Retrieval of Surface Solar Radiation from Himawari-8 measurements

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ABSTRACT: Surface solar radiation (SSR) is essential for calculating surface radiation budget and is a key parameter for climate change research. Accurate cloud optical properties are the important input parameters for calculating SSR for cloudy sky. In this study, a look-up table (LUT) method is developed to retrieve cloud optical properties (cloud phase, cloud optical thickness, cloud effective radius) from the Advanced Himawari Imager (AHI) instrument onboard the Himawari-8, a new generation geostationary meteorological satellite. Then, SSR is estimated from cloud optical properties and other auxiliary data (aerosol optical thickness, surface albedo, precipitable water vapor) by LUT method. Furthermore, to accelerate the calculation speed without loss accuracy, deep neural network (DNN) method is used to estimate SSR by learning input parameters (aerosol, cloud optical properties and other auxiliary data) and SSR simulated by RSTAR radiative transfer model. The estimated SSR for 2016 is validated at 122 radiation stations from several radiation networks located in the full disk regions of Himawari-8 data, with an RMSE of 112.14 Wm^{-2} for instantaneous SSR, 96.91 Wm^{-2} for hourly SSR, 29.30 Wm^{-2} for daily SSR, as well as an MBE of about 10 Wm^{-2}. Compared with the SSR estimated from conventional geostationary satellites, the accuracy of the SSR proposed by this study is significantly improved.

1. Introduction

Surface shortwave radiation (SSR), which is commonly referred to as the amount of shortwave (0.3-3.0μm) regions of solar energy relative to a horizontal surface, is the prime determinant of energy exchange between land, ocean and atmosphere (Houborg et al. 2007; Wild 2009). SSR is required by land surface models, hydrological models and ecological models in simulating land-atmosphere interactions. Accurate observation and estimation of SSR is essential for climate change research and forecasting.

Thus far, both polar-orbiting and geostationary satellite data can be used to estimate SSR over a wide range of regions. Polar-orbiting satellites such as Terra/MODIS, Aqua/MODIS, and NPP/VIIRS can provide both high spatial and spectral resolution measurements of targets (Platnick et al. 2015; Platnick et al. 2017), and can produce SSR estimates with high spatial resolution, but they cannot provide the diurnal variation of the SSR due to their low temporal resolution. In recent years, new-generation geostationary satellites, such as Himawari-8, GOES-R and FY-4, which have greatly improved in spatial, spectral and temporal resolutions, have provided new opportunities to access the SSR. Moreover, the amount of data generated by the new-generation geostationary satellites, such as Himawari-8, is large; consequently, a fast algorithm is required to process the data. For these large data, the numerous methods developed to estimate SSR from satellite data can be divided into three categories: empirical, physical and hybrid. To provide SSR estimates with both high accuracy and high speed, the hybrid methods have appeared. Takenaka et al. (2011) developed a novel method that used an artificial neural network (ANN) to approximate the radiative transfer model to estimate SSR using inputs of retrieved cloud properties from the geostationary satellite MTSAT. However, this algorithm lacked consideration of the aerosol influences on SSR, and the spatial and spectral resolution limitations of the MTSAT sensors made it difficult to obtain high-accuracy SSR estimates, especially in heavy aerosol regions.

As mentioned above, hybrid methods are a good way to form a balance between accuracy and calculation speed during SSR estimation, especially for geostationary satellites, which produce data at high frequency. In this study, a hybrid method (DNN-based) was developed to estimate solar radiation from Himawari-8 data with both high accuracy and at high speed by training a deep network using the output data of the RSTAR RTM (Nakajima and Tanaka 1986, 1988; Sekiguchi and Nakajima 2008), which is a general package for simulating radiation fields in the atmosphere-land-ocean system. This method includes two steps. The first step is to train the DNN models (clear sky and cloudy sky) by simulating SSR with RSTAR under many different solar, atmosphere and surface conditions. The second step is to estimate SSR using the trained DNN models based on input from Himawari-8 L2 atmospheric (aerosol and cloud) products and other auxiliary data (i.e., MODIS surface albedo and ERA 5 water vapor data).

