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Determining the most suitable empirical model for global solar radiation prediction in the lakes region

Ahmet Süslü[1]

[1]Isparta University of Applied Sciences, Graduate Education Institute, PhD, Isparta, Turkey,

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Corresponding Author
Ahmet Süslü
✉ mail@ahmetsuslu.com

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Abstract

In this study, it was aimed to determine the most suitable model for predicting global solar radiation in the Lakes Region (Isparta, Burdur, Antalya). Through ATATEK-Solar software, a total of 15 models were tested, including 14 empirical models from the literature and a new artificial intelligence-supported model. Each model was analyzed with three different optimization algorithms (Nelder-Mead Simplex, Pattern Search, Simulated Annealing). In province-based evaluations, the Model 9 (RMSE: 0.1507, R^2: 0.9990) for Isparta, and the Model 14 for Burdur and Antalya (RMSE: 0.1940, R^2: 0.9992 and RMSE: 0.2218, R^2: 0.9987, respectively) provided the most successful results. In regional analysis results, while the Model 5 (RMSE: 0.2626, R^2: 0.9980) gave the lowest average error, the Model 13 (RMSE: 0.2649, R^2: 0.9979, standard deviation: 0.0122) showed the highest consistency. These models were followed by the Model 6 (RMSE: 0.2646, R^2: 0.9979, standard deviation: 0.0444). Although the Model 15 gave the best results in Burdur and Antalya, it had a high standard deviation value (0.2201) due to its low performance in Isparta. The characteristic features of the Lakes Region, including the presence of lake ecosystems, elevation differences, and the resulting microclimatic diversity, necessitate a regional approach in predicting global solar radiation. In this context, the Model 13 has been determined as the most suitable model that can be used throughout the region with its low error rate and high consistency. The obtained results can provide reliable predictions in evaluating the solar energy potential of the region and designing solar energy systems.

Keywords: Solar energy, Global solar radiation, Empirical models, Lakes Region, ATATEK-Solar

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INTRODUCTION

The continuous increase in global energy demand and efforts to combat climate change have heightened interest in renewable energy sources. Solar energy, with its low carbon emissions and high potential, is among the key sustainable energy solutions (Külcü & Ersan, 2021). Turkey benefits from a significant solar energy potential, with an annual average sunshine duration of 2,741 hours and a total global solar radiation value of 1,527.46 kWh/m² (Ministry of Energy of Turkey, 2024). Solar energy is particularly advantageous due to its abundant availability and adaptability across diverse geographical and climatic conditions.

Accurate prediction of global solar radiation is critical for the design and performance evaluation of solar energy systems. Due to atmospheric conditions, geographical features, and climatic factors, regional differences are observed in radiation predictions. Considering the installation and operational costs of solar observation devices, the regional evaluation of prediction models becomes increasingly important (Süslü & Külcü, 2024).

The Lakes Region is a geographical area located in southwestern Turkey, encompassing the provinces of Isparta, Burdur, and Antalya. The region is notable for its agricultural production and renewable energy potential. Eğirdir Lake, Burdur Lake, and other water resources influence the microclimate of the area, causing local variations in solar radiation distribution. Greenhouse farming activities in Antalya and the region's agricultural irrigation needs support the development of solar energy applications. The Lakes Region is not only vital for its agricultural production but also for its unique geographical features that include diverse elevation levels and lake ecosystems, making it an ideal site for studying solar radiation variability. These factors underline the necessity for region-specific radiation models that account for such microclimatic differences. Antalya's extensive greenhouse farming activities require substantial energy inputs, positioning solar energy as a cost-effective and sustainable solution to meet these demands.

In the literature, various empirical models have been proposed for estimating global solar radiation. These models typically rely on parameters such as sunshine duration, temperature differences, and geographical factors. Almorox et al. (2005) examined the effects of regional adaptation of temperature-based models. Regional adaptation of solar radiation models has been shown to significantly enhance prediction accuracy, as highlighted by studies in Spain (Almorox & Hontoria, 2004) and Egypt (El-Metwally, 2005). These studies emphasize that localized optimization of model parameters improves the reliability of solar energy applications. Similarly, Külcü and Ersan (2021) conducted a study in Hatay Province, comparing the performance of different models and demonstrating that regionally optimized models provide higher accuracy.

