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Comparative Study of Horizontal Surface Solar Radiation for Different South Asian Zones

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ABSTRACT

This study presents a comparative analysis of solar radiation across selected South Asian regions using the Angstrom–Prescott linear regression model.This model estimates monthly average global solar radiation on horizontal surfaces from bright sunshine duration, considering latitude and longitude.The monthly average solar radiation data for 2025 were calculated and compared with model-based estimates across different zones, demonstrating strong agreement between observed and predicted values through graphical and statistical analyses. Among the eight locations we analyzed, Male received the highest annual solar radiation value 3890.61 MJ/m^2, whereas Kabul recorded the lowest 3146.65 MJ/m^2.The seasonal variations indicated that Male experienced higher solar radiation and brighter sunshine duration from February to June and July to September,with values ranging from (36.12 to 40.23 $KWh/m^2/d$).In contrast,Kabul's sunshine duration during the same periods was lower, ranging between (28.91 to 33.25 $KWh/m^2/d$). Both locations showed a decline in sunshine duration between October and January, with Male ranging from (40.31 to 38.96 $KWh/m^2/d$) and Kabul from (32.91 to 30.68 $KWh/m^2/d$).Additionally, clearness index analysis confirmed that Male experienced the clearest atmospheric conditions with minimal cloud cover, whereas Kabul was more affected by cloudiness. These results provide valuable insights for future solar energy assessments in South Asia.

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1. Introduction

Over the last few decades, renewable energy has undergone substantially transformation, emerging as a sustainable and an environmentally friendly alternative to conventional fossil fuels. Due to their virtually unlimited availability, renewable sources such as hydro-power, wind turbines, photovoltaic panels, solar thermal systems, and biomass plants now play a vital role in contributing to the electricity supply in many nations [1]. Among various renewable energy sources, the solar energy has recently gained significant attention because it can support long-term sustainable development, particularly in regions that receive high levels of solar radiation. Reliable information on the solar radiation is crucial for designing solar power systems, assessing agricultural productivity and understanding seasonal climate variations and their impacts on different sectors. Countries in South Asia—such as Bangladesh, India, and Nepal-possess naturally high solar potential, making accurate solar radiation estimation essential for planning effective national energy strategies.

A country's per person energy consumption is commonly regarded as a fundamental indicator of its social and economic development. At present, the global average energy consumption is approximately 2.37 kilowatts-hours per person [2]. Consequently, nations with limited access to energy often experience significant development disadvantages. The global population is projected to reach nearly 12 billion by 2100 [2]. With rapid technological advancement, global energy demand may increase to nearly five times the current level. Conventional energy sources such as coal, oil, natural gas, and wood, are limited and will be unable to sustain this increasing demand in the long term. Therefore, the ongoing energy crisis has made the transition from fossil fuels to renewable energy sources more urgent than ever. This urgency is particularly critical for developing and underdeveloped countries, where economic progress is strongly dependent on energy availability. Among all renewable energy sources, the solar energy is widely recognized as a clean, safe, abundant, and renewable source that can help meet future energy needs. Unlike thermal energy derived from fossil fuels, Solar Radiation (SR) refers to the natural electromagnetic energy that reaches the Earth, either directly or in a diffused form [2].

Utilizing solar energy effectively is essential for achieving long-term energy security in an environmentally sustainable manner. To estimate the amount of solar radiation, empirical models commonly utilize bright sunshine duration along with meteorological parameters, including geographical location and elevation. These approachess are generally referred to as sunshine-based models, which establish a relationship between the sunshine duration and the amount of global solar radiation reaching the Earth's surface [3]. Direct measurement of solar radiation using instruments such as pyranometers is expensive, requires specialized maintenance, and is often unavailable in many regions. Several South Asian countries have limited access to long-term ground-based solar radiation records. Additionally, the estimation of solar radiation is complicated by factors such as cloud cover, atmospheric aerosols, and seasonal variability. Consequently, satellite-based datasets, such as NASA's Surface Solar Energy (SSE) records, are frequently used to address data gaps. In the absence of ground-based measurements, researchers typically relay on historical satellite records. The present study utilizes monthly average daily global solar radiation data for the period 2025, obtained from the NASA Langley Research Center's Surface Solar Energy (SSE) database [4].

The primary objective of this research is to develop a mathematical model for estimating daily global solar radiation using freely available input parameters without requiring any financial resources. Policymakers, energy authorities, and stakeholders must prioritize the urgent need for effective energy planning by promoting clean and renewable energy alternatives. The adoption of renewable energy technologies helps reduce carbon emissions and establishes a resilient and sustainable energy foundation for future generations [5],[6].Empirical models are commonly utilized in the form of temperature-based,sunshine-dependent, or hybrid forms, in which the relationship between input variables and solar radiation (SR) is established using linear or nonlinear regression techniques,as well as polynomial equations [7].

In South Asian countries, including India, Bangladesh, Pakistan, and Nepal, have been actively investigating solar radiation using meteorological and satellite-based data. For example, India has well-established solar radiation monitoring networks; however, countries such as Bangladesh and Nepal largely rely on modeled datasets. Hybrid approaches that integrate empirical models with machine learning have demonstrated higher accuracy in estimating solar radiation. Although several studies have analyzed horizontal and tilted surface solar radiation in two or three South Asian countries, no comprehensive research has yet focused on estimating horizontal surface solar radiation using the Angstrom–Prescott empirical model across all eight South Asian regions. This research gap highlights the need for more accurate estimation of solar energy on horizontal surfaces, particularly in regions where direct solar radiation measurements are limited or unavailable.

The novelty of this research can be summarized as follows:

- Firstly, the study applies the Angstrom–Prescott model within a comparative framework, enabling solar radiation estimation across different South Asian zones rather than a single location.
- Secondly, it utilizes low cost and readily available input data, making the model suitable for data- scarce regions.
- Thirdly, by analyzing both spatial and seasonal variations in solar energy, the study identifies region-specific opportunities for renewable energy development.
- Finally, the research links solar radiation estimation with policy implications, demonstrating how accurate assessments can enhance energy planning and support long-term socio-economic development in South Asia.