2. Data and Methods

2.1. Data

Two types of data are used to estimate SSR. The first type is Himawari-8 data, including the L1 product and L2 aerosol product (AOT). L1 data were used to retrieve cloud properties including cloud phase, cloud optical thickness (COT) and cloud effective radius (CER) (Letu et al. 2016; Letu et al. 2019; Letu et al. 2020). The other type is auxiliary data, including the MODIS surface albedo product and ERA5 reanalysis data. The MCD43C3 (V006) surface albedo product derived from the combination of Terra and Aqua was used in this study. The MCD43C3 surface albedo product has a spatial resolution of 5 km and a 16-day periodic temporal resolution. To simplify the input of the solar radiation estimation from space, the monthly mean surface albedo is calculated based on the MCD43C3 16-day data.

To validate the estimated solar radiation from the Himawari-8 satellite, a total of 118 in-situ radiation stations from 4 networks located in Himawari-8 full-disk regions were used: 9 sites from the Australian Governments Bureau of Meteorology (BOM), 4 sites from the Baseline Surface Radiation Network (BSRN), 16 sites from the Global Moored Buoy Array (GTMBA) and 89 sites from the China Meteorological Administration (CMA). The BSRN, which was initiated by the World Climate Research Programme, aims to provide validation data with high accuracy at 1-min intervals. The measurement errors were about 5 Wm-2 for global solar radiation. The quality of BOM should be comparable with BSRN, because some of BOM sites are also part of BSRN. The quality of CMA may include erroneous and questionable values. Therefore, quality control tests were performed by a quality-assured scheme (Peng et al. 2020; Tang et al. 2010). As for GTMBA, data quality control is officially performed through a series of procedures on a daily and weekly basis (Yu et al. 2019). These stations, except for the CMA, provide high frequency SSR measurements of between 1-3 min, while the CMA provides hourly mean SSR measurements. Fig. 1 shows the spatial distribution of these 118 radiation stations. These sites from different networks located in the full-disk regions of Himawari-8 are representative for SSR validation. All the in-situ data with high quality were used in the study when there were quality flags in the files. Non-quality flagged data were checked manually, and low-quality data were omitted.

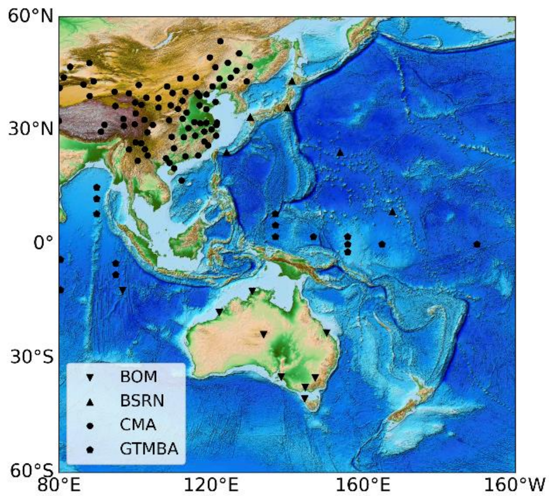

Fig. 1. Spatial distribution of radiation stations from 4 networks (BOM, BSRN, CMA, GTMBA) used to validate the performance of the estimated SSR. Different symbols represent different networks.

2.2. Solar radiation estimation algorithm

Fig. 2 shows the flowchart of solar radiation estimation with the Himawari-8 atmospheric products. First, DNN models for clear sky, cloudy sky (water and ice cloud) were generated by training using the output data of the atmospheric transfer model (RSTAR). During the training process, some methods were used to improve the performance of the DNN, such as the preprocessing by the z-score method and the new scaled exponential linear unit (SELU) activation function [42]. Second, solar radiation for clear and cloudy sky conditions were estimated by inputting the Himawari-8 L1 and L2 atmospheric products (aerosol and cloud products) along with other auxiliary data, such as the MODIS surface albedo and ERA5 PWV data. Third, validation of the estimated SSR was performed using data from a total of 118 in-situ radiation stations from 4 networks.

