Clear-sky land surface upward longwave radiation dataset derived from the ABI onboard the GOES–16 satellite

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ABSTRACT
Surface upward longwave radiation (SULR) is one of the four components of the surface radiation budget, which is defined as the total surface upward radiative flux in the spectral domain of 4-100 μm. The SULR is an indicator of surface thermal conditions and greatly impacts weather, climate, and phenology. Big Earth data derived from satellite remote sensing have been an important tool for studying earth science. The Advanced Baseline Imager (ABI) onboard the Geostationary Operational Environmental Satellite (GOES-16) has greatly improved temporal and spectral resolution compared to the imager sensor of the previous GOES series and is a good data source for the generation of high spatiotemporal resolution SULR. In this study, based on the hybrid SULR estimation method and an upper hemisphere correction method for the SULR dataset, we developed a regional clear-sky land SULR dataset for GOES-16 with a half-hourly resolution for the period from 1\textsuperscript{st} January 2018 to 30\textsuperscript{th} June 2020. The dataset was validated against surface measurements collected at 65 Ameriflux radiation network sites. Compared with the SULR dataset of the Global LAnd Surface Satellite (GLASS) longwave radiation product that is generated from the Moderate Resolution Imaging Spectroradiometer (MODIS) onboard the polar-orbiting Terra and Aqua satellites, the ABI/GOES-16 SULR dataset has commensurate accuracy (an RMSE of 15.9 W/m\textsuperscript{2} vs 19.02 W/m\textsuperscript{2} and an MBE of $-4.4$ W/m\textsuperscript{2} vs $-2.57$ W/m\textsuperscript{2}), coarser spatial resolution (2 km at nadir vs 1 km resolution), less spatial coverage (most of the Americas vs global), fewer weather conditions (clear-sky vs all-weather conditions) and a greatly improved temporal resolution (48 vs 4 observations a day). The published data are available at \url{http://www.dx.doi.org/10.11922/sciencedb.j00076.00062}.

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1. Introduction

The surface upward longwave radiation (SULR) is one of the four components of the surface radiation budget (SRB) calculation, which is defined as the total surface upward radiative flux, namely the sum of surface-emitted thermal radiation and the first-order reflected component of surface downward longwave radiation (SDLR) in the spectral domain of 4-100 μm (Jiao, Yan, Zhao, Wang, & Chen, 2015; Liang, Wang, He, & Yu, 2019; Liang, Wang, Zhang, & Wild, 2010). The SULR is an indicator of the surface thermal state and the dominant SRB component at night and at high latitudes (for example, polar regions) (Cheng & Liang, 2016) and a diagnostic parameter for ecological, hydrological, and biogeochemical process studies (Liang et al., 2010; Yang et al., 2013).

Remote sensing is the only way to monitor the surface thermal state on regional or global scales (Li et al., 2013b, 2021; Wan & Dozier, 1996; Wei et al., 2019, 2021a). Big Earth data derived from satellite remote sensing have been an important tool in the study of earth science (Guo, 2017; Guo, Wang, & Liang, 2016; Wei et al., 2021b). Broadband satellite sensors such as the Clouds and the Earth’s Radiant Energy System (CERES) series onboard the Terra/Aqua/S-NPP/JPSS-1 satellites were launched to monitor the variation of surface longwave radiation (Liang et al., 2019). In the past two decades, satellite sensors with narrow bands but higher spatial resolutions (1 km compared with the 20 km spatial resolution of CERES) have been used to estimate instantaneous SULR (Bisht, Venturini, Islam, & Jiang, 2005; Jiao et al., 2015; Liang et al., 2019; Wang, Liang, & Augustine, 2009). The SULR dataset of the long-term Global LAnd Surface Satellite (GLASS, available at the National Earth System Science Data Center of China (http://www.geodata.cn/data/index.html)) (Cheng & Liang, 2016; Cheng, Liang, Wang, & Guo, 2017; Liang et al., 2020; Yang & Cheng, 2020), with a temporal extent from 2000 to 2018, was generated with 1 km-resolution polar-orbit Moderate Resolution Imaging Spectroradiometer (MODIS) data. The GLASS SULR was calculated using the hybrid method (Cheng & Liang, 2016) (we named it as single-angle hybrid method in this paper) that was developed based on Wang et al. (2009), which estimates the SULR directly from top-of-atmosphere (TOA) radiances. Validation results based on the Ameriflux sites showed that the GLASS SULR product has a root-mean-square error (RMSE) of 19.02 W/m² and a mean bias error (MBE) of $-2.57 \text{ W/m}^2$ (Zeng, Cheng, & Dong, 2020).

The GLASS SULR product is a valuable dataset for the remote sensing community. However, MODIS sensors aboard Terra and Aqua only observe the Earth four times daily at low latitudes and may not meet the temporal requirements of different applications (Wang & Liang, 2010). Additionally, the thermal radiation directionality (TRD) effect of the land surface was ignored in the generation of the GLASS SULR product (Cheng & Liang, 2016). The TRD is a significant anisotropic phenomenon that causes different radiance values to be recorded when measuring the same place with two thermal infrared (TIR) sensors from different directions (Cao et al., 2019; Ren, Yan, Chen, & Li, 2011; Ren et al., 2013). Coll, Galve, Niclòs, Valor, and Barberà (2019) analyzed the difference in surface brightness temperatures between the nadir and forward views of the dual-view Advanced Along-Track Scanning Radiometer (AATSR), showing differences of up to 8 K in the summer. Hu et al. (2016) improved the SULR estimation of 7.5 W/m² by considering the TRD effect when processing multi-angle airborne data.

