remote sensing

Editorial

Editorial on New Challenges in Solar Radiation, Modeling and Remote Sensing

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1. Introduction

Accurate estimations or measurements of solar radiation are frequently required in many activities and studies in areas such as climatology, atmospheric physics and chemistry, energy and environment, ecosystems, and human health. In particular, the need to reduce the global carbon footprint and the associated increase in the penetration of renewables have increased the use of quality solar radiation data in a prominent way. Consequently, significant and continuous efforts at improving the retrieving and forecasting models for solar irradiance and for PV power as well can be inferred from the extensive number of papers and works now found in the literature. Good examples of this knowledge and the increase in contributions presenting solar radiation data for solar energy applications are described and compiled in the documents recently compiled in Task 16 of the IEA PVPS (the Photovoltaic Power Systems Program of the International Energy Agency) [1]. In parallel, remote sensing applications and capabilities are also growing quickly. New or updated satellite products, on-board instruments and retrieval techniques have emerged in the last few years. Moreover, the use of machine and deep learning methodologies with remote sensing data has been recently imposed, playing a major role in both understanding observations and generating new useful data [2].

The current Special Issue, named "New Challenges in Solar Radiation, Modeling and Remote Sensing" has gathered together some new developments and studies for modeling and forecasting solar radiation with better accuracy and reliability. Nowadays, the recent information and capabilities of remote sensing are combined with current and powerful algorithms (machine learning mostly) to improve the solar radiation databases and applications in many research areas. We, as Guest Editors, have taken the opportunity to receive, read and manage some novel and interesting contributions to this wide topic that are briefly summarized in the next section of this Editorial.

2. Contributions to this Special Issue

Modeling the solar irradiance components under cloudless conditions is an important function of satellite-based models for deriving surface solar irradiance [3]. The capabilities of the new version of the BRASIL-SR model for clear-sky modeling were analyzed by Casagrande et al. for several Brazilian sites, where large biomass fire activity can be expected [4]. Aerosol loading due to biomass burning effects can result in aerosol optical depth (AOD) values as high as 5.0, which are challenging conditions for clear-sky models. The performance of the new BRASIL-SR model presents low uncertainty using local aerosol information, and the model was comparable to McClear and REST when MERRA-2 reanalysis data were used as AOD inputs.

High aerosol loading due to forest fires and biomass burning contributes significantly to the attenuation of solar irradiance (mainly direct solar irradiance, but also global solar

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irradiance). In particular, India suffers from massive forest fires every year. In the work presented by Dumka et al., MODIS satellite imagery was used for detecting forest fires in the central Indian Himalayan region and radiative transfer modeling was used to evaluate the impact of the associated AOD increase on solar power production [5]. They found that smoke was the largest pure aerosol source followed by dust, which came from the northwest, and they concluded that the potential effect of forest fires has to be taken into account for energy management and planning at the country level.

Jan et al. presented a new model that used 16 channels of the Korean Geo-kompsat 2 Advanced Meteorological Imager (Gk2A/AMI) to train a machine learning model to make real-time estimations of surface solar irradiance in Korea [6]. A convolutional neural network (CNN) was the algorithm used for this purpose. The authors remarked that the accuracy of using a CNN model with satellite data is higher than that when using the GK2A/AMI operational solar irradiance product.

Machine learning algorithms are being frequently used nowadays in meteorological forecasting schemes and wider applications, and many new proposals are being presented in the literature. López-Cuesta et al. studied the blending of all-sky imager data and MSG SEVIRI imagery with machine learning algorithms for nowcasting solar irradiance using a forecasting horizon of 90 min at the 1 min timestamp [7]. In recent years, most of the methodologies proposed for nowcasting solar irradiance have been based on the use of all-sky cameras [8]. Satellite-based forecasting models have been traditionally used for forecasting horizons that are larger, but they can also be used for one- or two-hour nowcasting since the imagery dissemination is 15 min nowadays. This work shows that machine learning algorithms such as random forest can enhance the performance of forecasting model blending. In this paper, seven forecasting models were used for a site in southwestern Spain that were data-driven (persistence) and satellite-based with different visible channels and total-sky imagery models.