In this study, ATATEK-Solar software was utilized to evaluate global solar radiation prediction models for the Lakes Region. This software analyzes a total of 15 models, including 14 empirical models from the literature and a new artificial intelligence-supported model (Süslü & Külcü, 2024). ATATEK-Solar facilitates regional-scale model validation and comparative performance evaluation by employing Nelder-Mead Simplex, Pattern Search, and Simulated Annealing algorithms for model optimization.

This research aims to identify a suitable prediction model for the provinces in the Lakes Region, considering the region's microclimatic characteristics and geographical structure. To achieve this goal, each model was analyzed using three different optimization algorithms, and the results were statistically evaluated. By integrating empirical models and artificial intelligence, this study not only seeks to identify the most suitable model for the Lakes Region but also aims to establish a methodological framework that can be adapted for similar regions with diverse climatic conditions. The findings obtained may contribute to the planning of solar energy applications and the development of system designs in the region.

MATERIALS AND METHODS

Study Area and Dataset

This research was conducted for the Lakes Region, located in southwestern Turkey. The selected study area comprises the provinces of Isparta, Burdur, and Antalya, which exhibit varying elevations and microclimatic characteristics (Figure 1). While Antalya is situated at an average elevation of 39 m above sea level, Isparta and Burdur are located at elevations of 1,035 m and 957 m, respectively. As shown in Figure 1, the region is characterized by lake ecosystems, which contribute to the formation of distinctive microclimatic features.

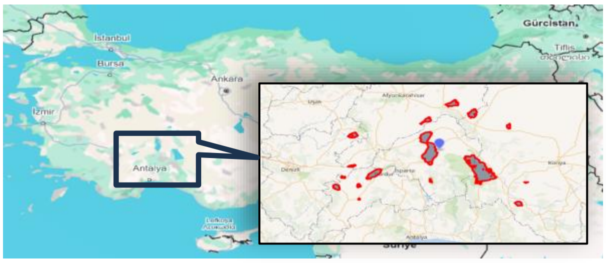

Figure 1. The location of the Lakes Region in Turkey and the distribution of its characteristic lakes.

The meteorological data used in this study were obtained from the Turkish State Meteorological Service. These long-term averaged data reflect the characteristic climatic properties of the region. The dataset includes the following parameters:

Monthly average sunshine duration (hours),
Monthly average temperature (°C),
Maximum and minimum temperature difference (°C),
Monthly total global solar radiation (MJ/m²-day),
Theoretical sunshine duration (hours),
Extraterrestrial radiation values (MJ/m²-day).

The solar radiation values were calculated as the monthly averages of daily totals derived from hourly measurements. The extraterrestrial radiation values (H_0) were computed using the following equations (Duffie & Beckman, 2006):

$$H_0 = \frac{24x3600xG_{sc}}{\pi}\left[1 + 0.033cos\left(\frac{360n}{365}\right)\right]\left[cos\varphi cos\delta sinw_s + \frac{\pi}{180}w_s sin\varphi sin\delta\right] \quad (1)$$

Where:
G_{sc}: Solar constant (1367 W/m²)
φ: Latitude angle
δ: Declination angle
w_s: Sunset hour angle
n: Day of the year (1–365)
The declination angle (δ) is calculated as:

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

The sunset hour angle (w_s) is calculated as:

$$w_s = arccos[-tan(\varphi)tan(\delta)] \tag{3}$$

The climatic characteristics of the region show that Antalya has the highest annual average sunshine duration at 8.43 hours/day, with Isparta and Burdur following at 7.55 and 7.45 hours/day, respectively. The average global solar radiation values were measured as 16.90 MJ/m²-day in Burdur, 16.29 MJ/m²-day in Antalya, and 13.35 MJ/m²-day in Isparta. These differences are attributed to the topographic diversity and the microclimatic effects of the lakes in the region.

Models and Optimization Methods

Models Used

In this study, a total of 15 models were used to predict global solar radiation, including 14 empirical models commonly cited in the literature and a newly developed artificial intelligence-supported model. The model analyses were conducted using ATATEK-Solar software (Süslü & Külcü, 2024). The models examined are presented in Table 1.

Table 1. Models optimized using ATATEK-Solar.

