#### Reviewer

#### **OVERALL**

1) **Comment:** The authors need to prove that SunDu Rs can add value to the 0.1 degree product, instead of cloud fraction data alone. I therefore suggest the authors perform a similar regression (GWR) analysis but using CERES data interpolated to 0.1 degree and 0.1 degree cloud, and compare the results with those using SunDu Rs.

**Reply:** The authors would like to thank anonymous reviewers for their valuable and constructive comments, which help us to further improve the manuscript. According to the reviewers' comments, we perform a similar GWR analysis but using CERES data interpolated to 0.1 degree and 0.1 degree cloud, and compare the results with those using SunDu  $R_s$ . As the subplots (c) and (d) of figure 1S shown, both data use same 0.1 degree cloud as auxiliary data to perform the GWR analysis. The differences are that GWR CF  $R_s$  are based on SunDu derived  $R_s$ , while GWR CERES CF 0.1 degree are based on the CERES data which interpolated to 0.1 degree. This results suggest that SunDu  $R_s$  can add value to the 0.1 degree product, instead of cloud fraction data alone (Lines 469-476).

"In order to prove that SunDu-derived  $R_s$  can add value to the 0.1 degree product, instead of cloud fraction data alone. We perform a similar GWR analysis but using CERES EBAF interpolated to 0.1 degree and 0.1 degree cloud, and compare the results with those using SunDu-derived  $R_s$  and 0.1 degree cloud (**Fig .9**). The results indicate that SunDu-derived Rs can add value to the 0.1 degree product and the merged  $R_s$  by using interpolated CERES EBAF and 0.1 degree cloud product are also similarly to



#### original CERES EBAF but not 0.1 degree cloud product."

Figure 9. Spatial distributions of monthly anomaly trends of surface solar radiation (Rs) from 2000 to 2017. The first line (a, b) shows the SunDu-derived Rs and CERES EBAF Rs; the Rs-derived GWR fusion methods are shown in the second line (c, d). Subplots (c) SunDu derived  $R_s$  incorporate only CF, and subplots (d) is the results of GWR analysis using CERES data interpolated to 0.1 degree and 0.1 degree cloud. The black dots on the maps represent significant trends (P<0.05).

# Merging ground-based sunshine duration observations with satellite cloud and aerosol retrievals to produce high resolution long term surface solar radiation over China

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#### Abstract

Although great progress has been made in estimating surface solar radiation  $(R_s)$ 22 from meteorological observations, satellite retrieval and reanalysis, getting best 23 estimated long-term variations in  $R_s$  are sorely needed for climate studies. It has been 24 25 shown that sunshine duration (SunDu)-derived  $R_s$  data can provide reliable long-term variability, but are avaliable at sparsely distributed weather stations. Here, we merge 26 SunDu-derived  $R_s$  with satellite-derived cloud fraction and aerosol optical depth (AOD) 27 28 to generate high spatial resolution  $(0.1^\circ)$   $R_s$  over China from 2000 to 2017. The geographically weighted regression (GWR) and ordinary least squares regression (OLS) 29 merging methods are compared, and GWR is found to perform better. Based on the 30 SunDu-derived  $R_s$  from 97 meteorological observation stations, which are co-located 31 with those that direct  $R_s$  measurement sites, the GWR incorporated with satellite cloud 32 fraction and AOD data produces monthly  $R_s$  with  $R^2 = 0.97$  and standard deviation = 33 11.14  $W/m^2$ , while GWR driven by only cloud fraction produces similar results with  $R^2$ 34 = 0.97 and standard deviation = 11.41 w/m<sup>2</sup>. This similarity is because SunDu-derived 35  $R_s$  has included the impact of aerosols. This finding can help to build long-term  $R_s$ 36 variations based on cloud data, such as Advanced Very High Resolution Radiometer 37 (AVHRR) cloud retrievals, especially before 2000, when satellite AOD retrievals are 38 not unavailable. The merged  $R_s$  product at a spatial resolution of 0.1° in this study can 39 be downloaded at https://doi.pangaea.de/10.1594/PANGAEA.921847 (Feng and Wang, 40 2020). 41 42 43

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#### 47 **Introduction**

A clear knowledge of variations in surface solar radiation  $(R_s)$  is vitally important 48 for an improved understanding of the global climate system and its interaction with 49 human activity (Jia et al., 2013; Myers, 2005; Schwarz et al., 2020; Wang and Dickinson, 50 51 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 52 the late 1980s and subsequent increase (global brightening) (Wild, 2009). The variation 53 in  $R_s$  is closely related to the Earth's water cycle, the whole biosphere, and the amount 54 of available solar energy. This situation emphasizes the urgency to develop reliable  $R_s$ 55 products to obtain the variability in  $R_s$ . 56

