Clear-Sky Shortwave Downward Flux at the Earth’s Surface: Ground-Based Data vs. Satellite-Based Data

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Abstract

The radiative flux data and other meteorological data in the BSRN archive start from 1992, but the RadFlux data, the clear-sky radiative fluxes at the BSRN sites derived through regression analyses of actually observed clear-sky fluxes, did not come into existence until the early 2000s, and at first, they were limited to the 7 NOAA SURFRAD and 4 DOE ARM sites, a subset of the BSRN sites. Recently, the RadFlux algorithm was applied more extensively to the BSRN sites for the production of clear-sky ground-based fluxes. At the time of this writing, there are 7119 site-months of clear-sky fluxes at 42 BSRN sites spanning the time from 1992 to late 2017. These data provide an unprecedented opportunity to validate the satellite-based clear-sky fluxes. In this paper, the GEWEX SRB GSW(V3.0) shortwave downward fluxes spanning 24.5 years from 1983-07 to 2007-12, the CERES SYN1deg(Ed4A) and EBAF(Ed4.0) shortwave fluxes spanning 2000-03 to mid-2017 are compared with their RadFlux counterparts on the hourly, 3-hourly, daily and monthly time scales. All the three datasets show reasonable agreement with their ground-based counterparts. Comparison of the satellite-based surface shortwave clear-sky radiative fluxes to the BSRN RadFlux analysis shows negative biases. Further analysis shows that the satellite-based atmosphere contains greater aerosol optical paths as well as more precipitable water than RadFlux analysis estimates.

Keywords: solar radiation, satellite, RadFlux, GEWEX SRB, CERES

1 Introduction

Although some places on Earth enjoy more sunny days than cloudy days on an annual basis, there is no place on Earth that is always cloud free. In fact, on a global scale, the Earth’s surface sees more cloudy sky than clear (i.e., cloud free) sky at any instant. Therefore, the so-called “clear-sky” radiation at the entire Earth’s surface for

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extended period of time are derived by 1.) determining average conditions without clouds; or 2.) using radiation transfer models depending upon the specification of the atmospheric state. For transmitting solar, or shortwave, fluxes through the atmosphere, the most important atmospheric state variables are atmospheric water vapor, or precipitable water, trace gases (i.e., ozone) and aerosol optical properties. However, the uncertainties of those quantities can be large, thus providing a challenge for the verification of the shortwave fluxes. Ground-based observations, or data derived thereof, serve as a benchmark for the satellite-based data.

The theoretical clear-sky radiation data make it possible to quantify the cloud forcing at both the surface and the top-of-atmosphere (TOA) as far as the shortwave and longwave radiative fluxes are concerned. Since the cloudiness can potentially change in the future climatic scenarios, quantitative knowledge of cloud radiative effect has long been used to assess the radiative influence on clouds on the climate system (e.g., Stephens et al. [32]). The clear-sky radiation data also enable the isolation of the effect of aerosols and precipitable water in the atmospheric radiative processes. For the solar energy industry, the clear-sky insolation is the maximum rate of solar energy that can potentially reach the solar energy collector at any given location. Though in cases of broken clouds, there can often be short bursts of positive cloud effect during which the solar insolation at a given spot goes beyond that of cloud free condition due to reflection of clouds while the spot is not in the shadow of the clouds.

Meteorological observations of solar radiation date back to more than a century ago, and records of data are available today through such as the World Radiation Data Centre (WRDC), Global Energy Balance Archive (GEBA) and, more recently, the state-of-the-art Baseline Surface Radiation Network (BSRN)[1], but these data often include influences by clouds of various types and heights, even though some stations have nearly continuous records for considerable numbers of years. These records, such as many of those with the BSRN archive, however, are interspersed with clear-sky episodes that are often sufficient for deducing continuous clear-sky values.

Since early 2000s, efforts have been made through development of the Radiative Flux Analysis (RadFlux) methodology, e.g. Long and Ackerman [2], and the application of the RadFlux has produced data that include clear-sky downward shortwave total, diffuse and direct horizontal fluxes among a number of other variables. The RadFlux algorithm works by fitting actually observed clear-sky total shortwave downward and diffuse fluxes to exponential functions of cosine of the solar zenith angle. At first, the RadFlux data were limited to the 4 Atmospheric Radiation Measurement (ARM) and 7 NOAA Earth System Research Laboratory (ESRL) Global Monitoring Division (GMD) Surface Radiation (SURFRAD) Network sites which are a subset of the BSRN. Later, the RadFlux algorithm was applied more broadly to other BSRN sites, and at the time of this writing, over 7000 site-months of RadFlux data are available from 42 BSRN sites, including the 7 SURFRAD sites, spanning the time from 1992 to late 2017. The availability of these data provides an unprecedented opportunity for us to evaluate the quality of the clear-sky fluxes
from NASA’s Global Energy and Water Experiment (GEWEX) Surface Radiation Budget (SRB) project and Clouds and the Earth’s Radiant Energy System (CERES) project.

The GEWEX SRB released its Version 3.0 of shortwave data (GSW V3.0) in 2011. The dataset spans 24.5 years from 1983-07 (standing for July 1983, henceforth the same date format) to 2007-12 and is on a quasi-equal-area grid system with 44,016 grid boxes. Its all-sky fluxes have been validated extensively against those of BSRN, WRDC and GEBA as well as data from the arrays of buoys in the tropical oceans deployed by Pacific Marine Environmental Laboratory (PMEL). Its clear-sky fluxes, however, have not quite been validated until now.

