Reviewer #1

OVERALL

1) Comment: This is a nice work, in which SunDu-derived surface solar radiation ($R_s$) data are merged with satellite-derived cloud fraction and AOD data to generate high spatial resolution ($0.1^\circ$) $R_s$ over China. Both direct $R_s$ observations (pyranometer data) at ~100 stations and sun duration records at 2400 stations are used in this study to demonstrate the reliable performances of the merging results. A striking result is that AOD plays a negligible role in the merging results, which indicates that the estimation method of $R_s$ from sunshine measurements is robust and reliable. The result is valuable because long-term AOD retrievals are not accessible when building long-term $R_s$ data. The paper is well organized. I suggest to accept this submission after following issues are addressed.

Reply: The authors would like to thank anonymous referee #1 for his detailed and helpful comments. Below are our point by point responses to his comments.

GENERAL COMMENTS

2) Comment: It is not clear how to calculate clear sky $R_s$ although a simple equation is given. A detailed introduction to the method is required since the conclusion mainly relies on the method. I wonder whether aerosol effect on $R_s$ is accounted for by Sunshine duration measurement or by the equation used for the calculation of clear sky $R_s$. Addition, pls introduce more clearly which data are used in the calculation of clear sky $R_s$. 
Reply: Following anonymous referee #1 comments, we have added the description of the calculation of clear sky $R_s$ (Lines 255-263):

“For the clear sky $R_s$, $\tau_{c,\text{dir}}$ and $\tau_{c,\text{dif}}$ are calculated using a modified broadband radiative transfer model by simplifying Leckner’s spectral model (Leckner, 1978), which the effect of transmittance functions of permanent gas absorption, Rayleigh scattering, water vapour absorption, ozone absorption, and aerosol extinction are parameterized using the surface air temperature, surface pressure, precipitable water, the thickness of the ozone layer, turbidity as inputs (Yang et al., 2006). Calculation of $R_s$ also includes impacts of aerosols because SunDu is impacted by changes in both clouds and aerosols (Wang, 2014).”


3) Comment: It was said that site dependent parameters were used in the equation 1 (e.q., $a_0$-$a_2$). I’m not sure how to derive these parameters at each station.

Reply: We added the details of these site dependent parameters (Lines 249-252):
“a₀, a₁, and a₂ are the station-dependent parameters by tuning this equation with measurements of Rₛ and SunDu and then the method is applied regionally (Wang, 2014). Instead using observations from weather stations in Japan (Yang et al., 2006), observations in CMA are used (Wang, 2014).”


4) Comment: Frankly speaking, I’m not comfortable with the statement that the CERES EBAF can be taken as the reference. This seems based on the result that the agreement between SunDu-derived Rs and EBAR is much better than that between SunDu-derived Rs and pyranometer measurements. My opinion is that there seems possibility that aerosol effects were not properly accounted for by both SunDu-derived and satellite Rs algorithm. I mean this possibility cannot be fully eliminated, so it is suggestive to discuss this issue in somewhere.

Reply: Thanks for your suggestion, we agree with anonymous referee #1 that the data uncertainties cannot be fully eliminated for both ground observations and satellite retrievals. As mentioned in data section, the uncertainties of CERES EBAF data, reported by (Kato et al., 2018), in all sky global annual mean Rₛ is 4 W/m². The
descriptions of uncertainties of SunDu derived $R_s$ are added (Lines 84-87). The satellite $R_s$ retrievals and SunDu derived $R_s$ are totally independent, but the high agreements of these two datasets indicate that they both are of higher accuracy. We will also discuss this issue in the revised manuscript (Lines 269-273):

“No though, SunDu data do not provide a direct estimate of $R_s$ and have the different sensitivity of atmospheric turbidity changes, compared with $R_s$ observations, they are still a good proxy for variations of $R_s$ (Manara et al., 2017).”

“The satellite $R_s$ retrievals and SunDu derived $R_s$ are totally independent, but the high agreements of these two datasets indicate that they both are of higher accuracy. Similar results are also reported by (Wang et al., 2015) that low agreement between SunDu derived $R_s$ and direct $R_s$ observation is likely due to the directional response errors of the direct observations of $R_s$."


MINOR ISSUES

5) **Comment:** Lines 31, ‘Based on the SunDu-derived Rs from 97 meteorological observation stations: : ’, the authors should mention that these 97 stations are co-located with those that direct Rs measurements sites.

**Reply:** Thanks for your suggestion, we will add this information in **Lines 31-32:**

“Based on the SunDu-derived $R_s$ from 97 meteorological observation stations, which are co-located with those that direct $R_s$ measurement sites…”

6) **Comment:** Lines 130-133, what about the quality of the datasets from (Tang et al. 2019) and (Stengel et al. 2020)? I suggest the authors add detailed descriptions of these datasets.

**Reply:** we added the description of these dataset (**Lines 136-146**):

“Validation against the BSRN data indicated that SSR-tang have the mean bias error (MBE) of -11.5 W/m$^2$ and root mean square error (RMSE) of 113.5 W/m$^2$ for the instantaneous $R_s$ estimates at 10 km scale, but (Tang et al., 2019) point out that care should be taken when using this dataset for trend analysis due to the absent of realistic aerosols input data. Stengel et al. (2020) also show that $R_s$ derived from Cloud_cci AVHRR-PMv3 reveals a very good agreement against BSRN stations, with low standard deviations of 13.8 W/m$^2$ and correlation coefficients above 0.98. While the bias for shortwave fluxes is small (1.9 W/m$^2$). However, default an aerosol optical depth
of 0.05 or data from Aerosol cci Level-2 or NASA MODIS Level-2 aerosol data are used in BUGSrad model to calculate clear sky $R_s$, indicating that impact of aerosols is not perfect parameterized in Cloud_cci AVHRR-PMv3.”


7) **Comment:** Lines 164 to 165, the authors show that interpolation results have uncertainties due to the lack of detailed high spatial resolution information. What about the performances of machine learning methods in simulation of $R_s$. I suggest add more references here.

**Reply:** we added the description of these dataset (Lines 183-189):

“The performances of different machine learning methods have been evaluated in many previous studies, including simulation $R_s$ at regional scale with support of satellite retrievals (Wei et al., 2019; Yeom et al., 2019) and site scale by using routine meteorological observations (Cornejo-Bueno et al., 2019; Hou et al., 2020). Whatever models or training data are selected, the impacts of spatial relationship are not taken
into account in these machine learning methods and therefore large number of input data are required to ensure accuracy.”


8) **Comment:** Line 178, “0.1” changes to “0.1°”.

**Reply:** Corrected as suggestions (Line 199).

9) **Comment:** Lines 177 to 179, the authors merge the SunDu-derived Rs data with satellite-derived cloud fraction (CF) and AOD data. Why not directly merging the SunDu-derived Rs data with current Rs products?
Reply: Merging current Rs products with SunDu-derived $R_s$ can also be applicable. Since many long-term $R_s$ satellite products use climatology aerosols data as input, in this study, we want to know whether the merged product can achieve reliable $R_s$ data without support of satellite derived aerosols input data.

10) Comment: Line 183, “sunDu” changes to “SunDu”.

Reply: We have deleted the sentence. (Line 209)

11) Comment: Add spatial resolution of each dataset and the references of each dataset in table 2.

Reply: Corrected as suggestions (Line 238).

12) Comment: Line 291, why not use MODIS AOD as input data in this study.

Reply: we added the description of why we did not use MODIS AOD as input (Lines 318-322):

“We did not use AOD from MODIS, because MODIS AOD conation missing values and can't meet the requirements of spatiotemporal continuity of AOD input in this study. In addition, MODIS AOD is only available under clear sky conditions while AOD provided by the assimilation system is averaged under all conditions.”

