounded by dense agricultural land and vegetation, reveals markedly different results compared to Chiang Mai and Ubon Ratchathani stations.

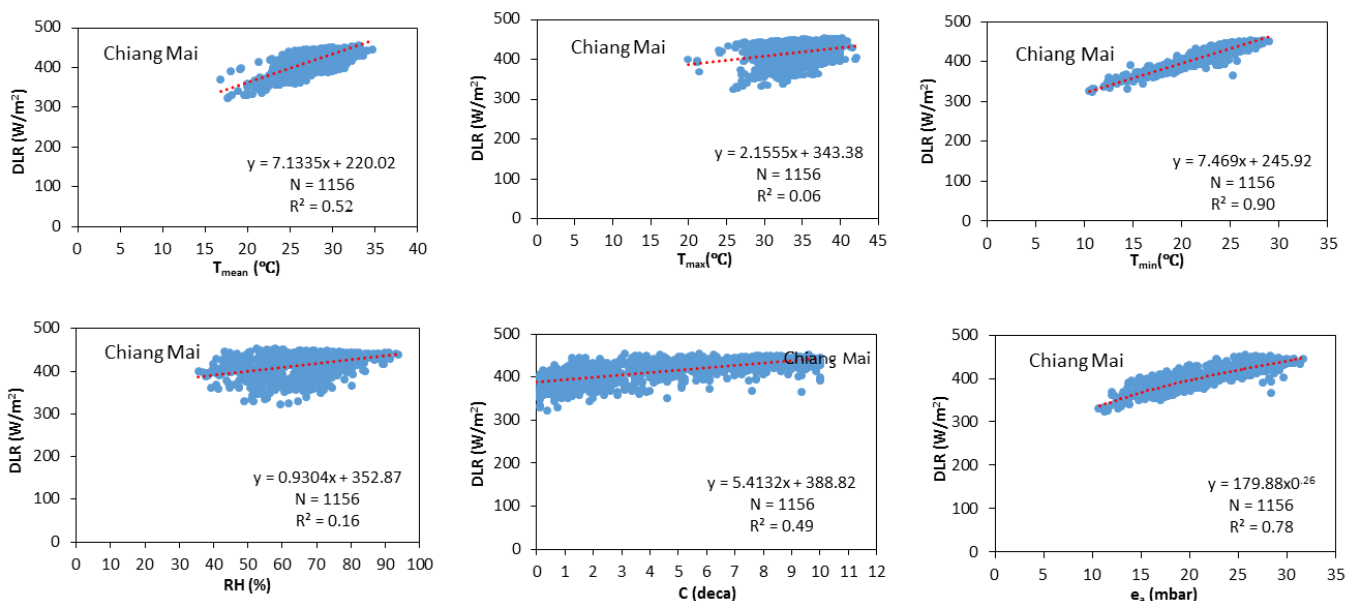


Fig. 5 Scatter plots showing the relationship between meteorological variables and DLR at the CM station.

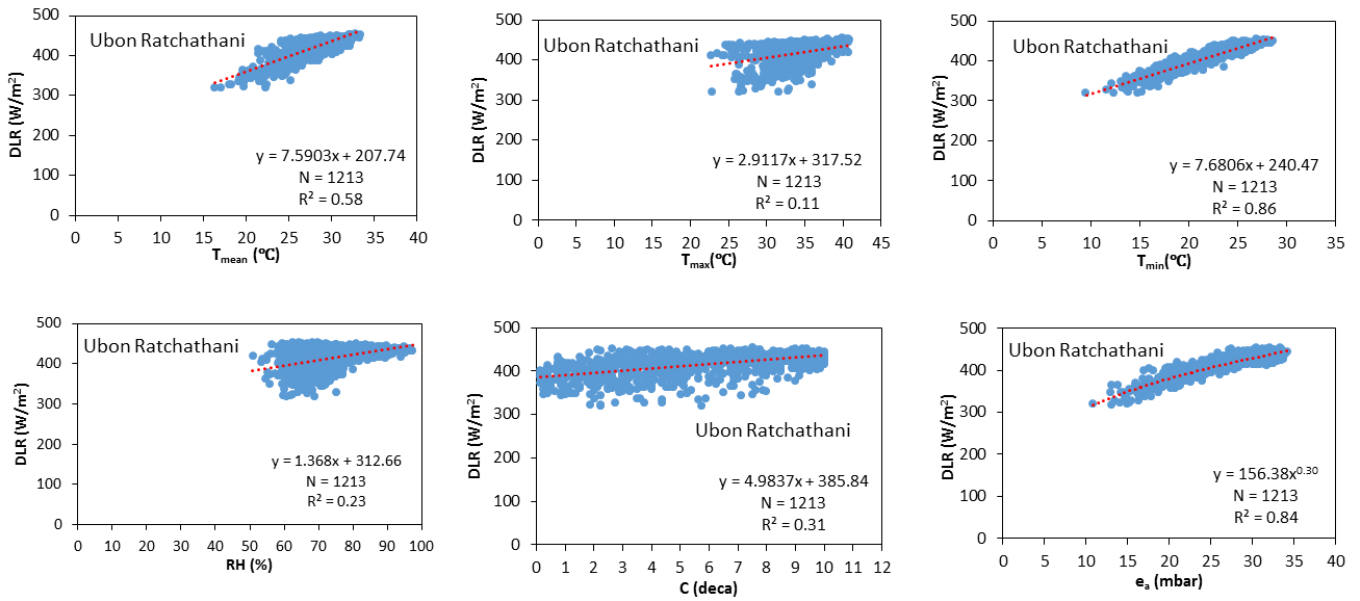


Fig. 6 Scatter plots showing the relationship between meteorological variables and DLR at the UB station.

