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Spatiotemporal Analysis of Surface Solar Radiation Variability Using ERA5-Land Data for Solar Energy System Applications in California

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Abstract:
Accurate solar radiation data are critical for optimizing solar energy systems and assessing renewable energy potential. While ground-based measurements offer high accuracy, their limited spatial and temporal coverage constrains their broader application. This study evaluates the performance of the ERA5-Land reanalysis dataset in estimating surface solar radiation by comparing it with high-resolution ground-based observations from the AmeriFlux network across six sites in California. Results indicate that ERA5-Land effectively captures both daily variability and long-term seasonal trends in solar radiation. Strong agreement between datasets is observed, with R^2 values ranging from 0.93 to 0.96 across all sites. These findings underscore the potential of ERA5-Land as a reliable and spatially comprehensive data source for solar energy modeling, particularly in regions with limited access to in-situ measurements.

Keywords: ERA5-Land, Remote Sensing, Solar Energy, Surface Solar Radiation.

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1. Introduction

Solar energy has emerged as a promising source of sustainable electricity generation, driven by the global transition toward renewable energy and increasing concerns over climate change (Niakan et al., 2020; Chen et al., 2023). As a clean, abundant, and renewable resource, solar energy offers significant advantages, including being a freely available source of energy (Lewis, 2007), and having no harmful impact on ecosystems, in contrast to the detrimental effects of fossil fuel exploitation (Schlamadinger et al., 1997). In addition, solar technologies such as photovoltaic systems and solar heaters have shown the highest growth among renewable energy sources due to their increasing efficiency and broad applicability in residential, industrial, and rural context (Kannan, 2016).
Solar irradiance, the measure of shortwave solar radiation reaching the Earth's surface (Iqbal, 2012), is a key parameter in assessing and forecasting solar energy potential. Accurate solar irradiance data are crucial for optimizing energy production (Wang, 2014), maintaining smart grid stability (Ghaderloo et al., 2023a), and improving storage management while reducing operational risks for solar energy systems (Ghaderloo et al., 2023b).
The most direct method to obtain solar irradiance is through ground-based measurements. When properly calibrated, in-situ data provide highly accurate and reliable information for local solar resource assessment (Yagli et al., 2020; Zambrano et al., 2020). However, high installation and maintenance cost, technical challenges,

limited historic records, and sparse spatial coverage restrict the widespread availability of ground stations (Salazar et al., 2020; Kim et al., 2020).

To address these limitations, researchers have turned to alternative methods, including machine learning (ML) approaches, which learn patterns from historical meteorological and irradiance data, enabling short-term and long-term predictions. For instance, Soleimani and Mohammadzadeh (2023) applied a range of next-generation ML algorithms for solar irradiance forecasting, finding that Random Forest outperformed other models and that optimization and feature selection notably improved the model performance. Similarly in other studies, researchers have employed different ML models and hybrid approaches to improve the accuracy of short-term solar irradiance forecasts using data from various regions and platforms, consistently demonstrating that ML-based models outperform traditional prediction techniques (Gala et al., 2016; Li et al., 2016; Sharma et al, 2018).

Another increasingly popular approach is the use of satellite remote sensing for estimating solar irradiance. Satellite-derived products offer consistent, large-scale coverage and fine temporal resolution, making them suitable for various environmental monitoring applications including soil moisture variations (Hosseini et al., 2023), as well as spatially explicit solar resource assessment (Yagli et al., 2020; Babar et al., 2020). However, the accuracy of these products must be validated against in-situ measurements (Gueymard, 2014), especially when applied to site-specific applications.

Building upon these developments, the main objective of this study is to conduct a spatiotemporal analysis of surface solar radiation variability using ERA5-Land data and validate its performance against high-quality ground-based observations. This approach aims to assess the reliability of satellite-derived solar irradiance estimates and explore their potential to overcome the spatial and temporal limitations of ground-based measurements, thereby supporting improved solar energy modeling and planning efforts.

