Surface Solar Radiation Compositions Observed from *Himawari-8/9* and Fengyun-4 Series

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**ABSTRACT:** Surface downward solar radiation compositions (SSRC), including photosynthetically active radiation (PAR), ultraviolet-A (UVA), ultraviolet-B (UVB), and shortwave radiation (SWR), with high spatial–temporal resolutions and precision are essential for applications including solar power, vegetation photosynthesis, and environmental health. In this study, an optimal algorithm was developed to calculate SSRC, including their direct and diffuse components. Key features of the algorithm include combining the radiative transfer model with machine learning techniques, including full consideration of the effects of aerosol types, cloud phases, and gas components. A near-real-time monitoring system was developed based on this algorithm, with SSRC products generated from *Himawari-8/9* and Fengyun-4 series data. Validation with ground-based data shows that the accuracy of the SWR and PAR compositions (daily mean RMSEs of 19.7 and 9.2 W m\(^{-2}\), respectively) are significantly better than those of state-of-the-art products from CERES, ERA5, and GLASS. The accuracy of UVA and UVB measurements is comparable with CERES. Characteristics of aerosols, clouds, gases, and their impacts on SSRC are investigated before, during, and post COVID-19; in particular, significant SSRC variations due to the reduction of aerosols and increase of ozone are identified in the Chinese central and eastern areas during that period. The spatial–temporal resolution of data products [up to \(0.05^\circ \) (10 min)\(^{-1}\) for the full-disk region] is one of the most important advantages. Data for the East Asia–Pacific region during 2016–20 is available from the CARE home page (www.slrss.cn/care/sp/pc/).

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Surface downward solar radiation (SSR) is an essential driving force that significantly influences energy exchange between Earth’s surface and atmosphere (Houborg et al. 2007; Wild 2009; Zhang et al. 2018; Liang et al. 2021; Wang et al. 2023). SSR can be divided into four compositions (SSRC) by wavelength that relate to different applications: shortwave radiation (SWR; 0.3–3.0 μm), which quantifies the overall solar energy resources (Gitelson et al. 2021), photosynthetically active radiation (PAR; 0.4–0.7 μm), corresponding to the energy used for photosynthesis and plant growth, and ultraviolet-A (UVA; 0.315–0.4 μm) and ultraviolet-B (UVB; 0.28–0.315 μm), which are associated with aging, sunburn, and even skin cancer (Dale et al. 2012). Discriminating between direct and diffuse components of SSRC is an important element for modeling canopy photosynthesis and the ecosystem’s carbon cycle (Wilton et al. 2011), as well as for solar energy applications and climate change studies (Takenaka et al. 2011; Zhang et al. 2016; Ma et al. 2020; Letu et al. 2020).

In situ measurements provide the most reliable SSR data with high precision; however, such measurement sites are sparsely distributed in most regions of the world, and not all of these sites can measure all four SSRC, especially PAR, UVA, and UVB (Rutan et al. 2015). In contrast, numerical modeling and satellite remote sensing approaches can be used to determine spatiotemporally continuous SSR values at both regional and global scales. The commonly used SSR data from numerical modeling, e.g., the European Centre for Medium-Range Weather Forecasts (ECMWF) next-generation reanalysis (ERA5) (Hersbach et al. 2020), have spatial and temporal resolutions (STR) of 0.25° and 1 h, respectively; however, their accuracy limits them to certain applications (Hersbach et al. 2020). There are also several state-of-the-art global satellite data-based SSR products, including the Clouds and the Earth’s Radiant Energy System (CERES) (Kato et al. 2013), the International Satellite Cloud Climatology Project flux dataset (ISCCP-FD) (Zhang et al. 2004), and the
Global Land Surface Satellite (GLASS) products (Zhang et al. 2014; Liang et al. 2021). All of the above products provide global data that can be used for surface radiation budget research; however, the spatial resolutions of CERES and the ISCCP-FD products are coarse (over 100 km), which limits their suitability for high-resolution studies. Although GLASS has a higher spatial resolution of 5 km, its products are only available over land areas. Currently, few existing and publicly released SSR products simultaneously provide all four SSRC in addition to their direct and diffuse components, except for CERES. Commonly used approaches to derive the SSR from satellite data include the radiative transfer (RT) model and a lookup table (LUT) that describes the relationship between satellite-observed spectral radiance and SSR (Rutan et al. 2015; Zhang et al. 2014). However, it is challenging to apply these methods for near-real-time (NRT) monitoring of SSR with high STR given the limited calculation efficiency and uncertainty caused by possible multiple solutions in the LUTs (Liang et al. 2006; Wang et al. 2021; Yu et al. 2021; R. Li et al. 2022).

