Variability in Direct and Diffuse Solar Radiation Across China From 1958 to 2017

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Abstract

Long-term variability of direct and diffuse solar radiation ($R_{dir}$ and $R_{dif}$) is essential for climate change study. However, $R_{dir}$ and $R_{dif}$ observations suffer from low spatiotemporal coverage and inhomogeneity. This study hybridized models to calculate $R_{dir}$ and $R_{dif}$ from sunshine duration and meteorological data at ~2,000 stations from 1958 to 2017 over China and demonstrated their reliability. We identified that $R_{dir}$ observations show a spurious steep downtrend before 1990 due to the sensitivity drift of the measuring instruments, implying an overestimation of global dimming. Long-term trends and spatiotemporal details in $R_{dir}$ and $R_{dif}$ were also revealed. From 1958 to 1989, our results show that $R_{dir}$ displays a significant downtrend ($−3.52$ W m$^{-2}$ per decade), whereas $R_{dif}$ shows a significant increasing trend ($0.84$ W m$^{-2}$ per decade), especially over the North China Plain. From 1990 to 2017, $R_{dir}$ decreases nonsignificantly by $−0.47$ W m$^{-2}$ per decade but $R_{dif}$ shows a slight decline of $−0.28$ W m$^{-2}$ per decade.

Plain Language Summary

The direct solar radiation ($R_{dir}$) and diffuse solar radiation ($R_{dif}$) dominate plant photosynthesis. In particular, due to higher light-use efficiency for canopy photosynthesis under $R_{dif}$ than $R_{dir}$, changes of fraction of $R_{dif}$ to $R_{dir}$ could substantially alter plant productivity and the efficiency of canopy gas exchange. However, $R_{dir}$ and $R_{dif}$ are not routinely observed and most available observations are of short duration. Even since 1993, there are fewer than 20 stations in China to measure $R_{dir}$ and $R_{dif}$. The sum of the observed $R_{dir}$ and $R_{dif}$ surface incident solar radiation ($R_s$), has been criticized as of significant inhomogeneity issue over China. In this study, we further demonstrated that this is primarily due to the sensitivity drift of pyrheliometer used to measure $R_{dir}$ before 1990. This study, based on sunshine duration and meteorological data, improved methods to estimate $R_{dir}$ and $R_{dif}$ across China from 1958 to 2017. For verifying their reliability of the long-term variability, we calculated the correlation coefficient, mean bias error, the sensitivity of $R_{dif}$ to $R_{dir}$, and so forth, compared to $R_{dir}$ and $R_{dif}$ from the weather stations. Finally, we used the derived data to describe the long-term variability from seasonal and spatial details of $R_{dir}$ and $R_{dif}$.

1. Introduction

The surface incident solar radiation ($R_s$) is an indispensable energy source on the Earth, consisting of direct solar radiation ($R_{dir}$) and diffuse solar radiation ($R_{dif}$) (Wild et al., 2005). They dominate plant photosynthesis (Alados et al., 2002; Stanhill & Cohen, 2001), land-atmosphere carbon (Mercado et al., 2009; Roderick et al., 2001), water exchange (Hong et al., 2015; Wang et al., 2007), and solar energy production (Kaygusuz, 2002; Wang et al., 2016). In particular, due to higher light-use efficiency for canopy photosynthesis under $R_{dif}$ than $R_{dir}$, changes of fraction of $R_{dif}$ to $R_{dir}$ could substantially alter plant productivity and the efficiency of canopy gas exchange (Knohl & Baldocchi, 2008; Mercado et al., 2009; Roderick et al., 2001; Wang et al., 2008). It has shown that the increase in the diffuse fraction enhanced the global land carbon sink by 23.7% during the period from 1960–1990 when $R_s$ substantially decreased during the global dimming period (Mercado et al., 2009).