13) Comment: Lines 316 to 317, SunDu derived Rs also contain the information of clouds, what about merging SunDu-derived Rs data only with AOD data?
Reply: We agree with reviewers that SunDu derived $R_s$ also contain the information of clouds. As cloud data can provide high resolution input data, we use cloud data to improve the spatial resolution of our merged data. We believe that with the support high resolution of AOD data, the merged data can produce more accurate results. However, the spatial resolution of current available AOD are 1 degree.

14) Comment: Lines 390 to 392, two validation sites are randomly selected to evaluate the seasonal and annual variations in $R_s$. I suggest two sites with high AOD values and low AOD values.

Reply: We have checked the selected validation sites. We added this information in the revised manuscript (Lines 422-423 and Lines 437-438).

“The multiyear mean of AOD from Changchun and BeiHai are 0.49 and 0.70, respectively.”

15) Comment: Line 474, “0.1” changes to “0.1°”.

Reply: Corrected as suggestions (Line 505).

16) Comment: Line 518, “0.1” changes to “0.1°”.

Reply: Corrected as suggestions (Line 555).

17) Comment: Lines 535 to 536, deleted “We also plan to expand our Rs dataset from 1983 to 2017 by using AVHRR based cloud retrievals.” Since this study focus the period
from 2000 to 2016.

Reply: Corrected as suggestions.
Reviewer #2

OVERALL

1) **Comment:** This study attempts to generate a high resolution surface solar radiation (Rs) dataset. The idea is to construct a linear model between station based Rs, cloud fraction and AOD, and applies the model to the full study domain (China). While this dataset can be potentially useful, I don’t understand how this approach could achieve a better accuracy than CERES 1 degree Rs product. This is because: (1) although the SunDu Rs can represent a much smaller area than the CERES 1 degree grid, SunDu Rs is validated using CERES Rs, which means that SunDu Rs cannot have a higher accuracy than CERES Rs, even at the 1 degree scale; (2) the AOD data used is still at 1 degree resolution. This does not add much finer information and may be the reason why AOD has little impact on the prediction results. Overall, I don’t see much value in this study unless the above question is addressed. Please see the specific comments below:

**Reply:** We realize that we have not clearly explained the significance of our work to generate high spatial resolution Rs data and the comparison results. We carefully think about all comments from anonymous referee #2. Below are our point by point responses to the comments.

MAJOR COMMENTS

2) **Comment:** The authors used SunDu Rs to train the model and to generate the high resolution Rs dataset. However, SunDu Rs is validated against CERES Rs, assuming that the latter has higher accuracy. On one hand, using grid based data to validate station
based data is not appropriate. There can be a lot of variability within this 1 degree box. The authors did compare SunDu Rs with observed Rs but argued that their agreement is not as good as that between SunDu Rs and CERES Rs, and that the agreement between the latter two proofs the reliability of SunDu Rs. I don’t agree with this argument. SunDu Rs should be directly validated against surface observed Rs. On the other hand, if CERES Rs is better than SunDu Rs, what’s the point of using SunDu Rs to generate the 0.1 degree dataset? I guess using CERES Rs with 0.1 cloud and AOD would achieve at least the same accuracy, if not better. Yet, it has the advantage of full spatial coverage than SunDu Rs.

Reply: We realize that we have not clearly explained the significance of our work and comparison results. In this study, we aim to build a reliable high resolution grid $R_s$ data by establishing the physical spatial relationship between ground based SunDu derived $R_s$ data with high resolution cloud satellite data with AOD to avoid the disadvantage of CERES for capturing the variability of $R_s$ within a 1 degree box. We have refined the description of our goals in the end of introduction (Lines 205-209): “Since current $R_s$ high quality $R_s$ such as CERES EBAF have low spatial resolution, the output of this study provides a reliable high resolution grid $R_s$ data to avoid the disadvantage of CERES EBAF for capturing the variability of $R_s$ within a 1 degree box and provide guidance to merge multisource data to generate long-term $R_s$ data over China.” We know that direct comparison between grid based data and station based data is not perfect. “However we show that the satellite $R_s$ retrievals and SunDu derived $R_s$ are totally independent, but the high agreements of these two datasets indicate that they
both are of higher accuracy. Similar results are also reported by (Wang et al., 2015) that low agreement between SunDu derived \( R_s \) and direct \( R_s \) observation is likely due to the directional response errors of the direct observations of \( R_s \)” (Lines 270-273). We know that direct comparison between grid based data and station based data is not perfect. But direct comparison are widely used as a tradeoff way for validation in many studies due to lack of reliable high resolution grid \( R_s \) data. In this study, we aim to build this reliable high resolution grid \( R_s \) data. One may argue that using CERES \( R_s \) with 0.1 cloud and AOD can also produce high resolution \( R_s \) data. However, there are large amount of input data are require to ensure the accuracy of CERES. Most of these input data in CERES have low spatial resolution and limited spatial coverage and are only available after 2000. SunDu \( R_s \) have long time records with large spatial coverage. The merged SunDu derived \( R_s \) data can overcome these disadvantages of CERES and have the possibilities to build long term \( R_s \) by using AVHRR data.

3) **Comment:** To proof the effect of fine resolution processing, a direct comparison with CERES should be provided. The authors can interpolate the CERES \( R_s \) to 0.1 degree and compare with their results. How difference are they? Are the differences physically explainable (i.e., related to cloud variability?).

**Reply:** Thanks for your suggestion. We have discussed this issue in the discussion section (Lines 542-545)

“By using spatial interpolation method, CERES \( R_s \) can also be downscaled to 1km or 30m. These interpolated CERES \( R_s \) data cannot represent the detailed \( R_s \) distributions at spatial resolution of 1km or 30m. Without additional high spatial resolution data,
interpolated cannot capture more detail variability of \( R_s \). High spatial resolution cloud data can provide more detail information of cloud variability.”

MINOR COMMENTS

4) **Comment:** What is the reason of the lower agreement between SunDu \( R_s \) and observed \( R_s \)?

**Reply:** The reason of the lower agreement between SunDu \( R_s \) and observed \( R_s \) have added in the revised manuscript (Lines 271-273)

“Similar results are also reported by (Wang et al., 2015) that low agreement between SunDu derived \( R_s \) and direct \( R_s \) observation is likely due to the directional response errors of the direct observations of \( R_s \).”


5) **Comment:** Why using CERES 1degree AOD? If spatial resolution matters, there are much finer products, such as the MODIS 1km and MODIS 3km products.

**Reply:** We have added the reasons in (Lines 319-323):

“We did not use AOD from MODIS, because MODIS AOD conation missing values and can’t meet the requirements of spatiotemporal continuity of AOD input in this study. In addition, MODIS AOD is only available under clear sky conditions while AOD provided by the assimilation system is averaged under all conditions.”

6) **Comment:** There are remote locations with very few SunDu stations, such as the
Tibet plateau, are the relationships applicable?

**Reply:** As shown in figure 9, the regional mean of the annual anomaly of the surface solar radiation ($R_s$) for zone II and zone VIII which are the regions such as the Tibet plateau. We notice that the merged $R_s$ (GWR-CF-AOD) can produce consistent variation of Rs compared with observed data, indicating the relationships are applicable.

7) **Comment:** It would be interesting to look at the spatial distribution of the coefficients. This can tell us some information about where clouds make a bigger impact and where aerosols are important.

**Reply:** According to the figure 6 in our previous study (Feng and Wang, 2019), cloud fraction shows strong negative correlation with $R_s$ in most parts of China, while slight weak correlation coefficient near the north border of China. While clear sky $R_s$, which are primarily impact by the atmospheric aerosol loading, generally have small the correlation coefficient with $R_s$ in most parts China.


8) **Comment:** What’s the unit of Figure 2?