The short-term forecasting of global irradiance with machine learning algorithms applied to total-sky imagery data was also presented in the work of Wu et al. for the Tibet region [9]. In this work, the authors used random forest and long short-term memory (LSTM) machine learning algorithms; both showed a good performance for a forecasting horizon of 1 h, but they cannot work properly for forecasting horizons longer than 4 h since the cloud cover (input into the model) loses correlation with global irradiance changes.

Day-ahead solar radiation forecasting was illustrated in the work presented by Park et al., where the authors combined sequence-domain forecasting using exogenous data and frequency-domain forecasting using solar radiation [10]. Different machine learning algorithms were used in each stage: LightGBM in the sequence stage and multilayer perceptron in the frequency stage. This hybrid approach was tested in South Korea, leading to much better results than the popular forecasting models based on the direct use of machine learning algorithms.

The use of remote sensing data for integrating the terrain topology effect in solar radiation data is another important activity that can help improve the accuracy and applications of solar radiation spatially distributed data. In this Special Issue, Zhang et al. used geostationary satellites (Himawari-8), along with the high temporal resolution and high spatial resolution of polar-orbiting satellites, to determine the daily average solar radiation with a high spatial resolution [11]. Another example is the use of the weather prediction and radiation flux model LDAPS-SOLWEIG to estimate information regarding usually shaded areas, sky-view factor and downward shortwave radiative flux in roads and lanes that also incorporates local topography [12]. This application was tested in South Korea and may be very useful in the management of roads vulnerable to winter freezing. In addition, to better determine the solar irradiation of rooftops in urban areas for solar cadaster applications, the study of Polo et al. presented the sensitivity of the solar potential of rooftops to the methodology for computing the digital surface model (DSM) [13]. LiDAR data and Google Earth imagery were used as different inputs for the DSM computation.

Additionally, the impact of the uncertainty in building heights and footprints was evaluated and compared to experimental data to estimate the solar radiation of a building rooftop.

Finally, as an example of applications of solar radiation derived from remote sensing techniques related to health, Lee et al. presented a novel and interesting study on determining the perceived temperature of road workers on a highway during summer [14]. Sky-view imagery and additional meteorological variables were used to model the mean radiant temperature applied to the workers according to the road material. The results of this study can be very useful in preventing heat stress for road workers through the proper classification of healthcare, work clothes and the workers themselves.

3. Summary and Future Directions

The applications and methods for developing more accurate knowledge around solar radiation as a renewable energy source are gaining interest due to the implications associated with carbon and fossil fuel reduction needs. Remote sensing methods and data are very powerful at both determining the spatial distribution of solar radiation and forecasting solar irradiance. On the other hand, the new models combining remote sensing data and machine learning algorithms are very promising in regard to retrieving and understanding complex meteorological information. This Special Issue presents 10 papers proposing and describing new ideas and studies in this context. Nevertheless, the topic is so large that a second edition will be issued in the next several months. The Guest Editors have the honor to witness the evolution of this topic through the papers submitted to this Special Issue.