2. Literature Review

Solar energy is one of the most plentiful and well-established renewable energy resources, with the Earth receiving far more solar energy than humanity could ever consume [8]. Significant advancements have been achieved in solar power technologies and overall system performance [9]. Besides, Global Horizontal Irradiance (GHI) data plays a pivotal role in the design, assessment and optimization of photovoltaic (PV) energy systems [10]. Among the SAARC countries, Afghanistan is the least developed in terms of energy access, with only about 30% of its population connected to electricity [11]. Persistent political instability has severely constrained solar power development, leading to a substantial gap between installed capacity and actual energy generation [12]. The accuracy of solar radiation estimation has been enhanced through calibrated Angstrom models applied across different temporal scales [13],[14]. India currently leads the SAARC region in terms of energy share and solar potential, with an estimated annual value of ($14.02\ \mathrm{MWh/m^2}$) [15]. However, Power circulation and distribution losses remain a critical challenge in several countries. For instance, nearly 10% of generated energy is wasted in Bangladesh due to infrastructural inefficiencies [16]. Machine Learning (ML) models have proven effective in estimating solar radiation by integrating satellite-derived and ground-based observations [17]. Furthermore, the concept of a SAARC super smart grid has been proposed as an optimal framework for regional power-sharing and energy security [18]. Recent advancements in machine learning and deep learning have substantially enhanced the accuracy of solar radiation and surface solar irradiance forecasting [19]. In Pakistan, seasonal tilt optimization of PV panels has been shown to improve incident irradiance and power output [20], while the adverse effects of dust accumulation on PV efficiency have been mitigated with sustainable cleaning strategies [21]. Gradient boosting models have been employed to separate direct and diffuse radiation components, thereby enriching forecasting capabilities across diverse climatic conditions [19][22].

Machine learning approaches have significantly improved daily solar radiation forecasting, particularly in complex terrains such as Bhutan, where solar potential is limited and primarily utilized for localized applications [23],[24]. In India, long-term meteorological datasets spanning 13 years have enabled ML models to achieve high predictive accuracy [25]. GHI also plays a crucial role not only in PV system performance assessment but also in applications such as vehicle climate control [26], [27]. Despite the emergence of advanced ML methods, Angstrom–Prescott empirical models remain fundamental, with recent studies incorporating additional meteorological parameters to enhance their accuracy [28]. Further progress includes the development of understandable machine learning models utilizing high-resolution datasets to predict Direct Normal Radiation (DNR) and Diffuse Horizontal Radiation (DHR), both of which are essential for improving PV system efficiency [29]. Empirical constants derived from regression-based and Angstrom models have improved solar radiation estimation in high-altitude regions, such as Nepal [30]. Hybrid techniques integrating real-time sensor measurements with satellite data continue to develop global solar resource assessment frameworks [31]. A recent hybrid deep learning framework published in Neural Computing and Applications[32], combines satellite imagery and tabular data, employing adjusted Random Forest and Generative Adversarial Networks (GAN) for image imputation, along with an LSTM model enhanced to capture seasonality and long-term trends, resulting in significantly enhanced

DHI forecasting accuracy.In humid subtropical climates, a recent study in India employed machine learning models to evaluate monthly average diffuse solar radiation using pyranometer measurements, and compared the results with empirical models, demonstrating that modern ML techniques outperform classical regression-based approaches in such regions[33]. Al-Shourbaji and Alameen [34] developed an Artificial Neural Network (ANN) for solar irradiance prediction, utilizing LIME and SHAP methods to identify the most essential meteorological features, thereby enhancing model simplicity and predictive accuracy. In addition, probabilistic machine-learning post-processing to ensemble weather forecasts (WRF) for solar irradiance prediction in Chile, enhancing both calibration and point forecast skill through a Distributional Regression Network (DRN) [35]. Despite these advancements, several research gaps remain. Many recent studies are highly region-specific (e.g., India and Chile) and fail to address the climatic heterogeneity and data scarcity prevalent across SAARC countries. Although hybrid and probabilistic models demonstrate strong predictive performance, their implementation for real time operational control of PV systems remains limited. Moreover, the lack of publicly available, high-resolution (both regional and temporal) GHI, DNI,and DHI datasets in many underdeveloped regions restricts the training and validation of advanced ML models. Finally, only a limited number of studies incorporate long-term climate variability or climate-change conditions into solar radiation forecasting models, which is crucial for planning future solar infrastructure in improving regions.

3. Materials and Methods

The amount of extraterrestrial solar radiation (H_0) received on a horizontal surface mainly depends on geographic latitude and is not affected by local environmental factors. However, as this radiation passes through the Earth's atmospheric envelope, it is modified by scattering and absorption caused by clouds and atmospheric aerosols. As a result, the actual global solar radiation reaching the Earth’s surface is strongly influenced by the local condition and is consistently lower than the corresponding extraterrestrial radiation.

The original Angstrom-type empirical model establishes a relationship between the monthly mean clearness index and the mean fraction of potential sunshine duration [36], [37], [38]-

$$\frac{\bar{H}}{\bar{H_0}} = a + b\frac{\bar{S}}{\bar{S_o}} \tag{1}$$

where, $\bar{H}$= Monthly mean daily solar radiation on a horizontal surface

$\bar{H}_0$= Monthly mean extraterrestrial radiation on a horizontal surface

a, b= Angstrom empirical constants

$\bar{S}$=Monthly mean hours of bright sunshine

$\bar{S_0}$=Monthly mean of the maximum possible daily sunshine duration or day length

$\frac{\bar{H}}{\bar{H_0}}$= Monthly mean clearness index

$\frac{\bar{S}}{\bar{S_o}}$ =Monthly mean proportion of potential sunshine hours

The key parameters involved in solar radiation geometry include the following [36] –

Solar Constant (I_{sc}): This represents the rate of solar energy received per unit surface area when the surface is oriented perpendicular to the Sun’s rays and located at the Earth’s mean distance from the Sun. It reflects the Sun’s power output in watts per square meter. The standard accepted value of the solar constant is approximately 1367 W/m^2.

Declination Angle (δ): This represents the angle between the Earth’s and the Sun’s centers, and its projection onto the Earth’s equatorial plane.This angle changes over the course of the year because of the axial tilt of the Earth and its elliptical path around the Sun.The mathematical expression for declination is given as follows [36]:

$$\delta = 23.45\, sin[\frac{360}{365}(284 + n)] \tag{2}$$

where, n is the day of the year.

Sunset Hour Angle (ω): This represents the hour angle at sunset (or sunrise) on a horizontal surface. It indicates the time interval between solar noon and either sunrise or sunset, depending on weather the hour angle is positive or negative [36].

$$\omega = cos^{-1}(-tan\varphi\, tan\delta) \tag{3}$$

where,φ is the latitude.