In recent years, the latest generation of geostationary satellites, such as Himawari-8 (Bessho et al. 2016; Letu et al. 2019), the Fengyun-4 series (Yang et al. 2017; J. Li et al. 2022), and the GOES-R series (Schmit et al. 2008), with STR values reaching kilometer and minute levels, have been launched successfully. These instruments provide an unprecedented opportunity to derive clouds (Ri et al. 2022) and SSRC data with a markedly higher STR than that of other state-of-the-art products, even for the sun glint region (Tana et al. 2023). In addition, the high STR of the data enables rapid variations in SSRC to be more effectively captured. Although we developed a benchmark SWR product based on Himawari-8 (now Himawari-9) in a previous study (Letu et al. 2021), the PAR, UVA, and UVB components were missing, in addition to all of the SSRC direct and diffuse components. In addition, the complexity of atmospheric conditions (gases, aerosols, and clouds) makes accurately estimating the SSRC more challenging. At present, high-precision SSRC products with a high STR have not been released, much less an NRT SSRC monitoring system. This issue limits SSRC applications, especially for the East Asia–Pacific (EAP) region, which is affected by significant air pollution, surface radiation change induced by human activity (Wang et al. 2018), and frequent natural disasters and meteorological variations.

Given the lack of reliable SSRC products with a high STR, in this study, we develop an SSRC algorithm to generate all-sky SSRC products, as well as their direct and diffuse components (eight parameters in total), over the EAP region with STR up to 0.05° (10 min)−1 for the full-disk region from 2016 to 2020, based on data from the Himawari-8/9 and Fengyun-4 satellites. The effects of clouds (water and ice clouds), aerosols (different aerosol types), water vapor, and ozone over each spectral region are also considered. In addition, a combination of the RT model and machine learning techniques is applied to construct an NRT SSRC monitoring system. Finally, the characteristics of aerosols, clouds, and gases before, during, and post COVID-19 are compared and analyzed, and their impacts on SSRC in the EAP region are revealed and quantified.

Data and methods
A key motivation for developing the SSRC algorithm presented in this study is integrating the strengths of each input data type to produce high-precision SSRC products with high STR, in addition to constructing an NRT SSRC monitoring system.

Input data. The satellite data used in this work include L1B data from the Advanced Himawari Imager (AHI) on board Himawari-8/9 and the Advanced Geostationary Radiation Imager (AGRI) on board FY-4A/4B, which have provided high STR observations over East Asia since 2015 and 2017, respectively. The AHI has 16 spectral bands ranging from 0.47 to 13.3 μm,
spatial resolutions ranging from 0.5 to 2 km, and a temporal resolution of 10 min for full-disk coverage. The AGRI has 14 spectral bands ranging from 0.47 to 13.5 μm, with spatial resolutions from 0.5 to 4 km and a temporal resolution of 15 min for full-disk coverage. The Himawari-8/9 and FY-4A/4B data can be downloaded from the JAXA P-Tree system (www.eorc.jaxa.jp/ptree/registration_top.html) and the CMA National Satellite Meteorological Center (NSMC) (http://www.nsmc.org.cn/nsmc/cn/home/index.html), respectively.