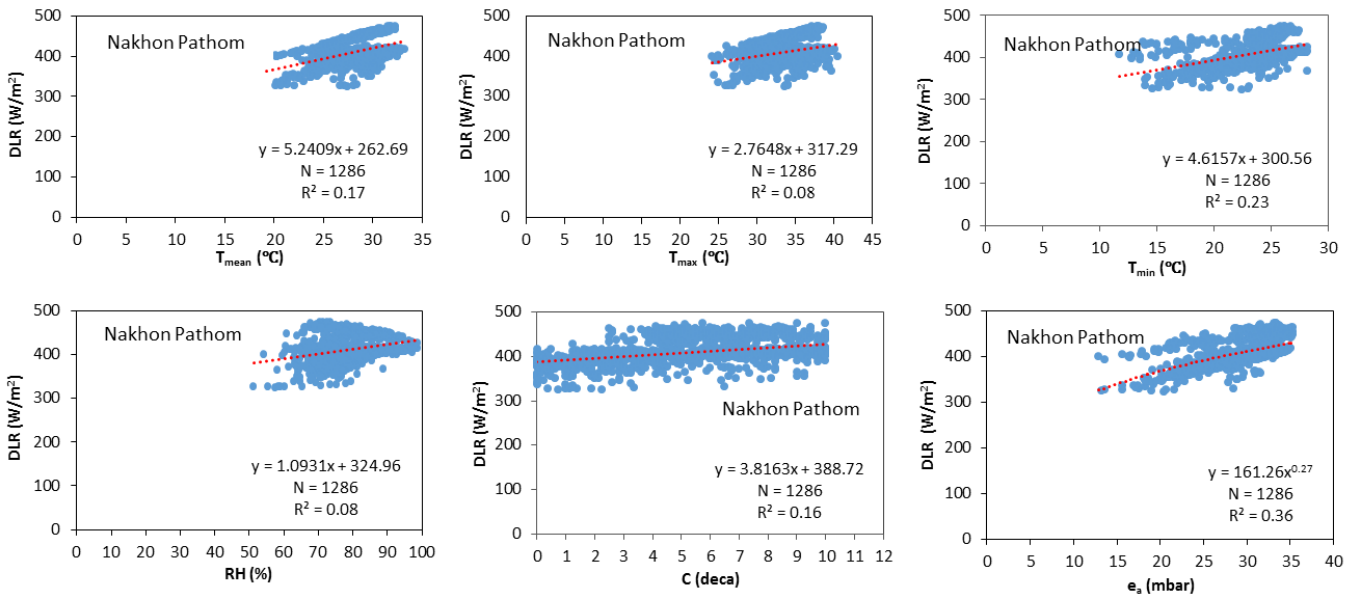


Fig. 7 Scatter plots showing the relationship between meteorological variables and DLR at the NP station.

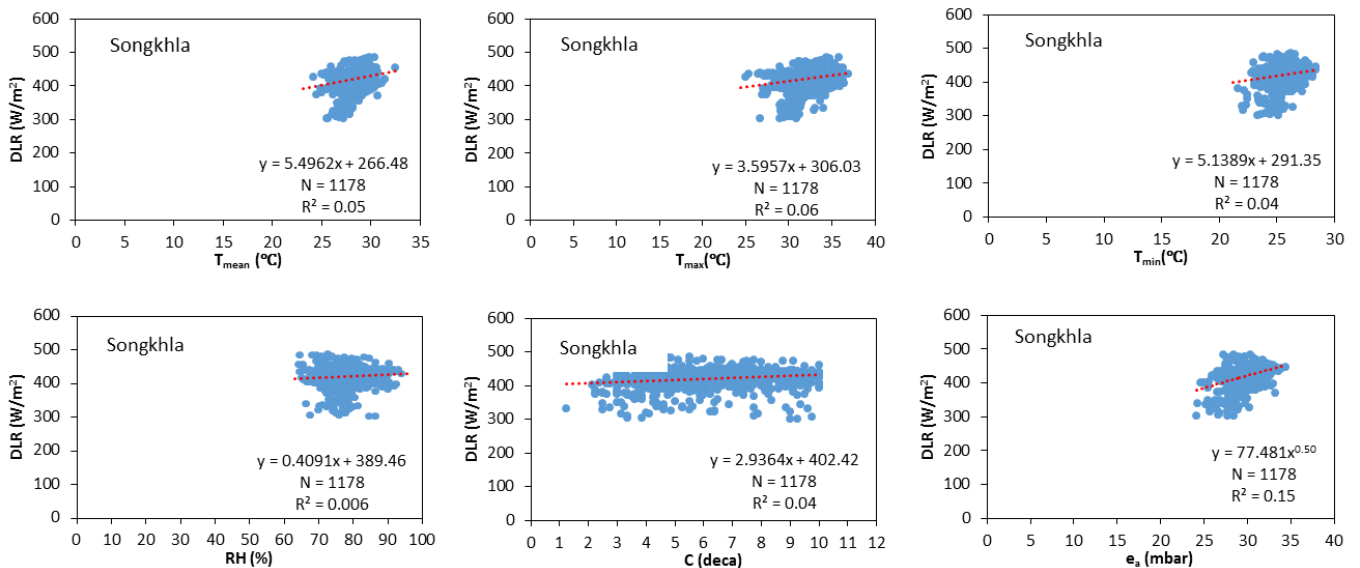


Fig. 8 Scatter plots showing the relationship between meteorological variables and DLR at the SK station.