**Reply:** We have added this information in the revised paper (**Lines 286-287**): “The unit of y-axis are w/m²”
Merging ground-based sunshine duration observations with satellite cloud and aerosol retrievals to produce high resolution long-term surface solar radiation over China

Fei Feng¹ † and Kaicun Wang² †

1. College of Forestry, Beijing Forestry University, Beijing 100083, China
2. State Key Laboratory of Earth Surface Processes and Resource Ecology, College of Global Change and Earth System Science, Beijing Normal University, Beijing, 100875, China

†These authors contributed equally to this work

Corresponding Author:

Fei Feng, College of Forestry, Beijing Forestry University, Email: forgetbear@bjfu.edu.cn;

Kaicun Wang, College of Global Change and Earth System Science, Beijing Normal University. Email: kcwang@bnu.edu.cn; Tel: +086 10-58803143; Fax: +086 10-58800059.
Abstract

Although great progress has been made in estimating surface solar radiation ($R_s$) from meteorological observations, satellite retrieval and reanalysis, getting best estimated long-term variations in $R_s$ are sorely needed for climate studies. It has been shown that sunshine duration (SunDu)-derived $R_s$ data can provide reliable long-term variability, but are available at sparsely distributed weather stations. Here, we merge SunDu-derived $R_s$ with satellite-derived cloud fraction and aerosol optical depth (AOD) to generate high spatial resolution (0.1°) $R_s$ over China from 2000 to 2017. The geographically weighted regression (GWR) and ordinary least squares regression (OLS) merging methods are compared, and GWR is found to perform better. Based on the SunDu-derived $R_s$ from 97 meteorological observation stations, which are co-located with those that direct $R_s$ measurement sites, the GWR incorporated with satellite cloud fraction and AOD data produces monthly $R_s$ with $R^2 = 0.97$ and standard deviation $= 11.14$ W/m$^2$, while GWR driven by only cloud fraction produces similar results with $R^2 = 0.97$ and standard deviation $= 11.41$ w/m$^2$. This similarity is because SunDu-derived $R_s$ has included the impact of aerosols. This finding can help to build long-term $R_s$ variations based on cloud data, such as Advanced Very High Resolution Radiometer (AVHRR) cloud retrievals, especially before 2000, when satellite AOD retrievals are not unavailable. The merged $R_s$ product at a spatial resolution of 0.1° in this study can be downloaded at https://doi.pangaea.de/10.1594/PANGAEA.921847 (Feng and Wang, 2020).
Introduction

A clear knowledge of variations in surface solar radiation ($R_s$) is vitally important for an improved understanding of the global climate system and its interaction with human activity (Jia et al., 2013; Myers, 2005; Schwarz et al., 2020; Wang and Dickinson, 2013; Wild, 2009, 2017; Zell et al., 2015). Direct measurements have shown that $R_s$ has significant decadal variability, namely, a decrease (global dimming) from the 1950s to the late 1980s and subsequent increase (global brightening) (Wild, 2009). The variation in $R_s$ is closely related to the Earth’s water cycle, the whole biosphere, and the amount of available solar energy. This situation emphasizes the urgency to develop reliable $R_s$ products to obtain the variability in $R_s$.

Great progress has been made in the detection of variability in $R_s$ by meteorological observations, satellite retrieval and radiation transfer model simulations or reanalysis $R_s$ products in previous studies (Rahman and Zhang, 2019; Wang et al., 2015). However, each estimation has its advantages and disadvantages. Direct observed data provide accurate $R_s$ records at short time scales; however, careful calibration and instrument maintenance are needed to maintain its long-term homogeneity. Previous studies have reported that direct observed $R_s$ over China may have major inhomogeneity problems due to sensitivity drift and instrument replacement (Wang, 2014; Wang et al., 2015; Yang et al., 2018). Before 1990, the imitations of the USSR pyranometers had different degradation rates of the thermopile, resulting in an important sensitivity drift. To overcome radiometer ageing problem, China replaced its instruments from 1990 to 1993. However, the new solar trackers failed frequently and introduced a high data missing rate for the direct radiation component of $R_s$ (Lu and Bian, 2012; Mo et al., 2008). After 1993, although the instruments were substantially improved, the Chinese-developed pyranometers still had high thermal offset with directional response errors,
and the stability of these instruments was also worse than that of the World Meteorological Organization (WMO) recommended first-class pyranometers (Lu et al., 2002; Lu and Bian, 2012; Yang et al., 2010). Yang et al. (2018) show that nearly half of observed $R_s$ (60 out of the 119 $R_s$ observed stations) have inhomogeneity issues. These artificial changes points in observed $R_s$ are mainly caused by instrument change (42 shifts), stations relocation (34 shifts), observation schedule change (20 shifts) and remaining 64 changepoints could not be identified.

SunDu data are relatively widely distributed and have a long-term record (Sanchezlorenzo et al., 2009; Wild, 2009). Existing studies have also confirmed that SunDu-derived $R_s$ data are reliable $R_s$ data, which can capture long-term trends of $R_s$ and reflect the impacts of both aerosols and clouds at time scales ranging from daily to decadal (Feng and Wang, 2019; Manara et al., 2015; Sanchezlorenzo et al., 2013; Sanchezromero et al., 2014; Tang et al., 2011; Wang et al., 2012b; Wild, 2016). Even though, SunDu data do not provide a direct estimate of $R_s$ and have the different sensitivity of atmospheric turbidity changes, compared with $R_s$ observations, they are still a good proxy for variations of $R_s$ (Manara et al., 2017).

Sunshine duration observations collected at weather stations in China have been used to reconstruct long-term $R_s$ (Che et al., 2005; Feng et al., 2019; He et al., 2018; He and Wang, 2020; Jin et al., 2005; Shi et al., 2008; Yang et al., 2006; Yang et al., 2020). Based on the global SunDu-derived $R_s$ records, He et al. (2018) found that SunDu permitted a revisit of global dimming from the 1950s to the 1980s over China, Europe, and the USA, with brightening from 1980 to 2009 in Europe and a declining trend $R_s$ from 1994 to 2010 in China. (Wang et al., 2015) found that the dimming trend from 1961 to 1990 and nearly constant zero trend after 1990 over China, as calculated from the SunDu-derived $R_s$, was consistent with independent estimates of AOD (Luo et al.,
2001); they also observed changes in the diurnal temperature range (Wang et al., 2012a; Wang and Dickinson, 2013) and the observed pan evaporation (Yang et al., 2015).

Although direct observations and SunDu-derived $R_s$ can provide accurate long-term variations in $R_s$, both direct observations and sunshine duration records are often sparsely spatially distributed.

Satellite $R_s$ retrievals and radiation transfer model simulations or reanalysis $R_s$ products can provide $R_s$ estimation with global coverage at high spatial resolution. However, model simulations and reanalysis $R_s$ products have substantial biases due to the deficiency of simulating cloud and aerosol quantities (Feng and Wang, 2019; Zhao et al., 2013). Previous comparative studies have shown that the accuracies of $R_s$ from reanalyses are lower than those of satellite products (Wang et al., 2015; Zhang et al., 2016) due to the good capability of capturing the spatial distribution and dynamic evolution of clouds in satellite remote sensing data.