Model No	Model	References
1	$\frac{H}{H_0} = c_1 + c_2\left(\frac{S}{S_0}\right)$	Angstrom (1924); Prescott (1940)
2	$\frac{H}{H_0} = c_1 + c_2\left(\frac{S}{S_0}\right)^{c_3}$	Elagib ve Mansell (2000)
3	$\frac{H}{H_0} = c_1^{\left(\frac{1}{S}\right)}$	El-Metwally (2005)
4	$\frac{H}{H_0} = \left[\frac{c_1\left(\frac{S}{S_0}\right)}{c_2 w_s}\right] + c_3 w_s$	Külcü (2015)
5	$\frac{H}{H_0} = c_1 + c_2\left(\frac{S}{S_0}\right) + c_3\left(\frac{S}{S_0}\right)^2 + c_4\left(\frac{S}{S_0}\right)^3$	Bahel et al. (1987)
6	$\frac{H}{H_0} = c_1 + c_2\left(\frac{S}{S_0}\right) + c_3 log\left(\frac{S}{S_0}\right)$	Ampratwum & Dorvlo (1999)
7	$\frac{H}{H_0} = c_1 + c_2 exp\left(\frac{S}{S_0}\right)$	Almorox & Hontoria (2004)
8	$\frac{H}{H_0} = c_1 + \left[c_2\left(\frac{S}{S_0}\right) + c_3\right]\varphi + c_3\left(\frac{S}{S_0}\right)$	Dogniaux & Lemoine (1983)
9	$\frac{H}{H_0} = c_1 + c_2 log\left(\frac{\frac{S}{S_0}}{w_s}\right) + c_3\left(\frac{S}{S_0}\right)$	Külcü (2019)
10	$\frac{H}{H_0} = c_1(\Delta T)^{0.5} + c_2$	Hargreaves et al. (1985)
11	$\frac{H}{H_0} = c_1 ln(\Delta T) + c_2$	Coppolino (1994)
12	$\frac{H}{H_0} = c_1[1 - exp - c_2(\Delta T)^{c_3}]$	Bristow & Campbell (1984)
13	$\frac{H}{H_0} = c_1 log\left[\left(c_2\frac{S}{S_0}\right) + (c_3\Delta T)\right] + c_4$	Külcü & Ersan (2024)
14	$\frac{H}{H_0} = c_1 log[(c_2 w_s) + (c_3\Delta T)] + c_4$	Külcü & Ersan (2024)
15	$\frac{H}{H_0} = c_1\left(\frac{S}{S_0}w_s\right)^{c_2} + c_3 log_{10}(1 + \Delta T) + c_4 sin(\varphi)cos\left(\frac{2\pi n}{365}\right) + c_5$	Süslü & Külcü (2024)

Where:
H : Daily global solar radiation reaching the Earth's surface (MJ/m²-day)
H_0 : Extraterrestrial radiation (MJ/m²-day)
S : Daily sunshine duration (hours)
S_0 : Theoretical sunshine duration (hours)
ΔT : Daily maximum and minimum temperature difference (°C)
w_s : Sunset hour angle
φ : Latitude angle
n : Day of the year (1–365)
c_1, c_2, c_3, c_4, c_5 : Model coefficients

Optimization Methods

The parameters of the algorithms used for model optimization were defined as follows:

1. Nelder-Mead Simplex Algorithm: Developed by Nelder and Mead (1965), this method is widely used for solving nonlinear optimization problems.

   - Initial step size: 0.1
   - Convergence tolerance: $1x10^{-8}$
   - Maximum number of iterations: 50,000
   - Simplex size: $n + 1$ (where n is the number of model parameters)

2. Pattern Search Algorithm: Proposed by Hooke and Jeeves (1961), this algorithm is a fundamental approach among derivative-free direct search methods.

   - Initial step size: 0.2
   - Reduction factor: 0.6
   - Number of direction vectors: $2n$ (where n is the number of model parameters)
   - Maximum number of iterations: 50,000

3. Simulated Annealing Algorithm: Developed by Kirkpatrick et al. (1983), this stochastic optimization method is inspired by the annealing process in metallurgy.

   - Initial temperature: 2.0
   - Cooling rate: 0.97
   - Acceptance probability for the Metropolis criterion: $\exp(-\Delta E/T)$
   - Maximum number of iterations: 50,000

The parameter ranges for optimization were determined based on prior studies in the literature and physical constraints. In the comparison of model performance, the RMSE (Root Mean Square Error) value was prioritized; for models with equal RMSE values, the R² (coefficient of determination) value was evaluated.