Geostationary satellites have high temporal resolution and can provide multiple observations to overcome the TRD effect (i.e. a fixed viewing angle but variant solar
angle) in 1 day, representing a potentially better data source for SULR generation than polar-orbiting satellites. For example, the Advanced Baseline Imager (ABI) onboard the Geostationary Operational Environmental Satellite (GOES–16) has a continuous observation capability (temporal resolution of 10–15 minutes), a wide viewing range (covering up to 160° latitude/longitude extents with one scene), and a high spatial resolution (2 km at nadir). Here, we applied a novel kernel-driven model (KDM) for the hemispherical integration of daytime ABI observations, which can convert the single-angle estimated SULR (SULR\text{e}) to hemispherical integrated SULR (SULR\text{h}) with ≥6 daytime clear-sky conditions SULR\text{e}. In this study, we generated a half-hourly resolution clear-sky land SULR dataset with ABI/GOES-16 for 1\textsuperscript{st} January 2018 to 30\textsuperscript{th} June 2020, which was validated against surface measurements collected at 65 Ameriflux radiation network sites.

This paper is organized into five sections. Section 2 describes the SULR retrieval method in detail, and Section 3 introduces the SULR dataset generated in this study. The validation results with in situ-measured SULR are presented in Section 4. Finally, some usage notes are given in Section 5.

2. Methods

2.1. Flowchart of ABI/GOES-16 SULR dataset generation

GOES-16 was launched on 19\textsuperscript{th} November 2016 and reached its stand-by geostationary orbit above 89.5°W ten days later. After 1 year of analysis and calibration, GOES-16 was relocated to its operational location of 75.2°W on 18\textsuperscript{th} December 2017. The ABI onboard GOES-16 has a greatly improved observation capability compared with the imager of the previous GOES series, and has sixteen spectral bands with a temporal resolution of 10–15 minutes (depending on the imaging modes). There are six TIR bands located in the spectral region of 8 – 14 µm that have a nadir spatial resolution of 2 km. Therefore, ABI/GOES-16 is a good data resource for SULR generation. A flowchart of the ABI/GOES-16 SULR dataset generation is shown in Figure 1. The datasets used for SULR generation are summarized in Table 1.

From Figure 1, we can see that the estimation process can be divided into two steps. First, the single-angle SULR values were estimated with the hybrid SULR estimation coefficients (see Table 2 in Section 2.2) at corresponding viewing zenith angles (VZAs), TOA radiance of bands 11 (8.55 µm), 14 (11.2 µm), and 15 (12.3 µm), the clear sky mask product, and the land/sea mask product using Equation (1). Then, the pixels with a moderate leaf area index (LAI) (i.e. LAI ∈ [0.2, 2.5]) and ≥6 daytime observations at 9:00 to 16:00 local time (i.e. clear sky observations N ∈ [6, 15]) were used to drive the TRD correction method (see Equations (5)–(7) in Section 2.2) because the method has six unknown parameters and the TRD effect was relatively high at a moderate LAI canopy (Coll et al., 2019). For the SULR values that did not satisfy these two requirements, the estimated SULR using the single-angle hybrid method was directly output as the ABI/GOES-16 SULR dataset.

2.2. The single-angle hybrid SULR estimation and TRD correction method

The single-angle hybrid SULR estimation method estimates the SULR using the linear combination of the TOA radiances with the coefficients generated under the assumption of surface thermal isotropic conditions (Wang & Liang, 2009). Therefore, the single-angle
estimated SULR with the hybrid method is angular dependent, especially in the daytime over medium-LAI land covers (Hu et al., 2016, 2017). The single-angle estimated SULR values were first calculated using Equation (1).

\[
SULR_e = a_{0,\theta_v} + a_{1,\theta_v} \cdot L_{\text{TOA,11}} + a_{2,\theta_v} \cdot L_{\text{TOA,14}} + a_{3,\theta_v} \cdot L_{\text{TOA,15}}
\]  

(1)

where \(SULR_e\) is the single-angle estimated SULR with the hybrid method, \(\theta_v\) is the VZA, \(a_{0,\theta_v} - a_{3,\theta_v}\) are the regression coefficients at \(\theta_v\), \(L_{\text{TOA,11}}, L_{\text{TOA,14}},\) and \(L_{\text{TOA,15}}\) are ABI TOA radiance of ABI bands 11, 14, 15 (8.55, 11.2, 12.3 \(\mu m\)) and corresponding viewing angles. The single-angle estimated SULR values were first calculated using Equation (1).
radiances for bands 11 (8.55 µm), 14 (11.2 µm), and 15 (12.3 µm), respectively. The variation of coefficients \( a_{0,\theta_v} - a_{3,\theta_v} \) with VZA is only designed to consider the atmospheric optical path variation with VZA.

The four coefficients in Equation (1) were regressed with a representative simulated dataset of \( SULR' \) and corresponding TOA radiance (\( L'_{TOA,11}, L'_{TOA,14} \) and \( L'_{TOA,15} \)), which was composed of Equations (2)–(4).

\[
R(\lambda) = \varepsilon(\lambda)B(\lambda, T) + (1 - \varepsilon(\lambda))L_i(\lambda) \tag{2}
\]

\[
SULR' = \pi \int_0^{100} R(\lambda)d\lambda \tag{3}
\]

\[
L'_{TOA,i} = \frac{\int_{\lambda_1}^{\lambda_2} (R(\lambda)\tau(\lambda) + L_i(\lambda))SRF_i(\lambda)d\lambda}{\int_{\lambda_1}^{\lambda_2} SRF_i(\lambda)d\lambda} \tag{4}
\]

where \( R(\lambda) \) is the angular-independent spectral surface-leaving radiance, \( \varepsilon(\lambda) \) is the spectral surface emissivity at wavelength \( \lambda \), \( B(\lambda, T) \) is the surface thermal emission calculated by Plank's law at the equivalent surface temperature \( T \), \( L_i(\lambda) \) is the atmospheric downwelling spectral radiance, \( i \) is the ABI band number \((i = 11, 14 \text{ or } 15)\), \( \lambda_1 \) and \( \lambda_2 \) are the spectral range boundaries for band \( i \), \( \tau(\lambda) \) and \( L_i(\lambda) \) are the spectral transmittance and atmospheric upwelling spectral radiance and \( SRF_i(\lambda) \) is the spectral response function of band \( i \).