Actual vapor pressure (e_a) emerges as the strongest predictor ($R^2 = 0.36$) following the power function $DLR = 161.26 \cdot e_a^{0.27}$, surpassing minimum temperature (T_{min} , $R^2 = 0.23$) which dominated at the other two stations. This pattern is consistent with the spatial distribution of precipitable water over Thailand, where moisture content in the atmosphere varies considerably across regions and land cover types [21]. This reversal is largely attributed to intensive Evapotranspiration from surrounding croplands, which releases substantial amounts of moisture into the atmosphere in a pattern that follows agricultural cycles rather than air temperature trends, allowing vapor pressure to drive DLR independently of thermal conditions a mechanism well-supported by the close coupling between net radiation and Evapotranspiration processes in agricultural landscapes [22].

Additionally, the Canopy Effect of dense trees and ground cover suppresses nocturnal T_{min} through radiative cooling, weakening its statistical link with DLR. The remaining variables — mean temperature (T_{mean} , $R^2 = 0.17$), cloud cover (C , $R^2 = 0.16$), maximum temperature (T_{max} , $R^2 = 0.08$), and relative humidity (RH , $R^2 = 0.08$) all show weak associations, collectively reflecting the complex microclimate of a green campus environment where buildings, large trees, water bodies, and agricultural plots create a spatially heterogeneous surface that no single variable can adequately capture, underscoring the necessity of a multiple regression approach for reliable DLR estimation at this site.

Finally, the analysis of the relationship between meteorological variables and downward longwave radiation (DLR) at Songkhla station ($N = 1,178$) reveals results that differ fundamentally from all previous stations, with R^2 values approaching zero across all variables. Actual vapor pressure (e_a) remains the strongest predictor at only $R^2 = 0.15$ following the power function $DLR = 77.481 \cdot e_a^{0.50}$, while all remaining variables show negligible associations T_{mean} ($R^2 = 0.05$), T_{max} ($R^2 = 0.06$), T_{min} ($R^2 = 0.04$), cloud cover ($R^2 = 0.04$), and relative humidity ($R^2 = 0.006$). These exceptionally weak correlations can be primarily attributed to the equatorial climate characteristics of southern Thailand, where consistently high temperature and humidity throughout the year [23] result in an extremely narrow range of variation in both DLR and meteorological variables, rendering linear regression unable to capture any meaningful signal. Furthermore, the atmospheric conditions in southern Thailand are complicated by transboundary haze episodes and fine particulate matter [24], which alters the absorptive and emissive properties of the atmosphere in ways that cannot be captured by standard surface meteorological measurements alone. Songkhla therefore represents the most challenging case for empirical DLR modeling among all stations examined, suggesting that reliable estimation at this site may require the incorporation of satellite-derived atmospheric products or additional variables that more directly characterize the optical and radiative properties of the local atmosphere beyond what ground-based station data can provide.

In summary, the analysis across these four stations demonstrates that Downward Longwave Radiation in Thailand is dictated by different atmospheric structures depending on geography. In regions with high air mass variability, like the North (CM) and Northeast (UB), temperature and vapor pressure serve as highly accurate proxies for DLR because the atmosphere responds systematically to thermal energy changes as a blackbody. However, in the Central and Southern regions, where humidity is constant or influenced by aerosols and sea breezes, these surface relationships weaken due to interference from particles and low-level clouds. Therefore, when selecting variables for predictive modeling, one

must prioritize the climatic stability of the specific area. Vapor pressure (e_a), in particular, proves to be a more universal and reliable predictor across all regions than relative humidity (RH) or visual cloud cover observations.

3.3 Models for estimating downwelling longwave radiation (DLR)

The graphs presented above clearly show that downward longwave radiation is related to meteorological variables. Based on this finding, seven models were developed to estimate longwave radiation. The models were constructed by analyzing the relationships between longwave radiation and meteorological variables using linear regression, which was selected after fitting the data with several functional forms, including power, exponential, and polynomial functions. Linear regression was ultimately adopted as it yielded the best performance in terms of R^2 and residual distribution. In addition, linear regression offers the advantage of parsimony and allows straightforward physical interpretation of individual variable coefficients, making it well-suited for practical application at meteorological stations. The statistical significance of each variable was evaluated using t-statistics and p-values. A suitable model was defined as one where all variable coefficients had t-statistics between -2 and 2 , and p-values less than 0.05 , indicating that each variable contributes significantly to explaining the variance in DLR at the 95% confidence level. This criterion also serves to prevent overfitting that may arise from including unnecessary variables in the model.

Due to differences in topography and climate conditions, meteorological data varied among the four stations: Chiang Mai (CM), Ubon Ratchathani (UB), Nakhon Pathom (NP), and Songkhla (SK). Therefore, the models were developed to account for these differences while maintaining applicability across all stations. The structure of the models for each station is summarized in Table 1, while the coefficients for each model at each station are shown in Tables 2–5.

Table 1 Models for estimating daily downward longwave radiation.