Great progress has been made in the detection of variability in  $R_s$  by 57 meteorological observations, satellite retrieval and radiation transfer model simulations 58 or reanalysis R<sub>s</sub> products in previous studies (Rahman and Zhang, 2019; Wang et al., 59 2015). However, each estimation has its advantages and disadvantages. Direct observed 60 data provide accurate  $R_s$  records at short time scales; however, careful calibration and 61 instrument maintenance are needed to maintain its long-term homogeneity. Previous 62 studies have reported that direct observed  $R_s$  over China may have major inhomogeneity 63 problems due to sensitivity drift and instrument replacement (Wang, 2014; Wang et al., 64 65 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. 66 To overcome radiometer ageing problem, China replaced its instruments from 1990 to 67 1993. However, the new solar trackers failed frequently and introduced a high data 68 missing rate for the direct radiation component of  $R_s$  (Lu and Bian, 2012; Mo et al., 69 2008). After 1993, although the instruments were substantially improved, the Chinese-70 developed pyranometers still had high thermal offset with directional response errors, 71

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 79 80 (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  $R_s$ 81 and reflect the impacts of both aerosols and clouds at time scales ranging from daily to 82 decadal (Feng and Wang, 2019; Manara et al., 2015; Sanchezlorenzo et al., 2013; 83 Sanchezromero et al., 2014; Tang et al., 2011; Wang et al., 2012b; Wild, 2016). Even 84 though, SunDu data do not provide a direct estimate of  $R_s$  and have the different 85 sensitivity of atmospheric turbidity changes, compared with  $R_s$  observations, they are 86 still a good proxy for variations of  $R_s$  (Manara et al., 2017). 87

Sunshine duration observations collected at weather stations in China have been 88 used to reconstruct long-term R<sub>s</sub> (Che et al., 2005; Feng et al., 2019; He et al., 2018; He 89 and Wang, 2020; Jin et al., 2005; Shi et al., 2008; Yang et al., 2006; Yang et al., 2020). 90 91 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, 92 and the USA, with brightening from 1980 to 2009 in Europe and a declining trend  $R_s$ 93 from 1994 to 2010 in China. (Wang et al., 2015) found that the dimming trend from 94 1961 to 1990 and nearly constant zero trend after 1990 over China, as calculated from 95 the SunDu-derived  $R_s$ , was consistent with independent estimates of AOD (Luo et al., 96

97 2001); they also observed changes in the diurnal temperature range (Wang et al., 2012a; 98 Wang and Dickinson, 2013) and the observed pan evaporation (Yang et al., 2015). 99 Although direct observations and SunDu-derived  $R_s$  can provide accurate long-term 100 variations in  $R_s$ , both direct observations and sunshine duration records are often 101 sparsely spatially distributed.

Satellite  $R_s$  retrievals and radiation transfer model simulations or reanalysis  $R_s$ 102 products can provide  $R_s$  estimation with global coverage at high spatial resolution. 103 However, model simulations and reanalysis  $R_s$  products have substantial biases due to 104 105 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 106 reanalyses are lower than those of satellite products (Wang et al., 2015; Zhang et al., 107 108 2016) due to the good capability of capturing the spatial distribution and dynamic evolution of clouds in satellite remote sensing data. 109

Table 1 lists the current satellite-based  $R_s$  products, which have been widely 110 validated in previous studies. Zhang et al. (2004) found that the monthly International 111 Satellite Cloud Climatology Project-Flux Data (ISCCP-FD) R<sub>s</sub> product had a positive 112 bias of 8.8 w/m<sup>2</sup> using Global Energy Balance Archive (GEBA) archived data as a 113 reference. By comparing 1151 global sites, Zhang et al. (2015) evaluated four satellite-114 based Rs products, including ISCCP-FD, the Global Energy and Water Cycle 115 Radiation Budget (GEWEX-SRB), 116 Experiment-Surface the University of Maryland/Shortwave Radiation Budget (UMD-SRB) and the Earth's Radiant Energy 117 System energy balanced and filled product (CERES EBAF), and concluded that CERES 118 EBAF shows better agreement with observations than other products. A similar overall 119 good performance of CERES EBAF can also be found (Feng and Wang, 2018; Ma et 120 al., 2015). 121