The global coordinated measurement of $R_s$ started in the 1950s at high level weather stations (Ohmura et al., 1989; Wild et al., 2017). The stations routinely observing $R_s$ are very sparsely distributed (Tang et al., 2011; Wang et al., 2015). Even worse, $R_{dir}$ and $R_{dif}$ are not routinely observed due to the cost, maintenance, and calibration of the equipment (Chukwujindu, 2017; Khorsanzadeh & Mohammadi, 2016). Especially in China, some issues with recorded observations existed including instrument aging and sensitivity drift before 1990, probably resulting in spurious dramatic downtrends in $R_s$ observation in China (Pandey & Katiyar, 2013; Tang et al., 2011; Wang, 2014). During the period of 1990–1993, China has replaced its
instruments to address the problem of instruments aging. To benefit calibration processes, an absolute pyrheliometer (PMO-6 No. 850406) and two H-F-type cavity pyrheliometers making up the national reference group of China, have been calibrated by references at the World Radiation Center every 5 years since 1991, and then they are used to calibrate all working instruments in China (Yang et al., 2007). Even though these instruments are better calibrated using a multistep method, the observations of solar radiation still lack spatiotemporal representation due to sparse sites and poor management of the network (Shi et al., 2008; Wang et al., 2015).

The Baseline Surface Radiation Network (BSRN) has a reputation of providing high-accuracy data with good maintenance protocols and frequent calibration (Augustine & Dutton, 2013; Wang et al., 2012a). It measures $R_s$, $R_{dir}$, and $R_{dif}$ directly and simultaneously according to the specifications of the World Climate Research Programme. Nonetheless, the BSRN was established in the early 1990s and only has approximately 50 sites worldwide (Ohmura et al., 1998).

Satellite retrievals can provide $R_s$ with continuous and high spatiotemporal resolution properties (Sanchez-Lorenzo et al., 2017), whereas satellite measurements are limited, as they only have available data dating back to the 1980s (Pinker et al., 2005). Satellite measurements also suffer from inhomogeneity issues due to different amounts and capabilities of data acquired from geostationary and polar orbit satellites (Dai et al., 2006). It was also suggested that $R_s$ data from satellite retrievals generally have worse agreement with ground-based observations where it snows (Pfeifroth et al., 2018; Wang et al., 2018). Few satellite products provide estimates of $R_{dir}$ and $R_{dif}$ for China.

A great deal of existing models can estimate $R_{dir}$ and $R_{dif}$ based on empirical statistical methods and physical mechanisms (El Mghouchi et al., 2016; Monteith, 1962). The establishment of diffuse radiation model usually correlates the diffuse fraction with the clearness index or relative sunshine duration. However, most existing models are only suitable for single weather condition (Yao et al., 2015), and they seem to lack universal applicability (Dervishi & Mahdavi, 2012; Khorasanizadeh & Mohammadi, 2016).

Therefore, it is of significance to offset the deficiencies of poor spatial coverage and temporal discontinuity existing in other data sets of $R_{dir}$ and $R_{dif}$. sunshine duration (SunDu), as a useful proxy of $R_s$, has been measured at approximately 2,400 stations over China since 1951 and does not suffer from the problem of instrument sensitivity drift and influences of instrument replacement (Sanchez-Lorenzo & Wild, 2012; Stanhill & Cohen, 2005; Wild, 2009), due to the advantage of recording SunDu (Wang et al., 2015). SunDu-derived $R_s$ has been proven to accurately depict the long-term variability in $R_s$ (He et al., 2018). Furthermore, certain impacts of both aerosols and clouds are also reflected in the derived $R_s$ data from this method [Tang et al., 2011; Wang et al., 2012b; Yang et al., 2006]. Previous research has estimated $R_{dir}$ (Tang et al., 2018) or $R_{dif}$ (Feng et al., 2018) based on sunshine duration, but they did not address the variability in long-term trends of $R_{dir}$ and $R_{dif}$.