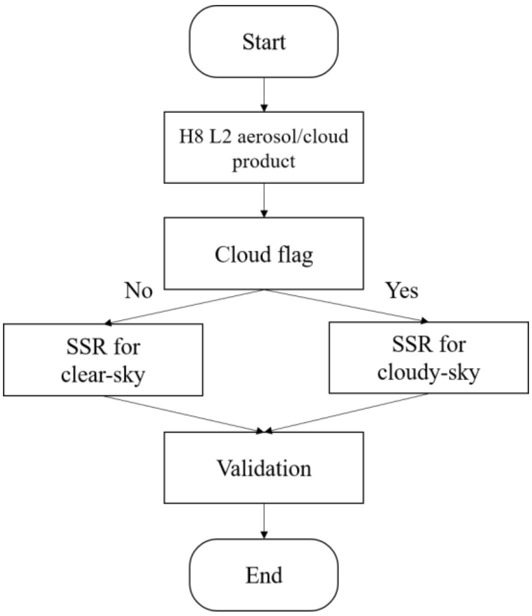

Fig. 2. Flowchart of solar radiation estimation using the Himawari-8 (H8) atmospheric products.

In this study, a five-layer neural network is proposed to estimate solar radiation from Himawari-8 satellite data. The structure of the neural network is shown in Fig. 3. The input layer of DNN accepts seven input parameters: solar zenith angle (SZA), aerosol optical thickness (AOT), precipitable water vapor (PWV), cloud phase (CP), cloud optical thickness (COT), cloud effective radius (CER), and surface albedo (Ag). There are three hidden layers that contain 256, 128 and 64 neurons, respectively. The output layer outputs 12 parameters: shortwave radiation (SW), photosynthetically active radiation (PAR), UVA, and UVB, direct and diffuse components at the surface, and the upward radiation at the TOA. To make the DNN more robust, several optimization methods were used, like normalize input data, using more flexible activation function, and optimizer. Detailed descriptions please refer to the reference (Ma et al. 2020).

3. Results

Fig. 3 shows the comparison results of the instantaneous SSR derived from Himawari-8 and ground measurements from a total of 29 stations from 3 networks (BOM, BSRN, and GTMBA) for 2016. The CMA stations, which do not provide instantaneous SSR measurements, are not shown. Overall, the SSR derived from Himawari-8 agrees well with the 29 ground measurements; the MBE, RMSE and R^2 are 8.1 Wm^{-2}, 125.9 Wm^{-2} and 0.84, respectively. The N in Fig. 8 indicates the number of samples used to evaluate the performance of the estimated SSR. For all 3 networks, the estimated SSR is slightly overestimated compared with the ground measurements, with MBEs ranging from 6.6 to 11.0 Wm^{-2}. The RMSEs for these 3 networks range from 117.4 to 133.0 Wm^{-2}, and the R^2 values for these 3 networks range from 0.83 to 0.85.