The CERES experiment of NASA was initiated in late 1990s. Its latest Synoptic 1° Edition 4A (SYN1deg Ed4A) data has hourly, 3-hourly, daily and monthly means on a uniform 1° latitude by 1° longitude resolution from 2000-03 to 2017-08. And the CERES Energy Balanced and Filled Edition 4.0 (EBAF Ed4.0) monthly mean data is obtained through further processing of the SYN1deg(Ed4A) with additional inputs, and its spatial resolution is the same as SYN1deg(Ed4A) and now is available for the period from 2000-03 to 2017-06. Wielick and Barkstrom [15] gave an overview of the CERES experiment and theoretical basis of its algorithm [16] for the SYN1deg products. Both the SYN1deg and EBAF data can be divided into two periods, the Terra-only period from 2000-03 to 2002-06, and the Terra-Aqua period from 2002-07 onward. **Terra** and **Aqua** refer to the satellites Terra (EOS AM-1) and Aqua (EOS PM-1), respectively.

Loeb et al. [17] provided details of the EBAF algorithm for adjusting the shortwave and longwave fluxes within the limit of uncertainties aimed to mitigate the imbalance in the average of global net radiation. In order to improve the quality of TOA broadband irradiance of the CERES clouds and radiative swath product, Rose et al. [18] developed an algorithm for adjusting inputs within their uncertainties by using Lagrangian multipliers. Kato et al. [19] applied a similar method to the EBAF surface product.

Rutan et al. [20] reviewed the methodology for CERES SYN1deg data, validated SYN1deg(Ed3A) product against ground-based observations, and intercompared it with other satellite-based data, including EBAF(Ed2.7). The latest SYN1deg(Ed4A) and EBAF(Ed4.0) products, however, are yet to be studied extensively. Not long ago, Loeb et al. [21] described the latest TOA Edition of EBAF Ed4.0 which incorporated all up to date algorithm improvements and consistent inputs throughout the CERES record.

Recently, we extensively compared the clear-sky shortwave downward fluxes from these three satellite-based datasets with the RadFlux data. It is found that they agree reasonably well with their ground-based counterparts although there is generally a noticeable, but not quite significant, negative bias. Based on the available aerosol optical depth (AOD) and precipitable water data at the BSRN sites, albeit limited in
space and time, that are coincident and collated with that of CERES SYN1deg, it appears that the clear-sky as depicted by the CERES SYN1deg(Ed4A) input data contains more aerosols and precipitable water than representative of the RadFlux surface flux analysis.

In this paper, we will 1.) Provide fundamental information about the ground-based RadFlux data and the three sets of satellite-based data, namely, the GEWEX SRB GSW(V3.0), the CERES EBAF(Ed4.0) and SYN1deg(Ed4A); 2.) Compare each satellite-based dataset with its RadFlux counterpart; 3.) Intercompare the three satellite-based datasets where appropriate; 4.) Discuss the possible cause of differences; and 5.) Summarize the results and conclusions.

2 The ground-based RadFlux data

At any location, if the aerosols and precipitable water in the atmosphere remain more or less unchanged, the clear-sky total shortwave downward flux and diffuse flux at the surface can be mathematically described with simple and elegant functions of the cosine of the solar zenith angle with considerable accuracy. Departure from the predictable behavior, such as caused by the presence of clouds, can thus be detected by mathematical means. The methodology of the RadFlux data is based on this idea.

Simply put, the RadFlux algorithm subjects high temporal resolution (1- to 5-minute data) regularly observed data to 4 tests [2]: 1.) a normalized total shortwave magnitude test; 2.) a maximum diffuse shortwave test; 3.) a rate of change of magnitude test; and 4.) a normalized diffuse ratio variability test. Through the tests, the clear-sky episodes can then be identified from recorded data which may otherwise be affected by the clouds. The total shortwave flux and the diffuse flux that fall within those clear episodes on a given day over a sufficient rang of solar zenith angles are each fitted to an exponential function of the cosine of the solar zenith angle modified by an amplitude factor. Using the fitted function, and interpolating the fit coefficients for cloudy days, the clear-sky data is then computed continuously at the same resolution as the input data. The identified clear-sky conditions have been verified against whole sky imagery, lidar data, observer reports and other models. Long and Ackerman [2] and Long and Gaustad [3] provide the details for performing the tests aimed to identify the clear-sky conditions. In addition to the shortwave clear-sky fluxes at the surface, the longwave clear-sky fluxes are also produced as part of the RadFlux data by Long and Turner [29] using methodology adapted from Marty and Philipona [4] and Durr and Philipona [5].

The RadFlux data were first produced for just the ARM sites and the 7 SURFRAD sites. Further efforts to apply the RadFlux algorithm to non-SURFRAD BSRN sites were made recently at ETH Zurich as reflected in Wild et al. [6] and Hakuba et al. [7] in which the RadFlux data were used in the study of the global mean energy balance
under clear-sky conditions through the Coupled Model Intercomparison Project Phase 5 (CMIP5) and cloud radiative effect (CRE).

Table 1 lists the 42 BSRN sites with RadFlux data. In Fig. 1, the upper panel shows the geographical locations of these BSRN sites, and the lower panel shows the months with available RadFlux data for each site.