Numbers	DLR models
Model 1	$DLR = a_0 e_a^{a_1}$
Model 2	$DLR = a_0 + a_1 e_a + a_2 T_{mean}$
Model 3	$DLR = a_0 + a_1 RH + a_2 T_{min}$
Model 4	$DLR = a_0 + a_1 T_{mean} + a_2 C$
Model 5	$DLR = a_0 + a_1 e_a + a_2 C + a_3 T_{mean}$
Model 6	$DLR = a_0 + a_1 RH + a_2 T_{min}$
Model 7	$DLR = a_0 + a_1 e_a + a_2 C + a_3 RH + a_4 T_{mean}$

Where e_a is the vapor pressure (hPa), T_{mean} is the daily mean air temperature ($^{\circ}C$), T_{min} is the daily minimum temperature ($^{\circ}C$), RH is the relative humidity (%), C is the cloud cover (in deca), and a_0, a_1, a_2, a_3, a_4 are the model coefficients.

Table 2 Model coefficients for the Chiang Mai station, where R^2 represents the coefficient of determination.

Number/ Coefficients	a_0	a_1	a_2	a_3	a_4	R^2
Model 1	179.88	0.26				0.78
Model 2	218.17	3.81	3.80			0.89
Model 3	233.30	0.32	7.01			0.74
Model 4	217.99	6.24	5.07			0.92
Model 5	217.93	1.72	3.40	5.03		0.95
Model 6	257.73	0.05	6.37	1.81		0.93
Model 7	179.89	0.73	3.40	0.38	6.34	0.95

Table 3 Model coefficients for the Ubon Ratchathani station, where R^2 represents the coefficient of determination.

Number/ Coefficients	a_0	a_1	a_2	a_3	a_4	R^2
Model 1	156.38	0.30				0.83
Model 2	246.28	3.86	2.33			0.84
Model 3	217.21	0.46	7.14			0.87
Model 4	197.66	6.99	4.32			0.80
Model 5	227.90	2.62	2.29	3.72		0.87
Model 6	228.33	0.31	6.92	0.91		0.88
Model 7	69.44	-1.33	2.29	1.49	9.31	0.88

Table 4 Model coefficients for the Nakhon Pathom station, where R^2 represents the coefficient of determination.

Number/ Coefficients	a_0	a_1	a_2	a_3	a_4	R^2
Model 1	161.26	0.27				0.34
Model 2	311.65	4.62	-1.39			0.37
Model 3	209.26	0.98	5.11			0.28
Model 4	250.70	4.94	3.56			0.32
Model 5	250.95	2.70	2.97	2.23		0.43
Model 6	275.94	0.44	3.59	2.54		0.34
Model 7	457.22	7.46	2.74	-1.8	-5.02	0.44

Table 5 Model coefficients for the Songkhla station, where R^2 represents the coefficient of determination.

Number/ Coefficients	a_0	a_1	a_2	a_3	a_4	R^2
Model 1	77.48	0.50				0.14
Model 2	165.59	5.74	2.99			0.15
Model 3	175.76	0.92	6.84			0.07
Model 4	123.72	9.33	5.26			0.17
Model 5	72.30	4.41	4.30	6.70		0.22
Model 6	203.60	0.38	6.65	2.94		0.10
Model 7	-924.87	-15.50	3.68	7.96	41.08	0.25

3.4 Model performance evaluation

To evaluate the accuracy and suitability of the developed models for estimating downward longwave radiation (DLR) from meteorological data, two main statistical indicators were employed, root mean square error relative to the mean measured values (RMSE) and mean bias error relative to the mean measured values (MBE). The details of these indicators are as follows.

RMSE is the square root of the mean of the squared differences between the predicted and observed values. It indicates the average magnitude of errors, with lower RMSE values representing higher model accuracy, as shown in equation (5). Meanwhile, MBE is the mean difference between predicted and observed values, considering the direction of the error, as shown in equation (6).

$$\%RMSE = \frac{\sqrt{\frac{\sum_{i=1}^N (DLR_{model} - DLR_{meas})^2}{N}}}{DLR_{meas}} \times 100 \quad (5)$$

$$\%MBE = \frac{\frac{\sum_{i=1}^N (DLR_{model} - DLR_{meas})}{N}}{DLR_{meas}} \times 100 \quad (6)$$

Where DLR_{model} refers to the downward longwave radiation estimated by the model (W/m^2), DLR_{meas} refers to the downward longwave radiation obtained from measurements (W/m^2),

DLR_{meas} represents the mean value of the measured downward longwave radiation (W/m^2) and N denotes the total number of data points used in the analysis.

To evaluate the accuracy of the seven developed models for the CM, UB, NP, and SK stations, meteorological data from 2022–2023 were used to calculate DLR based on the equations presented in Table 1-5. The DLR values estimated by the models were then compared with the observed measurements, and the RMSE and MBE were calculated to assess model performance. The results are presented as scatter plots showing the relationship between measured and modeled DLR for all four stations (Fig. 9–12). Additionally, graphs illustrating RMSE (%) and MBE (%) for each model at all stations are shown on Fig. 13.