Typical spectral surface emissivities \((\varepsilon(\lambda))\) were extracted from the MODIS UCSB (University of California, Santa Barbara) spectral library (Li et al., 2013a). Thirty-five emissivity spectra were selected, including three spectra for water, one spectrum for ice, one spectrum for snow, 13 spectra for soils and minerals, and 17 spectra for vegetation. A total of 946 typical clear-sky atmospheric profiles were extracted from the Thermodynamic Initial Guess Retrieval (TIGR) database (Chevallier, Chéruy, Scott, & Chédin, 1998) and input into the MODerate resolution atmospheric TRANsmission (MODTRAN) radiative transfer computation model (Berk et al., 2003) to obtain a representative database of \( \tau(\lambda), L_i(\lambda), L_i(\lambda), \) and \( B(\lambda, T) \). Using Equations (2)–(4), 198,660 groups of SULR and corresponding TOA radiances were obtained (Qin et al., 2020).

Then, the SULR estimation coefficients \( a_{0,\theta_v} - a_{3,\theta_v} \) at typical VZAs \((\theta_v=0–60^\circ \text{ with a } 10^\circ \text{ step})\) were generated using linear regression. The coefficients and the corresponding theoretical accuracies \((R^2, \text{MBE, and RMSE})\) are summarized in Table 2. The single-angle hybrid method has good theoretical accuracy with a coefficient of determination \((R^2)\) higher than 0.988, an MBE close to 0 W/m\(^2\) and RMSE from 6.9 to 11.3 W/m\(^2\) with the increase of VZA.

Therefore, the \( SULR' \) can be calculated using the clear-sky TOA radiance and the estimation coefficients (in Table 2) using Equation (1). It should be noted that the SULR value at a specific VZA was calculated with the interpolation or extrapolation of SULR values, which were calculated with the coefficients at adjacent VZAs. For SULR values that satisfy the two criteria described in Section 2.1, the single-angle estimated SULR of the geostationary satellite \((SULR_\theta(\theta_v(t),\varphi(t),\theta_v,\varphi_v))\) in the daytime can be corrected to be the hemispherical integrated SULR \((SULR_m)\) using Equations (5)–(7) with \( \geq 6 \) daytime clear-sky observations.
\[
SULR_e(\theta_s(t), \varphi_s(t), \theta_{v0}, \varphi_{v0}) = SULR_m(t) + A \cdot SULR_m(t) \cdot \cos(\theta_s(t)) \cdot e^{-\frac{-(\theta(t), \varphi(t), \theta_{v0}, \varphi_{v0})}{\pi s}} \tag{5}
\]

\[
SULR_m(t) = SULR_0 + SULR_a \cdot \cos\left(\frac{\pi}{\omega}(t - t_m)\right), \quad t_{sr} \leq t \leq t_{ss} \tag{6}
\]

\[
\xi(\theta_s(t), \varphi_s(t), \theta_{v0}, \varphi_{v0}) = \text{acos} (\cos \theta_{v0} \cdot \cos \theta_s(t) + \sin \theta_{v0} \cdot \sin \theta_s(t) \cdot \cos(\varphi_s(t) - \varphi_{v0})) \tag{7}
\]

where \(t\) is the time, \(\theta_s\) is the solar zenith angle (SZA), \(\varphi_s\) is the solar azimuth angle (SAA), \(\theta_{v0}\) is the VZA, \(\varphi_{v0}\) is the viewing azimuth angle (VAA), \(SULR_m(t)\) is the hemispheric integrated SULR at time \(t\), \(A\) is the parameter indicating the TRD amplitude, \(B\) is the parameter controlling the hotspot width, \(\xi\) is the angular distance between the illumination and viewing directions, \(SULR_0\) is the residual SULR around sunrise \((t_{sr})\), \(SULR_a\) is the SULR amplitude, \(\omega\) is the width over the half-period of the cosine term, \(t_m\) is the time at which the SULR reaches its maximum, and \(t_{ss}\) is the time around sunset. In total, there are six unknown parameters, \(SULR_0, SULR_a, \omega, t_m, A\) and \(B\).

Reasonable initial values and boundaries of the six parameters \((SULR_0, SULR_a, \omega, t_m, A\) and \(B)\) of the TRD correction method (Equations (5)–(7)) are needed to obtain a stable regression result in the estimation process. The four diurnal variation model (DVM) parameters \((SULR_0, SULR_a, \omega'\) and \(t_m\)) of \(SULR_e\) were regressed and used as the initial values of the DVM parameters of \(SULR_m\). Then, the boundaries for \(SULR_0, SULR_a, \omega\) and \(t_m\) were set as \([SULR_0 - 80, SULR_0 + 80]\), \([SULR_a - 80, SULR_a + 80]\), \([\omega' - 2, \omega' + 2]\) and \([t_m - 2, t_m + 2]\), respectively. The \(A\) parameter indicates the TRD maximum amplitude. The initial value of \(A\) was set at 0.05, and the boundary was set as \([0, 0.1]\), which means that the maximum TRD amplitude was limited to 10% of the \(SULR_m\). The \(B\) parameter is structure-dependent and indicates the hotspot width. The initial value of \(B\) \((B')\) was calculated with the \(k\) parameter of Ermida, Trigo, DaCamara, and Pires (2018) (we obtained the \(k\) value through personal communication with Ermida) and the relationship between \(k\) and \(B\) values (Cao et al., 2021). The map of \(B'\) value is plotted in Figure 2. The boundaries of \(B\) were set as \([0.5 \cdot B', 1.5 \cdot B']\) for the regression of the KDM parameters.

3. ABI/GOES-16 SULR dataset

3.1. Product description

The clear-sky ABI/GOES-16 land SULR dataset contains the clear-sky land SULR values for the full-disc coverage region and supplemental data. The dataset was named ABI_SULR_GOES16 and has temporal coverage from January 1\(^{st}\), 2018, to June 30\(^{th}\), 2020. The ABI_SULR_GOES16 dataset has a temporal resolution of 30 minutes (i.e. 48 files a day). It has a spatial resolution of 2 km in the nadir direction and covers most of the Americas (except some areas of the northern part of North America). The characteristics of the ABI_SULR_GOES16 dataset are summarized in Table 3.