Maximum Possible Sunshine Duration (S_0): It is also known as the day length which represents the total duration during which the sun remains above the horizon in a given day. Since 15 degrees of hour angle correspond to one hour, the potential maximum sunshine duration can be calculated accordingly [36].

$$S_0 = \frac{2}{15}\omega \tag{4}$$

where, ω is the sunset hour angle

Bright Sunshine (S): A crucial factor in estimating solar radiation is the length of daylight within a 24 hours period. The sunshine duration is typically computed using the following well-established solar geometry formulas [1].

$$\text{Sun rise} = 12 - \frac{1}{15^0}\cos^{-1}\left(\frac{-sin\varphi sin\delta}{cos\varphi cos\delta}\right) \quad (5)$$

$$\text{Sun set} = 12 + \frac{1}{15^0}\cos^{-1}\left(\frac{-sin\varphi sin\delta}{cos\varphi cos\delta}\right) \quad (6)$$

$$\text{Sun hour}, S = \text{Sunset} - \text{Sunrise} \quad (7)$$

Where, δ is the declination angle.

Extraterrestrial Radiation (H_0): It refers to the solar radiation that exists outside the Earth's atmosphere. The amount of radiation available on a specific day depends on the Earth's position along its orbital path around the Sun [38].

$$H_0 = I_{sc}\frac{24}{\pi}\left[1 + 0.033cos\frac{360n}{365}\right]\left[\frac{\pi\omega}{180}sin\varphi sin\delta + cos\varphi cos\delta cos\omega\right] \quad (8)$$

The monthly mean global solar irradiance was estimated using data obtained from a satellite-based climate and solar resource platform developed by NASA, as well as data calculated by the Angstrom Empirical model for eight weather monitoring centers across South Asia.

Table 1. Location of the selected 8 meteorological stations [39]

Meteorological Stations	Latitude (degree)	Longitude (degree)
Kabul	34.53	69.17
Dhaka	23.81	90.41
Thimphu	27.47	89.64
New Delhi	28.64	77.22
Male	4.18	73.50
Kathmandu	27.70	85.32
Islamabad	33.43	73.04
Colombo	6.93	79.86

In this study, the parameters H_0 and S_0 were evaluated on a monthly basis using equations (8) and (4), respectively Collares-Pereira and Rabl introduced a mathematical model for converting daily global solar radiation into hourly values. This model incorporates the coefficients a and b, which are explicitly defined within their formulation [40]

$$a = 0.409 + 0.5016\,sin(\omega - 60) \quad (9)$$

$$b = 0.6609 - 0.4767\,sin(\omega - 60) \quad (10)$$

3.1. Model Validation

To evaluate the accuracy of the model (Equations 11-13), several statistical indicators were applied, including Mean Bias Error (*MBE*), Root Mean Squared Error (*RMSE*), and the Correlation Coefficient (R^2). These indicators are commonly used to measure the difference between predicted values and observed measurements. A model is considered more reliable when it produces lower MBE and RMSE values, while a higher R^2 value preferably approaching unity, indicates a stronger agreement between the predicted and measured results. The mathematical formulations of these validation metrics are presented below.

Correlation coefficient of the solar radiation: [38]

$$R^2 = 1 - \frac{\sum_{i=1}^{m}(H_{predicted} - H_{measured})^2}{\sum_{i=1}^{m}(H_{predicted} - \bar{H})^2} \quad (11)$$

Error analysis of the solar radiation: [38]

Mean Bias Error =

$$MBE = \frac{\sum(H_{predicted} - H_{measured})}{m} \quad (12)$$

Root Mean Squared Error of the solar radiation =

$$RMSE = \sqrt{\frac{\sum(H_{predicted} - H_{measured})^2}{m}} \quad (13)$$

Table 2. Estimated Angles of declination for various months of a year [41]

Month	d represents the day corresponding to the i[th] date of the month	For the average date of each month		
		date	Day of the year	The solar declination angle
Jan	*i*	15	15	-21.27
Feb	31+ *i*	16	47	-13.00
Mar	59+ *i*	17	76	-2.02
Apr	90+ *i*	15	105	9.41
May	120+ *i*	16	136	19.03
Jun	151+ *i*	15	166	23.31
Jul	181+ *i*	16	197	21.35
Aug	212+ *i*	17	229	13.12
Sep	243+ *i*	16	259	1.81
Oct	273+ *i*	15	288	-9.60
Nov	304+ *i*	16	320	-19.38
Dec	334+ *i*	16	350	-23.37

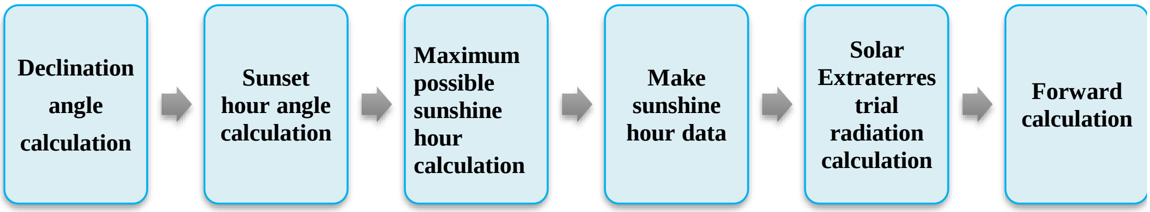


Figure 1. A systematic process for estimating solar radiation using sunshine duration and solar geometry

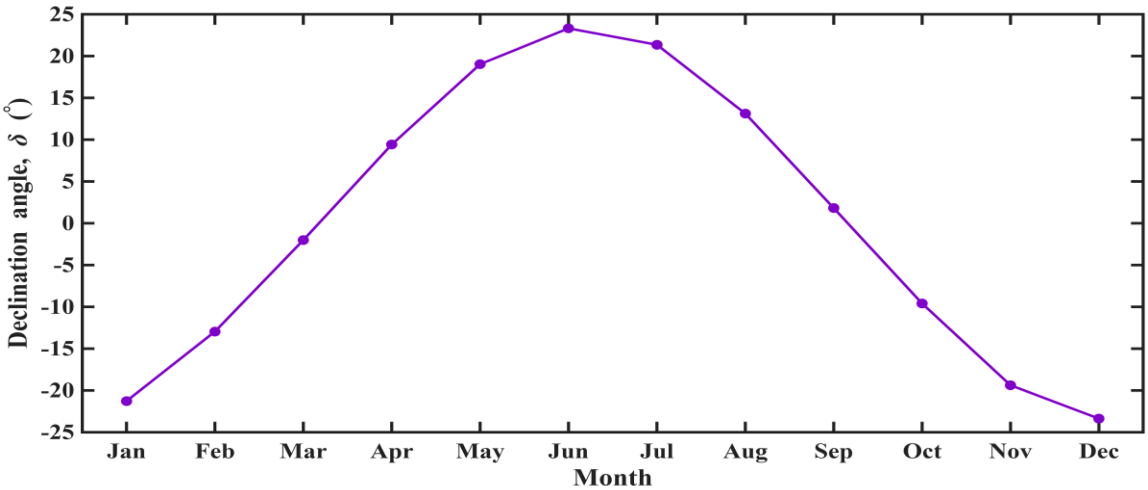


Figure 2. Monthly average daily sun declination angle for different South Asian zones