Table 1 lists the current satellite-based $R_s$ products, which have been widely validated in previous studies. Zhang et al. (2004) found that the monthly International Satellite Cloud Climatology Project-Flux Data (ISCCP-FD) $R_s$ product had a positive bias of 8.8 w/m² using Global Energy Balance Archive (GEBA) archived data as a reference. By comparing 1151 global sites, Zhang et al. (2015) evaluated four satellite-based $R_s$ products, including ISCCP-FD, the Global Energy and Water Cycle Experiment-Surface Radiation Budget (GEWEX-SRB), the University of Maryland/Shortwave Radiation Budget (UMD-SRB) and the Earth’s Radiant Energy System energy balanced and filled product (CERES EBAF), and concluded that CERES EBAF shows better agreement with observations than other products. A similar overall good performance of CERES EBAF can also be found (Feng and Wang, 2018; Ma et al., 2015).
### Table 1. Current satellite-derived surface solar radiation ($R_s$) products

<table>
<thead>
<tr>
<th>Satellite $R_s$ product</th>
<th>Source</th>
<th>Spatial resolution</th>
<th>Time range</th>
</tr>
</thead>
<tbody>
<tr>
<td>ISCCP-FD</td>
<td>ISCCP</td>
<td>2.5°</td>
<td>1983-2009</td>
</tr>
<tr>
<td>GEWEX-SRB</td>
<td>ISCCP-DX</td>
<td>1°</td>
<td>1983-2007</td>
</tr>
<tr>
<td>UMD-SRB</td>
<td>METEOSAT-5</td>
<td>0.5°</td>
<td>1983-2007</td>
</tr>
<tr>
<td>GLASS-DSR</td>
<td>Terra/Aqua, GOES, MSG, MTSAT</td>
<td>0.05°</td>
<td>2008-2010</td>
</tr>
<tr>
<td>CLARA-A2</td>
<td>AVHRR</td>
<td>0.25°</td>
<td>2001-present</td>
</tr>
<tr>
<td>MCD18A1</td>
<td>Terra/Aqua, MODIS</td>
<td>5.6 km</td>
<td>2001-present</td>
</tr>
<tr>
<td>Himawari-8 SWSR</td>
<td>Himawari-8</td>
<td>5 km</td>
<td>2001-present</td>
</tr>
<tr>
<td>SSR-tang</td>
<td>ISCCP-HXG, ERA5, MODIS</td>
<td>10 km</td>
<td>1982-2017</td>
</tr>
<tr>
<td>Cloud_cci AVHRR-PMv3</td>
<td>AVHRR/CC4CL</td>
<td>0.05°</td>
<td>1982-2016</td>
</tr>
</tbody>
</table>

Although CERES EBAF uses more accurate input data to provide $R_s$ data, its spatial resolution is only 1° (Kato et al., 2018). Since 2010, new-generation geostationary satellites have provided opportunities for high temporal and spatial resolution $R_s$ data, such as Himawari-8 (Hongrong et al., 2018; Letu et al., 2020). However, the time span of the new-generation satellite-based $R_s$ product is short. The long-term AVHRR records provide the possibility of building long-term radiation datasets. The CLoud, Albedo and RAdition dataset, the AVHRR-based data-second edition (CLARA-A2), covers a long time period, but the spatial resolution is only 0.25° (Karlsson et al., 2017). Recently, Tang et al. (2019) built a satellite-based $R_s$ (SSR-tang) dataset using ISCCP-HXG cloud data. By using a variety of cloud properties derived from AVHRR, Stengel et al. (2020) presented the Cloud_cci AVHRR-PMv3 dataset generated within the Cloud_cci project.

Validation against the BSRN data indicated that SSR-tang have the mean bias error (MBE) of -11.5 W/m² and root mean square error (RMSE) of 113.5 W/m² for the instantaneous $R_s$ estimates at 10 km scale, but Tang et al. (2019) point out that care should be taken when using this dataset for trend analysis due to the absent of realistic aerosols input data. Stengel et al. (2020) also show that $R_s$ derived from Cloud_cci
AVHRR-PMv3 reveals a very good agreement against BSRN stations, with low
standard deviations of 13.8 W/m² and correlation coefficients above 0.98. While the
bias for shortwave fluxes is small (1.9 W/m²). However, default an aerosol optical depth
of 0.05 or data from Aerosol cci Level-2 or NASA MODIS Level-2 aerosol data are
used in BUGSrad model to calculate clear sky $R_s$, indicating that impact of aerosols is
not perfect parameterized in Cloud_cci AVHRR-PMv3.

On the other hand, the long-term cloud records also contain uncertainties. For
eexample, ISCCP cloud products, which directly combine geostationary and polar
orbiter satellite-based cloud data, have large inhomogeneity due to different amounts of
data from polar orbit and geostationary satellites and their different capabilities for
detecting low-level clouds (Dai et al., 2006; Evan et al., 2007). This inhomogeneity of
the cloud products might introduce significant inhomogeneity to the $R_s$ values
calculated from the cloud products (Montero-Martín et al., 2020; Pfeifroth et al., 2018b),
and $R_s$ long-term variability estimation still needs improvement.

Efforts have been made to further improve $R_s$ products. Merging multisource data
has become an effective empirical method for improving the quality of $R_s$ products
(Camargo and Dorner, 2016; Feng and Wang, 2018; Hakuba et al., 2014; Journée et al.,
2012; Lorenzo et al., 2017; Ruiz-Arias et al., 2015). For instance, to produce
spatiotemporally consistent $R_s$ data, multisource satellite data are used in Global LAnd
Surface Satellite (GLASS) $R_s$ products (Jin et al., 2013). By merging reanalysis and
satellite $R_s$ data by the probability density function-based method, the reanalysis $R_s$
biases can be substantially reduced (Feng and Wang, 2018). This finding suggests that
fusion methods are effective ways to improve the estimation of $R_s$, especially when $R_s$
impact factors are considered (Feng and Wang, 2019). Although linear regression fusion
methods can produce $R_s$ data incorporated with $R_s$ impact factors, the stable regression
parameters might have negative effects on the final fusion results due to the complex characteristics of $R_s$ spatial-temporal variability.

On the other hand, the spatial resolution of $R_s$ data is crucial for regional meteorology studies, as the minimum requirement of the spatial resolution of $R_s$ data, as suggested by the Observing Systems Capabilities Analysis and Review of WMO OSCAR), is 20 km (Huang et al., 2019). Interpolation methods are often included in $R_s$ fusion methods to further improve the spatial resolutions of $R_s$ data (Loghmari et al., 2018). For example, Zou et al. (2016) estimated global solar radiation using an artificial neural network based on an interpolation technique in southeast China. By integrating $R_s$ data from 13 ground stations with Meteosat Second Generation satellite $R_s$ products, Journée and Bertrand (2010) found that kriging with the external drift interpolation method performed better than mean bias correction, interpolated bias correction and ordinary kriging with satellite-based correction. However, interpolation results have uncertainties due to the lack of detailed high spatial resolution information. Although traditional linear regression fusion methods can incorporate high spatial resolution data during the fusion process, the impacts of the stable regression parameters need further investigation.

The performances of different machine learning methods have been evaluated in many previous studies, including simulation $R_s$ at regional scale with support of satellite retrievals (Wei et al., 2019; Yeom et al., 2019) and site scale by using routine meteorological observations (Cornejo-Bueno et al., 2019; Hou et al., 2020). Whatever models or training data are selected, the impacts of spatial relationship are not taken into account in these machine learning based model and therefore large number of input data are required to ensure accuracy.

Geographically weighted regression (GWR) is an extension of the traditional
regression model by allowing the relationships between dependent and explanatory
variables to vary spatially. Researchers have examined and compared the applicability
of GWR for the analysis of spatial data relative to that of other regression methods (Ali
et al., 2007; Gao et al., 2006; Georganos et al., 2017; LeSage, 2004; Sheehan et al.,
2012; Zhou et al., 2019a). Due to the large spatial heterogeneity of $R_s$ over China, the
GWR method might produce accurate $R_s$ variability estimations with an improved
spatial resolution.

This study is established to merge SunDu-derived $R_s$ data with satellite-derived
cloud fraction (CF) and AOD data to generate high spatial resolution ($0.1^\circ$) $R_s$ over
China from 2000 to 2017. The GWR and ordinary least squares (OLS) regression
merging methods are compared. CF and AOD are important $R_s$ impact factors, however,
many long-term $R_s$ satellite products use climatology aerosols data as input. Whether
much improvement is made in merging SunDu-derived $R_s$ by incorporating AOD is also
evaluated in this study, instead of evaluating direct merging current $R_s$ products with
SunDu-derived $R_s$. Since current $R_s$ high quality $R_s$ such as CERES EBAF have low
spatial resolution, the output of this study provides a reliable high resolution grid $R_s$
data to avoid the disadvantage of CERES EBAF for capturing the variability of $R_s$
within a 1 degree box and provide guidance to merge multisource data to generate long-
term $R_s$ data over China.