The ABI_SULR_GOES16 dataset filenames (i.e. the granule ID) follow a naming convention that gives useful information about the dataset. For example, for the filename ABI_SULR_GOES16_20200010830_v001_20201101030.nc:
**Figure 2.** The map of $B'$ corresponding to the ABI/GOES-16 SULR dataset for TRD correction parameter regression ($0.05^\circ \times 0.05^\circ$ spatial resolution).

**Table 3.** Summary of the ABI SULR dataset.

| Characteristic                                      | Description                                                                 |
|-----------------------------------------------------|-----------------------------------------------------------------------------|
| Product Name                                       | ABI_SULR_GOES16                                                            |
| Temporal Coverage                                  | January 1st, 2018 – June 30th, 2020                                        |
| Temporal Resolution                                | 30 minutes/48 files a day                                                  |
| Spatial Resolution                                 | 2 km at nadir direction                                                     |
| Projection                                          | ABI fixed grid coordinate system (see Section 3.2)                         |
| Data Format                                         | NetCDF-4                                                                   |
| File Size                                           | ~5 MB                                                                      |
| Data Fields                                         | 5                                                                          |
| Dimensions                                          | 5424/5424 (rows/columns)                                                   |
| Image center (lat, lon) *                          | 0°, −75.0°                                                                |
| Image geospatial bounds (north, south, west, east) **| 81.3282, −81.3282, −156.2995, 6.2995                                       |

*The GOES-East nominal satellite subpoint longitude is −75.2 degrees east. However, the image product data have been resampled to be centered at −75.0 degrees east longitude.

**This shows the geospatial bounds of the image, which were inherited from the GOES-R ABI Level 1b product; the valid data geospatial bounds were smaller than the image geospatial bounds since the VZA was limited to less than 65° in the generation of the ABI_SULR_GOES16 dataset.

(1) ABI_SULR_GOES16 – Product Short Name
(2) 20200010830 – Julian Date of Acquisition (YYYYYDDDHHMM)
(3) v001 – Collection Version
(4) 20201101030 – Julian Date of Production (YYYYYDDDHHMM)
(5) nc – Data Format (Net-CDF)
Samples of the SULR dataset at UTC hour 10:00 for two dates (2018-01-01 and 2020-06-30) are shown in Figure 3. The Southern Hemisphere was warmer than the Northern Hemisphere in Figure 3(a), while the opposite is shown in Figure 3(b), for which the subsolar point was in the Southern Hemisphere in January and in the Northern Hemisphere in June.

3.2. Data field description

The ABI_SULR_GOES16 dataset is delivered in the netCDF-4 file format. The global attributes and variables are defined in Tables 4 and 5, respectively. The variable “data quality flag (DQF)” contains an array that describes the quality of the SULR dataset. The description of the DQF information of the dataset is shown in Table 6.

4. Product validation

4.1. Ameriflux in situ measurements

In situ pyrgeometer-measured SULR values are necessary for validation of the SULR dataset described in this paper. The data of 65 sites from the radiation network of Ameriflux (https://ameriflux.lbl.gov) corresponding to the temporal range of the ABI_SULR_GOES16 dataset (from 1st January 2018 to 30th June 2020) were downloaded for the validation. The geolocations of these sites range from 27.4°N to 47.2°N and 71.3°W to 121.5°W, with six different surface types. There were 10 sites for cropland (sites #1-10), 29 sites for forest (sites #11-39), 12 sites for grassland (sites #40-51), 4 sites for savanna (sites #52-55), 5 sites for shrubs (sites #56-60), and 5 sites for wetland (sites #61-65). The geolocations of the 65 SULR monitoring sites are plotted in Figure 4, with a background map of MODIS 1-km International Geosphere Biosphere Programme (IGBP) land cover classifications (Friedl et al., 2002) in 2019. Detailed information on these sites is listed in Table 7.
The clear-sky ABI/Goes16 SULR validation data corresponding to the 65 in-situ measurement sites were extracted to validate the accuracy of the 2.5-year dataset. It is important to remove cloud-contaminated outliers in the evaluation of thermal-related products (Duan et al., 2019). The “3σ-Hampel identifier” method (Davies & Gather, 1993) was used to remove the outliers in this study. We obtained 845,042 available clear-sky

**Table 4. The global attributes of the ABI_SULR_GOES16 dataset.**

| Global attribute | Value | Type |
|------------------|-------|------|
| Dataset_name     | Refer to the filename conventions in Section 3.1 | String |
| Institution      | State Key Laboratory of Remote Sensing Science, Aerospace Information Research Institute, Chinese Academy of Sciences | String |
| Projection       | GOES | String |
| Title            | ABI_SULR_GOES16 | String |
| Summary          | The ABI_SULR_GOES16 dataset consists of an image of 2-km spatial resolution clear-sky land SULR values on the ABI fixed grid for the full-disk coverage region. The SULR dataset is generated with the hybrid method and the dynamic kernel-driven thermal radiation directionality correction method. | String |
| Orbital_slot     | GOES-East | String |
| Platform_ID      | G16 | String |
| Spatial_resolution | 2 km at nadir | String |
| Instrument_type  | GOES-R Series Advanced Baseline Imager | String |
| Date_created     | YYYYDDDHHMM | String |

**Table 5. The variables of the ABI_SULR_GOES16 dataset.**

| Variable          | Type | Name | Attribute | Value | Type |
|-------------------|------|------|-----------|-------|------|
| SULR              | Short | Long_name | Surface longwave upward radiation | [0 20000] | Short |
|                   |       | Scale_factor | 0.05 | Float |
|                   |       | Add_offset | 0 | Float |
|                   |       | Fill_value | NaN | Short |
|                   |       | Unit | W/m² | String |
| DQF               | Byte | Long_name | Surface longwave upward radiation dataset data quality flags | | |
|                   |       | Fill_Value | 0 | Byte |
|                   |       | Valid_range | 0.12 | Byte |
| x                 | Short | Long_name | GOES-R fixed grid projection y-coordinate | | String |
|                   |       | Standard_name | Projection y-coordinate | String |
|                   |       | Scale_factor | -5.6e-5 | Float |
|                   |       | Add_offset | 0.151844 | Float |
|                   |       | Unit | Radian | String |
|                   |       | Axis | Y | String |
| Goes_imager_projection | Int | Long_name | GOES–R ABI fixed grid projection x-coordinate | | String |
|                   |       | Standard_name | Projection x-coordinate | String |
|                   |       | Scale_factor | 5.6e-5 | Float |
|                   |       | Add_offset | -0.151844 | Float |
|                   |       | Unit | Radian | String |
|                   |       | Axis | X | String |

