Earth Syst. Sci. Data Discuss., https://doi.org/10.5194/essd-2018-4
Manuscript under review for journal Earth Syst. Sci. Data
Discussion started: 28 March 2018

Global radiation, photosynthetically active radiation, and the diffuse components dataset of China, 1981–2010

Xiaoli Ren[1], Honglin He[1, 2], Li Zhang[1, 2], Guirui Yu[1, 2]

[1]Key Laboratory of Ecosystem Network Observation and Modeling, Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing, 100101, China
[2]College of Resources and Environment, University of Chinese Academy of Sciences, Beijing 100190, China

Correspondence to: Honglin He (hehl@igsnrr.ac.cn)

Abstract. Solar radiation, especially photosynthetically active radiation (PAR), is the main energy source of plant photosynthesis; and the diffuse component can enhance canopy light use efficiency, thus increasing ecosystem productivity. In order to predict the terrestrial ecosystem productivity precisely, we not only need global radiation and PAR as driving variables, but also need to treat diffuse radiation and diffuse PAR explicitly in ecosystem models. Therefore, we generated a series of radiation datasets, including global radiation, diffuse radiation, PAR, and diffuse PAR of China from 1981 to 2010, based on the observations of China Meteorology Administration (CMA) and Chinese Ecosystem Research Network (CERN). The dataset should be useful for the analysis of the spatio-temporal variations of solar radiation in China and the impact of diffuse radiation on terrestrial ecosystem productivity based on ecosystem models. The dataset is freely available from the Zenodo at the website of https://zenodo.org/record/1198894 (DOI: 10.11922/sciencedb.555).

1 Introduction

Solar radiation is the primary energy source for life on Earth(Wild, 2009), and the portion of global radiation with 400~700 nm wavelengths, i.e. photosynthetically active radiation (PAR), is critical for vegetation photosynthesis. Therefore, global radiation/PAR is a prerequisite for the modelling of terrestrial ecosystem productivity (Jacovides et al., 2007). Besides the quantity, the composition of global radiation/PAR, i.e. the proportion of diffuse/direct components, is also important (Farquhar and Roderick, 2003; Lauret et al., 2010), since the diffuse radiation can reduce photosynthetic saturation and increase the canopy light use efficiency (LUE), thereby enhancing the ecosystem carbon uptake (Kanniah et al., 2012; Mercado et al., 2009). The explicit treatment of diffuse radiation in ecological models is needed to accurately simulate the carbon dynamics of terrestrial ecosystems, making the diffuse radiation/diffuse PAR an important environmental driving factor (Gu et al., 2003; Kanniah et al., 2012; Mercado et al., 2009). The effects of diffuse radiation on ecosystem productivity have become a hot issue in carbon cycle research(Alton et al., 2007; Gu et al., 2002; Gu et al., 2003; Mercado et al., 2009; Zhang et al., 2011; Zhang et al., 2017). However, global radiation, PAR, diffuse radiation, and diffuse PAR are not generally measured like meteorological variables such as sunshine duration (Ren et al., 2014; Ren et al., 2013). So a long-term high-quality reanalysis dataset of global radiation, PAR, diffuse radiation, and diffuse PAR is required for better understanding the ecosystem carbon dynamics as well as their spatial and temporal variability.

Globally, a widespread decrease in solar radiation between the 1950s and 1980s has been detected, known as global dimming, with a partial recovery thereafter at many locations, known as global brightening (Wild, 2009; Wild et al., 2005). As a big country in the world, did China experience the same variation? Employing the observation data from national meteorological stations of China Meteorology Administration (CMA) and the field sites of Chinese Ecosystem Research Network (CERN), Ren et al. (Ren et al., 2014; Ren et al., 2013) parameterized the estimation models of global radiation, diffuse radiation, PAR, and diffuse PAR, and performed cross validation, which indicated high estimation accuracy. Then, the radiation dataset in China from 1981 to 2010 was generated, and the spatio-temporal variations were analysed. This dataset has been employed to estimate the above-ground biomass and net ecosystem productivity of alpine grasslands on Three-River Headwaters Region (Ren et al., 2017a; Zeng et al., 2017) and the gross primary productivity of the alpine grasslands on Tibetan Plateau(He et al., 2014; Ren et al., 2017b). We have published the monthly diffuse PAR spatial dataset in *China Scientific Data*, and briefly introduced the estimation method of diffuse PAR (Ren et al., 2017c). In this paper, we systematically described the estimation and interpolation methods of global radiation, diffuse radiation, PAR, and diffuse PAR, and provided the estimated values of model parameters as well as the accuracy of estimation and interpolation. The spatial dataset of monthly and yearly global radiation, diffuse radiation, PAR, and diffuse PAR in China from 1981 to 2010 (called radiation dataset for short hereafter) are shared in this paper, providing an integral radiation dataset for ecological modelling and the analysis of the effects of diffuse radiation on terrestrial ecosystem productivity.