Satellite $R_s$ product	Source	Spatial resolution	Time range
ISCCP-FD	ISCCP	2.5°	1983-2009
GEWEX-SRB	ISCCP-DX	1°	1983-2007
UMD-SRB	METEOSAT-5	0.5°	1983-2007
GLASS-DSR	Terra/Aqua, GOES, MSG, MTSAT	0.05°	2008-2010
CLARA-A2	AVHRR	0.25°	1982-2015
MCD18A1	Terra/Aqua, MODIS	5.6 km	2001-present
Himawari-8 SWSR	Himawari-8	5 km	2015-present
SSR-tang	ISCCP-HXG, ERA5, MODIS	10 km	1982-2017
Cloud_cci AVHRR- PMv3	AVHRR/CC4CL	0.05°	1982-2016

**Table 1.** Current satellite-derived surface solar radiation  $(R_s)$  products

Although CERES EBAF uses more accurate input data to provide  $R_s$  data, its 124 spatial resolution is only 1° (Kato et al., 2018). Since 2010, new-generation 125 geostationary satellites have provided opportunities for high temporal and spatial 126 resolution  $R_s$  data, such as Himawari-8 (Hongrong et al., 2018; Letu et al., 2020). 127 However, the time span of the new-generation satellite-based  $R_s$  product is short. The 128 long-term AVHRR records provide the possibility of building long-term radiation 129 datasets. The CLoud, Albedo and RAdiation dataset, the AVHRR-based data-second 130 edition (CLARA-A2), covers a long time period, but the spatial resolution is only 0.25° 131 (Karlsson et al., 2017). Recently, Tang et al. (2019) built a satellite-based  $R_s$  (SSR-tang) 132 dataset using ISCCP-HXG cloud data. By using a variety of cloud properties derived 133 from AVHRR, Stengel et al. (2020) presented the Cloud cci AVHRR-PMv3 dataset 134 generated within the Cloud cci project. 135

Validation against the BSRN data indicated that SSR-tang have the mean bias error (MBE) of -11.5 W/m<sup>2</sup> and root mean square error (RMSE) of 113.5 W/m<sup>2</sup> 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<sup>2</sup> and correlation coefficients above 0.98. While the bias for shortwave fluxes is small ( $1.9 \text{ W/m}^2$ ). 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.

147 On the other hand, the long-term cloud records also contain uncertainties. For example, ISCCP cloud products, which directly combine geostationary and polar 148 149 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 150 detecting low-level clouds (Dai et al., 2006; Evan et al., 2007). This inhomogeneity of 151 152 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), 153 and  $R_s$  long-term variability estimation still needs improvement. 154

Efforts have been made to further improve  $R_s$  products. Merging multisource data 155 has become an effective empirical method for improving the quality of  $R_s$  products 156 (Camargo and Dorner, 2016; Feng and Wang, 2018; Hakuba et al., 2014; Journée et al., 157 2012; Lorenzo et al., 2017; Ruiz-Arias et al., 2015). For instance, to produce 158 spatiotemporally consistent  $R_s$  data, multisource satellite data are used in Global LAnd 159 160 Surface Satellite (GLASS) R<sub>s</sub> products (Jin et al., 2013). By merging reanalysis and satellite  $R_s$  data by the probability density function-based method, the reanalysis  $R_s$ 161 biases can be substantially reduced (Feng and Wang, 2018). This finding suggests that 162 163 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 164 methods can produce  $R_s$  data incorporated with  $R_s$  impact factors, the stable regression 165

parameters might have negative effects on the final fusion results due to the complex characteristics of  $R_s$  spatial-temporal variability.

168 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, 169 as suggested by the Observing Systems Capabilities Analysis and Review of WMO 170 OSCAR), is 20 km (Huang et al., 2019). Interpolation methods are often included in  $R_s$ 171 fusion methods to further improve the spatial resolutions of  $R_s$  data (Loghmari et al., 172 2018). For example, Zou et al. (2016) estimated global solar radiation using an artificial 173 174 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, 175 Journée and Bertrand (2010) found that kriging with the external drift interpolation 176 177 method performed better than mean bias correction, interpolated bias correction and ordinary kriging with satellite-based correction. However, interpolation results have 178 uncertainties due to the lack of detailed high spatial resolution information. Although 179 traditional linear regression fusion methods can incorporate high spatial resolution data 180 during the fusion process, the impacts of the stable regression parameters need further 181 investigation. 182

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.