Statistical Analysis

The evaluation of model performance was conducted using the RMSE and R². These parameters were calculated using the following equations:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(H_{ip} - H_{io}\right)^2} \tag{4}$$

$$R^2 = \frac{\sum_{i=1}^{N}\left(H_{ip}-H_{ipa}\right)\left(H_{io}-H_{ioa}\right)}{\sqrt{\left[\sum_{i=1}^{N}\left(H_{ip}-H_{ipa}\right)^2\right]\left[\sum_{i=1}^{N}\left(H_{io}-H_{ioa}\right)^2\right]}} \tag{5}$$

Where:
H_{ip}: Predicted value
H_{io} : Observed value
H_{ipa} : Mean of predicted values
H_{ioa} : Mean of observed values
N : Number of data points

The RMSE value indicates the magnitude of the differences between predicted and observed values. A value close to zero signifies high prediction accuracy. The R^2 value reflects the explanatory power of the model, with values closer to 1 indicating higher performance (Duffie & Beckman, 2006).

ATATEK-Solar software performs comparative statistical analyses on a monthly basis for each model. These analyses include:

- Calculation of absolute and relative differences between predicted and observed values for each month,
- Examination of seasonal performance variations of the models,
- Assessment of annual average prediction accuracy,
- Analysis of the optimized values of model coefficients and their consistency with the literature.

The selection of the ATATEK-Solar software allowed for a comprehensive evaluation of model performance using multiple optimization algorithms (Nelder-Mead, Pattern Search, and Simulated Annealing). These approaches were chosen for their proven effectiveness in solar radiation modeling studies.

Model performance comparisons were conducted using a three-step evaluation approach:

1. In the first step, models were ranked based on RMSE values.
2. In the second step, R^2 values were examined, and the explanatory powers of the models were compared.
3. In the final step, the most successful models for each province were identified and evaluated in terms of regional applicability.

This comprehensive statistical analysis approach ensures an objective assessment of both individual model performances and their applicability on a regional scale.

Determining a Common Model for the Lakes Region

A systematic evaluation process was followed to identify a common model that can represent the Lakes Region. In this process, the performance rankings of the models were first created for each province based on their RMSE and R^2 values. Subsequently, the top five models for each province were identified, and the models common to all provinces were examined for their regional consistency. For this regional consistency assessment, the average performance values of the models across the three provinces and their standard deviations were calculated.

In selecting a regional model, not only the error values of the models but also their consistency across the region were considered. To achieve this, the ranking position of each model in the provinces, its average performance across the three provinces, and the standard deviation of these performance values were evaluated together. This comprehensive evaluation approach enabled the identification of the model demonstrating the most consistent performance at the regional scale.

RESULTS AND DISCUSSION

Evaluation of Model Performance

The analyses conducted using the ATATEK-Solar software revealed the performance values of the models for each province, as presented in Table 2. The results reflect the impact of diverse climatic and geographical conditions on model performance, highlighting variations between provinces. For example, certain models exhibited higher accuracy in specific provinces due to their microclimatic characteristics.

Table 2. Performance Values of Models for Each Province

Model No	Isparta		Burdur		Antalya	
	RMSE	R^2	RMSE	R^2	RMSE	R^2
1	0.2196	0.9980	0.3517	0.9973	0.3544	0.9966
2	0.2185	0.9980	0.2759	0.9983	0.3304	0.9970
3	2.7970	0.6711	1.8604	0.9232	1.5853	0.9314
4	0.7532	0.9761	0.6407	0.9909	0.4452	0.9946
5	0.2088	0.9982	0.2699	0.9984	0.3091	0.9974
6	0.2192	0.9980	0.2666	0.9984	0.3079	0.9974
7	0.2186	0.9980	0.4179	0.9961	0.3772	0.9961
8	0.2196	0.9980	0.3517	0.9973	0.3544	0.9966
9	0.1507	0.9990	0.3367	0.9975	0.3880	0.9959
10	0.3686	0.9943	0.4507	0.9955	0.3136	0.9973
11	0.3915	0.9936	0.4702	0.9951	0.3237	0.9971
12	0.3834	0.9938	0.4640	0.9952	0.3442	0.9968
13	0.2590	0.9972	0.2794	0.9983	0.2564	0.9982
14	0.3916	0.9936	0.4703	0.9951	0.2452	0.9984
15	0.5901	0.9854	0.1940	0.9992	0.2218	0.9987

For the analyses conducted for Isparta, the Model 9 provided the best results, with the lowest RMSE (0.1507) and the highest R^2 (0.9990). This model was followed by the Model 5 (RMSE: 0.2088, R^2: 0.9982) and the Model 2 (RMSE: 0.2185, R^2: 0.9980). These findings demonstrate the variability in model performance across regions and the importance of region-specific adaptations for accurate solar radiation predictions.