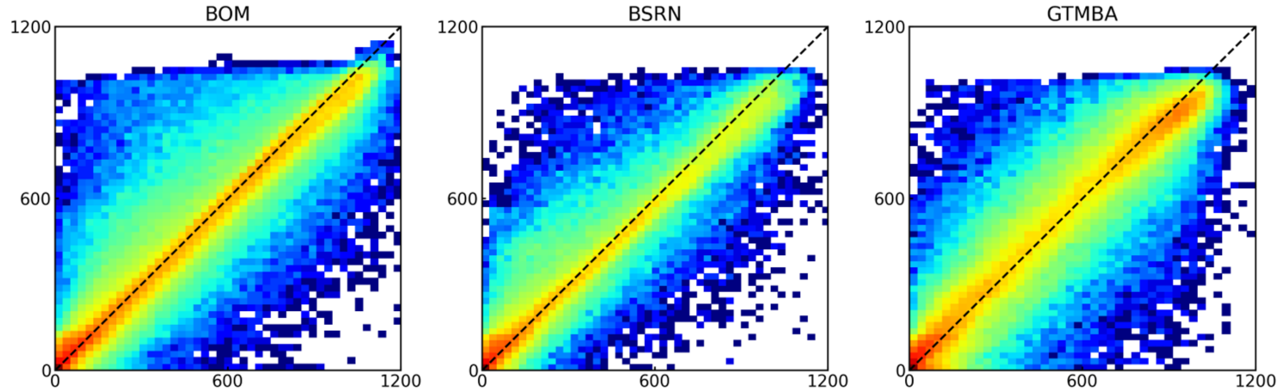

Fig. 3. Comparisons of estimated instantaneous SSR from 3 networks for 2016.

Fig. 4 shows the hourly SSR validation results at a total of 118 stations from 4 networks. In theory, Himawari-8 captures 6 images each hour because its temporal resolution is 10 min. Here, the estimated SSR data greater than or equal to 5 are used to calculate the hourly SSR. The estimated hourly SSR has an overall positive MBE value of 27.6 Wm^{-2}, an RMSE of 105.4 Wm^{-2} and an R^2 of 0.87. The MBEs for each network range from 7.3 to 28.6 Wm^{-2}, the RMSEs vary from 79.2 to 106.4 Wm^{-2}, and the R^2 values range from 0.87 to 0.92. Note that the hourly RMSE and R^2 values are improved for the hourly validation scale compared to the instantaneous results.

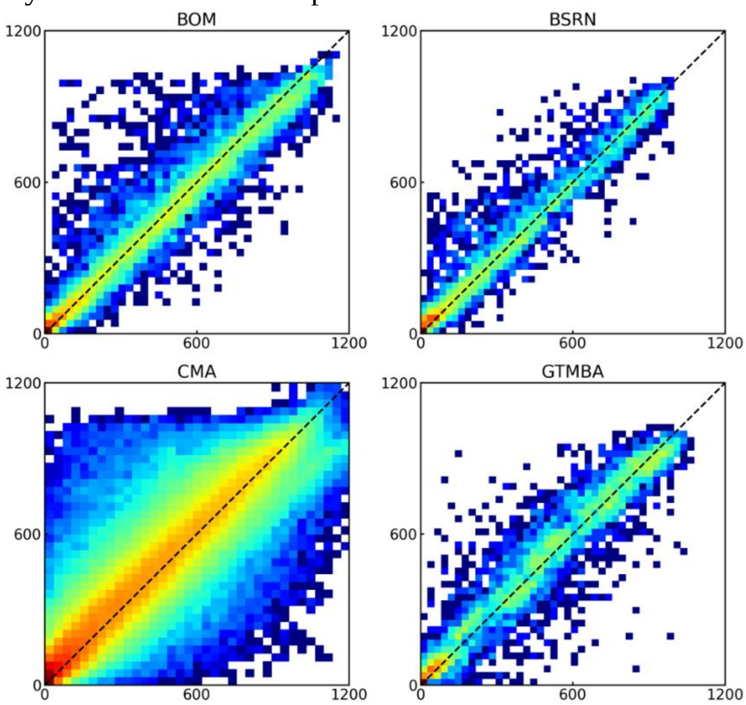

Fig. 4. Comparisons of estimated hourly SSR for 4 networks in 2016.

Fig. 5 presents the validation results of estimated daily SSR against ground SSR measurements.

The estimated daily SSR has an overall positive MBE value of 12.3 Wm^{-2}, an RMSE of 31.9 Wm^{-2} and an R^2 of 0.89. The MBEs for each network range from 1.4 to 15.1 Wm^{-2}, the RMSEs vary from 23.8 to 33.3 Wm-2, and the R^2 values range from 0.89 to 0.92. The daily RMSE of 33.3 Wm^{-2} estimated by this study at the CMA stations is comparable to the results of Tang et al. (2016), who combined geostationary satellite measurements from MTSAT and MODIS atmospheric products to estimate SSR at CMA stations over China with an RMSE of 34.2 Wm^{-2}.