190 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 198 199 cloud fraction (CF) and AOD data to generate high spatial resolution (0.1°)  $R_s$  over China from 2000 to 2017. The GWR and ordinary least squares (OLS) regression 200 merging methods are compared. CF and AOD are important Rs impact factors, however, 201 202 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 203 evaluated in this study, instead of evaluating direct merging current  $R_s$  products with 204 SunDu-derived  $R_s$ . Since current  $R_s$  high quality  $R_s$  such as CERES EBAF have low 205 spatial resolution, the output of this study provides a reliable high resolution grid  $R_s$ 206 data to avoid the disadvantage of CERES EBAF for capturing the variability of  $R_s$ 207 within a 1 degree box and provide guidance to merge multisource data to generate long-208 term  $R_s$  data over China. 209

**1. Data and Methodology** 

## 211 2.1. Ground-based observations 212 2.2.1 Direct observations

*R<sub>s</sub>* 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 216 collected, and we calculated monthly  $R_s$  values by averaging daily  $R_s$  values when daily 217 218 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-219 derived  $R_s$  are used as independent reference data to investigate the performances of the 220 fusion methods (Fig. 1). The whole area over China is further divided into nine zones 221 222 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 223 224 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.

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

237 CMDC is the China Meteorological Data Service Center. SunDu is the sunshine

238	duration data.	Rs i	s surface	solar	radiation	and AOD	is th	e aerosols	optical	der	pth
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Data Source	Derive d Parame ters	Spatial resolution	Version	Access Point	Notes	Reference
Direct <i>R<sub>s</sub></i> measurement data from CMDC	Rs	-	Version 1.0	http://data/ cma/cn/	Authenticatio n is required for the China data use policy	-
SunDu observations and other meteorological data	Rs	-	Version 1.0	http://data/ cma/cn/	Authenticatio n is required for the China data use policy	-
CERES EBAF	$R_s$	1 degree	Ed4.1	https://cer es.larc.nas a.gov/data /#ebaf- level-3b	A email address to order the data	(Kato et al., 2018)
CERES SYN1deg	AOD	1 degree	Ed4A	https://cer es.larc.nas a.gov/data /#syn1deg -level-3	A email address to order the data	(Rutan et al., 2015)
MODAL2 M CLD	cloud fraction	0.1 degree	-	https://neo .sci.gsfc.n asa.gov/vi ew.php?da tasetId=M ODAL2_ M_CLD_ FR	Directly download	(Platnick et al., 2017)

#### 239 2.2.2 SunDu-derived Rs

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).

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

$$R_c = \int (\tau_{c \ dir} + \tau_{c \ dif}) \times I_0 d_t \tag{2}$$

where n represents the measured SunDu, and K represents the theoretical value of the 248 SunDu. a<sub>0</sub>, a<sub>1</sub>, and a<sub>2</sub> are the station-dependent parameters by tuning this equation with 249 measurements of Rs and SunDu and then the method is applied regionally (Wang, 2014). 250 Instead using observations from weather stations in Japan (Yang et al., 2006), 251 252 observations in CMA are used (Wang, 2014).  $R_c$  is the daily total solar radiation at the surface under clear-sky conditions (Eq. 2).  $\tau_c$  dir and  $\tau_c$  dif represent the direct radiation 253 transmittance and the diffuse radiation transmittance under clear-sky conditions. I<sub>0</sub> is 254 the solar irradiance at the top of the atmosphere (TOA). For the clear sky  $R_s$ ,  $\tau_c$  dir and 255  $\tau_{c \text{ dif}}$  are calculated using a modified a broadband radiative transfer model by 256 simplifying Leckner's spectral model (Leckner, 1978), which the effect of 257 transmittance functions of permanent gas absorption, Rayleigh scattering, water vapour 258 absorption, ozone absorption, and aerosol extinction are parameterized using the 259 surface air temperature, surface pressure, precipitable water, the thickness of the ozone 260 layer, turbidity, sunshine duration as inputs (Yang et al., 2006). Calculation of  $R_s$  also 261 includes impacts of aerosols because SunDu is impacted by changes in both clouds and 262 aerosols (Wang, 2014). 263

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-279 derived  $R_s$  and CERES EBAF  $R_s$  estimates in different subregions. The statistics include 280 the mean absolute bias (MAB), standard deviation (Std) and root mean square error 281 282 (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 283 comparisons between SunDu-derived  $R_s$  and directly observed  $R_s$ . C-D represent 284 comparison between CERES EBAF  $R_s$  and directly observed  $R_s$ . S-C represent 285 comparisons between SunDu-derived  $R_s$  and CERES EBAF  $R_s$ . The unit of y-axis are 286  $w/m^2$ . 287



**Figure 3.** Similar to Figure 2, but this statistical summary is for  $\mathbb{R}^2$ .

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#### 291 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.