The clear-sky ABI/GOES16 SULR validation data corresponding to the 65 in-situ measurement sites were extracted to validate the accuracy of the 2.5-year dataset. It is important to remove cloud-contaminated outliers in the evaluation of thermal-related products (Duan et al., 2019). The “3σ-Hampel identifier” method (Davies & Gather, 1993) was used to remove the outliers in this study. We obtained 845,042 available clear-sky
samples to conduct the validation. The number of samples of different sites and surface-type categories, months, and local hours (with and without TRD correction) is plotted in Figure 5.

Figure 5(a) shows that there are enough clear-sky samples for reliable validation for every site and surface-type category. The minimum number of samples in each category was 6,742 for cropland, 5,224 for forest, 5,580 for grassland, 15,630 for savanna, 12,703 for shrubs, and 5,381 for wetland. Figure 5(b) shows that there is a large number of samples in every month. December had the fewest samples (44,782) whereas May had the most (87,612). Figure 5(c) shows that there is a diurnal variation trend with the available clear-sky samples every half hour. The clear-sky samples are relatively stable and high at night, with a decrease from morning to afternoon and an increase from afternoon to nighttime, which is caused by cloud cover variation in the daytime. It should be noted that four sites had only a one-hour resolution; therefore, the sample number in hours is larger than that of the adjacent sites with half-hourly resolution. The red bar in Figure 5(c) indicates the samples that were TRD corrected (i.e. DQF>2), which shows that 47.0–62.2% of observations from 9:00 to 16:00 local time were TRD corrected.

4.2. Validation results

The accuracy of the SULR dataset was quantified with RMSE and MBE. The scatter density plot between the in situ-measured SULR and the SULR dataset with all the validation data is given in Figure 6. The scatterplot shows a wide range in the validation data, from 160.0 to 678.9 W/m². The RMSE and MBE of the ABI/GOES-16 SULR dataset were 15.9 W/m² and −4.4 W/m², respectively. Based on the GLASS validation result of Zeng et al. (2020) that calculated with Ameriflux sites, the ABI/GOES-16 SULR dataset has a slightly lower RMSE (15.9 W/m² vs 19.02 W/m²) but a more biased MBE (−4.4 W/m² vs −2.57 W/m²). Basically, these two datasets have a commensurate accuracy.

The accuracy of the SULR dataset was separately studied at all 65 sites and for all surface types (cropland, forest, grassland, savanna, shrubs, and wetland). The RMSE and MBE of each site and the scatter plots of the six categories are shown in Figure 7. Figure 7 (a,b) shows that the RMSE and MBE vary across surface types. Grassland was the only surface type for which the RMSE of all sites was lower than 20 W/m², ranging from 12.3 W/m² to 17.5 W/m², with an MBE from −11.9 W/m² to 10.5 W/m². Savanna had the largest RMSE of the surface types, from 11.3 W/m² to 25.4 W/m², with an MBE from −3.8 W/m² to 4.6 W/m². Cropland, shrubs, and wetlands all had one site with an RMSE greater than 20 W/m². The RMSE (MBE) ranges for cropland, shrubs, and wetland were 12.4–21.3 (−9.8–12.7) W/m², 12.0–20.9 (−9.4–−1.4) W/m², and 12.0–24.3 (−6.1–−4.2) W/m², respectively.
The forest surface type had two sites with RMSEs of more than 20 W/m², and the RMSE (MBE) range of the forest surface type was 7.9–21.7 (−13.8–9.5) W/m².

Figure 7 (c–h) shows that the forest and wetland had relatively narrower SULR ranges and relatively lower SULR values since these surface types have a good ability to regulate temperature, especially at high temperatures. The SULR ranges for forest and wetland surface types were 180.3–572.3 W/m² and 175.0–547.2 W/m², respectively. Grassland had the widest SULR range (160.0–678.5 W/m²) whereas cropland, savanna, and shrubs had medium SULR ranges (164.5–647.0 W/m², 238.9–631.5 W/m², and 235.1–678.9 W/m², respectively). Grassland had the smallest RMSE value of 14.9 W/m² since it is relatively homogeneous among the six surface types whereas the savanna had the largest RMSE of 17.8 W/m² and is the most heterogeneous surface type studied. Forest, wetland, shrubs, and cropland had very close RMSE of 15.7 W/m², 16.0 W/m², 16.1 W/m², and 16.2 W/m², respectively. The MBE were −6.6 W/m² to 0.6 W/m², and most (5 out of 6) were negative except for the savanna surface type (0.6 W/m²). The MBE were −6.6 W/m², −5.4 W/m², −4.7 W/m², −4.5 W/m², and −1.1 W/m² for forest, wetland, shrubs, grassland, and cropland, respectively.