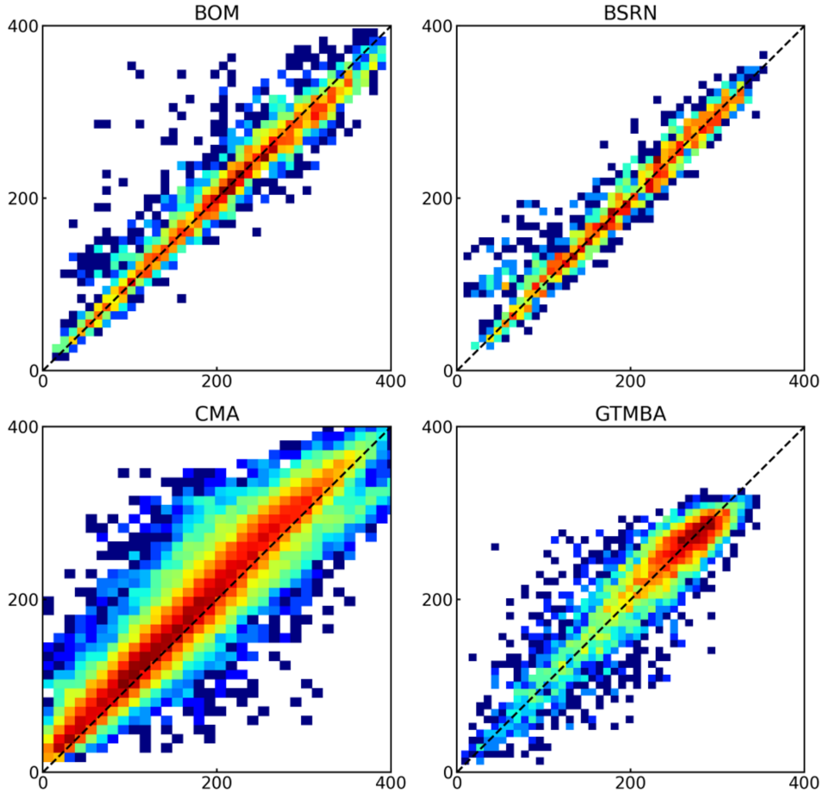

Fig. 5. Comparisons of estimated daily SSR with 4 networks for 2016.

4. Conclusion

This study developed a hybrid method (DNN-based) to estimate solar radiation from Himawari-8 L2 atmospheric products. The DNN models used in this study are trained by the output of a radiative transfer model (RSTAR); thus, the DNN traces back to the radiative transfer calculation. The estimated SSR were validated using 4 networks in the full-disk regions of Himawari-8 and obtained an RMSE of 125.9 Wm^{-2} for instantaneous SSR, 105.4 Wm^{-2} for hourly SSR, 31.9 Wm^{-2} for daily SSR, and MBE scores of 8.1, 27.6 and 12.3 Wm^{-2}, respectively. Compared with the traditional lookup table (LUT) method for estimating solar radiation, the DNN-based method developed in this study for estimating solar radiation from Himawari-8 L2 atmospheric products not only provides SSR results with high accuracy but also performs at high speed, making it suitable for use in near-real time solar radiation estimation applications. However, some aspects of this study could be improved in future works. First, this study used 1D RTM for the SSR estimation and neglected 3D cloud effects. Second, more complicated aerosol microphysical and optical properties (single-scattering albedo, asymmetry factor) could be replaced by instantaneous data rather than fixed values. Last, surface elevation changes (0 m is assumed) are not considered in the current algorithm because that would increase the size of the training data by several fold, which would make the DNN models hard to train. In our future work, we will not only consider the altitude, but also other parameters like ozone amount, single scattering albedo and asymmetry factor of aerosol, etc., to get a better DNN models to approximate radiative transfer calculation.

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