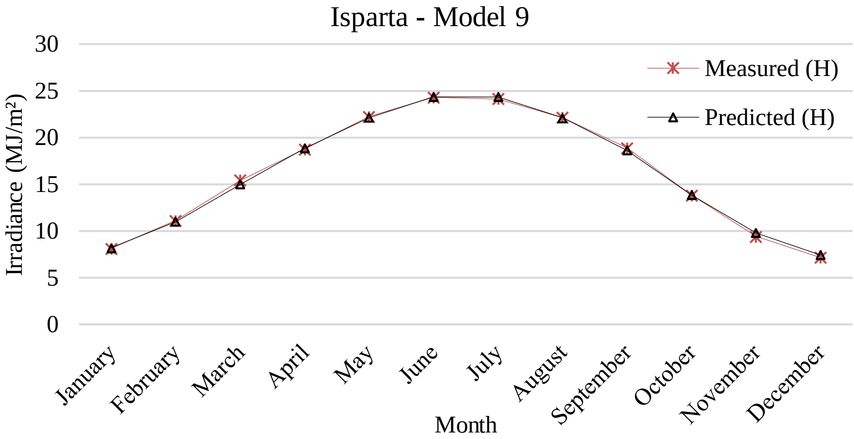

Figure 2. Best model graph for Isparta

In Figure 2, the comparison between the predicted and measured values for the Model 9 in Isparta is shown. The model's ability to accurately predict high radiation values, especially during summer months, ~~is observed.~~ underscores its adaptability to the region's microclimatic variations. This performance aligns with findings from Almorox et al. (2005), which emphasized the role of region-specific adaptations in enhancing model accuracy. Such reliable predictions are critical for optimizing agricultural planning and solar energy system placements in Isparta.

For Burdur, the Model 15 stood out with the lowest RMSE (0.1940) and the highest R^2 (0.9992). The Model 6 (RMSE: 0.2666, R^2: 0.9984) ranked second, followed by the Model 5 (RMSE: 0.2699, R^2: 0.9984). These results highlight the adaptability of Model 15 to Burdur's climatic conditions, particularly its ability to handle the transitional seasons effectively.

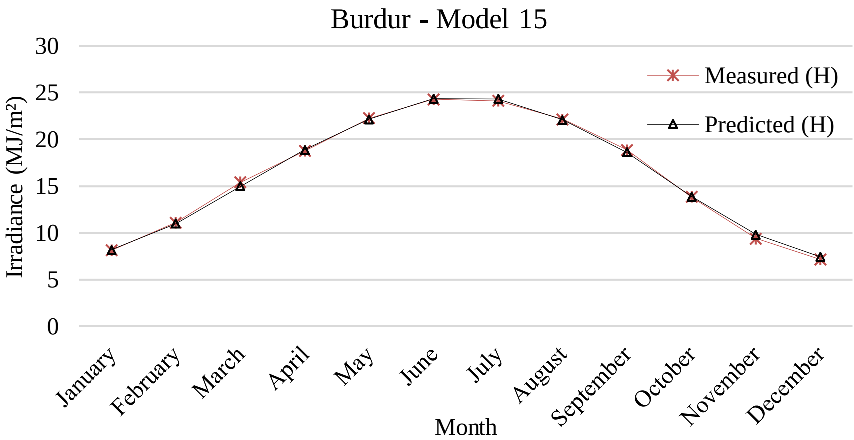

Figure 3. Best model graph for Burdur

Figure 3 presents the performance of the Model 15 for Burdur. As shown in the graph, the model closely follows the measured values throughout the year, achieving accurate predictions, particularly during transitional seasons. This performance is critical for solar energy applications in Burdur, where transitional seasons often affect energy demand and supply dynamics.