This study could improve methods to estimate $R_{dir}$ and $R_{dif}$ based on routine meteorological observations. The derived data are evaluated by in two steps that show their reliability at monthly and annual time scales. We then apply the models to ~2,000 stations over China from 1958 to 2017, which shows that $R_{dir}$ decreases by $−3.52$ W m$^{-2}$ per decade and $R_{dif}$ increases $0.84$ W m$^{-2}$ per decade from 1958 to 1989, and the trend in $R_{dir}$ after 1990 is nonsignificant.

2. Materials and Methods
2.1. Data

The observed $R_s$, $R_{dir}$, and $R_{dif}$ data sets were obtained from the BSRN (at 55 stations) and the China Meteorological Administration (CMA, at 122 stations). SunDu and other meteorological data (e.g., air temperature, relative humidity, and surface pressure) were also obtained from the CMA to estimate $R_{dir}$ and $R_{dif}$ at approximately 2,400 meteorological stations from 1958 to 2017. Note that total cloud cover data were from 1958 to 2014.

After preliminary quality checks including continuity and data length (at least 80% of the record duration at all timescales, that is, $≥24$ days per month, $≥292$ days per year, and $≥48$ years during the study period of 1958–2017), 62 sites from the CMA stations during the period 1970–1989 were involved in this study. Data during the period 1990–1993 were here excluded because of large errors from instrument replacement.
issues (Tang et al., 2011; Wang, 2014). Most of the CMA stations stopped observing \( R_{dir} \) and \( R_{dif} \) after 1993, and hence, only 16 stations (after the quality checks) continued to simultaneously monitor \( R_{dir} \), \( R_{dif} \), and \( R_{c_dir} \). Accordingly, 32 sites were selected from 55 BSRN global radiation stations from 1994 to 2015, whose instruments are of high accuracy, with good maintenance, frequent calibrations, and separate measurements of \( R_{dir} \), \( R_{c_dir} \), and \( R_{dif} \) (Ohmura et al., 1998). The spatial distribution of solar radiation stations is shown in Figure S1 in the supporting information. The stations used to study the long-term variability and more spatial details of \( R_{dir} \) and \( R_{dif} \) across China from 1958 to 2017 were also selected based on the above quality checks, with 2,188 sites in total.

### 2.2. Methods

The equations of \( R_{dir} \) and \( R_{dif} \) are regressed based on the observed direct and diffuse solar radiation from 16 CMA stations during the period 1994–2014. Analogously, the calculation formula for the monthly derived \( R_{dir} \) data set is improved based on that for the derived \( R_{dir} \) data set (He et al., 2018; Tang et al., 2018; Yang et al., 2006), as shown in equation (1):

\[
\frac{R_{dir}}{R_{c-dir}} = a_0 + a_1 \times (n/N) + a_2 \times (n/N)^2
\]  
(1)

\[
R_{c-dir} = \int \tau_{c-dir} \times I_0 \, dt
\]  
(2)

where \( a_0, a_1, \) and \( a_2 \) represent the regression coefficients of SunDu against the observed \( R_{dir} \) values in equation (1); \( n \) and \( N \) are the actual sunshine duration and the theoretical value of the sunshine duration without clouds, respectively. \( I_0 \) is the solar irradiance on a horizontal surface at the top of the atmosphere. \( R_{c-dir} \) is the direct solar radiation under clear-sky conditions. \( \tau_{c-dir} \) is the direct radiation transmittance under clear-sky conditions and is calculated using other meteorological data (including relative humidity, air temperature, and surface pressure) from the CMA stations, turbidity coefficient based on Hess et al. (1998), and ozone thickness based on the satellite products provided by National Aeronautics and Space Administration/Goddard Space Flight Center Ozone Processing Team [K Yang et al., 2006].

For the estimates of \( R_{dif} \), based on the relationship of transmittances between \( R_{dif}/R_{dir} \) and \( R_{c-dir}/R_{dir} \), this study develops a model equation (3):

\[
\frac{R_{dif}}{R_{dir}} = b_0 + b_1 \times \left( \frac{R_{dir}}{R_{0}} \right) + b_2 \times \left( \frac{R_{dir}}{R_{0}} \right)^2
\]  
(3)

where \( b_0, b_1, \) and \( b_2 \) represent regression coefficients of \( R_{dif}/R_{dir} \) against the observed \( R_{dif}/R_{dir} \) values in equation (3); \( R_0 \) is calculated by using the sunshine duration and other meteorological data from He et al. (2018); \( R_{dir} \) is the solar radiation on a horizontal surface at the top of the atmosphere.