From the development of models to estimate downward longwave radiation (DLR) using meteorological data (Fig. 9–12), it was found that the seven models showed different levels of accuracy, which were evaluated using RMSE and MBE, as shown in Fig. 13. For the CM station, models 1 and 7 gave the best results, with the lowest RMSE of 1.7% and 2.2%, respectively, and MBE values of 0.7% and 0.3%, respectively, indicating high accuracy with no clear bias, although model 7 performed slightly better due to its lower bias. Model 6 gave the next best result (RMSE = 2.3%, MBE = 0.4%), while model 2 showed the largest error (RMSE = 2.8%, MBE = 1.1%). For the UB station, models 5 and 7 performed best, both with the lowest RMSE of 2.2% and MBE of -0.7%, showing high accuracy and low overall error, meaning their predictions were closest to the measured values. Model 2 ranked next (RMSE = 2.5%, MBE = -0.6%), while models 3 and 6 had the highest errors (RMSE = 2.9%, MBE = -0.7%). For the NP station, model 3 produced the most accurate results (RMSE = 3.6%, MBE = 2.9%), followed by model 1 (RMSE = 3.7%, MBE = 2.9%), while models 4 and 6 had the highest errors (RMSE = 4.4%, MBE = 3.9% and 3.7%, respectively). For the SK station, models 1 and 5 performed best (RMSE = 2.5%, MBE = -1.0% and -1.4%, respectively), while model 2 showed the largest error (RMSE = 2.9%, MBE = -1.4%).

When comparing all four stations, models that combined several meteorological variables, such as temperature, vapor pressure, and cloud cover, consistently outperformed those relying on a single variable, with models 1, 3, 5, and 7 giving the best overall results. This is consistent with the physical framework established by Brutsaert [3] and its extension to all-sky conditions by Crawford and Duchon [2], which Tian et al. [25] evaluated globally and confirmed that the combined use of vapor pressure, air temperature, and cloud cover provides a robust physical basis for explaining DLR variability, with r^2 ranging from 0.87 to 0.98 across multiple datasets a range that aligns well with the results obtained at the CM and UB stations in this study. The error ranking across stations from lowest to highest was CM, UB, SK, and NP. These differences may be attributed to variations in local climate conditions, particularly cloud amount and atmospheric humidity, which influence DLR differently across regions. Notably, the relatively poorer performance at the SK station reflects the equatorial climate characteristics of southern Thailand, where the narrow range of variation in atmospheric variables limits the model's ability to capture DLR fluctuations a limitation consistent with findings by Tian et al. [25], who noted reduced effectiveness of Brutsaert's equation in regions of persistently high humidity and low temperature variability.