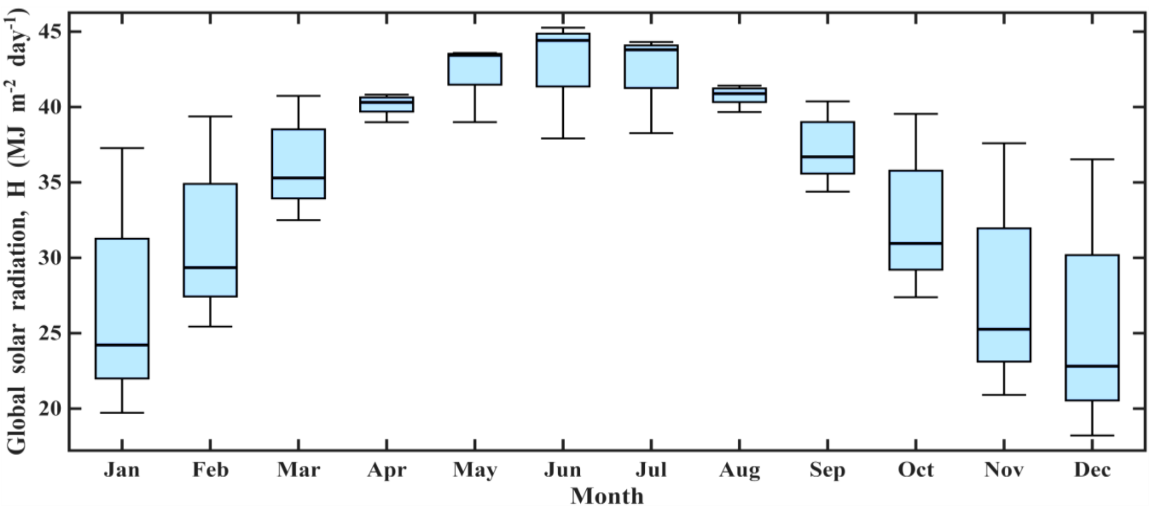


Figure 3. Menstruation box-whisker plot of solar radiation for 2025 in different South Asian zones

4. Results and Discussion

The clearness index and sunshine duration vary with the time of year (2025), the sky's condition and the geographic location. In this study, each month of the year is represented by a specific letter code: January (J), February (F), March (M), April (A), May (Ma), June (Ju), July (Jl), August (Au), September (S), October (O), November (N), December (D), Total (T). Similarly, each study location is denoted by a specific letter code: Kabul (Ka), Dhaka (Dh), Thimphu (Th), New Delhi (Nd), Male (Ml), Kathmandu (Kt), Islamabad (Id) and Colombo (Co).

Figure 3 illustrates the monthly variation of solar radiation intensity across different South Asian zones from January to December. The periods from February to June and from July to September, exhibit high solar radiation with low variability, indicating consistent and strong solar energy availability. In contrast, the months from October to January show lower radiation levels with higher variability, likely due to increased cloud cover and atmospheric fluctuations. Among the selected locations (Table 1), Male recorded the highest clearness index values throughout the year, indicating minimal atmospheric interference and favorable conditions for solar radiation estimation. Conversely, the lowest clearness index was observed in Kabul , suggesting heavy cloud cover and reduced solar radiation availability, as shown in Table 4. Due to its consistently high and stable clearness index, Male is identified as the most suitable location for accurate solar radiation estimation among the eight analyzed cities (Figure 4).

Figure 6 illustrates the lowest and highest recorded monthly mean daily solar energy values received on horizontal surfaces across eight South Asian locations. The lowest value was observed in June at Kabul (7.921 $\mathrm{KWh/m^2/y}$), a month characterized by frequent cloud cover. In contrast, the highest value was observed in March at Male (11.207 $\mathrm{KWh/m^2/y}$),when clearer sky conditions prevailed. Among all eight stations, the highest total annual solar radiation was recorded in Male (3890.61 $\mathrm{KWh/m^2/y}$), while the lowest was recorded in Kabul (3146.65 $\mathrm{KWh/m^2/y}$), as shown in Table 3. These findings highlight the combined influence of geographical location and atmospheric conditions on solar radiation availability. A conversion factor of 0.274 was applied to express solar radiation values in alternative units for comparison across zones.

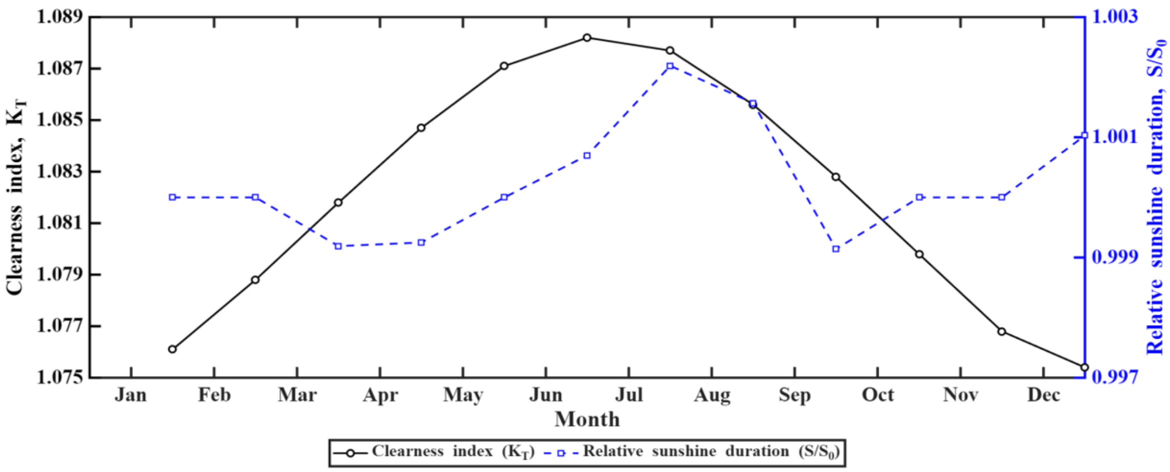
The bar graph for the year 2025 (Figure 5) shows clear seasonal variation in solar radiation. Radiation intensity increases during March–April and July–September, corresponding to the sun's movement toward the equator. On the other hand, radiation decreases from October to January, when the sun's apparent position shifts farther away (Table 2). A notable increase in radiation during February and March, which coincides with the sun's declination reaching its minimum (Figure 2). However, this increase is less observed during July–September.