For Antalya, the Model 15 also provided the most successful results (RMSE: 0.2218, R^2: 0.9987). The Model 14 (RMSE: 0.2452, R^2: 0.9984) and the Model 13 (RMSE: 0.2564, R^2: 0.9982) showed the second and third-best performances, respectively. The high accuracy of Model 15 highlights its robustness in capturing Antalya's complex climatic conditions, particularly during the high-radiation summer months.

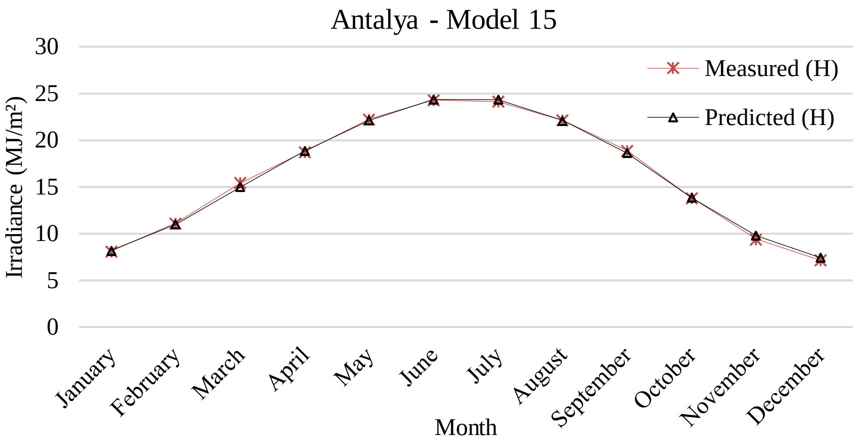

Figure 4. Best model graph for Antalya

Figure 4 illustrates the predictive performance of the Model 15 for Antalya. The model successfully captures Antalya's characteristic solar radiation profile and accurately reflects seasonal variations. This level of precision is crucial for planning solar energy projects, especially in Antalya, where the agricultural sector heavily relies on efficient energy usage during peak seasons.

Regional Model Performance Analysis

To evaluate the performance consistency of the models across the Lakes Region, the average performance values of each model for the three provinces and their standard deviations were calculated (Table 3).

Table 3. Regional performance metrics of models

Model No	Average RMSE	Standard Deviation	Average R^2
1	0.3086	0.0773	0.9973
2	0.2749	0.0559	0.9978
3	2.0809	0.6334	0.8419
4	0.6130	0.1555	0.9872
5	0.2626	0.0511	0.9980
6	0.2646	0.0444	0.9979
7	0.3379	0.1060	0.9967
8	0.3086	0.0773	0.9973
9	0.2918	0.1219	0.9975
10	0.3776	0.0693	0.9957
11	0.3951	0.0735	0.9953
12	0.3972	0.0610	0.9953
13	0.2649	0.0122	0.9979
14	0.3690	0.1156	0.9957
15	0.3353	0.2201	0.9944

These metrics provide valuable insights into the models' regional performance and consistency, which are critical for identifying models suitable for diverse microclimatic conditions in the Lakes Region. The relationship between the regional performance and consistency of the models is visualized in Figure 5. In the graph, the horizontal axis represents the average RMSE values, while the vertical axis shows the standard deviation values. Models located near the bottom-left corner of the graph demonstrate both low error and high consistency.

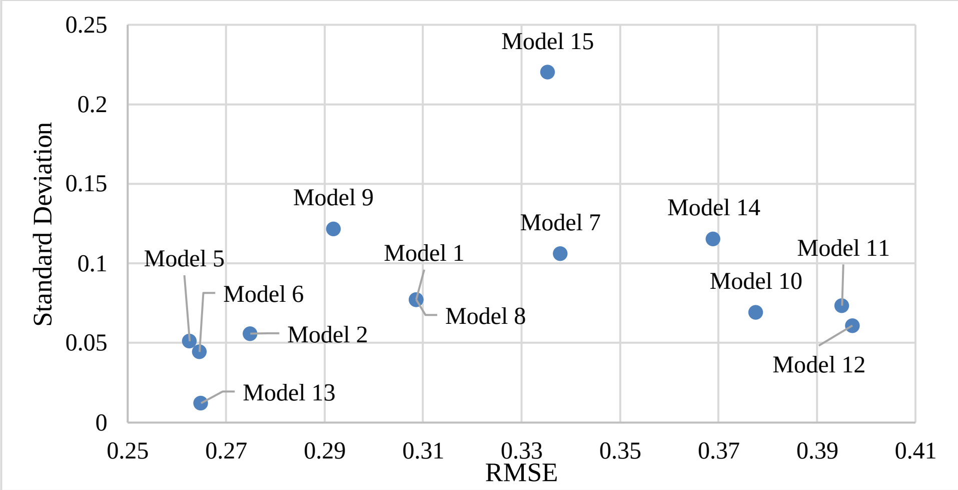

Figure 5. Distribution of Average RMSE and Standard Deviation Values of the Models