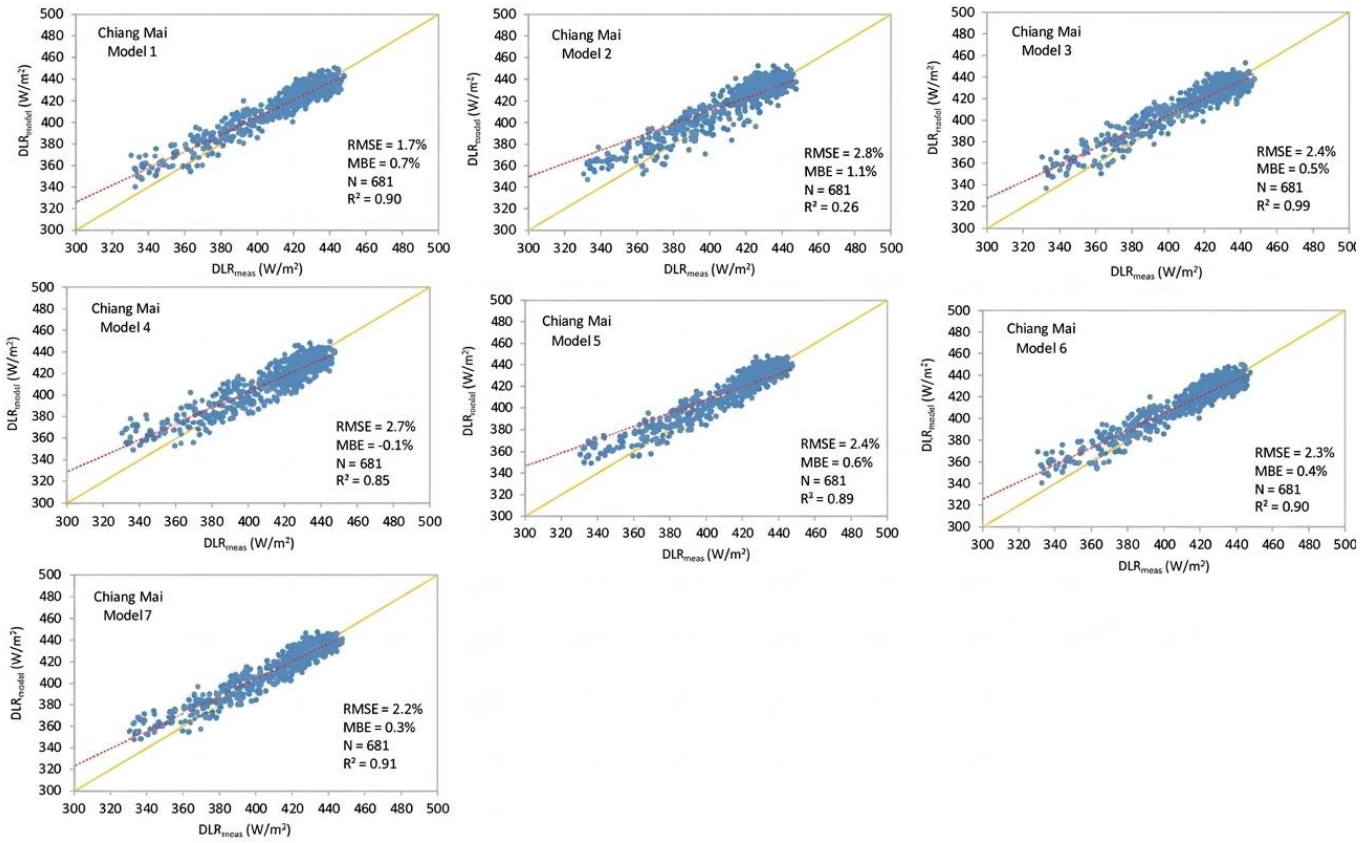


Fig. 9 Comparison between measured and modeled downward longwave radiation at the CM station.

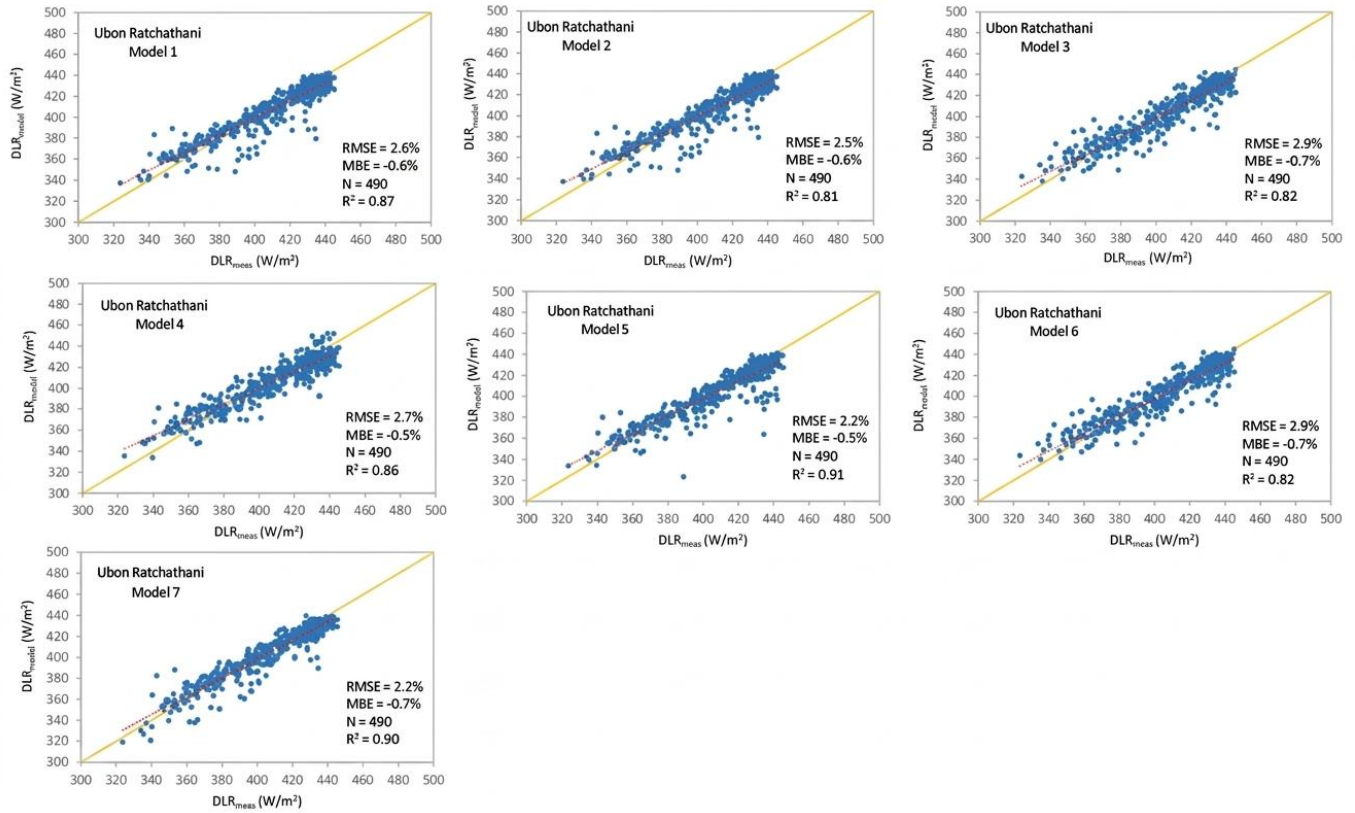


Fig. 10 Comparison between measured and modeled downward longwave radiation at the UB station.