Table 3. Monthly Average daily Solar radiation on Horizontal Surface ($\mathrm{MJ/m^2/d}$)

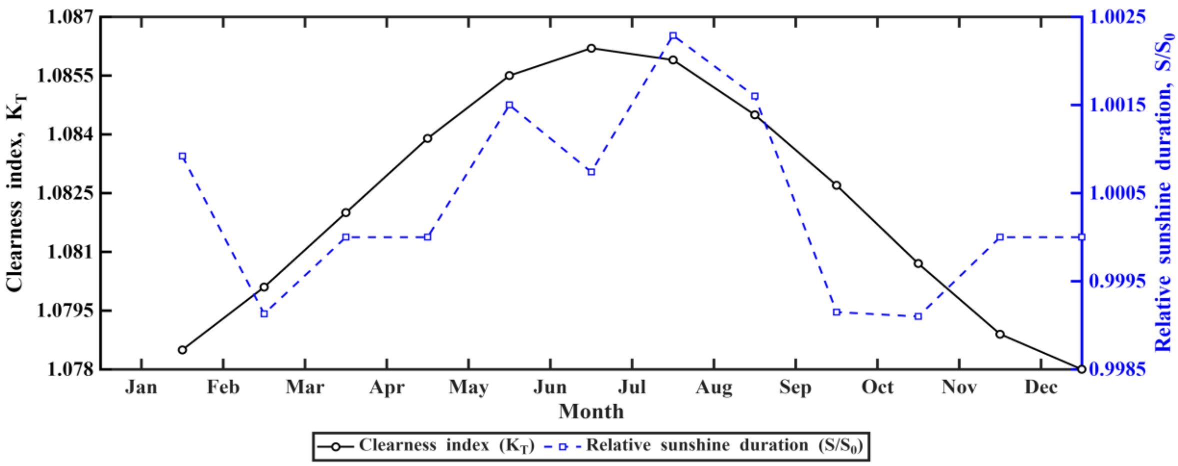
Mo	Ka	Dh	Th	Nd	Ml	Kt	Id	Co
J	30.68	34.99	33.69	32.23	38.96	33.60	31.19	38.71
F	32.75	36.74	35.53	35.11	40.41	35.45	33.22	40.19
M	33.74	37.49	36.35	35.96	40.90	36.28	34.18	40.71
A	32.78	36.47	35.36	34.97	39.75	35.28	33.22	39.57
Ma	30.44	34.24	33.10	32.70	37.52	33.02	30.90	37.35
Ju	28.91	32.81	31.65	31.24	36.12	31.57	29.38	35.96
Jl	29.52	33.35	32.20	31.80	36.62	32.12	29.97	36.46
Au	31.74	35.41	34.30	33.92	38.64	34.23	32.17	38.47
S	33.25	36.92	35.81	35.42	40.23	35.73	33.69	40.05
O	32.91	36.77	35.60	35.19	40.31	35.52	33.37	40.10
N	31.06	35.26	33.99	33.55	39.13	33.90	31.57	38.89
D	29.91	34.32	32.99	32.52	38.37	32.90	30.44	38.12
T	11484.14	12916.19	12484.27	12333.40	14199.30	12454.77	11654.78	14126.94

Table 4. Monthly average Clearness index ($\overline{K}_T = \frac{\overline{H}}{\overline{H}_0}$)

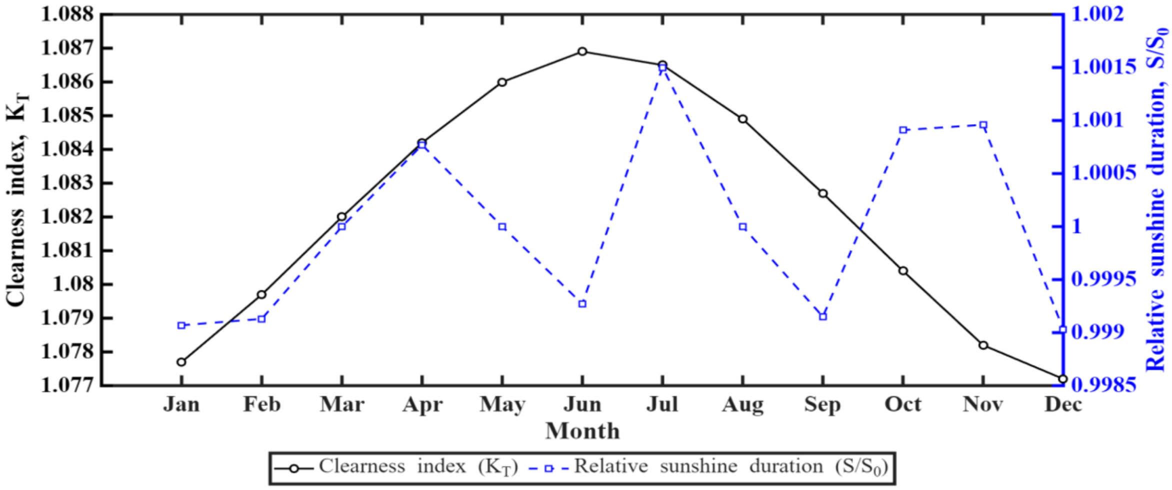
Mo	Ka	Dh	Th	Nd	Ml	Kt	Id	Co
J	1.076	1.079	1.078	1.078	1.082	1.078	1.077	1.081
F	1.079	1.080	1.080	1.080	1.082	1.080	1.079	1.082
M	1.082	1.082	1.082	1.082	1.082	1.082	1.082	1.082
A	1.085	1.084	1.084	1.084	1.083	1.084	1.085	1.083
Ma	1.087	1.085	1.086	1.086	1.083	1.086	1.087	1.083
Ju	1.088	1.086	1.087	1.087	1.083	1.087	1.088	1.084
Jl	1.088	1.086	1.087	1.087	1.083	1.087	1.088	1.083
Au	1.086	1.085	1.085	1.085	1.083	1.085	1.086	1.083
S	1.083	1.083	1.083	1.083	1.082	1.083	1.083	1.082
O	1.080	1.081	1.080	1.080	1.082	1.080	1.080	1.082
N	1.077	1.079	1.078	1.078	1.082	1.078	1.077	1.081
D	1.076	1.078	1.077	1.077	1.082	1.077	1.076	1.081