The auxiliary data used in this work include the 16-day-mean MODIS surface albedo product (MCD43C3) with a spatial resolution of 0.05° and ERA5 hourly reanalysis data of precipitable water vapor (PWV) and total column ozone (TCO) at a spatial resolution of 0.25° (Hersbach et al. 2020). These data are used to correct the SSRC estimation. To minimize the missing surface albedo values for the estimation, the monthly mean surface albedo was calculated based on the MCD43C3 data. Note that neglecting the surface and PWV correction would introduce approximately 5% and 10% uncertainties, respectively, in the SWR estimation (Zhang et al. 2019), with higher uncertainties in the UVA and UVB estimation if the actual ozone concentration values were not used in the calculation (Rutan et al. 2015).

**SSRC algorithm.** The SSRC algorithm comprises three steps, as shown in Fig. 1. The first step involves identifying cloudy/clear-sky pixels from the satellite datasets and resampling the auxiliary data to match the resolution of the L1B satellite data. The cloud
The detection module by Shang et al. (2017) is incorporated into the SSRC algorithm to distinguish haze from clouds in polluted areas. Cloud phases, such as ice, liquid, and mixed-phase material, are further determined for the cloudy pixels using a cloud phase module (Platnick et al. 2017).

Step two involves the retrieval of aerosols and clouds. For clear-sky pixels, an aerosol module is constructed that integrates various aerosol types [i.e., black carbon (BC), sulfate, sea salt, and dust] with different optical properties (i.e., size distribution parameters and refractive index) via the external mixture scheme during the RT calculation, following the configuration used in the global aerosol model (Shettle and Fenn 1979; Chen et al. 2022). Due to the lack of high STR aerosol satellite products integrating multiple aerosol types, an assimilated aerosol optical thickness (AOT) product (Yumimoto et al. 2017, 2018) with a continuous STR of 0.375° and 1 h is used for the SSRC estimation. For cloudy pixels, a cloud retrieval algorithm is developed to simultaneously retrieve the cloud optical thickness (COT) and cloud effective radius (CER) for water clouds and ice clouds based on the classic schemes of Nakajima and King (1990) and Nakajima and Nakajima (1995). In this approach, ice clouds are modeled using the Voronoi nonspherical ice crystal scattering model (Ishimoto et al. 2012; Letu et al. 2016), which has been widely used for many official satellite missions, including Himawari-8/9 AHI, GCOMC/SGLI, and EarthCARE (Letu et al. 2016, 2019).

Step three involves estimating the SSRC and outputting the results for the NRT monitoring system to capture rapid SSRC changes with high precision and STR, which are usually difficult to achieve. The SSRC estimation module is developed based on the mapping relationships between atmospheric conditions and the SSRC, as described by the RT calculation. The atmospheric conditions, including the COT, CER, and AOTs of the four aerosol types plus the auxiliary data, are evaluated comprehensively. The RT calculation is performed based on a sophisticated RT model (Nakajima and Tanaka 1986, 1988; Sekiguchi and Nakajima 2008). To achieve NRT monitoring of SSRC, a machine learning solver is further developed to significantly accelerate the RT calculations following the scheme of Shi et al. (2020). Examples of pixel-level cloud phase, main aerosol type, PWV, and TCO data are shown in Fig. 2.

Finally, a total of eight SSRC parameters (the direct and diffuse components of SWR, PAR, UVA, and UVB) are estimated from the SSRC algorithm and output to the NRT monitoring system. Figure 3 shows an effect drawing of the user-friendly interface of the NRT SSRC monitoring system. Users can click the satellite button option to select SSRC results and then access the radiation compositions option, which includes SWR, PAR, UVA, and UVB data. Details of the direct and diffuse components at a user-defined target time, as well as the video before or after a few hours of the target time, are all displayed. The SSRC products and NRT system is available on the Cloud, Atmospheric Radiation and Renewal Energy Application (CARE) home page (www.slrss.cn/care/sp/pcl).