We used the observed \( R_{dir} \) (or \( R_{dif} \)), sunshine duration, and other climatic factors from 1994 to 2014 to obtain the 16 sets of regression coefficients based on equation (1) (3) (Table S1); and their spatial distribution is illustrated in Figure S2. Then, approximately 2,000 sites were matched to 16 radiation observations stations based on distance, ensuring that each site can be assigned a set of the regression coefficient from its nearest site among the 16 radiation stations (Figure S3). Finally, we applied equation (1) (3) again to calculate the \( R_{dir} \) (or \( R_{dif} \)) values from 1958 to 2017 for each station (~2,000 stations in China) when the observed sunshine duration and other climatic factors (e.g., air temperature, relative humidity, and surface pressure) were available.

### 2.3. Models Performances

To assess the derived \( R_{dir} \) and \( R_{dif} \), the estimations of monthly averages at the 16-pair stations were compared with the observations from 1994 to 2014 over China. Considering the uncertainty of the annual timescale of CMA observations due to the impacts of problems such as instrument sensitivity drift, we utilized the observations from 32 BSRN stations to further verify the reliability of the long-term changes in the derived data by examining the sensitivity of \( R_{dif} \) to \( R_{dir} \). We calculated a polynomial regression model to assess the sensitivity of \( R_{dif} \) to \( R_{dir} \) at the annual timescale, which is the slope of the linear regression line between annual anomaly \( R_{dif} \) and \( R_{dir} \). Other statistical indicators include the following: the correlation coefficient (\( r \)), mean bias error (\( bias \)), root-mean-square error, and relative root-mean-square error.
3. Results and Discussion

3.1. Comparisons of the Observed and Derived $R_s$, $R_{dir}$, and $R_{dif}$

Compared to previous studies, the derived data show good performance to reproduce the monthly $R_{dir}$ ($R_{dif}$) estimates with a higher correlation coefficient of 0.96 (0.98) and a smaller mean bias of 3.41 W m$^{-2}$ ($-0.02$ W m$^{-2}$) (Figures 1a and 1b and Table S4) (Li et al., 2011; Tang et al., 2018). The observed trends in $R_s$ and $R_{dir}$ appear to be steeper (likely spurious) than the derived trends during the period 1970–1989 (Figures 1c1 and 1d1). It has been verified that the spurious trend in the observed $R_s$ may be due to the observations from the CMA radiation stations experiencing the negative influence of instrument sensitivity drift and instrument aging before 1990 (Wang, 2014; Wang et al., 2015; Yang et al., 2018), and the same is true for the pyrheliometer used to measure $R_{dir}$ in this study, implying an overestimation of global dimming in China. However, this issue is almost not present in the SunDu-derived radiation data sets. The light sensitive paper used to measure SunDu is replaced each day, and therefore, SunDu-derived $R_{dir}$ does not have such a sensitivity drift problem. After 1993 when the CMA stations have finished the instrument replacement activity and improved calibrations, the derived and observed radiation have similar variations (Figures 1c2, 1d2, and 1e2). In brief, the derived radiation data can effectively describe the monthly average values and temporal variability as proxies of the observation data.