The hourly and daily means of the data are computed directly from the original 1-, 2-, 3- or 5-minute means, and the monthly means are computed from the daily means. To control the quality, we require that at least 95% of the original records are available for an hourly or a daily mean to be computed, and at least 80% of daily means are available for a monthly mean to be computed. Discussions about the effect of missing records in averaging the BSRN data can be found in Roesch et al. [30].

Table 1. BSRN sites, in latitudinally descending order, with RadFlux clear-sky data. The geographic information includes latitude (Lat.), longitude (Lon.), elevation (H) and full name. The SURFRAD sites are indicated in boldface in full name.

<table>
<thead>
<tr>
<th>No.</th>
<th>Site</th>
<th>Lat. (°)</th>
<th>Lon. (°)</th>
<th>H (m)</th>
<th>Full Name</th>
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<td>ALE</td>
<td>82.4900</td>
<td>-62.4200</td>
<td>127</td>
<td>Alert, Lincoln Sea</td>
</tr>
<tr>
<td>02</td>
<td>NYA</td>
<td>78.9333</td>
<td>11.9500</td>
<td>11</td>
<td>Ny Alesund, Spitsbergen (N), Germany/Norway</td>
</tr>
<tr>
<td>03</td>
<td>BAR</td>
<td>71.3167</td>
<td>-156.6000</td>
<td>8</td>
<td>Barrow, Alaska, USA</td>
</tr>
<tr>
<td>04</td>
<td>LIN</td>
<td>52.2167</td>
<td>14.1167</td>
<td>125</td>
<td>Lindenberg, Offenbach am Main, Germany</td>
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<tr>
<td>05</td>
<td>CAB</td>
<td>51.5072</td>
<td>4.5667</td>
<td>0</td>
<td>Cabauw, Lopik, Utrecht, The Netherlands</td>
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<tr>
<td>06</td>
<td>REG</td>
<td>50.2000</td>
<td>-104.7167</td>
<td>587</td>
<td>Regina, Saskatchewan, Canada</td>
</tr>
<tr>
<td>07</td>
<td>PAL</td>
<td>48.7167</td>
<td>2.2000</td>
<td>156</td>
<td>Palaiseau Cedex, France</td>
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<tr>
<td>08</td>
<td>FPE</td>
<td>48.3167</td>
<td>-105.1000</td>
<td>634</td>
<td>Fort Peck, Montana, SURFRAD, USA</td>
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<tr>
<td>09</td>
<td>PAY</td>
<td>46.8167</td>
<td>6.9500</td>
<td>491</td>
<td>Payerre, Vaud Canton, Switzerland</td>
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<tr>
<td>10</td>
<td>CAR</td>
<td>44.0500</td>
<td>5.0333</td>
<td>100</td>
<td>Carpentras, France</td>
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<tr>
<td>11</td>
<td>SXF</td>
<td>43.7300</td>
<td>-96.6200</td>
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<tr>
<td>12</td>
<td>SAP</td>
<td>43.0600</td>
<td>141.3283</td>
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<tr>
<td>13</td>
<td>CNR</td>
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<td>-1.6010</td>
<td>471</td>
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<tr>
<td>14</td>
<td>PSU</td>
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<td>-77.9333</td>
<td>376</td>
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<tr>
<td>15</td>
<td>BOS</td>
<td>40.1333</td>
<td>-105.2333</td>
<td>1689</td>
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<tr>
<td>16</td>
<td>BON</td>
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<tr>
<td>17</td>
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<td>-105.0000</td>
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<tr>
<td>18</td>
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<td>-75.7167</td>
<td>34</td>
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<tr>
<td>19</td>
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<td>-116.0167</td>
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<tr>
<td>20</td>
<td>E13</td>
<td>36.6000</td>
<td>-97.5000</td>
<td>318</td>
<td>S. Great Plains ARM Ext. Facil. 13, USA</td>
</tr>
<tr>
<td>21</td>
<td>BIL</td>
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<td>-97.5167</td>
<td>318</td>
<td>Billings, Oklahoma, ARM/CART, USA</td>
</tr>
<tr>
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<td>TAT</td>
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<td>140.1333</td>
<td>25</td>
<td>Tateno, Tsukuba City, Japan</td>
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<td>23</td>
<td>GCR</td>
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<td>98</td>
<td>Goodwin Creek, Mississippi, SURFRAD, USA</td>
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<tr>
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<td>130.3750</td>
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<tr>
<td>25</td>
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<tr>
<td>26</td>
<td>SBO</td>
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<td>34.7667</td>
<td>500</td>
<td>Sede Boquer (Sde Boker Kibbutz), Israel</td>
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<tr>
<td>27</td>
<td>ÎZA</td>
<td>28.5000</td>
<td>-16.3000</td>
<td>2381</td>
<td>Izana, Tenerife, Canary Islands, Spain</td>
</tr>
<tr>
<td>28</td>
<td>SOV</td>
<td>24.9167</td>
<td>46.4167</td>
<td>650</td>
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<tr>
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<td>124.1633</td>
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<tr>
<td>30</td>
<td>MNN</td>
<td>24.2883</td>
<td>153.9833</td>
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<td>31</td>
<td>KWA</td>
<td>8.7167</td>
<td>167.7333</td>
<td>10</td>
<td>Kwajalein, Marshall Islands, USA</td>
</tr>
</tbody>
</table>
The satellite-based data