Figure 4 demonstrates a case of surface solar radiation monitoring in the Tibetan Plateau, where the shallow convective cloud occurred. Results indicate that the new product reveals the fine spatiotemporal variation of SWR well, by capturing more details owing to its high STR advantage, in comparison to that of CERES and ERA5 with STR of 1° h⁻¹ and 0.25° h⁻¹, particularly from 1500 to 1800 LT when the SWR varies rapidly owing to the occurrence of clouds. In addition, a generally more accurate estimation of daily SWR from the new product is identified based on the validation of the ground-based measurements near Namtso Lake.

**Product characteristics and new features**

The new features of the SSRC products presented in this study include simultaneously providing direct and diffuse components, multiple SSRC compositions, high STR data, and...
comprehensively considering the effects of cloud phase, aerosol types, and gas absorption. To achieve this, SSRC must be accurately estimated, including their direct and diffuse components; to do so, the atmospheric transmittance must be calculated, where different aerosol types (where absorption or scattering dominate), cloud phases (spherical or nonspherical scattering), and the molecular atmosphere (gas absorption or Rayleigh scattering) exert distinct impacts (e.g., Fig. 2). The SSRC algorithm is developed using a combination of the RT model and DNN techniques based on Himawari-8/9 and FY-4A/4B data. This algorithm is capable of deriving the direct and diffuse components by considering the full physical RT process operating within each spectral range. Figure 5 illustrates the instantaneous global, direct, and diffuse components of SWR, PAR, UVA, and UVB, which are much more plentiful than our previous work (Letu et al. 2021). The spatial distributions of the four SSRC products are highly variable and follow similar variation trends due to the solar position and atmospheric opacity. The high SSRC values are mainly located in areas of clear sky with low solar zenith angles and vice versa. In terms of the direct and diffuse components, the direct components of SWR, PAR, and UVA account for the majority of radiation in high-value regions; in contrast, the diffuse components of UVB are generally dominant (83.32% on average) in the full-disk region due to the higher-frequency scattering effects. In combination with the COT information shown in Fig. 2, thick clouds can be inferred to significantly inhibit direct radiation, especially ice clouds, whereas thin clouds tend to increase the diffuse radiation of SSRC, particularly when the COT is around 2.

The spatial characteristics of the SSRC products were evaluated through comparisons with corresponding state-of-the-art products from CERES, ERA5, and GLASS. Figure 6 shows the daily mean SWR and PAR values on 1 August 2016, in which the zoomed inset areas depict the regional SSRC distribution in southeastern China. The broad spatial distributions of
SWR and PAR from the four products are similar, with high values recorded along a belt at a latitude of 30°N, particularly in the Tibetan Plateau region, and low values at high southern latitudes. However, the SSRC products generated in this work resolve more details of SWR and PAR even for the daily mean values, with a significantly higher spatial resolution of 0.05° than the 1.00° and 0.25° resolutions of CERES and ERA5, respectively. Based on the
inset zoomed results, more subtle changes in SWR and PAR across both land and ocean are identified from Himawari-8, whereas both the CERES and ERA5 products only capture the broader trends. The GLASS products have the same spatial resolution of 0.05°; however, these data are only available over land and do not reveal variations in SWR and PAR over the ocean.

In terms of the UVA and UVB products shown in Fig. 7, the high and low value distributions are similar to those of SWR and PAR in Fig. 6. The higher spatial resolution of the SSRC products depict subtle variations in UVA and UVB, whereas the CERES results are pixelated due to their lower resolution. The spatial patterns of UVA and UVB in the Himawari-8 and CERES products are generally similar, with a latitudinal variation trend recorded from north to south. The UVB values of CERES are slightly lower than those of Himawari-8 in the clear sky; however, their absolute values are very small. Note that there are currently no UVA or UVB data available from ERA5 or GLASS.