1. Data and Methodology

2.1. Ground-based observations

2.2.1 Direct observations

$R_s$ direct observations from 2000 to 2017 are obtained from the China
Meteorological Data Service Center (CMDC, http://data/cma/cn/) of the China
Meteorological Administration (CMA). TBQ-2 pyranometers and DFY4 pyranometers
have been used to measure $R_s$ since 1993. Daily $R_s$ values from 97 $R_s$ stations are collected, and we calculated monthly $R_s$ values by averaging daily $R_s$ values when daily observed data are available for more than 15 days for each month at each radiation station. These monthly $R_s$ values from direct measurements and collocated SunDu-derived $R_s$ are used as independent reference data to investigate the performances of the fusion methods (Fig. 1). The whole area over China is further divided into nine zones by the K-mean cluster method based on geographic locations and multiyear mean $R_s$ using 97 $R_s$ direct observation sites, as shown in Figure 1. The download instructions of the $R_s$ direct observations can be found in table 2.

Figure 1. The 2,400 sunshine duration (SunDu) merging sites are shown as light brown points, and 97 independent validation sites, including $R_s$ direct measurements and SunDu-derived $R_s$ measurements, are shown as brown red points. The whole region is classified into nine subregions (I to IX) by the K-mean cluster method based on geographic locations and multiyear mean $R_s$ using 97 $R_s$ direct observation sites. The
base hillshade map was produced by an elevation map of China using the global digital
elevation model (DEM) derived from the Shuttle Radar Topography Mission 30
(SRTM30) dataset.

Table 2. Summary of availability information for all source data used in this study.

CMDC is the China Meteorological Data Service Center. SunDu is the sunshine
duration data. $R_s$ is surface solar radiation and AOD is the aerosols optical depth.

<table>
<thead>
<tr>
<th>Data Source</th>
<th>Derived Parameters</th>
<th>Spatial resolution</th>
<th>Version</th>
<th>Access Point</th>
<th>Notes</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Direct $R_s$ measurement data from CMDC</td>
<td>$R_s$</td>
<td>-</td>
<td>Version 1.0</td>
<td><a href="http://data/cma/cn/">http://data/cma/cn/</a></td>
<td>Authentication is required for the China data use policy</td>
<td>-</td>
</tr>
<tr>
<td>SunDu observations and other meteorological data</td>
<td>$R_s$</td>
<td>-</td>
<td>Version 1.0</td>
<td><a href="http://data/cma/cn/">http://data/cma/cn/</a></td>
<td>Authentication is required for the China data use policy</td>
<td>-</td>
</tr>
<tr>
<td>CERES EBAF</td>
<td>$R_s$</td>
<td>1 degree</td>
<td>Ed4.1</td>
<td><a href="https://ceres.larc.nasa.gov/data/#ebaf-level-3b">https://ceres.larc.nasa.gov/data/#ebaf-level-3b</a></td>
<td>A email address to order the data</td>
<td>(Kato et al., 2018)</td>
</tr>
<tr>
<td>CERES SYN1deg</td>
<td>AOD</td>
<td>1 degree</td>
<td>Ed4A</td>
<td><a href="https://ceres.larc.nasa.gov/data/#syn1deg-level-3">https://ceres.larc.nasa.gov/data/#syn1deg-level-3</a></td>
<td>A email address to order the data</td>
<td>(Rutan et al., 2015)</td>
</tr>
<tr>
<td>MODAL2 MCLD</td>
<td>cloud fraction</td>
<td>0.1 degree</td>
<td>-</td>
<td>Directly download</td>
<td></td>
<td>(Platnick et al., 2017)</td>
</tr>
</tbody>
</table>

2.2.2 SunDu-derived $R_s$

Sunshine duration observations (SunDu) and other meteorological data (e.g., air
temperature, relative humidity and surface pressure) from 1980 to 2017, which were
collected from approximately 2,400 meteorological stations (http://data/cma/cn/) from
the CMA, are used to calculate the SunDu-derived $R_s$ (Fig. 1). $R_s$ values are calculated
following the method of the revised Ångström-Prescott equation (Eq. (1-2)) (He et al.,
2018; Wang, 2014; Wang et al., 2015; Yang et al., 2006).

$$\frac{R_s}{R_c} = a_0 + a_1 \frac{n}{K} + a_2 \left(\frac{n}{K}\right)^2$$  \hspace{1cm} (1)

$$R_c = \int (\tau_{c,\text{dir}} + \tau_{c,\text{dif}}) \times I_0 dt$$  \hspace{1cm} (2)

where $n$ represents the measured SunDu, and $K$ represents the theoretical value of the
SunDu. $a_0$, $a_1$, and $a_2$ are the station-dependent parameters by tuning this equation with
measurements of $R_s$ and SunDu and then the method is applied regionally (Wang, 2014).
Instead using observations from weather stations in Japan (Yang et al., 2006),
observations in CMA are used (Wang, 2014). $R_c$ is the daily total solar radiation at the
surface under clear-sky conditions (Eq. 2). $\tau_{c,\text{dir}}$ and $\tau_{c,\text{dif}}$ represent the direct radiation
transmittance and the diffuse radiation transmittance under clear-sky conditions. $I_0$ is the solar irradiance at the top of the atmosphere (TOA). For the clear sky $R_s$, $\tau_{c,\text{dir}}$ and
$\tau_{c,\text{dif}}$ are calculated using a modified a broadband radiative transfer model by
simplifying Leckner’s spectral model (Leckner, 1978), which the effect of transmittance
functions of permanent gas absorption, Rayleigh scattering, water vapour absorption,
ozone absorption, and aerosol extinction are parameterized using the surface air
temperature, surface pressure, precipitable water, the thickness of the ozone layer,
turbidity, sunshine duration as inputs (Yang et al., 2006). Calculation of $R_s$ also includes
impacts of aerosols because SunDu is impacted by changes in both clouds and aerosols
(Wang, 2014).

Based on the classified subregions using 97 direct $R_s$ observations in Figure 1, the
intercomparison results in Figure 2 and Figure 3 show that the agreement between
SunDu-derived $R_s$ and CERES EBAF $R_s$ estimates is better than that between the direct
observations and SunDu-derived $R_s$ estimates, which is likely due to the inhomogeneity issue of direct $R_s$ observations over China, as mentioned in many previous studies (Wang, 2014; Yang et al., 2018). The satellite $R_s$ retrievals and SunDu derived $R_s$ are totally independent, but the high agreements of these two datasets indicate that they both are of higher accuracy. Similar results are also reported by (Wang et al., 2015) that low agreement between SunDu derived $R_s$ and direct $R_s$ observation is likely due to the directional response errors of the direct observations of $R_s$.

The SunDu-derived $R_s$ observations, excluding SunDu observations located at direct observation sites, are used for merging. Ten percent merging observations are randomly selected for GWR parameter optimization. The download instructions of the SunDu observations can be found in table 2.
Figure 2. Statistical summary of annual anomaly $R_s$ from direct observed $R_s$, SunDu-derived $R_s$ and CERES EBAF $R_s$ estimates in different subregions. The statistics include the mean absolute bias (MAB), standard deviation (Std) and root mean square error (RMSE). We use MAB due to the cancelling out effect of positive bias and negative bias. Nine subregions (I to IX) over China are shown in Figure 1. S-D represent comparisons between SunDu-derived $R_s$ and directly observed $R_s$. C-D represent comparison between CERES EBAF $R_s$ and directly observed $R_s$. S-C represent comparisons between SunDu-derived $R_s$ and CERES EBAF $R_s$. The unit of y-axis are w/m$^2$.

Figure 3. Similar to Figure 2, but this statistical summary is for $R^2$.