2 Data and Method

The schematic workflow of the radiation dataset production is shown in Fig. 1. Since the observation sites of sunshine duration are widely distributed in China (756 sites), we first expanded the observation data of global radiation, diffuse radiation, and PAR from 122 sites, 81 sites and 39 sites to 756 sites based on sunshine duration data through estimation models, respectively. Then diffuse PAR, which has few observation sites in China, was estimated through the empirical relationship with global radiation, diffuse radiation and PAR. Finally, ANUSPLIN software(Hutchinson, 2001) was employed to acquire the spatial global radiation, diffuse radiation, PAR, and diffuse PAR data. The details are described in the following sections.

2.1 Observation data and quality control

2.1.1 Basic data

The basic data used here include daily sunshine duration, global radiation, diffuse radiation, and PAR observation data (Fig. 2), as well as Digital Elevation Model (DEM) data. The observed daily sunshine duration data (756 meteorological stations), global radiation data (122 meteorological stations), and diffuse radiation data (81 meteorological stations) during 1981 to 2010 were provided by CMA (http://data.cma.cn). We also used the daily global radiation and PAR data observed in 39 CERN field sites during 2004 to 2010 (http://www.cern.ac.cn). The DEM data (500m×500m) was from the Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences (http://www.resdc.cn). It should be noted that due to the station adjustment of CMA in 1993, the number of stations observing diffuse radiation dropped from more than 70 to 17 after 1993. In sum, there are 81 stations that have more than 1-year record of diffuse radiation during the period of 1981 to 2010(Ren et al., 2013).

2.1.2 Quality control of observation data

Quality control is an important part of reanalysis dataset production. Observations with poor quality may offset the parameter values of estimation models, thus affecting the quality of generated dataset. The CMA and CERN have performed basic quality control on the observational data (Shi et al., 2008). We made further quality checks according to the following criteria: 1) daily sunshine duration cannot be bigger than the daily possible sunshine duration; 2) daily extra-terrestrial radiation must be bigger than daily global radiation; 3) daily PAR cannot exceed daily global radiation, and the ratio between daily PAR and daily extra-terrestrial radiation cannot be larger than 40%; 4) daily diffuse radiation cannot exceed daily global radiation, and need to satisfy the requirements for overcast and clear skies described by Eq.1 (Reindl et al., 1990; Ren et al., 2013).

$$\begin{cases} Q_d/Q \geq 0.9 \text{ , for } Q/Q' < 0.2 \\ Q_d/Q \leq 0.8 \text{ , for } Q/Q' > 0.6 \end{cases} \quad (1)$$

where Q_d, Q, and Q' represents daily diffuse radiation, daily global radiation, and daily extra-terrestrial radiation, respectively.

2.2 The expansion/estimation of radiation data at site scale

The coverage of radiation stations in CMA is limited, thus we used estimation models to expand daily global radiation, diffuse radiation, and PAR at site scale based on the widely distributed daily sunshine duration observations. Diffuse PAR is not generally measured, thus estimated using the empirical relationships with global radiation, diffuse radiation, and PAR.

(1) The expansion of global radiation

Previous studies indicated that global radiation in China was estimated more accurately using sunshine duration than other predictors such as temperature, through the comparison of multiple global radiation models(Chen et al., 2004). So we used the Angstrom model (Eq. 2) to expand daily global radiation (Angstrom, 1924; Chen et al., 2004; Ren et al., 2017a). The model was parameterized using daily global radiation and sunshine duration data in 122 CMA stations. Then the daily global radiation of 756 CMA stations was derived using the informed model and sunshine duration data in 756 CMA stations.

$$k_t = \frac{Q}{Q'} = a + b\frac{n}{N} \tag{2}$$

where k_t represents clearness index, defined as the ratio of the daily global radiation (Q) to the daily extra-terrestrial radiation (Q'); n and N are the actual and possible daily sunshine duration; a and b are undetermined parameters.

(2) The expansion of diffuse radiation

There are many radiation decomposition models relating daily diffuse radiation with daily diffuse fraction, including Liu & Jordan model(Liu and Jordan, 1960), Page model(Page, 1961), Reindl model(Reindl et al., 1990), Boland model(Boland et al., 2001) and so on. Using data from several sites in Europe, Africa, Australia, and Asia, Lauret et al.(Lauret et al., 2010) indicated that Boland model (Eq. 3) had better or similar performance with other models but with a much simpler model structure. We also compared several models and found that the Boland model is the best one in our case (Ren et al., 2013). So we parameterized Boland model using daily global radiation and diffuse radiation data, and then expanded the daily diffuse radiation data from 81 CMA stations to 756 CMA stations.

$$k_d = \frac{Q_d}{Q} = \frac{1}{\exp(c + d \cdot k_t)} \tag{3}$$

Earth Syst. Sci. Data Discuss., https://doi.org/10.5194/essd-2018-4
Manuscript under review for journal Earth Syst. Sci. Data
Discussion started: 28 March 2018

where k_d represents the daily diffuse fraction, defined as the ratio of daily diffuse radiation (Q_d) to global radiation (Q); c and d are undetermined parameters.