In addition to the high spatial resolution of the SSRC products, they also have a high temporal resolution. Figure 8 shows comparisons of diurnal global, direct, and diffuse SWR, as
well as PAR, UVA, and UVB for Himawari-8, CERES, and ERA5 against ground-based observations at the Xianghe measurement site (39.78°N, 116.98°E) from 1 to 5 July 2016. Note that the temporal resolutions of CERES and ERA5 are 1 h, whereas the Himawari-8 and ground-based measurement frequency is 10 min. The four SWR data products show generally good agreement on both clear- and cloudy-sky days; however, the Himawari-8 data provide more consistent SWR with the ground-based measurements, especially when the SWR varies significantly on cloudy-sky days. Based on Figs. 8b–d, Himawari-8 clearly captures more detailed changes in SWR due to its higher temporal resolution than that of CERES and ERA5 and generally distinguishes the direct and diffuse components more accurately irrespective of which of the two components dominates.

Figure 8e illustrates that the Himawari-8-derived PAR values correspond well to the in situ measurements; in contrast, the corresponding ERA5 and CERES products tend to be underestimated. Figures 8b–e also reveal the better performance of Himawari-8 in the estimation of SWR (direct, diffuse, and global components) and PAR during conditions of air pollution, e.g., from 3 to 5 July 2016 when the averaged AOT was around 1.0 (Fig. 8a), while both CERES and ERA5 products exhibited larger discrepancies for the same period. In terms of UVA and UVB, there are no available data from ERA5. Figure 8f shows that the Himawari-8 derived UVA follows the diurnal variation trends recorded in ground-based measurement more consistently than CERES, while both Himawari-8 and CERES UVB data are generally comparable with over- and underestimation, respectively (Fig. 8g). Note that UVB accounts for only a very small proportion of solar radiation.

The performance of the daily SSRC products was also investigated by collecting all the data from 2016 from seven sites in the Baseline Surface Radiation Network (BSRN) and the
Xianghe site. Detailed description of each site used in this study is illustrated in Table 1. Note that only the Xianghe site provides SWR, PAR, UVA, and UVB measurements simultaneously. Since the GLASS SWR and PAR products are provided on a daily scale, validation with GLASS was also conducted. Table 2 summarizes the quantitative statistical parameters used for the evaluation. The daily mean rRMSEs and correlation coefficient (R) of the SWR and PAR from SSRC products (10.94% and 14.37%, 0.97 and 0.97) are smaller than the equivalent values for other widely used products, including CERES (13.48% and 15.27%, 0.96 and 0.96), ERA5 (19.38% and 27.48%, 0.92 and 0.92) and GLASS (15.96% and 15.06%, 0.94 and 0.94). Note CERES and GLASS have a smaller rMBE of SWR and PAR than others. In addition, the SSRC products show comparable UVA and UVB accuracy to CERES (rRMSEs of UVA and UVB of 17.33% and 23.12%, respectively, for SSRC products and 19.72% and 29.23%, respectively, for CERES).

To quantitatively evaluate the accuracy of the instantaneous retrieval, we also validate the instantaneous SWR in different atmospheric (i.e., clear sky, cloudy sky with water or ice crystal) and surface (snow/ice-free or coverage) conditions, which further confirms the availability and robustness of the new products, though more uncertainties occurred in the existence of cloudy sky and snow/ice ground at the same time (Figs. S1–S4 in the online supplemental material; https://doi.org/10.1175/BAMS-D-22-0154.2). Moreover, validation of the new products at the hourly scale also indicates a higher consistency of SWR to the ground-based measurement (i.e., hourly mean RMSE of 72.9, 95.7, and 121.6 W m−2 for Himawari-8, CERES, and EAR5) (Fig. S6), which are shown in the supplemental material, in addition to the validation of retrievals by FY-4A (Figs. S7 and S8) and comparison in the overlapping regions between Himawari-8 and FY-4A, with similar accuracy (relative error of about 18.62%) (Fig. S5).