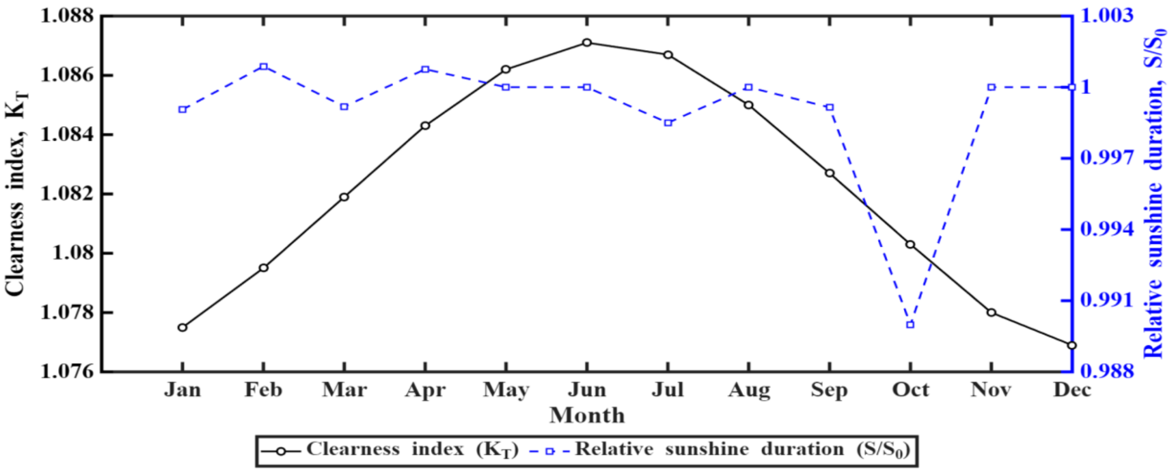
(a - Kabul)



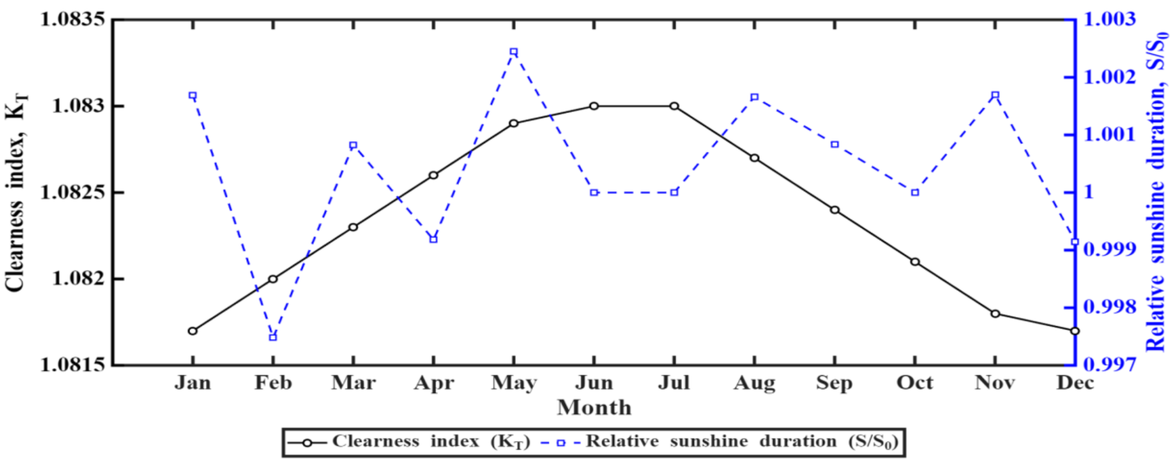
(b -Dhaka)



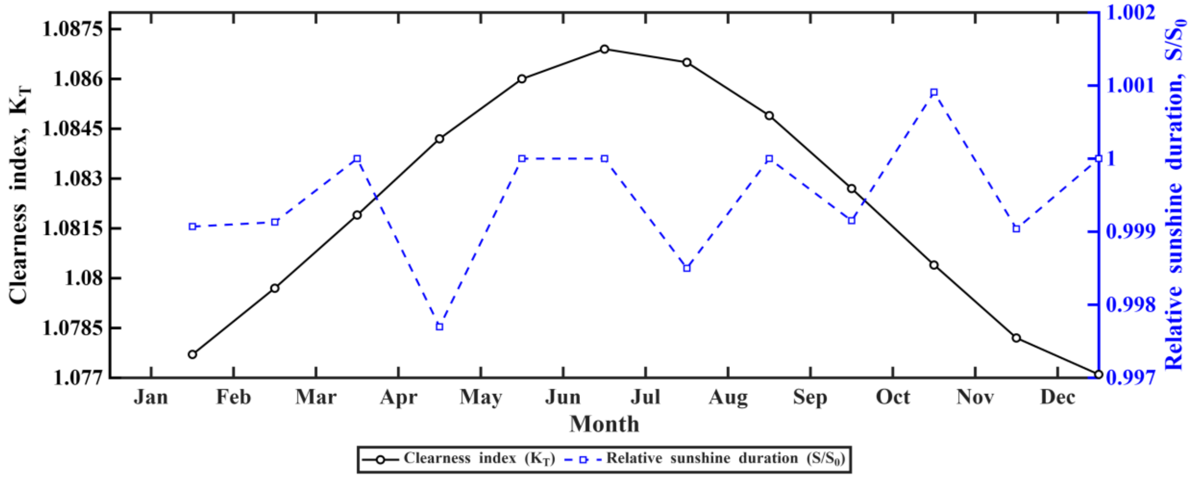
(c - Thimphu)