2.2. Satellite data

$R_s$ data from the Clouds and Earth’s Radiant Energy System energy balanced and
filled product (CERES Synoptic (CERES) EBAF) surface product (edition 4.1) (Kato et al., 2018), cloud fraction from MODAL2 M CLD data product (Platnick et al., 2017) and AOD from the CERES SYN1deg) edition 4A product (Doelling et al., 2013) are collected in this study. CERES EBAF $R_s$ data are used as reference data. AOD from CERES SYN1deg and cloud fraction from MODAL2 M CLD are used as input data for fusion methods.

CERES is a 3-channel radiometer measuring three filtered radiances, including shortwave (0.3-5 µm), total (0.3-200 µm) and window (8-12 µm). $R_s$ from CERES EBAF are adjusted using radiative kernels, including bias correction and Lagrange multiplier processes. The input data of CERES EBAF are adjusted during the product generating process constrained by CERES observations at the TOA. The biases in temperature and specific humidity from the Goddard Earth Observing System (GEOS) reanalysis are adjusted by atmospheric infrared sounder (AIRS) data. Cloud properties, such as optical thickness and emissivity, from MODIS and geostationary satellites are constrained by cloud profiling radar, Cloud-Aerosol Lidar, and Infrared Pathfinder Satellite Observations (CALIPSO) detectors and CloudSat. The uncertainties of CERES EBAF data, reported by (Kato et al., 2018), in all sky global annual mean $R_s$ is 4 W m$^{-2}$. Previous studies (Feng and Wang, 2019; Feng and Wang, 2018; Ma et al., 2015; Wang et al., 2015) have shown that the CERES EBAF surface product provides reliable estimations of $R_s$.

CERES SYN1deg AOD derived from an aerosol transport model, named Atmospheric Transport and Chemistry Modelling (MATCH) (Collins et al., 2001), which assimilates MODIS AOD data, is used to obtain spatiotemporally consistent AOD data. Different aerosol constituents, including small dust (<0.5 µm), large dust (>0.5 µm), stratosphere, sea salt, soot and soluble, are used to compute the optical
thickness for a given constituent optical thickness for a given constituent. We did not use AOD from MODIS, because MODIS AOD contains missing values and can't meet the requirements of spatiotemporal continuity of AOD input in this study. In addition, MODIS AOD is only available under clear sky conditions while AOD provided by the assimilation system is averaged under all conditions.

Cloud fraction data from MODAL2 M CLD are collected as input cloud fraction data with a spatial resolution of 0.1° and time span from 2000 to 2017 (Platnick et al., 2017). The MODAL2 M CLD data are synthesized based on the cloud data from MOD06. Cloud fraction data from MOD06 are generated by the cloud mask product of MOD35 with a spatial resolution of 1 km. The MOD35 cloud mask is determined by applying appropriate single field of view (FOV) spectral tests to each pixel with a series of visible and infrared threshold and consistency tests. Each land type has different algorithms and thresholds for the tests. For each pixel test, an individual confidence flag is determined and then combined to produce the final cloud mask flag. The three confidence levels included in the cloud mask flag output are (i) high confidence for cloudless pixels (Group confidence values > 0.95); (ii) low confidence for unobstructed views on the surface (Group confidence values Q ≤ 0.66); and (iii) values between 0.66 and 0.95, and spatial and temporal continuity tests are further applied to determine whether the pixel is absolutely cloudless. Then, the cloud fraction is calculated from the 5 x 5-km cloud mask pixel groupings, i.e., given the 25 pixels in the group, the cloud fraction for the group equals the number of cloudy pixels divided by 25.

2.3. Methods
2.3.1 Fusion models

OLS regression and GWR are used to build fusion methods for estimating $R_s$ data. Clouds fraction and AOD have been important factors that affect variations in $R_s$. We compare different combinations of input data for the fusion methods, which can be
classified into two types. The first type only contains cloud fraction data. The second type contains clouds fraction and AOD (Feng and Wang, 2020).

The OLS regression model is a commonly used model to estimate dependent variables by minimizing the sum of square differences between the independent and dependent variables. GWR is a regression model that allows the relationships between the independent and dependent variables to vary by locality (Brunsdon et al., 2010; Brunsdon et al., 1998). GWR deviates from the assumption of homoskedasticity or static variance but calculates a specific variance for data within a zone or search radius of each predictor variable (Brunsdon et al., 1998; Fotheringham et al., 1996; Sheehan et al., 2012). The regression coefficients in GWR are not based on global information; rather, they vary with location, which is generated by a local regression estimation using subsampled data from the nearest neighbouring observations. The principle of GWR is described as follows:

\[ y_i = \delta(i) + \sum_k \delta_k(i)x_{ik} + \varepsilon_i \]  \hspace{1cm} (3)

where \(y_i\) is the value of \(R_s\) unit \(i; i=1,2,...,n\), \(n\) denotes location \(i\), \(x_{ik}\) indicates the value of the \(x_{ik}\) variable, such as cloud fraction and AOD, and \(\varepsilon\) denotes the residuals. \(\delta_{(i)}\) is the regression intercept. \(\delta_k(i)\) is the vector of regression coefficients determined by spatial weighting function \(w(i)\), which is the weighting function quantifying the proximities of location \(i\) to its neighbouring observation sites; \(X\) is the variable matrix, and \(b\) is the bias vector.

\[ \delta_k(i) = (X^Tw(i)X)^{-1}X^Tw(i)b \]  \hspace{1cm} (4)

The weighting functions are generally determined using the threshold method, inverse distance method, Gauss function method, and Bi-square method. Due to the irregular distribution of observation sites and computer ability, the adaptive Gaussian
function method is selected as a weighting function that varies in extent as a function of \( R_s \) observation site density.

\[
w_{ij} = \exp(-\left(\frac{d_{ij}}{b}\right)^2)
\]

(5)

where \( w_{ij} \) is the weighting function for observation site \( j \) that refers to location \( i \); \( d_{ij} \) denotes the Euclidian distance between \( j \) and \( i \); and \( b \) is the size of the neighbourhood, the maximum distance away from regression location \( i \), called “bandwidth”, which is determined by the number of nearest neighbour points (NNPs).

### 2.3.2 GWR parameter comparison

To perform the local regression for every local area, the numbers of NNPs are required to estimate spatially varying relationships between CF, AOD and \( R_s \) in the GWR-based fused method. To identify the best combination of parameter values, we test the numbers of NNPs ranging from 29 to 1000. Ten percent of merging SunDu-derived \( R_s \) data are randomly selected to validate these GWR parameters (Fig. 1). The results show that \( R^2 \) increases and bias decreases when the number of NNPs decreases. However, when the NNP is smaller than 30, the GWR-based fusion method produces spatially incomplete \( R_s \) data due to the local collinearity problem with large spatial variability. Therefore, 30 is selected as the NNP parameter (Table 3).

### Table 3. Statistical summary of GWR parameter optimization. NPP is the number of nearest neighbour points. GWR-CF presents the GWR-based fused method using only cloud fraction (CF) input, and GWR-CF-AOD presents that of using both CF and aerosol optical depth (AOD) as input. MAB is the mean absolute bias. Std is the standard deviation. RMSE is the root mean square error.

<table>
<thead>
<tr>
<th>NNP</th>
<th>( R^2 )</th>
<th>Bias</th>
<th>MAB</th>
<th>Std</th>
<th>RMSE</th>
<th>( R^2 )</th>
<th>Bias</th>
<th>MAB</th>
<th>Std</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>29</td>
<td>0.91</td>
<td>-0.21</td>
<td>7.45</td>
<td>9.90</td>
<td>9.90</td>
<td>0.91</td>
<td>-0.13</td>
<td>7.47</td>
<td>9.93</td>
<td>9.92</td>
</tr>
<tr>
<td>30</td>
<td>0.91</td>
<td>-0.23</td>
<td>7.45</td>
<td>9.90</td>
<td>9.90</td>
<td>0.91</td>
<td>-0.14</td>
<td>7.47</td>
<td>9.92</td>
<td>9.91</td>
</tr>
</tbody>
</table>
3. Results

3.1 Site validation

Based on the independent SunDu validation sites, both the GWR and OLS methods explain 97%~86% of \( R_s \) variability (Fig. 4). The GWR method generally shows an improved performance compared with the OLS method due to the representativeness of the spatial heterogeneity relationship between \( R_s \) and its impact factors in GWR. Both the GWR and OLS methods produce better simulations of \( R_s \) if satellite and AOD data are incorporated.