**Analysis before, during, and post COVID-19 restrictions**

The advances in the constructed SSRC algorithm enable NRT monitoring of SSRC with high STR in the EAP region, which allows detailed regional analysis to be performed. As an application of the algorithm used in this study, we analyze the impacts of atmospheric parameters on the SSRC before, during, and post COVID-19 restrictions. Figure 9 illustrates the spatial variations of monthly averaged AOT, COT, and SWR in February 2019 and 2020, corresponding to the periods preceding and during the initial COVID-19 outbreak, respectively. As shown by the difference in AOT, atmospheric aerosols are significantly reduced (approximately 0.14 and 32.30%) in most of the Chinese central and eastern (CCE) regions, mainly as a result of the decreased emissions caused by the pandemic prevention and control measures implemented...
in China in early 2020. In contrast, the AOT in northeast India and northern Laos increased between these two periods. The COT in most CCE areas generally decreases coincident with the decrease in aerosol concentrations. Variations in the SWR follow the COT changes in most of the full-disk regions, indicating the dominant role of clouds in SWR. However, minimal changes are recorded in the SWR changes in the north of the CCE area due to the interaction of the reduced AOT and increased COT. On average across the full-disk region, variations in SSRC are not apparent (data not shown) during the studied period. Due to the specificity and complexity of the variation of aerosols, clouds, and SWR in the CCE area, the influence

Fig. 8. Comparison of diurnal variations in SSRC between CERES (1 h), ERA5 (1 h), Himawari-8 (10 min), and ground-based measurements (10 min) at the Xianghe site from 1 to 5 Jul 2016. (a) AOTs of total aerosols and COT, (b) global SWR, (c) direct SWR, (d) diffuse SWR, (e) PAR, (f) UVA, and (g) UVB.

Table 1. Information on validation sites used in this study.

<table>
<thead>
<tr>
<th>Site</th>
<th>Latitude</th>
<th>Longitude</th>
<th>Elevation (m)</th>
<th>Network</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alice Springs</td>
<td>23.80°S</td>
<td>133.89°E</td>
<td>547</td>
<td>BSRN</td>
</tr>
<tr>
<td>Darwin</td>
<td>12.42°S</td>
<td>130.89°E</td>
<td>30</td>
<td>BSRN</td>
</tr>
<tr>
<td>Fukuoka</td>
<td>33.58°N</td>
<td>130.37°E</td>
<td>3</td>
<td>BSRN</td>
</tr>
<tr>
<td>Howrah</td>
<td>22.55°N</td>
<td>88.31°E</td>
<td>51</td>
<td>BSRN</td>
</tr>
<tr>
<td>Lauder</td>
<td>45.05°S</td>
<td>169.69°E</td>
<td>350</td>
<td>BSRN</td>
</tr>
<tr>
<td>Sapporo</td>
<td>43.06°N</td>
<td>141.33°E</td>
<td>17.2</td>
<td>BSRN</td>
</tr>
<tr>
<td>Tateno</td>
<td>36.06°N</td>
<td>140.13°E</td>
<td>25</td>
<td>BSRN</td>
</tr>
<tr>
<td>Xianghe</td>
<td>39.78°N</td>
<td>116.98°E</td>
<td>32</td>
<td>—</td>
</tr>
</tbody>
</table>

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of atmospheric conditions on the SSRC was also investigated in an oceanic area at a similar latitude to the east of Japan (EJP) as a comparison.