To further confirm the dependence of the derived $R_{dif}$ to $R_{dir}$ at the annual timescale, a higher-accuracy radiation observation data set from the BSRN stations was adopted as a criterion. Based on the annual anomalies in $R_{dif}$ and $R_{dir}$, the sensitivities of $R_{dif}$ to $R_{dir}$ are shown in Figure 2. More than 57% of the BSRN stations and derived stations both have sensitivities of less than 0.0. The overall sensitivity of $R_{dif}$ to $R_{dir}$ is $-0.06 \pm 0.03$ ($p < 0.001$) for the ~2,000 derived radiation stations in China and $-0.08 \pm 0.03$ ($p < 0.001$) for the BSRN radiation stations, which indicates that the annual variation of $R_{dif}$ and $R_{dir}$ is roughly negative correlated. Therefore, the derived data based on SunDu might accurately describe the relationship between $R_{dif}$ and $R_{dir}$. These results can also prove that the derived $R_{dif}$ and $R_{dir}$ are credible to depict the long-term variability of solar radiation.

Figure 1. (a and b) comparison of the observed and derived solar radiation data in China. The color bar denotes the scattering density, which is defined as the number of points in each 100×100 grid. Anomaly time series are shown by the observed (in solid lines) and derived (in dotted lines) $R_s$ (in black), $R_{dir}$ (in red), and $R_{dif}$ (in blue) data sets during the two periods of 1970–1989 (figures 1c1, 1d1, and 1e1, at 62 radiation observation stations) and 1994–2014 (figures 1c2, 1d2, and 1e2, at 16 radiation observation stations), respectively.
3.2. Spatiotemporal Variations in the Derived $R_s$, $R_{dir}$, and $R_{dif}$

3.2.1. Time Series and Trends

Table 1 describes the decadal trends in the derived $R_s$, $R_{dir}$, and $R_{dif}$ from approximately 2,000 stations over China during the three periods. The period of 1958–1989 is known as global dimming (Gilgen et al., 1998; Ohmura, 2009; Ohmura et al., 1998; Wild, 2009), when the trends are declining for both $R_s$ ($-2.68$ W m$^{-2}$ per decade, $p < 0.05$) and $R_{dir}$ ($-3.52$ W m$^{-2}$ per decade, $p < 0.05$) but increasing for $R_{dif}$ ($0.84$ W m$^{-2}$ per decade, $p < 0.05$) (Figure 3a and Table 1) almost without the influence of the sensitivity drift. The average trend in $R_s$ of the four models from Coupled Model Intercomparison Project Phase 5 Goddard Institute for Space Studies is consistent with our result during the period of global dimming (Wang et al., 2015). For seasonal variations, $R_{dir}$ in the warm season decreases more greatly than that in the cold season ($-4.14$ vs. $-2.75$ W m$^{-2}$ per decade) (Figures 3b and 3c and Table 1). $R_{dif}$ correspondingly shows a

Table 1

|                  | 1958–1977 | 1958–1989 | 1990–2017 |
|------------------|-----------|-----------|-----------|
|                  | Annual    | Warm      | Cold      | Annual    | Warm      | Cold      | Annual    | Warm      | Cold      |
| $R_s$            | $-1.95^{**}$ | $-2.67^{**}$ | $-1.20^{**}$ | $-2.68^{**}$ | $-3.02^{**}$ | $-2.24^{**}$ | $-0.76^{*}$ | $-2.09^{**}$ | $0.58$ |
| $R_{dir}$        | $-2.30^{**}$ | $-3.20^{**}$ | $-1.36^{**}$ | $-3.52^{**}$ | $-4.14^{**}$ | $-2.75^{**}$ | $-0.47$ | $-1.72^{**}$ | $0.78^{*}$ |
| $R_{dif}$        | $0.35^{**}$ | $0.53^{**}$ | $0.16^{**}$ | $0.84^{**}$ | $1.12^{**}$ | $0.51^{**}$ | $-0.28^{**}$ | $-0.37^{**}$ | $-0.20$ |

$^{**}$95% confidence level.  $^{*}$90% confidence level.
larger increasing trend in the warm season (1.12 W m\(^{-2}\) per decade, \(p < 0.05\)) than that in the cold season (0.51 W m\(^{-2}\) per decade, \(p < 0.05\)), which may enhance plant photosynthesis in the warm season through the diffuse radiation fertilization thereby increasing global primary production (Rap et al., 2018).