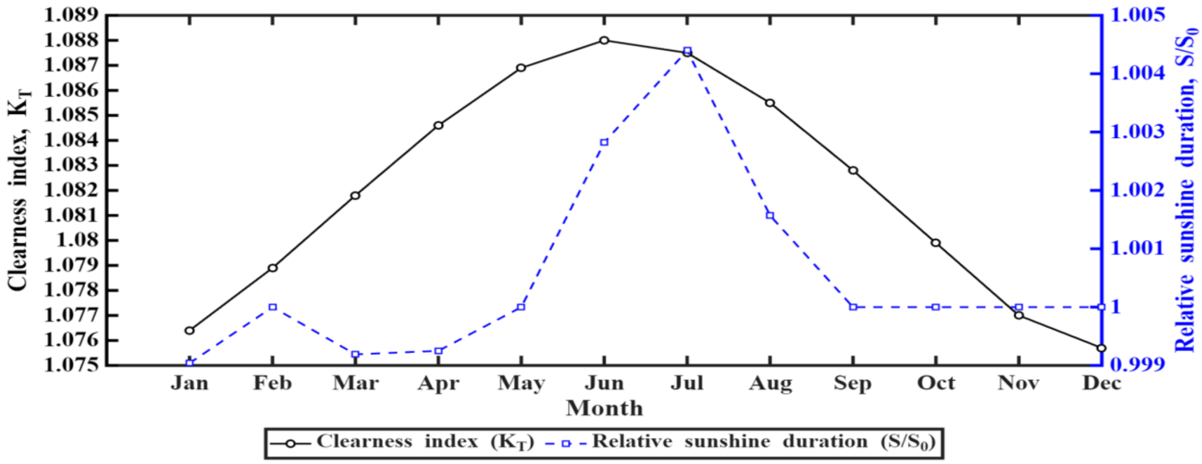
(d - New Delhi)



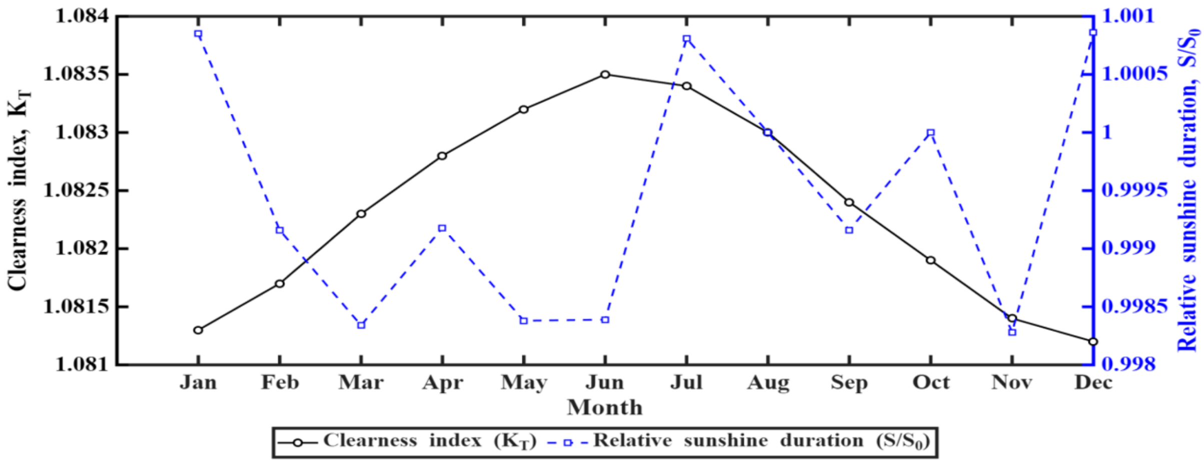
(e - Male)



(f - Kathmandu)



(g - Islamabad)



(h - Colombo)

Figure 4. Zone-wise comparison of sunshine duration and day length with respect to the clearness index

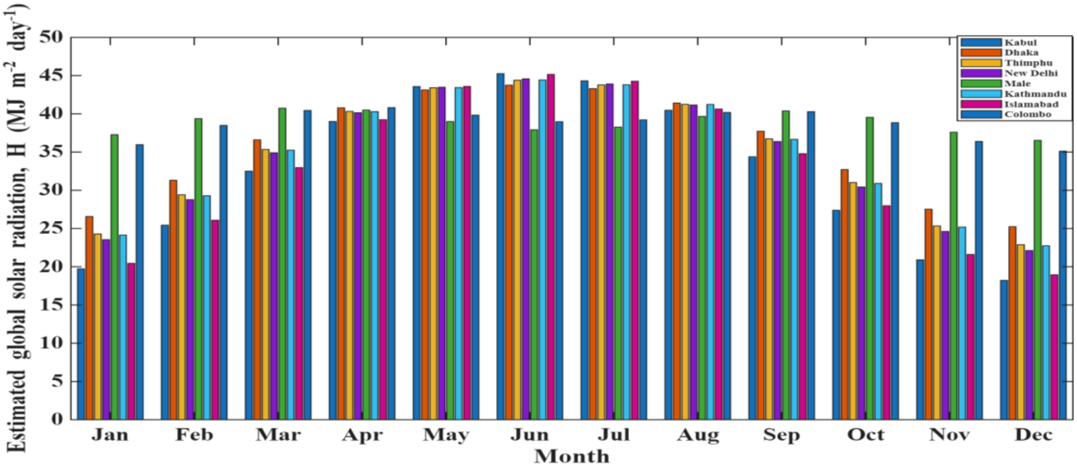


Figure 5. Monthly estimated solar radiation for 1 year (2025) in different South Asian zones