299 CERES is a 3-channel radiometer measuring three filtered radiances, including shortwave (0.3-5  $\mu$ m), total (0.3-200  $\mu$ m) and window (8-12  $\mu$ m).  $R_s$  from CERES 300 301 EBAF are adjusted using radiative kernels, including bias correction and Lagrange multiplier processes. The input data of CERES EBAF are adjusted during the product 302 generating process constrained by CERES observations at the TOA. The biases in 303 304 temperature and specific humidity from the Goddard Earth Observing System (GEOS) reanalysis are adjusted by atmospheric infrared sounder (AIRS) data. Cloud properties, 305 such as optical thickness and emissivity, from MODIS and geostationary satellites are 306 constrained by cloud profiling radar, Cloud-Aerosol Lidar, and Infrared Pathfinder 307 Satellite Observations (CALIPSO) detectors and CloudSat. The uncertainties of 308 CERES EBAF data, reported by (Kato et al., 2018), in all sky global annual mean  $R_s$  is 309 4 W m<sup>-2</sup>. Previous studies (Feng and Wang, 2019; Feng and Wang, 2018; Ma et al., 310 2015; Wang et al., 2015) have shown that the CERES EBAF surface product provides 311 312 reliable estimations of  $R_s$ .

313 CERES SYN1deg AOD derived from an aerosol transport model, named 314 Atmospheric Transport and Chemistry Modelling (MATCH) (Collins et al., 2001), 315 which assimilates MODIS AOD data, is used to obtain spatiotemporally consistent 316 AOD data. Different aerosol constituents, including small dust ( $<0.5 \mu$  m), large dust 317 ( $>0.5 \mu$  m), 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 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.

Cloud fraction data from MODAL2 M CLD are collected as input cloud fraction 323 data with a spatial resolution of 0.1° and time span from 2000 to 2017 (Platnick et al., 324 2017). The MODAL2 M CLD data are synthesized based on the cloud data from 325 326 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 327 applying appropriate single field of view (FOV) spectral tests to each pixel with a series 328 329 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 330 flag is determined and then combined to produce the final cloud mask flag. The three 331 confidence levels included in the cloud mask flag output are (i) high confidence for 332 cloudless pixels (Group confidence values > 0.95); (ii) low confidence for unobstructed 333 views on the surface (Group confidence values  $Q \le 0.66$ ); and (iii) values between 0.66 334 and 0.95, and spatial and temporal continuity tests are further applied to determine 335 whether the pixel is absolutely cloudless. Then, the cloud fraction is calculated from 336 337 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. 338

## 339 2.3. Methods 340 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 346 variables by to minimizing the sum of square differences between the independent and 347 dependent variables. GWR is a regression model that allows the relationships between 348 the independent and dependent variables to vary by locality (Brunsdon et al., 2010; 349 Brunsdon et al., 1998). GWR deviates from the assumption of homoskedasticity or 350 static variance but calculates a specific variance for data within a zone or search radius 351 352 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; 353 rather, they vary with location, which is generated by a local regression estimation using 354 subsampled data from the nearest neighbouring observations. The principle of GWR is 355 described as follows: 356

$$y_i = \delta(i) + \sum_k \delta_k(i) x_{ik} + \varepsilon_i$$
(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.

$$\delta_k(i) = (X^T w(i) X)^{-1} X^T w(i) b \tag{4}$$

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.

$$w_{ii} = \exp(-(d_{ii}/b)^2)$$
(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).