To quantitatively investigate the influence of atmospheric parameters on SSRC, the daytime surface radiative forcing (DSRF) was calculated to indicate the difference between the net daytime SSRC with and without that parameter in this study. Figure 10 shows the monthly DSRF variations of PWV and ozone over CCE and EJP regions in February from 2019 to 2022. Overall, PWV has a minimal effect on UVA and UVB while exerting a significant influence on SWR among four SSRC, particularly direct SWR, due to its strong absorption in the near-infrared spectrum (e.g., 1.38, 1.87, and 2.7 μm) (Wei et al. 2019). In contrast, ozone has an impact on each SSRC, especially UVB. Moreover, a significant variation in the DSRF of each SSRC due to ozone is identified over the CCE areas since the COVID-19 outbreak, indicating that ozone levels increased after 2019 (by 8.83% and 16.3% in 2020 and 2021, respectively). This change may have been caused by decreases in nitrogen oxides over the CCE area that introduced more radicals for the production of ozone (Zhang et al. 2021).

In contrast to the PWV and ozone, almost all aerosol types have the same effects on direct SSRC by cooling the ground surface and diffuse SSRC by warming the ground surface, with exception of BC, which exerts a negative effect on both DSRF types (not shown). Since the impacts of BC, dust, and sea salt on SSRC are relatively small over the CCE and EJP areas, we only illustrate the results of total aerosols and sulfate (Fig. 11). As shown, there are clear variations in both direct and diffuse DSRF<sub>SWR</sub> due to total aerosols over the CCE area before, during, and post COVID-19 restrictions. Statistical analysis demonstrates that the global DSRF<sub>SWR</sub> (direct + diffuse) due to total aerosols varied from −30.30 to −25.03 W m<sup>−2</sup> between 2019 and 2020; in particular, the decrease in anthropogenic sulfate emission played a dominant role in the DSRF variation during that period as it contributed 83.11%. Since aerosols have a stronger backscattering effect, the DSRF of the direct component is generally higher than that of the diffuse component. Note that the aerosol emission and their DSRF seem to be similar in 2019 and 2022, i.e., before and post the COVID-19. In contrast to the significant variations recorded over the CCE area, minimal change occurred in the DSRF over the EJP area.

### Table 2. Summary of the daily mean SWR, PAR, UVA, and UVB at eight sites in 2016. Note that seven sites are from the BSRN and one is the Xianghe site.

<table>
<thead>
<tr>
<th>SSRC</th>
<th>Metric</th>
<th>Himawari-8</th>
<th>CERES</th>
<th>ERAS5</th>
<th>GLASS</th>
</tr>
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<tbody>
<tr>
<td>SWR</td>
<td>rRMSE (%)</td>
<td>10.94</td>
<td>13.48</td>
<td>19.38</td>
<td>15.96</td>
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<tr>
<td></td>
<td>rMBE (%)</td>
<td>1.74</td>
<td>0.12</td>
<td>3.29</td>
<td>−0.07</td>
</tr>
<tr>
<td></td>
<td>R</td>
<td>0.97</td>
<td>0.96</td>
<td>0.92</td>
<td>0.94</td>
</tr>
<tr>
<td>PAR</td>
<td>rRMSE (%)</td>
<td>14.37</td>
<td>15.27</td>
<td>27.48</td>
<td>15.06</td>
</tr>
<tr>
<td></td>
<td>rMBE (%)</td>
<td>10.65</td>
<td>−5.25</td>
<td>18.85</td>
<td>4.24</td>
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<tr>
<td></td>
<td>R</td>
<td>0.97</td>
<td>0.96</td>
<td>0.92</td>
<td>0.94</td>
</tr>
<tr>
<td>UVA</td>
<td>rRMSE (%)</td>
<td>17.33</td>
<td>19.72</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td></td>
<td>rMBE (%)</td>
<td>12.63</td>
<td>−9.40</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td></td>
<td>R</td>
<td>0.98</td>
<td>0.96</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>UVB</td>
<td>rRMSE (%)</td>
<td>29.23</td>
<td>23.12</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td></td>
<td>rMBE (%)</td>
<td>16.47</td>
<td>−16.70</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td></td>
<td>R</td>
<td>0.96</td>
<td>0.97</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>STR</td>
<td>0.05° (10 min)&lt;sup&gt;−1&lt;/sup&gt;</td>
<td>1° h&lt;sup&gt;−1&lt;/sup&gt;</td>
<td>0.25° h&lt;sup&gt;−1&lt;/sup&gt;</td>
<td>0.05° day&lt;sup&gt;−1&lt;/sup&gt;</td>
<td></td>
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</tbody>
</table>
Based on the absolute DSRF values shown in Fig. 12, clouds still play a dominant role in affecting the SSRC over the CCE and EJP regions both before and post COVID-19 restrictions, except for UVB, upon which ozone exerts the strongest influence (Fig. 10). In contrast to aerosols, clouds over the EJP region generally show more significant radiation effects than those over the CCE area from 2019 to 2022, except for the ice clouds, which underwent a rapid decrease over the EJP area in 2020. In contrast, the DSRF changes due to water clouds were relatively smaller, although a slight increase in diffuse DSRF was recorded in both CCE and EJP areas after 2019. In the CCE area, the global DSRF$_{SWR}$ (direct + diffuse) values of water
Fig. 10. Monthly averaged DSRF variations of water vapor and ozone on SSRC (SWR, PAR, UVA, and UVB) and their direct and diffuse components over the CCE (land) and EJP (sea) areas from February 2019 to 2022. The 90% and 50% CIs indicate the percentile ranges from the 5th to 95th percentiles and from the 25th to 75th percentiles, respectively.