3.1 The GEWEX SRB GSW(V 3.0) data

The NASA GEWEX SRB shortwave algorithm GSW was based on the Pinker and Laszlo [8] algorithm, and its Version 3 (GSW V3.0) products were released in 2011. Its inputs include 1.) cloud parameters from the International Satellite Cloud Climatology Project (ISCCP) pixel-level DX product; 2.) moisture from the Goddard Earth Observing System (GEOS); 3.) atmospheric column ozone from the Total Ozone Mapping Spectrometer (TOMS), the Operational Vertical Sounder, the Ozone Monitoring Instrument (OMI), and the Stratospheric Monitoring Ozone Blended Analysis (SMOBA); and 4.) surface spectral albedos derived from 5 surface types of Matthews [9] and incorporated in the model of Briegleb et al. [10]. More detailed information is available in Stackhouse et al. [11], and Zhang et al. [12, 13] and, in the latter two, the GSW(V3.0) all-sky shortwave downward fluxes were extensively validated against the BSRN data.

The GSW(V3.0) products are on a quasi-equal-area grid system consisting of 44,016 grid boxes. The latitudinal resolution is always 1° while the longitudinal resolution changes from 1° around the Equator to 120° around the Poles. The temporal resolutions are 3-hourly, 3-hourly-monthly, daily and monthly, and the data span 24.5 years from 1983-07 to 2007-12. The products have been used in numerous studies [14]. The clear-sky shortwave downward fluxes are not only part of the final products, but, along with the cloudy-sky shortwave downward fluxes and cloud fractions, are an intermediate step for computing the cloudy-sky shortwave downward fluxes.

3.2 The CERES SYN1deg(Ed4A) data

The CERES SYN1deg inputs consist of atmospheric profiles from GEOS-4 and -5, cloud data from MODIS imagery at CERES footprints and geostationary 3-hourly imagery, aerosol properties from MODIS and Model of Atmospheric Transport and CHmestry (MATCH), ozone profile from SMOBA, measured surface spectral albedo
categorized according to the IGBP scene types, surface broadband albedo derived from clear-sky TOA observations, and snow and ice from National Snow and Ice Data Center (NSIDC) and NOAA.

The Langley Fu-Liou radiative transfer code [22-23] is used to compute the hourly fluxes. The clear-sky surface shortwave downward fluxes are computed when the sky conditions over the CERES footprints are identified as entirely cloud-free, and temporal interpolations are used when clouds are present. If cloudy condition persists for an extended period of time over a footprint, it may cause insufficient sampling of clear-sky condition and thus a missing value in the monthly mean clear-sky flux.

3.3 The CERES EBAF(Ed4.0) data

The CERES EBAF(Ed4.0) data, an update from the EBAF(Ed2.8) data, comprises only monthly means on the same 1° latitude by 1° longitude grid system as that of SYN1deg(Ed4A), and it now spans the period from 2000-03 to 2017-06. The EBAF surface product is derived from its TOA counterpart.

The SYN1deg daily means and the Single Scanner Footprint (SSF) TOA and Surface Fluxes and Clouds as well as the geostationary imager daily data are primary inputs of the EBAF algorithm for all-sky fluxes. For clear-sky TOA fluxes, the SSF1deg monthly mean fluxes are first derived from the SSF product, then the narrowband-to-broadband correction is performed to get the monthly mean shortwave and longwave fluxes, and finally the adjustment of the fluxes is made based on the energy imbalance at TOA.

The clear-sky condition normally does not persist for continuous clear-sky observation, and for this reason, the broadband clear-sky flux estimates derived from MODIS over the cloud-free portions of CERES footprints are used to supplement the clear-sky data. The final monthly mean is a cloud-free fraction-weighted average of such instantaneous clear-sky fluxes. The cloud fraction for a CERES cloud-free footprint is set to be less than 0.1%, and when the cloud fraction is between 0.1% and 95%, the clear-sky fluxes are derived from MODIS. According to Loeb et al. [21], there are times when the sky is identified as cloud-free while in actuality the cloud fraction is appreciable. The aerosol in the vicinity of clouds can be humidified as a result of higher relative humidity [22], and the light scattering coefficient of the aerosol can thus be increased, which lowers the shortwave flux that reaches the surface.

In addition to the EBAF TOA data, the inputs for the EBAF surface flux computation include data from AIRS (Atmospheric Infrared Sounder on Aqua), CALIPSO (Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observations), and CloudSat, all belonging to the satellite constellation A-Train. These additional data are used to determine the uncertainties of input properties of the surface, atmosphere and
clouds. Constraining the surface fluxes by CERES observations requires adjusting these properties within their uncertainties.

As at the TOA, the monthly mean clear-sky fluxes at the surface are also averages of computed instantaneous clear-sky fluxes weighted by cloud-free fractions.

4 Comparisons of the satellite-based data with the ground-based data

In addition to the nearly 8-year period from 2000-03 to 2007-12 that coincides with CERES, the time span of the GEWEX SRB GSW(V3.0) data covers nearly 17 years before the age of CERES, and the BSRN data also precedes CERES by more than 8 years. So we first evaluate the GEWEX SRB data and CERES data separately over their own different time spans, then over their overlapping years to facilitate intercomparisons between the different datasets.