372 **2.3.2 GWR parameter comparison** 

To perform the local regression for every local area, the numbers of NNPs are 373 required to estimate spatially varying relationships between CF, AOD and  $R_s$  in the 374 GWR-based fused method. To identify the best combination of parameter values, we 375 test the numbers of NNPs ranging from 29 to 1000. Ten percent of merging SunDu-376 377 derived  $R_s$  data are randomly selected to validate these GWR parameters (Fig. 1). The results show that R<sup>2</sup> increases and bias decreases when the number of NNPs decreases. 378 However, when the NNP is smaller than 30, the GWR-based fusion method produces 379 spatially incomplete  $R_s$  data due to the local collinearity problem with large spatial 380 variability. Therefore, 30 is selected as the NNP parameter (Table 3). 381

382

**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.

NINID	GWR-CF						GWR-CF-AOD			
NNP	$\mathbb{R}^2$	Bias	MAB	Std	RMSE	$\mathbb{R}^2$	Bias	MAB	Std	RMSE
29	0.91	-0.21	7.45	9.90	9.90	0.91	-0.13	7.47	9.93	9.92
30	0.91	-0.23	7.45	9.90	9.90	0.91	-0.14	7.47	9.92	9.91

31	0.91	-0.24	7.45	9.90	9.90	0.91	-0.14	7.47	9.91	9.91
32	0.91	-0.25	7.46	9.91	9.91	0.91	-0.14	7.47	9.91	9.90
33	0.91	-0.26	7.47	9.92	9.92	0.91	-0.15	7.46	9.90	9.90
34	0.91	-0.27	7.47	9.93	9.93	0.91	-0.14	7.46	9.90	9.89
35	0.91	-0.28	7.48	9.94	9.94	0.91	-0.14	7.46	9.89	9.88
36	0.91	-0.28	7.49	9.94	9.94	0.91	-0.14	7.46	9.89	9.88
37	0.91	-0.29	7.49	9.95	9.95	0.91	-0.14	7.46	9.88	9.87
38	0.91	-0.30	7.50	9.96	9.96	0.91	-0.14	7.46	9.88	9.87
39	0.91	-0.31	7.51	9.98	9.98	0.91	-0.14	7.46	9.87	9.87
40	0.91	-0.32	7.52	9.99	9.99	0.91	-0.14	7.46	9.87	9.87
50	0.90	-0.38	7.62	10.12	10.12	0.91	-0.12	7.51	9.91	9.91
100	0.89	-0.57	8.20	10.90	10.91	0.90	-0.02	7.86	10.31	10.30
500	0.81	-1.08	10.89	14.50	14.54	0.86	0.20	9.55	12.45	12.45
1000	0.75	-1.13	12.60	16.57	16.61	0.82	0.26	10.68	13.84	13.85

#### 389 **3. Results**

#### **390 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 397 398 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 399 rather than the SunDu-derived Rs. Both the GWR and OLS methods explain 91%~82% 400 of  $R_s$  variability by using direct observations as reference data. Similarly, the GWR 401 method exhibits better performances than the OLS-based fusion method, with an R<sup>2</sup> of 402 0.91 and root mean square error (RMSE) ranging from 19.89 to 19.97 W/m<sup>2</sup> at the 403 404 monthly time scale (Table 4).



405

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 SunDuderived  $R_s$  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. GWRCF 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.