(3) The expansion of PAR

The PAR model (Eq. 4), which has been proved applicable in China (Ren et al., 2014; Zhu et al., 2010), was used to expand the daily PAR data from 39 CERN filed sites to 756 CMA stations. Firstly, we used the daily PAR and global radiation data measured in 39 CERN field sites to estimate the model parameters, and then utilized the informed model and expanded daily global radiation data to expand daily PAR data.

$$PAR = [e + f \cdot \ln(k_t)] \cdot Q \qquad (4)$$

where e and f are undetermined parameters.

(4) The estimation of diffuse PAR

Diffuse PAR is usually roughly estimated by multiplying PAR and the diffuse fraction of global radiation. However, the diffuse fraction of global radiation is not equivalent to the diffuse fraction of PAR, since the latter is significantly greater than the former under clear skies, while almost equivalent under cloudy skies(Ren et al., 2014; Spitters et al., 1986). So the Spitters model (Spitters et al., 1986) (Eq. 5) was applied to estimate the daily diffuse PAR of 756 CMA stations.

$$PAR_d = [1 + 0.3 \cdot (1 - k_d)^2] \cdot k_d \cdot PAR \qquad (5)$$

where PAR_d represents diffuse PAR.

2.3 The generation of radiation dataset

ANUSPLIN software(Hutchinson, 2001) was utilized to generate the reanalysis radiation dataset with 10km×10km spatial resolution in China from 1981 to 2010. ANUSPLIN is a widely used spatial interpolation package, developed by the Center for Resource and Environmental Studies at the Australian National University (Hijmans et al., 2005; Hutchinson, 1995). This software implemented thin plate smoothing splines, which can incorporate the covariates in addition to the independent spline variables. We used three-dimensional spline to interpolate radiation data, with latitude and longitude as the

Earth Syst. Sci. Data Discuss., https://doi.org/10.5194/essd-2018-4
Manuscript under review for journal Earth Syst. Sci. Data
Discussion started: 28 March 2018

independent variables and the elevation as the covariate. The specific steps of this process are shown in Fig. 3. The main procedures are as follows.

1) Daily radiation data is scaled to monthly and formatted following the instructions of ANUSPLIN using MATLAB software; the DEM data is resampled to 10km×10km using ArcGIS software.

2) Determine the specific parameter values in the command files of Splina.exe and Lapgrd.exe, which are sub-modules of ANUSPLIN.

3) Construct the spline using Splina.exe and interpolate the radiation data using Lapgrd.exe.

4) Convert the output ASCII files to ArcGIS GRID files.

3 Description and analysis of the radiation dataset

The radiation dataset has four subsets, including global radiation, diffuse radiation, PAR, and diffuse PAR in China with 10km×10km from 1981 to 2010. Each subset has 12×30×2 monthly files and 30×2 yearly files, except diffuse PAR, which only has 30×2 yearly files. We provide two formats for each data file, i.e. ArcGIS GRID and ASCII Text, as well as the Python code for the conversion from Text to GRID. To be comparable with each other, the units of radiation data are all set to MJ m^{-2} $month^{-1}$ (monthly)/ MJ m^{-2} yr^{-1} (yearly).

It should be noted that the measuring systems of PAR include radiation flux density (W m^{-2}) and photosynthetic photon flux density (μmol m^{-2} s^{-1}), which are convertible through a conversion coefficient of 4.57 μmol J^{-1}. The users can convert the unit of PAR/diffuse PAR from MJ m^{-2} to mol m^{-2} if needed.

The spatial patterns of global radiation, diffuse radiation, PAR, and diffuse PAR are shown in Fig. 4. We can see that the distribution of radiation in China is inhomogeneous. The global radiation and PAR are higher in the northwest and lower in the southeast, while the diffuse radiation and diffuse PAR are higher in the south and west and lower in the north. Because the south has more cloudy days and more precipitation than other regions, so the diffuse radiation is high there although the global radiation is rather low.