In the period of 1990–2017, the derived \(R_s\) data depict a downward trend (−0.76 W m\(^{-2}\) per decade, \(p < 0.10\)). The satellite retrievals of \(R_s\) (Wu & Fu, 2011) also show a downward trend during this period. Our estimation in the trend of \(R_s\) is also similar to the result of Allen et al. (2013) based on 42 climate models from Coupled Model Intercomparison Project Phase 5 during the period of 1990–2007 (−0.8 ± 0.4 W m\(^{-2}\) per decade).

Particularly, in the warm season of 1990–2017, the negative trend in \(R_s\) is more apparent (by −2.09 W m\(^{-2}\) per decade, \(p < 0.05\)) (Table 1).

In general, the variation in \(R_s\) is steeper than that in \(R_s\) during the period 1958–2017, showing a significant decreasing trend (Table 1). \(R_{dir}\) increases by 0.53 W m\(^{-2}\) per decade (\(p < 0.05\)) in the warm season, and increases by 0.16 W m\(^{-2}\) per decade (\(p < 0.05\)) in the cold season from 1958 to 2017 (Figures 3b and 3c and Table 1). Our results are similar to Feng and Li (2018) who utilized a backpropagation artificial neural network (BP network) to estimate \(R_s\), \(R_{dir}\), and \(R_{dif}\) at 45 stations from 1958 to 2016 over China.

### 3.2.2. Spatial Patterns of Trends

Figure 4 shows the spatial distribution of the trends in \(R_s\), \(R_{dir}\), and \(R_{dif}\) and total cloud cover over China at different timescales. The derived \(R_s\) and \(R_{dir}\) data show an overall decline over China during the period of
Figure 4. Maps of annual and seasonal trends in the derived solar radiation (W m$^{-2}$ per decade) and total cloud cover (per decade) from ~2,000 stations over China during the three periods of (a) 1958–2017, (b) 1958–1989, and (c) 1990–2017 (1990–2014 for c4, c8, and c12). The sites with significant trends ($p < 0.05$) are distributed in Figure S4 (in the supporting information).
1958–2017 (with more than 78% of sites) at annual and seasonal timescales, especially in the North China Plain. However, \( R_{df} \) data show significant increasing trends there (Figure 4a), likely because of the increasing trend in aerosol loading in the areas (Li et al., 2016). It is worth noting that the spatial difference of their trends seems not be affected by the spatial pattern of ~2,000 meteorological stations in China matching the 16 radiation observation stations (Figures S3 and 4).

From 1958 to 1989, the spatial pattern of the derived \( R_{dir} \) is similar to that of the derived \( R_s \), with a significant decrease over most parts of China (with more than 75% of sites) at annual and seasonal timescales (Figure 4b). In contrast to the \( R_{df} \) data, the derived \( R_{df} \) data show significant continuous increasing trends, especially over the North China Plain. In the southern China, there are nonsignificant decreasing trends in \( R_{df} \) at annual timescale (Figures 4b and S4), mainly due to the offset effect of its opposite trends in different seasons, that is, the trends of \( R_{df} \) are negative in the cold season but positive in the warm season.

From 1990 to 2017, \( R_s \) shows decreasing trends over China at annual and warm seasonal timescales, except in the Pearl River Basin (Figure 4c). These trend patterns at the annual timescales are consistent with the findings of Xia (2010) and Wang and Wild (2016). For \( R_{dir} \), the spatial distribution of its trends is similar to \( R_s \) at different timescales. In the warm season, \( R_s \) and \( R_{dir} \) data both show negative trends in almost whole China (Figures 4c and S4). In the cold season, however, they show significant positive trends over the Loess Plateau, the Szechwan Basin, and the Yangtze River Basin (Figures 4c and S4). The seasonal differences also occur in \( R_{df} \) during this period, but mainly over the Szechwan Basin, the North China Plain, and parts of the southeastern China. The trends in \( R_{df} \) are significant with the 95% confidence level in the northern China at different timescales (Figure S4). These seasonal and regional details in solar radiation variability could provide effective information for the analysis of plant photosynthesis.