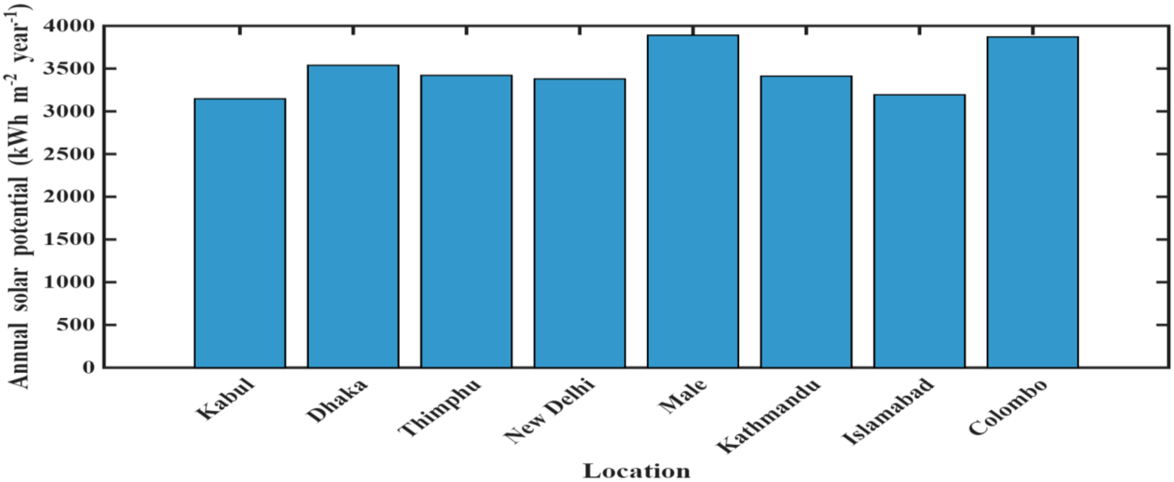


Figure 6. Annual solar radiation potential in different South Asian zones

Overall, the monthly average solar radiation values across the eight South Asian locations provide valuable insights into regional solar energy potential and highlight the role of atmospheric conditions and solar geometry. Generally, all stations show a uniform monthly average radiation pattern throughout the year 2025. The annual average of solar radiation values were calculated as 3146.65 $KWh/m^2/y$ for Kabul, 3539.04 $KWh/m^2/y$ for Dhaka, 3420.69 $KWh/m^2/y$ for Thimphu, 3379.35 $KWh/m^2/y$ for New Delhi , 3890.61 $KWh/m^2/y$ for Male, 3412.61 $KWh/m^2/y$ for Kathmandu, 3193.41 $KWh/m^2/y$ for Islamabad and 3870.78 $KWh/m^2/y$ for Colombo. Based on these results, the regions with the most key potential are ranked as follows: Male > Colombo > Dhaka > Thimphu > Kathmandu > New Delhi > Islamabad > Kabul (Figure 6).

Table 5. Verification of model outcomes among Mean Bias Error (*MBE*),Root Mean Square Error (*RMSE*), and the Correlation Coefficient (R^2) for different South Asian Zones

Locations	R^2	*MBE*	*RMSE*	Ref	Period
Dh	0.889	0.018	0.2404	[42]	1961-2013
Nd	0.91	_	0.04	[43]	1980-2020
Kt	0.991	-0.033	0.225	[4]	1983-2005
Id	0.007	0	6.72	[23]	2022

In the statistical assessment, Kathmandu exhibited a relatively high coefficient of determination (R^2 = 0.991), indicating strong agreement with the observed data, as shown in Table 5. In contrast, other regions recorded comparatively lower R^2 values, suggesting weaker predictive accuracy compared to the mean of the measured observations. Therefore, the Angstrom-type empirical model for Kathmandu yielded the lowest RMSE and MBE values, confirming its superior predictive performance among the South Asian locations investigated.

5. Limitations of the study and the future work

Solar energy has become one of the leading renewable energy sources in South Asia. Improvements in high-efficiency Solar panels, low-cost materials, and better energy storage systems are expected to further support this growth. Additionally, the integration of machine learning techniques for solar radiation forecasting can improve prediction accuracy, enhance grid stability, and assist in designing efficient solar energy systems. Despite these advancements, challenges such as seasonal fluctuations, irregular sunlight, limited land availability, inadequate infrastructure, and financial limitations persist. Besides, climate change may also impact solar radiation patterns, underscoring the need for continuous monitoring and regular model updates.To build a sustainable solar-based energy system in the region, these barriers must be addressed through innovation, proper planning, and supportive policies.

6. Conclusion

Energy plays a fundamental role in life for both individuals and nations. Yet, the world is currently facing a severe energy crisis. Among the alternative solutions, solar energy appears exceptional promise, however, its performance varies with time and geographical location. This study demonstrates that solar radiation exhibits clear seasonal variations influenced by the day of the year and the altitude of a given location. The amount of solar energy reaching the Earth's surface is essential for various fields, including hydrology, agriculture, climatology, and meteorological modeling. Because solar energy is more variable than other energy sources, solar power systems must be installed in optimal locations to maximize efficiency and output. Among the eight analyzed locations, Male received the highest amount of annual solar energy at 3890.61 MJ/m², while Kabul recorded the lowest amount of solar energy over the year at 3146.65 MJ/m². Significantly, this research demonstrates that the Angstrom based linear regression model is efficiently applicable to solar radiation data measurements for the eight South Asian cities studied. Statistically, Kathmandu demonstrated the best model performance, recording the highest R^2 value (0.991) and the lowest error indices (MBE = –0.033, RMSE = 0.225). In contrast, the three countries(Dhaka, New Delhi, Islamabad) exhibited comparatively lower R^2 values and higher RMSE and MBE scores, indicating weaker model performance.The remaining four countries could not be reliably estimated using the Angstrom empirical model. Hence, their corresponding MBE, $RMSE$, R^2 values were not obtained.This is significant because it demonstrates the potential for estimating solar energy availability even when direct measurements are not always available, which is essential for designing and sizing solar systems.Based on the model measured data , solar radiation increased from July to September (36.12 to 40.23$\mathrm{KWh/m^2/d}$) for Male, (28.91 to 33.25 $\mathrm{KWh/m^2/d}$) for Kabul and in most other regions. Among the eight locations studied, Male showed the most significant solar energy potential, followed by: Male > Colombo > Dhaka > Thimphu > Kathmandu > New Delhi > Islamabad > Kabul.

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Nomenclature

a	Angstrom empirical constant (-)
b	Angstrom empirical constant (-)
$\bar{H}$	Monthly mean daily solar radiation on a horizontal surface $(MJ/m^2/d)$
$\bar{H}_0$	Monthly mean extraterrestrial radiation on a horizontal surface $(MJ/m^2/d)$
$\frac{\bar{H}}{\bar{H}_0}$	Monthly mean clearness index (-)
$H_{measured}$	Measured value of solar radiation$(MJ/m^2/$

	d)
$H_{predicted}$	Predicted value of solar radiation($MJ/m^2/d$)
I_{sc}	Solar constant (W/m²)
$\overline{K}_T$	Clearness index (-)
m	Total number of observation points (-)
n	Day of the year
S	Bright sunshine duration(hour)
S_0	Maximum sunshine duration(hour)
$\bar{S}$	Monthly mean hours of bright sunshine(hour)
$\overline{S_0}$	Monthly mean of the maximum possible daily sunshine duration or day length(hour)
$\frac{\bar{S}}{\overline{S_o}}$	Monthly mean proportion of potential sunshine hours (-)
δ	Declination angle(°)
ω	The sunset hour angle (°)
φ	Latitude (°)

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