According to the results of the regional analysis, the Model 13 demonstrated the most consistent performance across the region, with the lowest standard deviation (0.0122). The stability of Model 13 aligns with findings from previous studies, where regionally adapted models demonstrated high consistency across diverse climatic conditions (Almorox et al., 2005). This was followed by the Model 6 (standard deviation: 0.0444) and the Model 5 (standard deviation: 0.0511), both of which also produced stable results regionally. This highlights the robustness of these models in handling the diverse microclimatic conditions present in the Lakes Region. This is clearly shown in Figure 5, where these models are clustered in the lower-left corner of the graph.

Although the Model 15 performed best in Burdur and Antalya, its relatively poor performance in Isparta resulted in a high standard deviation (0.2201). Similarly, while the Model 9 achieved the best results in Isparta, its performance declined in the other provinces. These results suggest that while certain models excel in specific provinces, they may lack adaptability across the entire region, emphasizing the importance of selecting models with both accuracy and consistency.

When examining the average RMSE values of the models, the Model 5 had the lowest value (0.2626), followed by the Model 13 (0.2649) and Model 6 (0.2646) models. These three models also showed high explanatory power, with average R^2 values exceeding 0.9978. Such performance indicates their potential application in regional energy planning and agricultural optimization, where reliable solar radiation predictions are critical.

CONCLUSION

In this study, 15 different models were tested to determine the most suitable model for predicting global solar radiation in the Lakes Region. The performance of the models was analyzed using the ATATEK-Solar software with three different optimization algorithms, and the results were evaluated at both the provincial and regional levels.

In the provincial evaluations, the Model 9 provided the best results for Isparta, with the lowest RMSE (0.1507) and the highest R^2 (0.9990). In contrast, the Model 15 performed best for Burdur and Antalya, with RMSE and R^2 values of 0.1940 and 0.9992, and 0.2218 and 0.9987, respectively. However, performance differences in other provinces limited the regional applicability of these models.

According to the results of the regional analysis, the Model 5 and the Model 13 were identified as the two most successful models. The Model 5 achieved the lowest average error (RMSE: 0.2626, R^2: 0.9980), while the Model 13 demonstrated similar performance with an RMSE of 0.2649 and R^2 of 0.9979. These two models were followed by the Model 6, with an RMSE of 0.2646 and R^2 of 0.9979.

When examining regional consistency, the Model 13 produced the most stable results, with the lowest standard deviation (0.0122). This value indicates that the model can provide consistent predictions despite varying climatic and geographical conditions in the region. The Model 6 (standard deviation: 0.0444) and the Model 5 (standard deviation: 0.0511) also exhibited stable performance across the region.

Although the Model 15 produced the best results in some provinces, its high standard deviation (0.2201) indicated weaker regional consistency. Similarly, while the Model 9 achieved high performance at the provincial level, it did not generate consistent results across the region.

Considering the characteristic features of the Lakes Region, including the presence of Eğirdir Lake, Burdur Lake, and other water bodies, as well as the elevation differences and the resulting microclimatic diversity, a regional approach is necessary for global solar radiation prediction. In this context, the Model 13 stands out as the most suitable model for regional use, with its low error rate and high consistency. The model provides acceptable error levels for all three provinces and produces reliable predictions under varying climatic conditions in the region.

Compliance with Ethical Standards

Peer-review

Externally peer-reviewed.

Declaration of Interests

The author has no conflict of interest to declare.

Author contribution

The author read and approved the final manuscript. The author verifies that the Text, Figures, and Tables are original and that they have not been published before.