### 3.3. Variation of Solar Radiation in Relation to Key Factors

It is obvious that \( R_s \) is affected mostly by clouds, aerosols, and water vapor through the atmosphere (Horseman et al., 2008; Qian et al., 2015; Ramanathan et al., 1989; Warren et al., 2007). Clouds directly reduce \( R_s \) by reflecting a large portion of solar radiation into space and scattering a small portion of solar radiation (Cess et al., 1995; Kasten & Czeplak, 1980); aerosols and water vapor reduce \( R_s \) through absorption and scattering effects. The scattering portion eventually arrives at the Earth’s surface in the form of \( R_{df} \) (Ramanathan et al., 2001).

The variations in total cloud cover (at the rightmost column of Figure 4) can only explain the trend changes in solar radiation during the period of 1990–2014, which is in agreement with the previous studies (Luo et al., 2000; Yang et al., 2013). The contribution of aerosols to long-term solar radiation variations should be considered, but it is difficult to be quantified due to aerosol direct and indirect effect on solar radiation. Based on the model only considering aerosol direct plus first indirect effect, increasing air pollution alone can account for 2.6 W m\(^{-2}\) of the decreasing solar radiation in the part of United States (Liepert, 2002). Li et al. (2018) found that \( R_s \) may be highly sensitive to aerosol-related parameters (such as single scattering albedo), by analyzing a station with collocated \( R_s \) and aerosol observations in Xianghe, China. After the volcanic eruption in 1991, significant decreasing \( R_s \) should appear due to the effect of the large amount of aerosols. However, the total cloud cover declines significantly much from 1991 to 1992 in China (Figure S5 in the supporting information), which could weaken the decreasing extent of solar radiation caused by aerosols from the volcanic eruptions. The changes of water vapor can also lead to the reduction in \( R_{dir} \) and an increase in \( R_{df} \) (Wang et al., 2018).

### 4. Conclusions

This study reconstructed a comprehensive data set of \( R_{dir} \) and \( R_{df} \) over most of all China to offset the deficiencies of poor spatial coverage and temporal discontinuity. Due to the simple physical models and mathematical methods involved, the derived data sets in this study show better performance in temporal variability and spatial details with high correlation coefficients (0.96 and 0.98) and relatively small standard deviations (15.49 and 5.93 W m\(^{-2}\)) at the monthly timescale. Simultaneously, the derived data can describe the relationship between \( R_{df} \) and \( R_{dir} \) at the annual timescale, increasing the credibility of the derived \( R_{df} \) and \( R_{dir} \) from sunshine duration. Furthermore, we estimated the long-term trends of \( R_s \) and \( R_{dir} \), suggesting that the sensitivity drift of the pyrheliometer used to measure \( R_{dir} \) implies an overestimation of global dimming in China.
before 1990. From 1958 to 1989, the new and more believable $R_{dir}$ decreases by $-3.52$ W m$^{-2}$ per decade and $R_{dif}$ increases by $0.84$ W m$^{-2}$ per decade. After that, the trend in $R_{dir}$ does not change significantly ($-0.47$ W m$^{-2}$ per decade, $p > 0.10$), but $R_{dif}$ shows a slight decline ($-0.28$ W m$^{-2}$ per decade, $p < 0.05$). Moreover, $R_{dir}$ and $R_{dif}$ from estimated data both have steeper trends in the warm season than those in the cold season.

These regional details and seasonal differences in the $R_{dir}$ and $R_{dif}$ trends will be beneficial to advance the current understanding of variability in solar radiation and the study of plant photosynthesis and land-atmosphere interaction. Actually, due to the use of local meteorological parameters to estimate $R_{dir}$ and $R_{dif}$, the models should also be adapted to different terrain areas and climate zones around the world.

**Author Contributions**

K. W. conceived the study. Y. H. conducted the analysis and wrote the initial draft of the paper. All authors participated in interpreting and revising the paper.

**Competing Financial Interests**

The authors declare no competing interests.

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