Direct observations from 2000 to 2016 are also used to further evaluate the performance of the fusion methods (Fig. 4). The comparative result shows that both fusion methods show slightly reduced performances when using direct \( R_s \) observations rather than the SunDu-derived \( R_s \). Both the GWR and OLS methods explain 91%~82% of \( R_s \) variability by using direct observations as reference data. Similarly, the GWR method exhibits better performances than the OLS-based fusion method, with an \( R^2 \) of 0.91 and root mean square error (RMSE) ranging from 19.89 to 19.97 W/m\(^2\) at the monthly time scale (Table 4).
Figure 4. Comparison of surface solar radiation ($R_s$) derived from the GWR method and the OLS method. Subplots (a, c, e, g) represent validation results using SunDu-derived $R_s$ data as a reference, while that of subplots (b, d, f, h) use directly observed $R_s$ data. Subplots (a, b, c, d) denote the GWR validation results, and subplots (e, f, g, h) denote the OLS validation results.

Table 4. Validation of fusion methods driven by cloud fraction (CF) and AOD. GWR-CF and OLS-CF represent the GWR fusion method and OLS fusion method driven only by CF. GWR-CF-AOD and OLS-CF-AOD represent GWR and OLS fusion methods driven by CF and AOD, respectively.
To analyse the impacts of AOD on the GWR fusion results, the GWR driven with only CF (GWR-CF) and GWR driven with CF and AOD (GWR-CF-AOD) are compared. Two validation sites (Chang Chun, 43.87°N 125.33°E and Bei Hai, 21.72°N...
109.08°E) are randomly selected to evaluate the seasonal and annual variations in $R_s$ derived from the GWR method (Fig. 5). The multiyear mean of AOD from Changchun and BeiHai are 0.49 and 0.70, respectively. As shown in subplots (a and b), both GWR-CF and GWR-CF-AOD produce similar seasonal variation patterns compared with SunDu-derived $R_s$ and CERES EBAF $R_s$ data. Small differences are found in the seasonal variation in $R_s$ derived from GWR regardless of whether AOD was incorporated. Examination of the annual variation $R_s$ from the GWR-CF and GWR-CF-AOD are shown in subplots (c and d) of Figure 5. The two fusion methods also produce similar annual $R_s$ variations. The similar performances of the GWR-CF and GWR-CF-AOD might suggest that the impacts of AOD have already been included in the SunDu-derived $R_s$ site data.

Figure 5. Seasonal and annual variations in $R_s$ at two sites: Chang Chun (a and c, 43.87°N and 125.33°E) and Bei Hai (b and d, 23.50°N, 99.72°E). SunDu $R_s$ is the SunDu-derived $R_s$ data, and GWR-CF $R_s$ is $R_s$ produced by the GWR method.
incorporating only the cloud fraction. GWR-CF-AOD is $R_s$ produced by the GWR method incorporating cloud fraction and AOD. The multiyear mean of AOD from Changchun and BeiHai are 0.49 and 0.70, respectively.

We also analyse the performances of fusion methods for different seasons at all validation sites, as shown in Table 4. At seasonal scales, both the GWR-CF and GWR-CF-AOD methods have high $R^2$ values ranging from 0.94 to 0.96, compared with direct $R_s$ measurement or SunDu-derived $R_s$. GWR-CF and GWR-CF-AOD show slight differences, indicating that both fusion methods produce consistent $R_s$ seasonal variation patterns, which might be because the impacts of AOD have already been included in the SunDu-derived $R_s$ site data at seasonal time scales. Comparatively, the GWR methods perform best in autumn, with RMSEs ranging from 9.23 W/m$^2$ to 9.56 W/m$^2$ followed by winter, spring and summer. Both the GWR-CF and GWR-CF-AOD methods produce similar annual variations in $R_s$ from 2000 to 2016, with $R^2$ values ranging from 0.57 to 0.58 (Table 4). The statistics indicate that the GWR can produce reasonable seasonal and annual variations in $R_s$.

### 3.3 Multiyear mean and long-term variability in $R_s$

Figure 6 shows the performance of GWR-CF and GWR-CF-AOD on simulating the multiyear mean $R_s$ by using 97 direct $R_s$ observation sites and independent SunDu-derived $R_s$ sites. Based on direct $R_s$ measurements, both GWR-based methods show good performances with high $R^2$ (0.89–0.95) and low RMSE (11.03–11.11 W/m$^2$), and few differences are found for the GWR merging results, whether or not AOD is taken as input data (Table 4).
Figure 6. Comparison of multiyear mean surface solar radiation ($R_s$) derived from the GWR method. Subplots (a, c) represent validation results using SunDu-derived $R_s$ data as a reference, while that of subplots (b, d) use direct observed $R_s$ data.

The spatial distributions of the multiyear means of $R_s$ from 2000 to 2017 are shown in Figure 7. The SunDu sites show that $R_s$ is high in northwest China, ranging from 180 to 300 W/m², and low in eastern China, ranging from 120 to 180 W/m². Both the GWR-CF and GWR-CF-AOD methods show consistent $R_s$ spatial patterns with SunDu-derived $R_s$ observations and CERES EBAFs, indicating that the relationship between $R_s$ and impact factors is not linearly stable and is closely related to spatial position. The spatial distribution of the $R_s$ trend derived from the GWR method is also consistent with the SunDu-derived $R_s$ trend, especially in western China (Fig. 8).
Figure 7. Spatial distribution of multiyear mean monthly surface solar radiation ($R_s$) from 2000 to 2017. The first line (a, b) shows the observed multiyear mean monthly $R_s$ from SunDu and CERES EBAF; the multiyear mean monthly $R_s$ derived from the GWR method are shown in the second line (c, d), respectively.

Figure 8. Spatial distributions of monthly anomaly trends of surface solar radiation ($R_s$) from 2000 to 2017. The first line (a, b) shows the SunDu-derived $R_s$ and CERES EBAF
$R_s$; the $R_s$-derived GWR fusion methods are shown in the second line (c, d). Subplots (c) incorporate only CF, and subplots (d) incorporate CF and AOD. The black dots on the maps represent significant trends (P<0.05).

Based on the classified subregions using 97 direct $R_s$ observations in Figure 1, the regional means of $R_s$ annual anomaly variation from 2000 to 2016 are shown in Figure 9. Compared with observations, both the GWR-CF and GWR-CF-AOD methods produce consistent long-term $R_s$ trends with SunDu-derived $R_s$ and CERES EBAF $R_s$ (Figures 2, 3 and 9), indicating that the GWR-CF and GWR-CF-AOD methods can produce reasonable annual $R_s$ variations over China.

In zones I and II, located in northern arid/semiarid regions, the annual anomaly $R_s$ variation shows small fluctuations ranging from -10 to 10 W/m$^2$. In contrast, zones IV, V, VIII and IX covering the Sichuan Basin, Yunnan-Guizhu Plateau, Qinghai-Tibet Plateau and North China Plain show large $R_s$ variation trends. Li et al. (2018) found a sharply increasing $R_s$ trend over East China, especially in the North China Plain, which is due to controlling air pollution and reducing aerosol loading. However, our results indicate that the increased surface solar radiation in North China is not confirmed by satellite retrieval (CERES) and SunDu-derived $R_s$. 
Figure 9. The regional mean of the annual anomaly of the surface solar radiation ($R_s$) for different subregions. Nine subregions (I to IX) over China are shown in Figure 1. Direct $R_s$ observations, SunDu-derived $R_s$, and CERES EBAF are shown as black lines, green lines and red lines, respectively. Light and dark blue represent the $R_s$ variation derived from the GWR-CF and the GWR-CF-AOD methods.