2. Methodology

This study focuses on the state of California, covering a 10-year period from 2011 to 2021. The selection of California is motivated by its diverse climatic zones, significant solar energy potential, and availability of both satellite and ground-based solar radiation data.

2.1. Satellite-Based Solar Radiation Data

To estimate surface solar radiation, we used the ERA5-Land dataset, produced by the European Centre for Medium-Range Weather Forecasts (ECMWF). ERA5-Land is the land component of the fifth-generation European ReAnalysis (ERA5), providing hourly data from 1950 to near real-time. Specifically, we utilized the variable surface_solar_radiation_downwards, which represents the amount of shortwave solar radiation reaching the Earth's surface, accumulated over each day (Muñoz Sabater, 2019). The units of this variable are joules per square meter (J m^{-2}). ERA5-Land data were accessed and extracted using Google Earth Engine (GEE).

2.2. Ground-based observations:

To validate the satellite-derived estimates, ground-based solar radiation measurements were obtained from the AmeriFlux network (www.ameriflux.lbl.gov), which provides incoming shortwave radiation data with a half-hourly temporal resolution and units in watts per square meter (W m^{-2}). Due to data availability constraints, we filtered out stations without solar radiation data or with less than four years of records during the study period. As a result, six stations were selected: Bouldin Island Alfalfa (Bi1), Bouldin Island Corn (Bi2), Mayberry Wetland (MYB), Sherman Island Restored Wetland (SNE), Tonzi Ranch (TON), and Vaira Ranch-Ione (VAR).

2.3. Data analysis:

Since ground-based measurements are recorded in high temporal resolution, while ERA5-Land data represent temporal accumulation over time steps, preprocessing was required to ensure comparability. First, we aggregated the ground-based half-hourly observations to daily totals and converted the units from W m^{-2} to J m^{-2} by applying appropriate conversion factors. This harmonization allowed for direct comparison with the daily-accumulated ERA5-Land data.

For validation, we conducted a temporal analysis by comparing the time series of daily solar radiation values from both datasets across the 10-year period. Root Mean Square Error (RMSE) was calculated to assess the absolute differences between ERA5-Land estimates and ground-based observations. Additionally, Pearson correlation coefficients were computed to evaluate the degree of agreement between the two datasets in capturing temporal patterns of solar radiation. The results are visualized through time series plots and scatterplots, as shown in figures below.

3. Results and Discussion

Figure 1 presents the daily accumulated solar radiation derived from the ERA5-Land dataset and ground-based observations from the AmeriFlux network (reference dataset). Overall, both datasets show consistent seasonal trends, with higher solar radiation during the summer months and lower values during winter, reflecting the expected solar cycle and interannual variability.

To quantify the differences between the two datasets, the RMSE was calculated for each site. Among all sites, MYB showed the highest RMSE value of 5121196 J m^{-2}, Bi1 recorded the lowest RMSE at 3,852,077 J m^{-2}, indicating a closer alignment between ERA5-Land estimates and in-situ measurements.

This figure also highlights a key advantage of satellite datasets such as ERA5-Land, their continuous and extended temporal coverage compared to in-situ data. Despite filtering out stations with very short records, three sites namely Bi1, Bi2, and SNE still show relatively limited temporal coverage in the AmeriFlux dataset. This underscores the utility of satellite-based products in ensuring long-term data availability, especially in regions with sparse observational networks such as California.

On average, the discrepancies between the two datasets are not substantial, suggesting that ERA5-Land provides a reliable estimate of daily solar radiation trends across California. However, site-specific variability remains evident, likely influenced by local land cover characteristics, microclimatic conditions, and spatial resolution differences between the gridded reanalysis data and point-based ground observations.

Figure 2 further validates the ERA5-Land dataset by comparing the correlation between satellite-derived solar radiation and AmeriFlux measurements. The results show a strong linear relationship between the two datasets across all six sites, with R^2 values ranging from 0.93 to 0.96. This high level of correlation underscores the consistency and reliability of ERA5-Land in capturing daily solar radiation dynamics, reinforcing its potential for use in data-sparse regions and solar energy modeling applications.