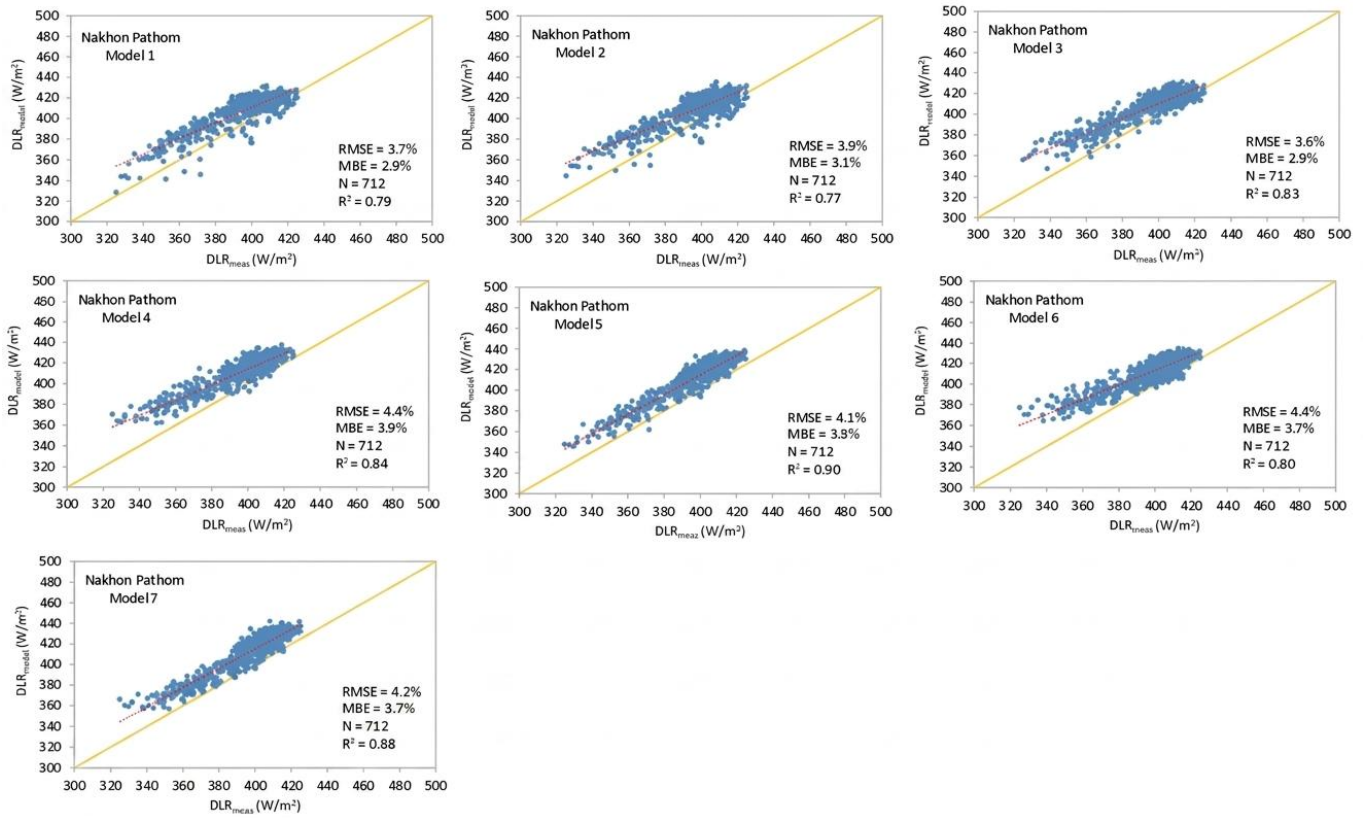


Fig. 11 Comparison between measured and modeled downward longwave radiation at the NP station.