4. Discussion

4.1 Impact factors of $R_s$

In this study, we merged more than 2400 sunshine duration-derived $R_s$ site data with MODIS CF and AOD data to generate high spatial resolution ($0.1^\circ$) $R_s$ over China from 2000 to 2017. The results show that the GWR method incorporated with CF and
AOD (GWR-CF-AOD) performs best, indicating the non-neglected role of clouds and aerosols in regulating the variation in $R_s$ over China.

Clouds and aerosols impact the solar radiation reaching the surface by radiative absorption and scattering (Tang et al., 2017). Recent $R_s$ trend studies over Europe suggest that CF may play a key role in the positive trend of $R_s$ since the 1990s (Pfeifroth et al., 2018a). In terms of input data, our results also indicate that the cloud fraction might be a major factor affecting $R_s$, which is consistent with our previous studies (Feng and Wang, 2019).

Changes in aerosol loading have also been reported to be an important impact factor (Che et al., 2005; Li et al., 2018; Liang and Xia, 2005; Qian et al., 2015; Xia, 2010; Zhou et al., 2019b). The atmospheric visibility data show that the slope of the linear variation in surface solar radiation with respect to atmospheric visibility is distinctly different at different stations (Yang et al., 2017), implying that the relationship between $R_s$ and aerosols varies with location.

4.2 Performances of the fusion methods

The good overall performances of the GWR model have been reported in many previous studies, including geography (Chao et al., 2018; Georganos et al., 2017), economics (Ma and Gopal, 2018), meteorology (Li and Meng, 2017; Zhou et al., 2019a), and epidemiology (Tsai and Teng, 2016). Chao et al. (2018) used the GWR method to merge satellite precipitation and gauge observations to correct biases in satellite precipitation data and downscale satellite precipitation to a finer spatial resolution at the same time. Zhou et al. (2019a) used GWR to analyse haze pollution over China and found that the GWR estimate was better than the OLS estimate, with an improvement in correlation coefficient from 0.20 to 0.75.

Compared with other traditional interpolation methods, such as optimal
interpolation (OI), GWR can theoretically integrate geographical location and \( R_s \) impact factors for spatial \( R_s \) estimations and reflect the non-stationary spatial relationship between \( R_s \) and its impact factors. The thin plate spline method can include CF and AOD as covariates to simulate the approximately linear dependence of these impact factors on \( R_s \), but this linear function cannot fully describe the relationship among CF, AOD and \( R_s \) (Hong et al., 2005).

Comparison results from (Wang et al., 2017) also indicate that the GWR method is better than the multiple linear regression method and spline interpolation method for near surface air temperature. By using spatial interpolation method, CERES EBAF \( R_s \) can also be downscaled to 1km or 30m. These interpolated CERES \( R_s \) data cannot represent the detailed \( R_s \) distributions at spatial resolution of 1km or 30m due to the variability of \( R_s \) within a 1 degree box. Without additional high spatial resolution data, interpolated cannot capture more detail variability of \( R_s \).

5. Data availability

The merged \( R_s \) product by GWR methods with cloud fraction and AOD data as input in this study are available at [https://doi.pangaea.de/10.1594/PANGAEA.921847](https://doi.pangaea.de/10.1594/PANGAEA.921847) (Feng and Wang, 2020).

6. Conclusions

Accurate estimation of \( R_s \) variability is crucially important for regional energy budget, water cycle and climate change studies. Recent studies have shown that SunDu-derived \( R_s \) data can provide reliable long-term \( R_s \) series. In this study, we merged SunDu-derived \( R_s \) data with satellite-derived cloud fraction (CF) and aerosol optical
depth (AOD) data to generate high spatial resolution (0.1°) $R_s$ over China from 2000 to 2017 (Feng and Wang, 2020). The GWR and OLS merging methods were also compared.

Our results show that the spatial resolutions of all fusion results are improved to 0.1° by incorporating MODIS cloud fraction data. The GWR shows better performance than OLS, with increases in $R^2$ by 9.21%~12.81% and RMSEs reduced by 49.56%~54.68%, indicating that $R_s$ has complex characteristics of spatial variability over China, which has also indicated the necessity of the high spatial resolution of $R_s$ data. As clouds and aerosols play vital roles in the variability in $R_s$, apparent improvements in the results of SunDu-derived $R_s$ data merging are found if both cloud fraction and AOD are incorporated. Based on the merging results incorporating only cloud fraction, cloud fraction is suggested to be the major factor impacting $R_s$, which explained approximately 86%~97% of $R_s$ variability. Generally, SunDu-derived $R_s$ data merging results derived from GWR show more consistent multiyear mean $R_s$ and long-term $R_s$ trends compared with those from OLS. Our results show that the improvement in $R_s$ variability estimation is closely related to $R_s$ impact factors and $R_s$ spatial heterogeneity. The merged $R_s$ products derived from GWR-CF-AOD can be downloaded at https://doi.pangaea.de/10.1594/PANGAEA.921847.

Acknowledgements

This study was funded by the National Key Research & Development Program of China (2017YFA06036001), the National Natural Science Foundation of China (41525018), the Fundamental Research Funds for the Central Universities (#BLX201907), and the State Key Laboratory of Earth Surface Processes and Resource Ecology (U2020-KF-02). We would like to thank Chengyang Xu, Yuna Mao, Jizeng Du,
Runze Li, Qian Ma, Guocan Wu, and Chunlue Zhou for their insightful comments. We are grateful to Amelie Driemel for her help of uploading the data in PANGAEA. The cloud data can be downloaded from https://neo.sci.gsfc.nasa.gov/view.php?datasetId=MODAL2_M_CLD_FR. The CERES SYN data can be downloaded from https://ceres.larc.nasa.gov/data/.
References


Doelling, D. R., Loeb, N. G., Keyes, D. F., Nordeen, M. L., Morstad, D., Nguyen, C.,
Interpolation for CERES Flux Products, J. Atmos. Ocean Technol., 30, 1072-1090,
2013.

Evan, A. T., Heidinger, A. K., and Vimont, D. J.: Arguments against a physical long‐

Feng, F. and Wang, K.C.: Determining Factors of Monthly to Decadal Variability in
Surface Solar Radiation in China: Evidences From Current Reanalyses, J.

Feng, F. and Wang, K. C.: Merging Satellite Retrievals and Reanalyses to Produce
Global Long-Term and Consistent Surface Incident Solar Radiation Datasets,

by merging satellite cloud and aerosol data with ground-based sunshine duration

Feng, Y., Chen, D., and Zhao, X.: Estimated long-term variability of direct and diffuse

Fotheringham, A. S., Charlton, M., and Brunsdon, C.: The geography of parameter
space: an investigation of spatial non-stationarity, Int. J. Geogr. Inf. Syst., 10, 605-
627, 1996.


Letu, H., Yang, K., Nakajima, T. Y., Ishimoto, H., Nagao, T. M., Riedi, J., Baran, A. J.,


Sanchezlorenzo, A., Calbó, J., Brunetti, M., and Deser, C.: Dimming/brightening over the Iberian Peninsula: Trends in sunshine duration and cloud cover and their


Tsai, P. and Teng, H.: Role of Aedes aegypti (Linnaeus) and Aedes albopictus (Skuse) in local dengue epidemics in Taiwan, BMC Infectious Diseases, 16, 662, 2016.


Radiation by Machine Learning and Deep Neural Network Models Using Data Provided by the COMS MI Geostationary Satellite: A Case Study in South Korea, Sensors (Basel), 19, 2019.