REFERENCES

Almorox, J., & Hontoria, C. (2004). Global solar radiation estimation using sunshine duration in Spain. *Energy Conversion and Management, 45*(9–10), 1529–1535. https://doi.org/10.1016/j.enconman.2003.08.022

Almorox, J., Benito, M., & Hontoria, C. (2005). Estimation of monthly Angström-Prescott equation coefficients from measured daily data in Toledo, Spain. *Renewable Energy, 30*(6), 931–936. https://doi.org/10.1016/j.renene.2004.08.002

Ampratwum, D.B., Dorvlo, A.S.S. (1999). Estimation of solar radiation from the number of sunshine hours. *Applied Energy* 63: 161–7.

Angstrom, A. (1924). Solar and terrestrial radiation. *Quarterly Journal of the Royal Meteorological Society, 50*(210), 121–126. https://doi.org/10.1002/qj.49705021008

Bahel, V., Bakhsh, H., & Srinivasan, R. (1987). A correlation for estimation of global solar radiation. *Energy, 12*(2), 131–135. https://doi.org/10.1016/0360-5442(87)90117-4

Bristow, K. L., & Campbell, G. S. (1984). On the relationship between incoming solar radiation and daily maximum and minimum temperature. *Agricultural and Forest Meteorology, 31*(2), 159–166. https://doi.org/10.1016/0168-1923(84)90017-0

Coppolino, S. (1994). A new correlation between clearness index and relative sunshine. *Renewable Energy, 4*(4), 417–423. https://doi.org/10.1016/0960-1481(94)90049-3

Dogniaux, R., & Lemoine, M. (1983). Classification of radiation sites in terms of different indices of atmospheric transparency. In W. Palz (Ed.), *Solar energy research and development in the European Community, series F* (Vol. 2, pp. 151–163). Dordrecht: Reidel. https://doi.org/10.1007/978-94-009-7112-7_7

Duffie, J. A., & Beckman, W. A. (2013). *Solar engineering of thermal processes* (4th ed.). John Wiley & Sons. https://doi.org/10.1002/9781118671603

Elagib, N. A., & Mansell, M. G. (2000). New approaches for estimating global solar radiation across Sudan. *Energy Conversion and Management, 41*(5), 419–434. https://doi.org/10.1016/S0196-8904(99)00123-5

El-Metwally, M. (2005). Sunshine and global solar radiation estimation at different sites in Egypt. *Journal of Atmospheric and Solar-Terrestrial Physics, 67*(14), 1331–1342. https://doi.org/10.1016/j.jastp.2005.04.004

Ersan, R., & Külcü, R. (2024). Development of new models using empirical modeling of global solar radiation and its application in Usak City, Turkey. *Tekirdağ Ziraat Fakültesi Dergisi, 21*(4).

Hargreaves, G. H., & Samani, Z. A. (1985). Reference crop evapotranspiration from temperature. *Applied Engineering in Agriculture, 1*(2), 96–99. https://doi.org/10.13031/2013.26773

Hooke, R., & Jeeves, T. A. (1961). "Direct Search" solution of numerical and statistical problems. *Journal of the ACM, 8*(2), 212–229. https://doi.org/10.1145/321062.321069

Kirkpatrick, S., Gelatt, C. D., & Vecchi, M. P. (1983). Optimization by simulated annealing. *Science, 220*(4598), 671–680. https://doi.org/10.1126/science.220.4598.671

Külcü, R. (2015). Isparta ili için yeryüzüne ulaşan güneş ışınımının modellenmesi. *Süleyman Demirel Üniversitesi Ziraat Fakültesi Dergisi, 10*(1), 19–26.

Külcü, R. (2019). Advanced solar radiation models using logarithmic functions. *Energy Science Journal, 15*(3), 203–210.

Nelder, J. A., & Mead, R. (1965). A simplex method for function minimization. *The Computer Journal, 7*(4), 308–313. https://doi.org/10.1093/comjnl/7.4.308

Prescott, J. A. (1940). Evaporation from a water surface in relation to solar radiation. *Transactions of the Royal Society of South Australia, 64*(1), 114–118.

Süslü, A., & Külcü, R. (2024). Global güneş ışınımı tahmin modelleri için ATATEK-Solar yazılımının geliştirilmesi. *Akademia Doğa ve İnsan Bilimleri Dergisi, 10*(1), 62–73.

Türkiye Enerji Bakanlığı. (2024). Güneş enerjisi. *T.C. Enerji ve Tabii Kaynaklar Bakanlığı*. Erişim 17 Kasım 2024, https://enerji.gov.tr/bilgi-merkezi-enerji-gunes