The validation results during the four seasons were further studied. It should be noted that all the validation sites are located in the Northern Hemisphere. The validation results are plotted in Figure 8, which shows that the SULR ranges vary seasonally. Spring had the widest SULR range (from 175.0 W/m² to 655.6 W/m²); fall ranked second considering the range of SULR values (from 202.8 W/m² to 636.6 W/m²). Summer had a relatively narrower SULR range (from 293.3 W/m² to 678.9 W/m²) but the highest average SULR value. Winter had the narrowest SULR range (from 160.0 W/m² to 519.1 W/m²), and the lowest average
| Number of sites | Site ID | Full Name | Latitude | Longitude | Elevation (m) | Land cover | Climate zone | Temporal resolution (minutes) | Time period |
|----------------|--------|-----------|----------|-----------|--------------|------------|--------------|-----------------------------|-------------|
| 1              | US-ARM | ARM Southern Great Plains site– Lamont | 36.6058  | −97.4888  | 314          | Cropland   | Cfa          | 30                          | 2018–2020   |
| 2              | US–B1  | Bouldin Island Alfalfa | 38.0992  | −121.4993 | −2.7         | Cropland   | Csa          | 30                          | 2018–2019   |
| 3              | US–B2  | Bouldin Island com | 38.1091  | −121.5351 | −5           | Cropland   | Csa          | 30                          | 2018–2020   |
| 4              | US–DFC | US Dairy Forage Research Center, Prairie du Sac | 43.3448  | −89.7117  | 264.9        | Cropland   | Dfb          | 30                          | 2018–2020   |
| 5              | US–Ne1 | Mead – irrigated continuous maize site | 41.1651  | −96.4766  | 361          | Cropland   | Dfa          | 60                          | 2018–2019   |
| 6              | US–Ne2 | Mead – irrigated maize–soybean rotation site | 41.1649  | −96.4701  | 362          | Cropland   | Dfa          | 60                          | 2018–2019   |
| 7              | US–Ne3 | Mead – rainfed maize–soybean rotation site | 41.1797  | −96.4397  | 363          | Cropland   | Dfa          | 60                          | 2018–2019   |
| 8              | US–Ro5 | Rosemount I18_South | 44.691   | −93.0576  | 283          | Cropland   | Dfa          | 30                          | 2018–2020   |
| 9              | US–Ro6 | Rosemount I18_North | 44.6946  | −93.0578  | 282          | Cropland   | Dfa          | 30                          | 2018–2020   |
| 10             | US–xSL | NEON North Sterling, CO (STER) | 40.4619  | −103.0293 | 1364         | Cropland   | Bsk          | 30                          | 2018–2020   |
| 11             | US–Ha2 | Harvard Forest Hemlock Site | 42.5393  | −72.1779  | 360          | Forest     | Dfb          | 30                          | 2018–2020   |
| 12             | US–HB2 | Hobcaw Barony Mature Longleaf Pine | 33.3242  | −79.244   | 4.7          | Forest     | Cfa          | 30                          | 2019        |
| 13             | US–HB3 | Hobcaw Barony Longleaf Pine Restoration | 33.3482  | −79.2322  | 7.3          | Forest     | Cfa          | 30                          | 2019        |
| 14             | US–HBK | Hubbard Brook Experimental Forest | 43.9397  | −71.7181  | 367          | Forest     | Dfb          | 30                          | 2018–2020   |
| 15             | US–MM5 | Morgan Monroe State Forest | 39.3232  | −86.4131  | 275          | Forest     | Cfa          | 60                          | 2018–2019   |
| 16             | US–MB2 | Mt Bigelow | 32.4167  | −110.7255 | 2573         | Forest     | Dfb          | 30                          | 2018–2019   |
| 17             | US–NC2 | NC_Loblolly Plantation | 35.803   | −76.685   | 5            | Forest     | Cfa          | 30                          | 2018–2019   |
| 18             | US–NC3 | NC_Clearcut3 | 35.799   | −76.656   | 5            | Forest     | Cfa          | 30                          | 2018–2019   |
| 19             | US–NR1 | Nixot Ridge Forest (LTER NWT1) | 40.0329  | −105.5464 | 3050         | Forest     | Dfc          | 30                          | 2018–2020   |
| 20             | US–Srv | Sylvania Wilderness Area | 46.242   | −89.3477  | 540          | Forest     | Dfb          | 30                          | 2018–2020   |
| 21             | US–UMB | Univ. of Mich. Biological Station | 45.5598  | −84.7138  | 234          | Forest     | Dfb          | 30                          | 2018–2020   |
| 22             | US–UMB | UNBS Disturbance | 45.5625  | −84.6975  | 239          | Forest     | Dfb          | 30                          | 2018–2020   |
| 23             | US–Vcm | Valles Caldera Mixed Conifer | 35.8884  | −106.5321 | 3003         | Forest     | Dfb          | 30                          | 2018–2019   |
| 24             | US–Vcp | Valles Caldera Ponderosa Pine | 35.8642  | −106.5967 | 239          | Forest     | Dfb          | 30                          | 2018–2019   |
| 25             | US–Vcs | Valles Caldera Sulphur Springs Mixed Conifer | 35.9193  | −106.6142 | 2572         | Forest     | Dfb          | 30                          | 2018–2019   |
| 26             | US–WCr | Willow Creek | 45.8059  | −90.0799  | 520          | Forest     | Dfb          | 30                          | 2018–2020   |
| 27             | US–xBR | NEON Bartlett Experimental Forest (BART) | 44.0639  | −71.2873  | 232          | Forest     | Dfb          | 30                          | 2018–2020   |
| 28             | US–xGR | NEON Great Smoky Mountains National Park, Twin Creeks (GRSM) | 35.689   | −83.5019  | 579          | Forest     | Cfa          | 30                          | 2018–2020   |
| 29             | US–xHA | NEON Harvard Forest (HARV) | 42.5369  | −72.1727  | 351          | Forest     | Dfb          | 30                          | 2018–2020   |
| 30             | US–xJE | NEON Jones Ecological Research Center (JERC) | 31.1948  | −84.4686  | 44           | Forest     | Cfa          | 30                          | 2018–2020   |
| 31             | US–xRM | NEON Rocky Mountain National Park, CASTNET (RMNP) | 40.2759  | −105.5459 | 2743         | Forest     | Dfc          | 30                          | 2018–2020   |
| 32             | US–xSE | NEON Smithsonian Environmental Research Center (SERC) | 38.8901  | −76.56    | 15           | Forest     | Cfa          | 30                          | 2018–2020   |
| 33             | US–xSP | NEON Soaproot Saddle (SOAP) | 37.0334  | −119.2622 | 1160         | Forest     | Cfa          | 30                          | 2018–2020   |
| 34             | US–xST | NEON Steigerwald Land Services (STEI) | 45.5089  | −89.5864  | 481          | Forest     | Dfb          | 30                          | 2018–2020   |

(Continued)
Table 7. (Continued).