Figure 3 presents the average monthly of daily accumulated solar radiation between ERA5-Land and AmeriFlux observations across different sites. This comparison reveals strong seasonal patterns and close agreement between the two datasets. As expected, solar radiation increases from January, peaks during summer months (May–July), and declines toward December, reflecting the annual solar cycle. Across all sites, ERA5-Land closely tracks the observed AmeriFlux values, with slight overestimations during winter months and some underestimations during peak summer months, particularly at the MYB site. The average differences remain relatively small, indicating the ability of ERA5-Land to reliably capture the seasonal variability of solar radiation.

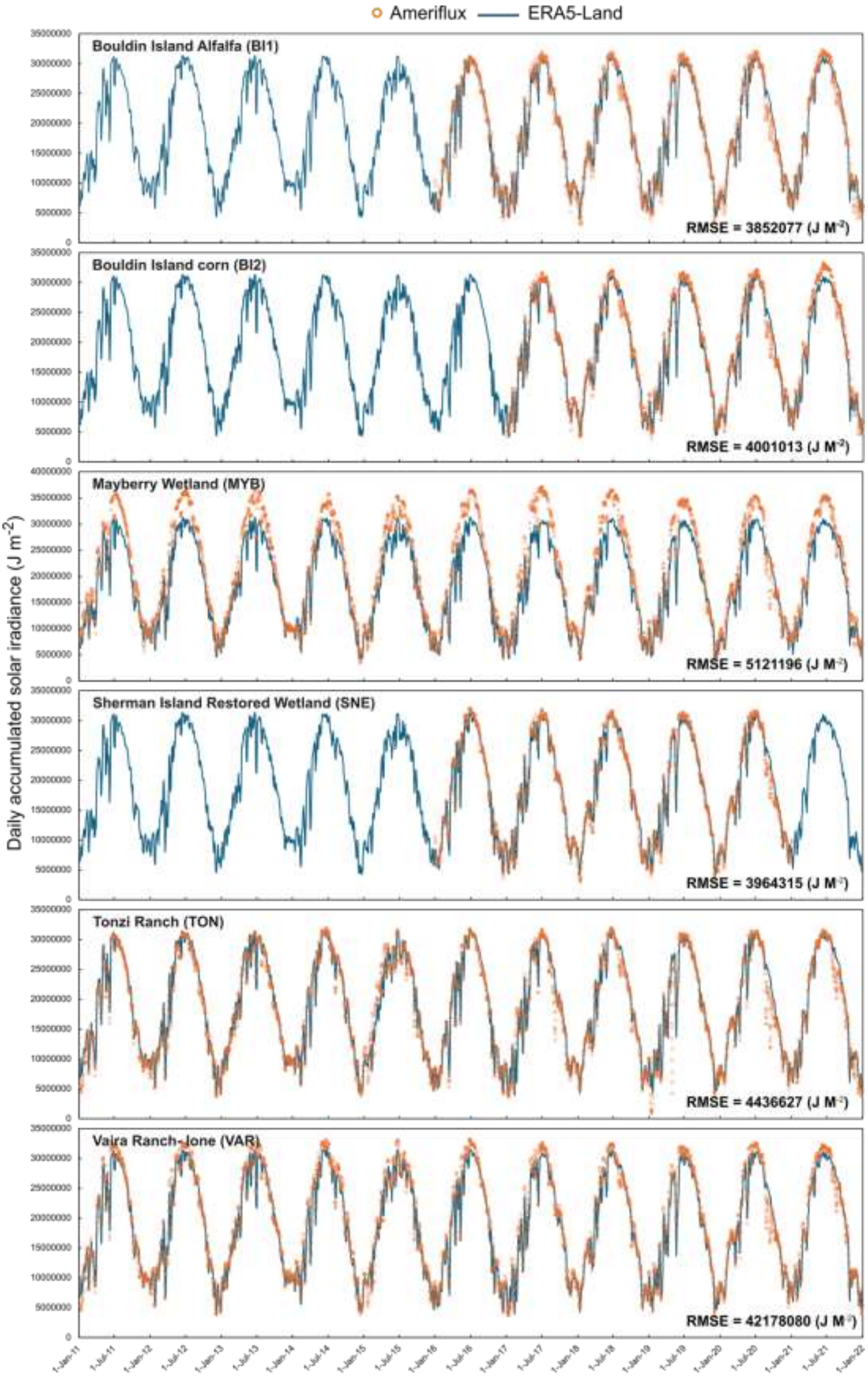

Figure 1. Temporal variation of daily accumulated solar radiance estimated by ERA5-Land dataset and measured by Ameriflux (reference) for various sites, from 2011 to 2021 over the state of California.

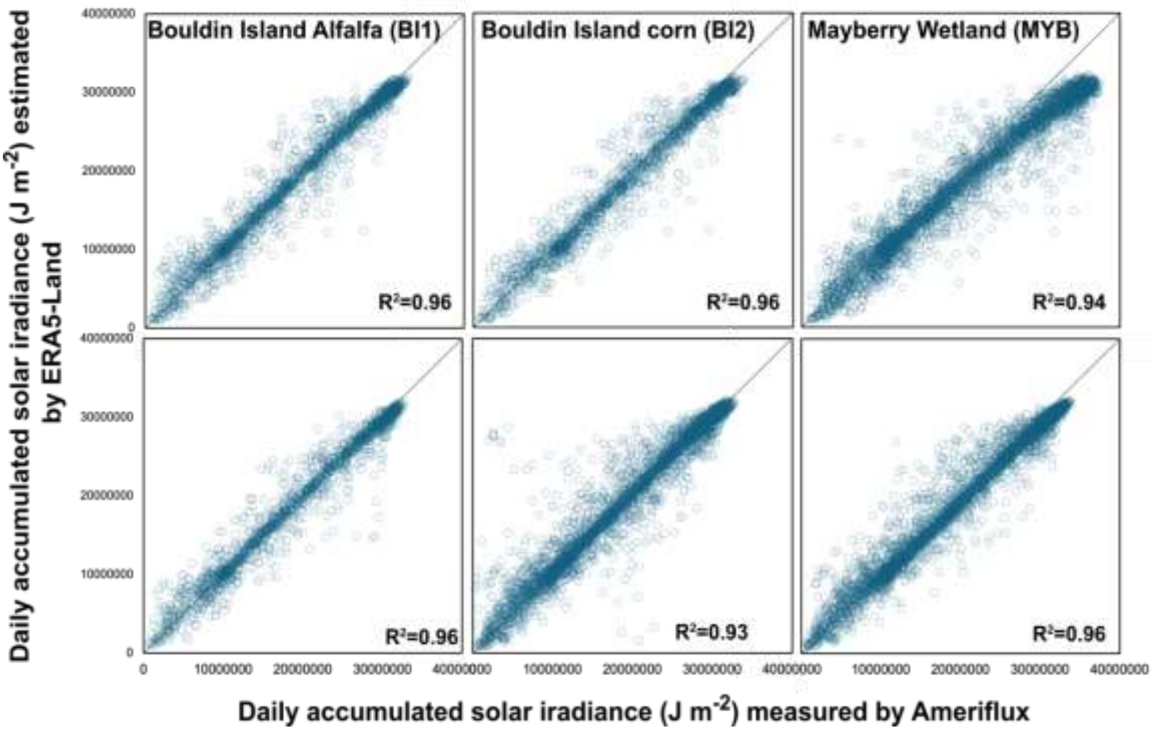

Figure 2. Daily accumulated solar radiance estimated by ERA5-Land dataset compared to solar radiance measured by Ameriflux (reference) for various sites, from 2011 to 2021 over the state of California.