Fig. 11. As in Fig. 10, but for aerosol types.
clouds and ice clouds varied by 5.54 and 14.00 W m\(^{-2}\) between February 2019 and 2020, respectively, indicating a decrease in water and ice clouds. Note that the calculated DSRF values only represent daytime SSRC variations; thus, any nighttime effects are excluded.

**Summary**

Until now, deriving surface downward solar radiation compositions (SSRC) from traditional satellites (e.g., MTSAT) has been a major challenge due to their limited spatial and temporal resolutions (STR) and spectral information. Traditional estimation algorithms also limit the potential for high-precision, near-real-time monitoring of SSRC. In this study, we develop a sophisticated retrieval algorithm for the estimation of SSRC based on Himawari-8/9 and Fengyun-4 series. All-sky SSRC products are achieved and a near-real-time monitoring system is further established over the East Asia–Pacific (EAP) region. The advantages of the SSRC products are unique as they provide shortwave radiation (SWR), photosynthetically active radiation (PAR), ultraviolet-A (UVA), and ultraviolet-B (UVB), as well as their direct and diffuse components simultaneously, with high STR and high precision. Validation of the obtained SSRC products against ground-based measurements demonstrates significantly better performance than those of CERES, ERA5, and GLASS in determining SWR and PAR. The accuracy of UVA and UVB is comparable to CERES, while STR features up to 0.05° (10 min)\(^{-1}\) for the full-disk region are outstanding.

The initial application study demonstrates the advantage of the near-real-time monitoring system in capturing detailed variations of SSRC in regional analysis (e.g., Tibetan Plateau area) and characterization of the effects of atmospheric parameters on SSRC. Significant changes in SSRC due to decreased aerosols, especially anthropogenic sulfate, and increased ozone are identified in the Chinese central and eastern (CCE) area before, during, and post the introduction of COVID-19 pandemic containment measures in China in 2020. Quantitative evaluations reveal that ozone exerts a significant impact on the UVB, while clouds

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Fig. 12. As in Fig. 10, but for different cloud phases.
represent the most important factors influencing SWR, PAR, and UVA in the CCE region during the studied period. The algorithm developed in this study can also be applied to other international geostationary satellites such as the GOES-R series. Moreover, it is promising to merge Himawari-8 and FY-4, as well as other geostationary satellite sensors to provide greater spatial coverage and higher accuracy, particularly over the overlapping regions, which will be conducted in the next step.

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Data availability statement. The developed SSRC monitoring system and related products are available via the CARE home page (www.slrss.cn/care/sp/pc/).
References