4.1 GEWEX SRB GSW(V3.0)-RadFlux comparison

The GEWEX SRB GSW(V3.0) 3-hourly data are centered on GMT hours 0:00, 3:00, 6:00, ..., 21:00, and daily and monthly means are derived in local time. Fig. 2 shows the GSW(V3.0)-RadFlux (GSW(V3.0) minus RadFlux) comparison for the period from 1992-01 to 2007-12. For the 3-hourly and daily data, the scatter density is shown for their large numbers of data points. The 3-hourly plots consist of only fluxes larger than 0 while daily and monthly means include 0 values during nighttime as required by the definitions of daily and monthly means, which is why the 3-hourly bias has a larger absolute value. Since the length of daytime for any given location on multiyear average is 12 hours, including nighttime values of 0 would double the number of data points and thus having the absolute value of the bias halved, which would then be about the same as those of daily and monthly means; the RMS error would also be reduced by a factor of \( \sqrt{2} \). Table 2 summarizes the 3-hourly, daily and monthly mean comparison statistics.

In Fig. 3, the 3-hourly comparisons are made in 0.05-sized bins of cosine of solar zenith angle, or \( \cos(SZA) \). Although the bias in the majority of bins are negative, it is nonetheless positive in 3 bins midway through the range of \( \cos(SZA) \). The maximum bias magnitude occurs on the absolute scale (left panel) when the Sun is around the overhead position, or in the last bin of \( \cos(SZA) \). On the relative scale (right panel), however, it is when the Sun is close to the horizon, or in the first bin of \( \cos(SZA) \), that the maximum bias magnitude takes place. Starting from the zenith, or the overhead position, the relative bias remains just a few percent or less, or significantly less than 10%, until the solar zenith angle goes beyond 70°. The
standard deviation shows a generally increasing trend relative to cos(SZA) on the absolute scale but a decreasing one on the relative scale.

Table 2. Statistics of GEWEX SRB GSW(V3.0)-RadFlux clear-sky surface shortwave downward flux comparison for the period from 1992-01 to 2007-12. The symbol $\rho$ stands for correlation coefficient, $\sigma$ for standard deviation in W m$^{-2}$, and $\mu_{GSW}$ for the mean of GSW(V3.0) fluxes in W m$^{-2}$.

<table>
<thead>
<tr>
<th>Temporal Scale</th>
<th>Bias</th>
<th>RMS</th>
<th>$\rho$</th>
<th>$\sigma$</th>
<th>$\mu_{GSW}$</th>
<th>N</th>
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<tr>
<td>3-Hourly</td>
<td>-6.51</td>
<td>37.12</td>
<td>0.9932</td>
<td>36.54</td>
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</table>

4.2 The CERES SYN1deg(Ed4A) and EBAF(Ed4.0)-RadFlux comparisons and intercomparison between SYN1deg(Ed4A) and EBAF(Ed4.0)

Fig. 4 compares the SYN1deg(Ed4A) hourly, daily and monthly means with their RadFlux counterparts from 2000-04 to 2017-06. The hourly means are centered on GMT hours 0:30, 1:30, 2:30, ..., 23:30, and the daily means in local solar time are derived from the hourly means. Note again that the hourly means do not include nighttime hours, so the hourly bias is about 2 times of those of daily and monthly means. The comparison statistics are summarized in Table 3.

Table 3. Statistics of CERES SYN1deg(Ed4A)-RadFlux clear-sky surface shortwave downward flux comparison for the period from 2000-04 to 2017-06. The symbol $\rho$ stands for correlation coefficient, $\sigma$ for standard deviation in W m$^{-2}$, and $\mu_{SYN}$ for the mean of SYN1deg(Ed4A) fluxes in W m$^{-2}$.

<table>
<thead>
<tr>
<th>Temporal Scale</th>
<th>Bias</th>
<th>RMS</th>
<th>$\rho$</th>
<th>$\sigma$</th>
<th>$\mu_{SYN}$</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hourly</td>
<td>-16.91</td>
<td>33.75</td>
<td>0.9952</td>
<td>29.21</td>
<td>447.58</td>
<td>2131927</td>
</tr>
<tr>
<td>Daily</td>
<td>-8.84</td>
<td>16.08</td>
<td>0.9917</td>
<td>13.43</td>
<td>230.40</td>
<td>172017</td>
</tr>
<tr>
<td>Monthly</td>
<td>-8.83</td>
<td>12.75</td>
<td>0.9964</td>
<td>9.20</td>
<td>230.29</td>
<td>5647</td>
</tr>
</tbody>
</table>

Fig. 5 shows the hourly comparison statistics in the same fashion as that of Fig. 3. Both the bias magnitude and standard deviation increase monotonically with cos(SZA) on the absolute scale (left panel) and decrease monotonically on the relative scale (right panel). The sign of the bias is consistently negative through the gamut of cos(SZA).

The EBAF(Ed4.0) data has only monthly means, and it is compared with the RadFlux in Fig. 6 for the period from 2000-04 to 2017-06. Compared with SYN1deg(Ed4A), EBAF(Ed4.0) improves in high-latitude regions as both the 60° poleward bias and standard deviation improves; globally, the bias improves also, but the standard deviation increases slightly.
In Fig. 7, both the SYN1deg(Ed4A) and EBAF(Ed4.0) monthly means are compared with RadFlux data on a site-by-site basis from 2000-04 to 2017-06. In both panels, it is obvious that EBAF(Ed4.0) agrees better with RadFlux than SYN1deg(Ed4A) at most sites.