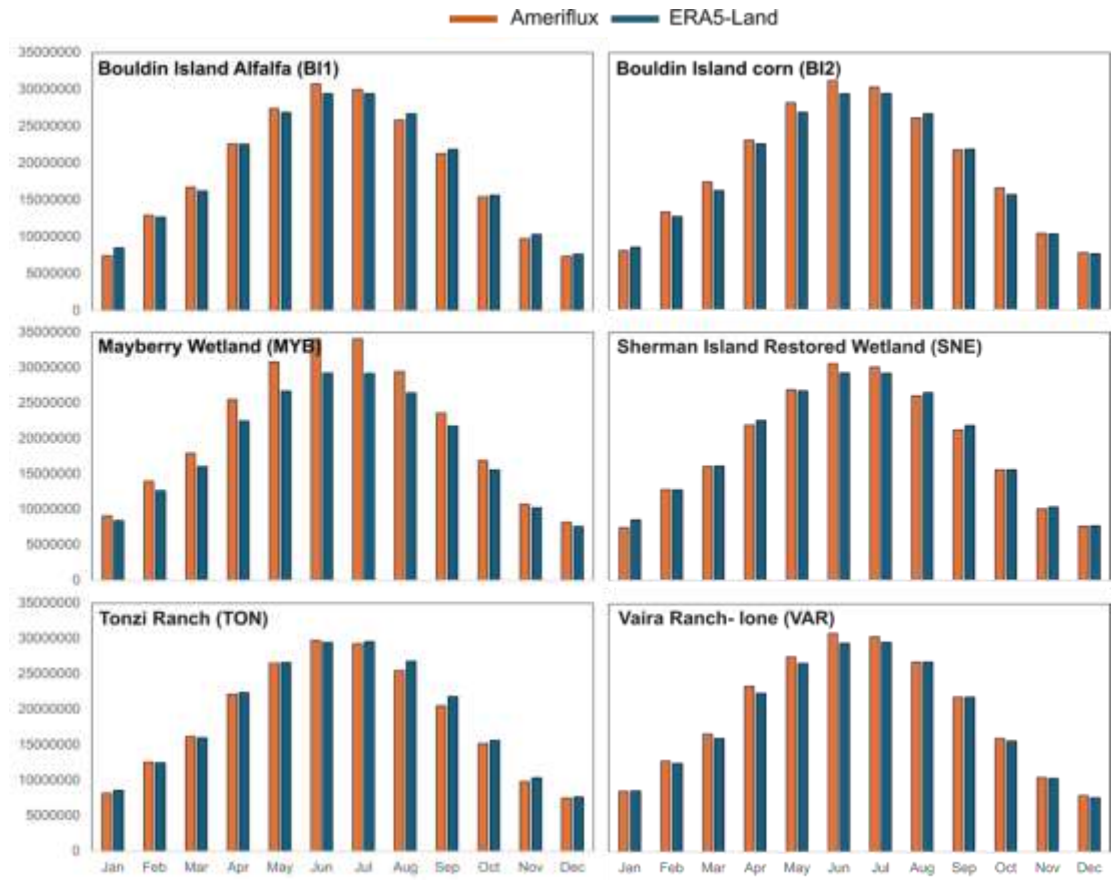

Figure 3. Average monthly of daily accumulated solar radiance estimated by ERA5-Land dataset and measured by Ameriflux (reference) for various sites, from 2011 to 2021 over the state of California.

4. Conclusion

This study assessed the reliability of the ERA5-Land reanalysis dataset for estimating daily surface solar radiation across diverse California landscapes by comparing it with ground-based measurements from six AmeriFlux sites. The findings demonstrate that ERA5-Land effectively captures the temporal dynamics and seasonal variability of solar radiation, closely aligning with in-situ observations. RMSE values indicated generally low discrepancies, and strong linear correlations across sites further validated ERA5-Land's performance.

Importantly, the study highlights the added value of ERA5-Land in providing continuous, long-term coverage, addressing key limitations of ground-based networks, such as short observational records and sparse spatial distribution. Despite some site-specific biases, particularly during peak radiation periods, ERA5-Land proves to be a robust alternative for solar irradiance monitoring. Its reliability and spatial coverage make it a valuable tool for solar energy assessment, forecasting, and planning, particularly in data-limited environments.

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