	Time scale	Ref	R2	Bias	Std	RMSE
GWR-CF	monthly	SunDu R <sub>s</sub>	0.97	-1.17	11.41	11.47
GWR-CF-AOD	monthly	SunDu R <sub>s</sub>	0.97	-0.82	11.14	11.17
OLS-CF	monthly	SunDu Rs	0.86	-3.80	25.03	25.32
OLS-CF-AOD	monthly	SunDu R <sub>s</sub>	0.89	-1.37	22.10	22.15
GWR-CF	monthly	Direct Obs	0.91	4.88	19.29	19.89
GWR-CF-AOD	monthly	Direct Obs	0.91	5.24	19.27	19.97
OLS-CF	monthly	Direct Obs	0.82	2.18	26.73	26.82
OLS-CF-AOD	monthly	Direct Obs	0.85	4.64	24.71	25.15
GWR-CF	spring	SunDu R <sub>s</sub>	0.95	-1.3	11.5	11.57
GWR-CF-AOD	spring	SunDu R <sub>s</sub>	0.95	-0.86	11.2	11.23
OLS-CF	spring	SunDu R <sub>s</sub>	0.77	-4.97	23.65	24.16
OLS-CF-AOD	spring	SunDu R <sub>s</sub>	0.84	-1.35	19.85	19.9
GWR-CF	summer	SunDu R <sub>s</sub>	0.9	-2.09	14.08	14.23
GWR-CF-AOD	summer	SunDu R <sub>s</sub>	0.9	-1.38	13.76	13.82
OLS-CF	summer	SunDu R <sub>s</sub>	0.65	-6.49	26.18	26.97
OLS-CF-AOD	summer	SunDu R <sub>s</sub>	0.77	-1.37	21.17	21.22
GWR-CF	autumn	SunDu R <sub>s</sub>	0.95	-1.27	9.48	9.56
GWR-CF-AOD	autumn	SunDu R <sub>s</sub>	0.96	-1.04	9.17	9.23
OLS-CF	autumn	SunDu R <sub>s</sub>	0.67	-3.22	25.62	25.82
OLS-CF-AOD	autumn	SunDu R <sub>s</sub>	0.71	-1.97	23.79	23.87
GWR-CF	winter	SunDu R <sub>s</sub>	0.94	0.01	9.87	9.86
GWR-CF-AOD	winter	SunDu R <sub>s</sub>	0.94	0.04	9.78	9.78
OLS-CF	winter	SunDu R <sub>s</sub>	0.63	-0.37	24.16	24.16
OLS-CF-AOD	winter	SunDu R <sub>s</sub>	0.65	-0.78	23.41	23.42
GWR-CF	annual	Direct Obs	0.37	5.62	4.73	10.42
GWR-CF-AOD	annual	Direct Obs	0.37	5.98	4.79	10.53
OLS-CF	annual	Direct Obs	0.30	3.06	5.01	15.01
OLS-CF-AOD	annual	Direct Obs	0.33	5.45	4.89	13.34
GWR-CF	annual	SunDu R <sub>s</sub>	0.57	-1.19	4.30	6.76
GWR-CF-AOD	annual	SunDu R <sub>s</sub>	0.58	-0.84	4.30	6.68
OLS-CF	annual	SunDu R <sub>s</sub>	0.35	-3.58	5.63	15.17
OLS-CF-AOD	annual	SunDu R <sub>s</sub>	0.39	-1.23	5.44	13.40
GWR-CF	annual mean	SunDu R <sub>s</sub>	0.94	-1.50	6.63	6.76
GWR-CF-AOD	annual mean	SunDu R <sub>s</sub>	0.95	-1.15	6.41	6.47
OLS-CF	annual mean	SunDu R <sub>s</sub>	0.62	-3.90	17.11	17.46
OLS-CF-AOD	annual mean	SunDu R <sub>s</sub>	0.71	-1.58	14.90	14.90
GWR-CF	annual mean	Direct Obs	0.89	5.08	9.85	11.03
GWR-CF-AOD	annual mean	Direct Obs	0.89	5.43	9.75	11.11
OLS-CF	annual mean	Direct Obs	0.70	2.57	16.31	16.42
OLS-CF-AOD	annual mean	Direct Obs	0.77	4.88	14.00	14.75

#### 417 **3.2** Seasonal and annual variations in $R_s$

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  $R_s$ 421 derived from the GWR method (Fig. 5). The multiyear mean of AOD from Changchun 422 423 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 424 SunDu-derived  $R_s$  and CERES EBAF  $R_s$  data. Small differences are found in the 425 seasonal variation in  $R_s$  derived from GWR regardless of whether AOD was 426 427 incorporated. Examination of the annual variation Rs from the GWR-CF and GWR-CF-AOD are shown in subplots (c and d) of Figure 5. The two fusion methods also 428 429 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 430 the SunDu-derived  $R_s$  site data. 431



434 43.87°N and 125.33°E) and Bei Hai (b and d, 23.50°N, 99.72°E). SunDu  $R_s$  is the 435 SunDu-derived  $R_s$  data, and GWR-CF  $R_s$  is  $R_s$  produced by the GWR method

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incorporating only the cloud fraction. GWR-CF-AOD is *R<sub>s</sub>* 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 439 validation sites, as shown in Table 4. At seasonal scales, both the GWR-CF and GWR-440 CF-AOD methods have high R<sup>2</sup> values ranging from 0.94 to 0.96, compared with direct 441  $R_s$  measurement or SunDu-derived  $R_s$ . GWR-CF and GWR-CF-AOD show slight 442 differences, indicating that both fusion methods produce consistent  $R_s$  seasonal 443 444 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 445 GWR methods perform best in autumn, with RMSEs ranging from 9.23W/m<sup>2</sup> to 9.56 446 W/m<sup>2</sup> followed by winter, spring and summer. Both the GWR-CF and GWR-CF-AOD 447 methods produce similar annual variations in  $R_s$  from 2000 to 2016, with R<sup>2</sup> values 448 ranging from 0.57 to 0.58 (Table 4). The statistics indicate that the GWR can produce 449 reasonable seasonal and annual variations in  $R_s$ . 450

#### 451 **3.3** Multiyear mean and long-term variability in *R*<sub>s</sub>

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 SunDuderived  $R_s$  sites. Based on direct  $R_s$  measurements, both GWR-based methods show good performances with high R<sup>2</sup> (0.89~0.95) and low RMSE (11.03~11.11 W/m<sup>2</sup>), and few differences are found for the GWR merging results, whether or not AOD is taken as input data (**Table 4**).