4.3 The intercomparison between the three satellite-based datasets

The common period covered by all the three datasets, the GEWEX SRB GSW(V3.0) and the CERES SYN1deg(Ed4A) and EBAF(Ed4.0), is from 2000-04 to 2007-12. Fig. 8 compares the three datasets over this period with RadFlux, respectively.

The GEWEX SRB GSW(V3.0) has the smallest bias magnitude and thus the most symmetric histogram about 0, but its standard deviation is somewhat larger than both the CERES SYN1deg(Ed4A) and EBAF(Ed4.0). The comparison statistics of all the 3 datasets are summarized in Table 4.

Table 4. Statistics of GEWEX SRB GSW(V3.0)-RadFlux, CERES SYN1deg(Ed4A)-RadFlux and EBAF(Ed4.0)-RadFlux clear-sky monthly mean surface shortwave downward fluxes for the period from 2000-04 to 2007-12. The symbol ρ stands for correlation coefficient, σ for standard deviation in W m⁻², and μDATA for the mean of fluxes of each respective dataset in W m⁻².

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Bias</th>
<th>RMS</th>
<th>ρ</th>
<th>σ</th>
<th>μDATA</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>GSW(V3.0)</td>
<td>-5.29</td>
<td>12.59</td>
<td>0.9941</td>
<td>11.42</td>
<td>232.96</td>
<td>2347</td>
</tr>
<tr>
<td>SYN1deg(Ed4A)</td>
<td>-9.43</td>
<td>13.27</td>
<td>0.9966</td>
<td>9.33</td>
<td>228.82</td>
<td>2347</td>
</tr>
<tr>
<td>EBAF(Ed4.0)</td>
<td>-7.61</td>
<td>12.23</td>
<td>0.9963</td>
<td>9.57</td>
<td>230.65</td>
<td>2347</td>
</tr>
</tbody>
</table>

5 Statistical Analysis of the Biases

So far, each of the biases we have discussed is, in a statistical sense, a single sample. We might want to know how robust these biases are, or how they are statistically distributed, and how wide their 95% confidence intervals are.

Here we attempt to answer these questions by means of the bootstrap method with regard to the biases of monthly means as presented in Fig. 8 from two different perspectives.

5.1 Treating each site-month as an independent probabilistic event

At any given ground-based site, the availability of a given monthly mean occurs, in a sense, randomly. A number of reasons could and have caused disruptions of continuous recording. And it's quite possible that there is absolutely no record at the site for the entire period of interest. A given site-month is spatiotemporally unique, strictly speaking, though long records at a given site may exhibit stable
statistical features. From the point of view of statistics, the set of comparable pairs of data in each case can be viewed as a realization of random sampling from the continuum of space and time, or more specifically, from the Earth’s surface and the years in which these scientific experiments are being conducted. Any given site-month of record could very well have been replaced by a different one. So in the bootstrapping sampling in this case, we literally let each and every site-month of record have an equal chance to appear and reappear without the limit on the number of repetitions.

In Fig. 11, the left panels show the 100,000 bootstrap samplings. Information about bootstrapping can be found in Shao and Tu[28]. The scatter plot is for the GEWEX SRB GSW(V3.0)-RadFlux comparison. The 3 quasi-normal distribution curves are for the GSW(V3.0), SYN1deg(Ed4A) and EBAF(Ed4.0), respectively, and the 95% confidence intervals of their biases are, respectively, (-5.76, -4.83), (-9.81, -9.06) and (-8.00, -7.22), and their corresponding widths are 0.93, 0.75 and 0.78. The units are all in W m⁻². The narrow widths of the 95% confidence intervals indicate that the bias computed from such a number of site-months of records from such a geographic range and time span is fairly robust. The lack of overlapping space under the 3 quasi-normal curves implies that the differences between the 3 datasets are statistically significant, albeit, the differences are small in magnitude. The normal-like distribution also suggests that the number of bootstrap samplings is sufficient. In fact, the kurtoses of the 3 curves are 0.0048, -0.0021 and 0.0050, respectively, very close to 0, which means their distributions are close to normal distributions.

5.2 Treating each site as an independent probabilistic event

Observational data at a given site may have unique characteristics in its accuracy as well as level of agreement with satellite-based data due to the unique geography of the site and the climatology associated with it. Lengths of records vary from site to site, often dramatically, thus giving different weights to different sites in the global bias. These different weights inevitably cause either over-representing or under-presenting of either “good” or “bad” sites. So a particular sample as presented in Fig. 8 may be accidentally good or bad. In both theory and reality, any given site may have as long a record as any other site. So a question that arises naturally is what if a “bad” site has long records and thus contributing more to the global estimate of bias.