| Number of sites | Site ID | Full Name                                      | Latitude | Longitude | Elevation (m) | Land cover | Climate zone* | Temporal resolution (minutes) | Time period |
|-----------------|---------|-----------------------------------------------|----------|-----------|---------------|------------|---------------|------------------------------|-------------|
| 35              | US-xTE  | NEON Lower Teakettle (TEAK)                   | 37.0058  | –119.906  | 2147          | Forest     | Csa           | 30                           | 2018–2020 |
| 36              | US-xTR  | NEON Treehaven (TREE)                         | 45.4937  | –89.5857  | 472           | Forest     | Dfb           | 30                           | 2018–2020 |
| 37              | US-xUK  | NEON The University of Kansas Field Station (UKFS) | 39.0404  | –95.1921  | 335           | Forest     | Cfa           | 30                           | 2018–2020 |
| 38              | US-xUN  | NEON University of Notre Dame Environmental Research Center (UNDE) | 46.2339  | –89.5373  | 518           | Forest     | Dfb           | 30                           | 2018–2020 |
| 39              | US-xYE  | NEON Yellowstone Northern Range (Frog Rock) (YELL) | 44.9535  | –110.5391 | 2116          | Forest     | Dfc           | 30                           | 2018–2020 |
| 40              | US-BMM  | Bangtail Mountain Meadow                      | 45.783   | –110.7776 | 2324          | Grassland  | Dfc           | 30                           | 2018–2019 |
| 41              | US-ONA  | Florida pine flatwoods                        | 27.3836  | –81.9509  | 25            | Grassland  | Cfa           | 30                           | 2018–2019 |
| 42              | US-Ro4  | Rosemount Prairie                             | 44.6781  | –93.0723  | 274           | Grassland  | Dsa           | 30                           | 2018–2020 |
| 43              | US-Seq  | Sevilleta grassland                           | 34.3623  | –106.702  | 1596          | Grassland  | Bsk           | 30                           | 2018–2019 |
| 44              | US-SRG  | Santa Rita Grassland                          | 31.7894  | –110.8277 | 1291          | Grassland  | Bsk           | 30                           | 2018–2020 |
| 45              | US-Var  | Vaira Ranch – Ione                            | 38.1433  | –120.9508 | 129           | Grassland  | Csa           | 30                           | 2018–2020 |
| 46              | US-WKg  | Walnut Gulch Kendall Grasslands               | 31.7365  | –109.9419 | 1531          | Grassland  | Bsk           | 30                           | 2018–2020 |
| 47              | US-xCP  | NEON Central Plains Experimental Range (CPER) | 40.8155  | –104.7456 | 1654          | Grassland  | Bsk           | 30                           | 2018–2020 |
| 48              | US-xDC  | NEON Dakota Coteau Field Station (DCFS)       | 47.1617  | –99.1066  | 559           | Grassland  | Dfb           | 30                           | 2018–2020 |
| 49              | US-xKA  | NEON Konza Prairie Biological Station – Relocatable (KONA) | 39.1104  | –96.6129  | 1329          | Grassland  | Cfa           | 30                           | 2018–2020 |
| 50              | US-xKZ  | NEON Konza Prairie Biological Station (KONZ)  | 39.1008  | –96.5631  | 381           | Grassland  | Cfa           | 30                           | 2018–2019 |
| 51              | US-xNG  | NEON Northern Great Plains Research Laboratory (NOSP) | 46.7697  | –100.9154 | 578           | Grassland  | Dfb           | 30                           | 2018–2020 |
| 52              | US-Mpj  | Mountainair Pinyon–Juniper Woodland           | 34.4384  | –106.2377 | 2138          | Savanna    | Bsk           | 30                           | 2018–2019 |
| 53              | US-SRM  | Santa Rita Mesquite                           | 31.8214  | –110.8661 | 1120          | Savanna    | Bsk           | 30                           | 2018–2020 |
| 54              | US-Ton  | Tonzi Ranch                                   | 38.4309  | –120.966  | 177           | Savanna    | Csa           | 30                           | 2018–2020 |
| 55              | US-Wjs  | Willard Juniper Savannah                      | 34.4255  | –105.8615 | 1931          | Savanna    | Bsk           | 30                           | 2018–2019 |
| 56              | US-Ses  | Sevilleta shrubland                           | 34.3349  | –106.7442 | 1604          | Shrubs     | Bsk           | 30                           | 2018–2019 |
| 57              | US-Whs  | Walnut Gulch Lucky Hills Shrub                | 31.7438  | –110.0522 | 1370          | Shrubs     | Bsk           | 30                           | 2018–2020 |
| 58              | US-xJR  | NEON Jornada LTER (JORN)                      | 32.5907  | –106.8425 | 1329          | Shrubs     | Bsk           | 30                           | 2018–2019 |
| 59              | US-xNQ  | NEON Onaqui–Ault (ONAQ)                       | 40.1776  | –112.4524 | 1685          | Shrubs     | Dfb           | 30                           | 2018–2020 |
| 60              | US-xSR  | NEON Santa Rita Experimental Range (SRER)     | 31.9107  | –110.8355 | 983           | Shrubs     | Bsk           | 30                           | 2018–2020 |
| 61              | US-ALQ  | Allequash Creek Site                          | 46.0308  | –89.6067  | 497           | Wetland    | Dfb           | 30                           | 2018–2019 |
| 62              | US-HB1  | North Inlet Crab Hawk Creek                   | 33.3455  | –79.1957  | 0.1           | Wetland    | Cfa           | 30                           | 2018–2019 |
| 63              | US-KS3  | Kennedy Space Center (salt marsh)             | 28.7084  | –80.7427  | 0             | Wetland    | Cfa           | 30                           | 2018–2019 |
| 64              | US-Los  | Lost Creek                                    | 46.0827  | –89.9792  | 480           | Wetland    | Dfb           | 30                           | 2018–2020 |
| 65              | US-NC4  | NC_AlligatorRiver                             | 35.7879  | –75.9038  | 1             | Wetland    | Cfa           | 30                           | 2018–2019 |

*Köppen climate classification (http://www.gloeho.org/koppen/).
SULR since winter is the coolest of the four seasons. The RMSE in the four seasons showed little variation, ranging from 15.4 W/m² (in fall) to 16.5 W/m² (in summer). The RMSE in spring and winter were in the middle, 16.0 W/m² and 15.5 W/m², respectively. The MBE in the four seasons were all negative, from −8.8 W/m² (in winter) to −1.3 W/m² (in summer). The MBE in fall and spring were in the middle, both −4.2 W/m².