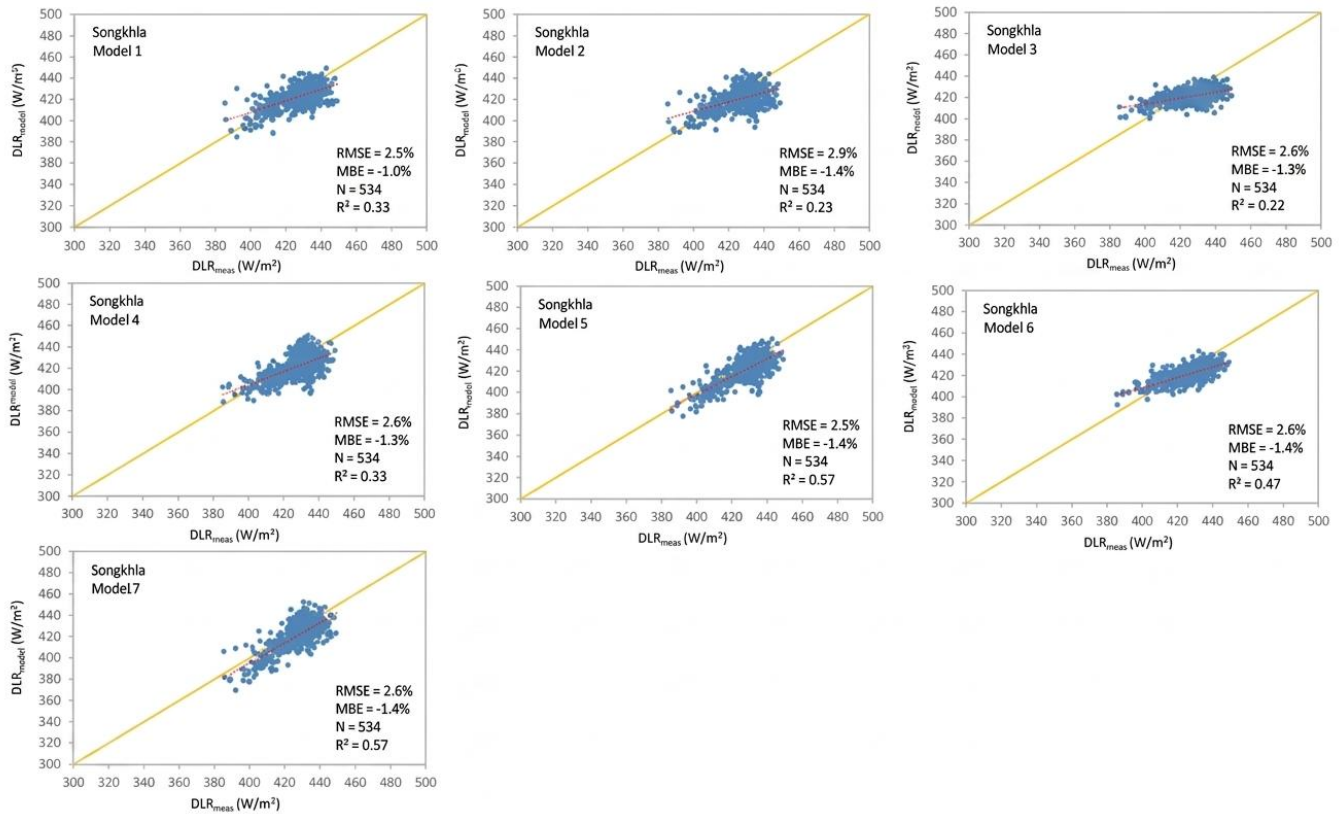


Fig. 12 Comparison between measured and modeled downward longwave radiation at the SK station.

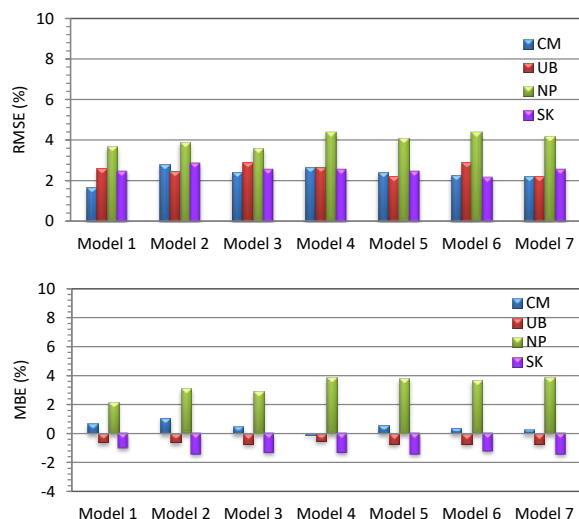


Fig. 13 The RMSE and MBE values obtained from comparing the model's calculated results with the observed measurements.

In summary, the evaluation of the seven models demonstrated that they can effectively estimate daily DLR, with modeled values showing good agreement with measurements across all stations, yielding RMSE in the range of 1.7–4.4% and MBE in the range of -1.4% to 3.9%. Compared to the machine learning approach of Feng et al. [26], which employed five methods including gradient boosting regression tree (GBRT) across 27 globally distributed stations and achieved a best-model RMSE of 17.50 W m⁻² on the daily time scale, the multivariate linear regression models developed in this study demonstrate competitive or superior accuracy within the specific climatic context of Thailand. A key advantage of the present approach is that it relies solely on standard meteorological station observations without requiring downward shortwave radiation (DSR) measurements or large training datasets, while remaining physically interpretable [26]. These results indicate that the developed models offer a satisfactory level of accuracy and are well-suited for practical DLR estimation at the study sites.

4. Conclusion

This study focused on the statistical characteristics of longwave radiation using data from four meteorological stations: Chiang Mai, Ubon Ratchathani, Nakhon Pathom, and Songkhla, covering a 6-year period (2018–2023). The results showed that longwave radiation varied both daily and seasonally. The values started to increase from January and reached the highest during the rainy season (May–September), then decreased or remained stable until December. For example, Songkhla had the highest daily average value of 38.38 MJ/m²•day, while Chiang Mai, Ubon Ratchathani, and Nakhon Pathom had maximum averages of 37.80, 37.63, and 36.14 MJ/m²•day, respectively. In the cold season, especially in January and December, the values dropped significantly, which corresponds to the changes in solar radiation and weather conditions. In addition to statistical analysis, mathematical models were developed to estimate longwave radiation using multiple linear regressions with common meteorological variables such as mean air temperature, maximum and minimum air temperature, relative humidity, cloud cover, and vapor pressure, resulting in seven models for each station. The data were divided into two sets: training (2018–2021) and testing (2022–2023). The model performance was evaluated using RMSE and MBE. The results showed that: Chiang Mai: RMSE 1.7–2.8%, MBE -0.1 to 1.1% high accuracy and low error. Ubon Ratchathani: RMSE 2.2–2.9%, MBE -0.7 to -0.5% high accuracy with little bias. Nakhon Pathom:

RMSE 3.6–4.4%, MBE 2.2–3.9% tendency to overestimate significantly. Songkhla: RMSE 2.2–2.9%, MBE -1.4 to -1.0% good accuracy but slightly underestimated. Based on RMSE, the ranking of accuracy was Chiang Mai, Ubon Ratchathani, Songkhla, Nakhon Pathom. Although the Nakhon Pathom model was the least accurate, its errors were still within an acceptable range for practical use, especially in areas lacking direct radiation measurement instruments. In conclusion, the models developed in this research can effectively replace direct longwave radiation measurements using special instruments. They provide a satisfactory level of accuracy and have strong potential for applications in energy, agriculture, and sustainable climate management.

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Declaration of Interest Statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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