Here we assume that the site-by-site, or site-wise, biases behind the data in Fig. 8 are truthfully characteristic of the sites associated with them, and assign the same weight to each site-wise bias in bootstrap sampling. (These site-wise biases are not shown, but they look qualitatively the same as Fig. 7.) In other words, we will give each site, “good” or “bad”, the equal opportunity to participate in the evaluation of the global bias. There are 31 sites with valid records, ranging from 21 to 93 monthly means at a site from 2000-04 to 2007-12. Given the possible number of different bootstrap samples of \( \binom{2n-1}{n} \) data points, the number 100,000 is pretty remote from oversampling even for 31 data points.
The right panels in Fig. 11 show the 100,000 bootstrap samples. The biases computed from equally-weighted site-wise biases are -5.38, -8.77 and -6.93 W m\(^{-2}\) for GSW(V3.0), SYN1deg(Ed4A) and EBAF(Ed4.0), respectively, not dramatically different from those given in the figure. Apparently, the appearance and disappearance of sites in a random manner can have more notable effects. This is to say, if we let all the 31 sites have the same chance to appear, reappear or disappear in participating the calculation of the global bias, then the distribution of the bias will be much wider than in the case discussed in last section, as indicated by the 95% confidence intervals or widths thereof given in the figure.

The overlapping of the 3 curves in the lower-right panel of Fig. 11 shows random appearance and disappearance of the sites can sometimes blur the differences between the 3 datasets, even between the 2 extreme sets, the GSW(V3.0) and EBAF(V4.0).

In the absolute sense, however, even the boundaries of the 95% confidence intervals are not dramatically different from the biases given in Fig. 8.

So the statistics we presented in earlier sections are pretty robust.

### 6 Discussion and Conclusions

In spite of the generally negative biases, the 3 satellite-based datasets agree reasonably well with their RadFlux counterparts. The biases and variability thereof can probably be attributed mostly to uncertainties in the effects of aerosols and precipitable water.

When clouds are absent or artificially removed in computer models, aerosols and precipitable water emerge as leading actors in creating variability and uncertainties in the radiative fluxes, though to a much lesser extent compared to that of clouds.

The flux data at some BSRN sites are supplemented with AODs from the Aerosol Robotics Network (AERONET) [25] at 7 wavelengths varying from around 300 nm to over 1000 nm and precipitable water; at the 7 SURFRAD sites, a subset of BSRN, AODs at 5 wavelengths varying from around 415 nm to around 870 nm and the Angstrom exponent computed from 500 nm and 870 nm are available from the Multifilter Rotating Shadowband Radiometer (MFRSR) [26-27]. Though the availability of these data is haphazard, we manage to derive the AODs at 550 nm and 840 nm using the Angstrom exponent derived from the available AODs or directly taken when available as in the case of SURFRAD sites. These data in the form of monthly means are then compared with their CERES counterparts.
Fig. 9 shows how the CERES monthly mean AOD at 550 nm, AOD at 840 nm and precipitable water compare with their BSRN counterparts. The appreciable positive biases in all three scatter plots tend to show that, according to satellite-derived data, the loads of aerosols and water vapor in the atmosphere are systematically more than those from ground-based observations. These results at least partly explain why the satellite-derived clear-sky shortwave downward fluxes exhibit systematic negative biases.

As mentioned earlier, the sub-pixel clouds that go undetected may humidify aerosols nearby [21], enhancing their light scattering ability [22]. This phenomenon can potentially increase the AOD as observed by instruments on-board satellites and consequently decrease the surface downward shortwave flux under a sky treated as clear in spite of the opposite.

Fig. 10 shows that the CERES SYN1deg(Ed4A)-BSRN AOD difference at 550 has a correlation coefficient of -0.4908 with their corresponding clear-sky shortwave flux differences; similarly, their precipitable water difference is correlated with their corresponding clear-sky shortwave difference with a coefficient of -0.3176. Both correlation coefficients are appreciable.

According to the analysis of Long and Ackerman [2], the uncertainty of the RadFlux clear-sky shortwave downward fluxes is comparable to that of measuring instruments which is estimated to be 15 W m⁻² or 3% whichever is larger for the 1-to 5-minute average of total shortwave downward fluxes; uncertainties for hourly, daily and monthly averages are estimated to be 19, 11 and 7 W m⁻², respectively as Dutton et al. show [31]. And according to Kato et al. [19], the uncertainty of irradiance based on satellite-derive cloud and aerosol information is 12 W m⁻² for monthly mean gridded values of irradiances over the land.

Based on these additional data and information regarding uncertainties, the level of agreement between the satellite-based clear-sky shortwave downward fluxes at the Earth’s surface and the ground-based RadFlux is remarkably good. The generally negative biases can be attributed at least in part to discrepancies in AODs and the precipitable water. The bootstrap analysis of the biases indicate that they are very well within the ranges of possible variabilities, and the statistics from observations at this spatiotemporal scale are robust.

**Acknowledgments**

The authors wish to thank Martin Wild, Maria Z. Hakuba and Doris Folini for executing the RadFlux algorithm for non-SURFRAD BSRN sites and making their results available. We also thank David Rutan for making the BSRN AODs and precipitable water data available. This work was funded under the NASA Earth Science Mission, Radiation
Science Program, Dr. Hal Maring, program manager. Additional funding for data production and archival came from the Earth Science Mission, Dr. Jack Kaye.

References


2011; 21(1): 10-2.