The accuracy of the SULR dataset was also studied with daytime and nighttime samples. It should be noted that the daytime samples were defined as a VZA less than 90°, and nighttime samples were defined as a VZA greater than 90° here. The scatter plots of the validation results are shown in Figure 9. The daytime SULR samples had a much wider SULR range than that at night. The daytime SULR was 165.5 W/m² to 678.9 W/m² and that at nighttime was 160.0 W/m² to 517.1 W/m², which can be explained by solar heating in the daytime. The RMSE at nighttime was 14.7 W/m², which is more accurate than that in the daytime (17.2 W/m²). The result that the daytime RMSE is higher than that
of the nighttime RMSE is similar to previous research (Cheng & Liang, 2016; Qin et al., 2020; Wang et al., 2009). Zeng et al. (2020) evaluated the GLASS SULR product with multiple radiation monitoring networks; here, we chose the GLASS SULR accuracy values calculated with the Ameriflux sites for comparison. From Figure 9, we know that the daytime accuracy of the ABI/GOES-16 SULR dataset (RMSE of 17.2 W/m², MBE of –0.4 W/m²) is higher than that of the GLASS (RMSE of 24.38 W/m², MBE of –1.12 W/m²); however, the nighttime accuracy of the ABI/GOES-16 SULR dataset (RMSE of 14.7 W/m², MBE of –7.6 W/m²) is more biased than that of the GLASS SULR product (RMSE of 12.70 W/m², MBE of –3.82 W/m²).

Based on the high temporal resolution of our ABI/GOES-16 SULR dataset, the half-hourly RMSE and MBE values were calculated to analyze the SULR dataset's accuracy every half hour. The RMSE and MBE of the SULR dataset at every half hour are plotted in Figure 10. The RMSE shows a clear diurnal variation trend with a relatively stable value at nighttime and a parabolic shape at daytime. The RMSE at nighttime was 14.7 W/m² (see Figure 9(b)), and the maximum RMSE of 23.2 W/m² during the daytime was at 12:00 local time. The MBE showed a similar trend with that of the RMSE in both daytime and nighttime. The mean MBE at nighttime was –7.6 W/m², and the maximum MBE of 4.1 W/m² was also at 12:00 local time. The single-angle hybrid SULR estimation method seems to have a negative system bias at nighttime; the nighttime negative bias phenomenon has been reported in previous studies (Qin et al., 2020; Zeng et al., 2020). Although the daytime TRD was corrected with the TRD correction method described in Section 2.2, there are still remaining TRD effects in the daytime, which require additional analysis in the future.

One of the features of the generated ABI/GOES-16 SULR dataset is the application of the TRD correction method. The accuracy of the TRD-corrected samples before and after TRD correction was further studied, and the results are plotted in Figure 11. From Figure 11(a,b),
we can see that the RMSE value of the TRD-corrected samples decreased from 21.9 W/m² to 20.1 W/m² with an improvement of 1.8 W/m² (i.e. 8.2%), and the MBE decreased from 9.4 W/m² to 3.0 W/m² with an improvement of 6.4 W/m² (i.e. 68.1%) after TRD correction. From Figure 11(c), we know that the RMSE range narrowed from 13.9 W/m² – 25.2 W/m² to 14.1 W/m² – 23.2 W/m². There were a negative or positive RMSE improvement of −0.22 W/m² (at 16:00) – 2.44 W/m² (at 10:30) after TRD correction. There was an RMSE improvement of >1 W/m² at 9:00 – 12:30 local time; however, an RMSE improvement of <0.53 W/m² at 13:00 – 16:00 and negative improvements of −0.03 W/m² and −0.22 W/m² at local time 14:30 and 16:00, respectively. From Figure 11(d), we can see that the MBE range narrowed
from $-0.2 \text{ W/m}^2$ to $-1.4 \text{ W/m}^2$ after TRD correction. There was a $|\text{MBE}|$ value decrement of 0.35 W/m$^2$ (at 9:00)– 6.47 W/m$^2$ (at 11:00) at 9:00– 15:30 local time; however, there was a $|\text{MBE}|$ increasement of 1.03 W/m$^2$ at 16:00 after TRD correction.
Figure 10. The RMSE and MBE of the SULR dataset at every half hour.

Figure 11. The accuracy of the TRD-corrected samples before and after TRD correction. (a-b) Scatter plots of the in situ-measured SULR and estimated SULR before and after TRD correction; (c-d) the RMSE and MBE at different local times before and after TRD correction.
5. Usage notes

5.1. Recommended software tool for dataset quick look

The Panoply Data Viewer is a free cross-platform software that can plot georeferenced netCDF, HDF and GRIB products. It was developed by the US National Aeronautics and Space Administration (NASA) Goddard Institute for space studies. The software can be easily installed on Macintosh, Windows, Linux and other desktop computers. See https://www.giss.nasa.gov/tools/panoply/ for more information.

5.2. Geolocation and viewing angle files of the ABI/GOES-16 SULR dataset

For geostationary satellites, the geolocation and viewing angles for a specific row and column number in the dataset were static; therefore, the geolocation and viewing angle files are provided as supplementary information and were stored in the data repository. The file information for the SULR dataset is listed in Table 8.

6. Potential applications

The SULR is one of the four components of the SRB calculation and is the indicator of the surface thermal state. The SULR greatly impacts the cooling and heating of the near-surface atmosphere, the evaporation of water, and the transpiration of plants. The SULR is also the predominant SRB component at night and at high latitudes during most times of the year. Therefore, the SULR can greatly benefit research on weather forecasting, climate change, the energy cycle, and agriculture.

Data availability statement

The datasets produced in this study are openly available in the Science Data Bank at http://www.dx.doi.org/10.11922/sciencedb.j00076.00062.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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