458

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 462 in Figure 7. The SunDu sites show that  $R_s$  is high in northwest China, ranging from 180 463 to 300 W/m<sup>2</sup>, and low in eastern China, ranging from 120 to 180 W/m<sup>2</sup>. Both the GWR-464 CF and GWR-CF-AOD methods show consistent Rs spatial patterns with SunDu-465 derived  $R_s$  observations and CERES EBAFs, indicating that the relationship between 466  $R_s$  and impact factors is not linearly stable and is closely related to spatial position. The 467 spatial distribution of the  $R_s$  trend derived from the GWR method is also consistent with 468 the SunDu-derived R<sub>s</sub> trend, especially in western China (Fig. 8). In order to prove that 469 SunDu-derived  $R_s$  can add value to the 0.1 degree product, instead of cloud fraction 470 data alone. We perform a similar GWR analysis but using CERES EBAF interpolated 471

to 0.1 degree and 0.1 degree cloud, and compare the results with those using SunDuderived  $R_s$  and 0.1 degree cloud (**Fig .9**). The results indicate that SunDu-derived Rs can add value to the 0.1 degree product and the merged  $R_s$  by using interpolated CERES EBAF and 0.1 degree cloud product are also similarly to original CERES EBAF but not 0.1 degree cloud product.



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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).



**Figure 9.** 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 Rs and CERES EBAF  $R_s$ ; the  $R_s$ -derived GWR fusion methods are shown in the second line (c, d). Subplots (c) SunDu derived  $R_s$  incorporate only CF, and subplots (d) is the results of GWR analysis using CERES data interpolated to 0.1 degree and 0.1 degree cloud. 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 10. 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 10), 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<sup>2</sup>. 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 10. 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.

516

#### 517 **4. Discussion**

#### 518 **4.1 Impact factors of** *Rs*

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°)  $R_s$  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.

#### 536 **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 542 precipitation data and downscale satellite precipitation to a finer spatial resolution at 543 the same time. Zhou et al. (2019a) used GWR to analyse haze pollution over China and 544 found that the GWR estimate was better than the OLS estimate, with an improvement 545 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  $R_s$ .

560

#### 561 **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 <u>https://doi.pangaea.de/10.1594/PANGAEA.921847</u> (Feng and Wang, 2020).

#### 565 **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 SunDuderived  $R_s$  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 573 0.1° by incorporating MODIS cloud fraction data. The GWR shows better performance 574 than OLS, with increases in  $R^2$  by 9.21%~12.81% and RMSEs reduced by 575 49.56%~54.68%, indicating that  $R_s$  has complex characteristics of spatial variability 576 over China, which has also indicated the necessity of the high spatial resolution of  $R_s$ 577 data. As clouds and aerosols play vital roles in the variability in  $R_s$ , apparent 578 improvements in the results of SunDu-derived  $R_s$  data merging are found if both cloud 579 fraction and AOD are incorporated. Based on the merging results incorporating only 580 cloud fraction, cloud fraction is suggested to be the major factor impacting  $R_s$ , which 581 explained approximately  $86\% \sim 97\%$  of  $R_s$  variability. Generally, SunDu-derived  $R_s$  data 582 merging results derived from GWR show more consistent multiyear mean Rs and long-583 term  $R_s$  trends compared with those from OLS. Our results show that the improvement 584 in  $R_s$  variability estimation is closely related to  $R_s$  impact factors and  $R_s$  spatial 585 heterogeneity. The merged  $R_s$  products derived from GWR-CF-AOD can be 586 downloaded at https://doi.pangaea.de/10.1594/PANGAEA.921847. 587

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596	cloud data	can	be do	wnloaded	from
597	https://neo.sci.gsfc.nas	a.gov/view.php?datas	etId=MODAL2_	M_CLD_FR.	The
598	CERES SYN data can	be downloaded from	https://ceres.larc.	nasa.gov/data/	
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