[14] List of publications that used GEWEX SRB data: https://gewex-srb.larc.nasa.gov/common/php/SRBused_publications.php


Fig. 1. RadFlux clear-sky shortwave downward fluxes at 1-, 2-, 3- or 5-minute intervals are available for 42 BSRN sites, including 7 SURFRAD sites. The upper panel shows the geographical locations of the 42 sites, and the lower panel shows the available 7119 site-months of data from 1992 to late 2017.
Fig. 2. Comparison of the GEWEX SRB GSW(V3.0) with the RadFlux clear-sky shortwave downward fluxes at the Earth’s surface over the period from 1992-01 to 2007-12. The upper, middle, and lower panels are, respectively, the 3-hourly, daily and monthly means. The scatter density is used for the 3-hourly and daily means. The comparison statistics given in the scatter or scatter density plots are for, respectively, the “Global” (which means all comparable data points are included), “60° Poleward” and “60° Equatorward”. The symbol ρ stands for correlation coefficient, σ for standard deviation, μBSRN for the BSRN mean flux, and the μSRB is the SRB mean flux. Subsequent scatter or scatter density plots are annotated the same way. The bin size is 10 W m⁻² for the hourly mean histogram and 5 W m⁻² for the daily and monthly mean histograms. The “clear-sky Type 2” refers to the computed clear-sky fluxes.
when clouds are actually present but artificially removed. Both the RadFlux and the satellite-based data contain such data.

Fig. 3. The GSW(V3.0)-BSRN bias and standard deviation ($\sigma$) of 3-hourly mean clear-sky shortwave downward fluxes over the period from 1992-01 to 2007-12 in 0.05-sized bins of cos(SZA). The left panel shows the bias and $\sigma$ on the absolute scale and the number of data points (N), and the right panels shows the bias and $\sigma$ as percentage of the mean fluxes ($\mu_{BSRN}$). The horizontal axis at the top shows the SZA corresponding to the center of the bin.
Fig. 4. Comparison of the CERES SYN1deg(Ed4A) with the RadFlux clear-sky shortwave downward fluxes at the Earth’s surface over the period from 2000-04 to 2017-06. The upper, middle, and lower panels are, respectively, the hourly, daily and monthly means. The scatter density is used for the hourly and daily means. The bin size is 10 W m$^{-2}$ for the hourly mean histogram and 5 W m$^{-2}$ for the daily and monthly mean histograms.
Fig. 5. The SYN1deg(Ed4A)-BSRN bias and standard deviation (σ) of hourly mean clear-sky shortwave downward fluxes over the period from 2000-04 to 2017-06 in 0.05-sized bins of cos(SZA). The left panel shows the bias and σ on the absolute scale and the number of data points (N), and the right panel shows the bias and σ as percentage of the mean fluxes (μBSRN). The horizontal axis at the top shows the SZA corresponding to the center of the bin.

Fig. 6. Comparison of the CERES EBAF(Ed4.0) with the RadFlux clear-sky shortwave downward fluxes at the Earth’s surface over the period from 2000-04 to 2017-06. The EBAF data is available as monthly means. The bin size of the histogram is 5 W m⁻².
Fig. 7. The bias and standard deviation (σ) from CERES EBAF(Ed4.0) and SYN1deg(Ed4A)-BSRN monthly mean clear-sky shortwave downward flux comparison over the period from 2000-04 to 2017-06 on a site-by-site basis. The left panel is on the absolute scale in the unit of W m⁻², and the right vertical axis (N) is the number of data points; the right panel is on the relative scale as percentage of the mean flux (µBSRN) as indicated on the right vertical axis.
Fig. 8. The GEWEX SRB GSW(V3.0), SVN1deg(Ed4A) and CERES EBAF(Ed4.0) local monthly mean clear-sky shortwave downward flux comparison with BSRN over the period from 2000-04 to 2017-12 over which the 3 datasets overlap.
Fig. 9. The CERES SYN1deg(Ed4A) monthly mean AODs at 550 nm and 840 nm and precipitable water (w) against their BSRN counterparts. The AERONET AODs at various wavelengths are available for selected non-SURFRAD site-months, and the MFRSR AODs at various wavelengths are available for the SURRAD sites. The BSRN AODs at 550 nm and 840 nm are derived using the Angstrom exponent. The data show that the atmosphere for the satellite-based algorithms systematically has more aerosol as well as precipitable water.
Fig. 10. The CERES SYN1deg(Ed4A)-BSRN monthly mean clear-sky shortwave downward flux difference versus their AOD counterpart at 550 nm and precipitable water counterpart. Both are appreciably negatively correlated, which is physically sensible. N is the number of data points, and ρ is the correlation coefficient. The BSRN sites with AOD at 550 nm concurrent with SYN1deg(Ed4A) fluxes are NYA, BAR, CAB, PAL, FPE, SXF, PSU, BOS, BON, BOU, CLH, DRA, GCR, BER and SBO; with w are NYA, BAR, CAB, PAL, BOU, CLH, BER and SBO.

Fig. 11. Bootstrapping analysis of the monthly mean biases as presented in Fig. 8. The left panels show the 100,000 resamplings of the 2347 site-month biases; the right panels show the 100,000 resampling of the 31 site-wise monthly mean biases with all site-wise biases equally weighted. The upper panels show the 100,000 realizations in the two kinds of resampling of the GEWEX SRB GSW(V3.0)-RadFlux biases.
The symbol $\sigma$ stands for the standard deviation of each individual realization of resampling. The lower panels show the distributions of the 100,000 realizations of resampling of the GEWEX SRB GSW(V3.0)-, CERES SYN1deg(Ed4A)- and EBAF(Ed4.0)-RadFlux biases, respectively.