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References

1. Sengupta, M.; Habte, A.; Wilbert, S.; Gueymard, C.; Remund, J. *Best Practices Handbook for the Collection and Use of Solar Resource Data for Solar Energy Applications: Third Edition*; Report IEA-PVPS 16-04:2021; International Energy Agency: Paris, France, 2021. Available online: https://iea-pvps.org/key-topics/best-practices-handbook-for-the-collection-and-use-of-solar-resource-data-for-solar-energy-applications-third-edition/ (accessed on 15 May 2023).
2. Aleissaee, A.A.; Kumar, A.; Anwer, R.M.; Khan, S.; Cholakkal, H.; Xia, G.-S.; Khan, F.S. Transformers in Remote Sensing: A Survey. *Remote Sens.* **2023**, *15*, 1860. [CrossRef]
3. Antonanzas-Torres, F.; Urraca, R.; Polo, J.; Perpiñán-Lamigueiro, O.; Escobar, R. Clear Sky Solar Irradiance Models: A Review of Seventy Models. *Renew. Sustain. Energy Rev.* **2019**, *107*, 374–387. [CrossRef]
4. Casagrande, M.S.G.; Martins, F.R.; Rosário, N.E.; Lima, F.J.L.; Gonçalves, A.R.; Costa, R.S.; Zarzur, M.; Pes, M.P.; Pereira, E.B. Numerical Assessment of Downward Incoming Solar Irradiance in Smoke Influenced Regions—A Case Study in Brazilian Amazon and Cerrado. *Remote Sens.* **2021**, *13*, 4527. [CrossRef]
5. Dumka, U.C.; Kosmopoulos, P.G.; Patel, P.N.; Sheoran, R. Can Forest Fires Be an Important Factor in the Reduction in Solar Power Production in India? *Remote Sens.* **2022**, *14*, 549. [CrossRef]
6. Jang, J.-C.; Sohn, E.-H.; Park, K.-H. Estimating Hourly Surface Solar Irradiance from GK2A/AMI Data Using Machine Learning Approach around Korea. *Remote Sens.* **2022**, *14*, 1840. [CrossRef]
7. López-Cuesta, M.; Aler-Mur, R.; Galván-León, I.M.; Rodríguez-Benítez, F.J.; Pozo-Vázquez, A.D. Improving Solar Radiation Nowcasts by Blending Data-Driven, Satellite-Images-Based and All-Sky-Imagers-Based Models Using Machine Learning Techniques. *Remote Sens.* **2023**, *15*, 2328. [CrossRef]
8. Yang, D.; Wang, W.; Gueymard, C.A.; Hong, T.; Kleissl, J.; Huang, J.; Perez, M.J.; Perez, R.; Bright, J.M.; Xia, X.; et al. A Review of Solar Forecasting, Its Dependence on Atmospheric Sciences and Implications for Grid Integration: Towards Carbon Neutrality. *Renew. Sustain. Energy Rev.* **2022**, *161*, 112348. [CrossRef]
9. Wu, L.; Chen, T.; Ciren, N.; Wang, D.; Meng, H.; Li, M.; Zhao, W.; Luo, J.; Hu, X.; Jia, S.; et al. Development of a Machine Learning Forecast Model for Global Horizontal Irradiation Adapted to Tibet Based on Visible All-Sky Imaging. *Remote Sens.* **2023**, *15*, 2340. [CrossRef]
10. Park, J.; Park, S.; Shim, J.; Hwang, E. Domain Hybrid Day-Ahead Solar Radiation Forecasting Scheme. *Remote Sens.* **2023**, *15*, 1622. [CrossRef]

11. Zhang, Y.; Chen, L. Estimation of Daily Average Shortwave Solar Radiation under Clear-Sky Conditions by the Spatial Downscaling and Temporal Extrapolation of Satellite Products in Mountainous Areas. *Remote Sens.* **2022**, *14*, 2710. [CrossRef]
12. Kwon, H.-G.; Yang, H.; Yi, C. Study on Radiative Flux of Road Resolution during Winter Based on Local Weather and Topography. *Remote Sens.* **2022**, *14*, 6379. [CrossRef]
13. Polo, J.; García, R.J. Solar Potential Uncertainty in Building Rooftops as a Function of Digital Surface Model Accuracy. *Remote Sens.* **2023**, *15*, 567. [CrossRef]
14. Lee, H.; Kwon, H.-G.; Ahn, S.; Yang, H.; Yi, C. Estimation of Perceived Temperature of Road Workers Using Radiation and Meteorological Observation Data. *Remote Sens.* **2023**, *15*, 1065. [CrossRef]