The annual values of global radiation, diffuse radiation, PAR, and diffuse PAR in China from 1981 to 2010 are listed in Table 1. The average value of global radiation, diffuse radiation, PAR, and diffuse PAR is 5270.0, 2477.0, 2164.5, 1106.9 MJ m^{-2} yr^{-1}, respectively. The global radiation in China was declining during 1980s, and then started to recover, which was consistent with the global findings (Wild, 2009). There were dramatic increases of diffuse radiation in 1982, 1983, 1991, and 1992, which may be caused by the El Chinchon eruption in 1982 and the Pinatubo eruption in 1991(Ren et al., 2013). More

Earth Syst. Sci. Data Discuss., https://doi.org/10.5194/essd-2018-4
Manuscript under review for journal Earth Syst. Sci. Data
Discussion started: 28 March 2018

detailed discussion about the spatio-temporal variations of radiation in China during 1981-2010 has been reported in previous papers (Ren et al., 2014; Ren et al., 2013).

4 Validation of the radiation dataset

4.1 Validation of data expansion at site scale

Due to the highly heterogeneous topography and climate of China, we estimated the model parameters for eight different geographical regions according to Chinese Physical Geography Division(Zhao, 1997), including Northwest China, Inner Mongolia, Northeast China, North China, Central China, South China, Southwest China, and Qinghai-Tibet Plateau.

To validate the precision of data expansion at site scale, we utilized leave-one-out cross validation method to calibrate and check the location and time independence of the Angstrom model, Boland model and PAR model. Taking time expansion of global radiation for example, we used the sunshine duration and global radiation data of 29 years out of 30 years to calibrate the Angstrom model and used the data of the last one year to perform validation. This process was repeated 30 times, and then the average model performance, measured by correlation coefficient (R) and root mean square error (RMSE), can be derived. In the case of site expansion, we leaved the data of one site out and fitted the model with the rest data for the number of sites times, and then average performance of site expansion can be derived.

Table 2 showed the estimated parameter values and validation results for the models, which indicated that the data expansion at site scale in all regions of China had high accuracy. Almost all the correlation coefficients exceeded 0.8, only the Boland model in Qinghai-Tibet Plateau was an exception, which might be caused by the large differences in climatic conditions among the sparse stations there.

4.2 The prediction standard error of spatial interpolation

The ANUSPLIN software can not only interpolate the climatic data but also estimate the prediction standard error(Hutchinson, 2001). The spatial distribution of the interpolation error for global radiation, diffuse radiation, PAR, and diffuse PAR is shown in Fig. 5. The mean error for yearly global radiation, diffuse radiation, PAR, and diffuse PAR is 280.8, 98.9, 107.7, 40.9 MJ m^{-2} yr^{-1}, respectively; and the relative error is 5.3%, 4.0%, 5.0%, and 3.7%, respectively.

The interpolation error in the north western part of the Qinghai-Tibet Plateau is relatively large, probably because the meteorological stations there are very limited (Fig. 2). Because of the absence of observations in Taiwan, the interpolation

Earth Syst. Sci. Data Discuss., https://doi.org/10.5194/essd-2018-4
Manuscript under review for journal Earth Syst. Sci. Data
Discussion started: 28 March 2018

error there is rather large compared with other areas. It should be noted that the data around the border also have relatively large error, because we do not have the observation data beyond the border.

5 Data availability

The dataset is freely available from the Zenodo at the website of https://zenodo.org/record/1198894 (DOI: 10.11922/sciencedb.555). Users can find the dataset freely accessible, although some users may need to use a keyword search ('global radiation China') to establish initial access. There are four folders for global radiation (i.e., Global radiation.zip), diffuse radiation (i.e., Diffuse radiation.zip), PAR (i.e., PAR.zip), and diffuse PAR (i.e., Diffuse PAR.zip), respectively, and a description text file (i.e., Readme.txt). There are two formats for each data, i.e. ArcGIS GRID and ASCII Text, along with the Python code for the conversion from Text to GRID.

6 Conclusions

Solar radiation is pivotal to the modelling of terrestrial ecosystem productivity, and the quantity and quality of solar radiation are both important because of the differences between vegetation light use efficiency for direct and diffuse light. A reanalysis spatial radiation dataset, i.e., monthly and yearly global radiation, diffuse radiation, PAR, and diffuse PAR in China from 1981 to 2010, were produced based on several estimation models and the observation data from CMA and CERN. It provides a series of systematic and integral radiation data for the community of ecological modelling, making the analysis of the effects of solar radiation and its diffuse components on terrestrial ecosystem productivity in China more convenient.

Author contribution

X. R. and H.H. designed the study; X. R. collected the data, performed data processing and production, and wrote the manuscript. L. Z. provided help in collecting data; G. Y. gave technical guidance.

Competing interests

The authors declare no competing financial interests.

Acknowledgements

We are very grateful to CMA, CERN for providing the observation data. This work was supported by the National Key R&D Program of China (grant number 2016YFC0500204), and the National Natural Science Foundation of China (grant number 31700417).

References

Alton, P. B., North, P. R., and Los, S. O.: The impact of diffuse sunlight on canopy light-use efficiency, gross photosynthetic product and net ecosystem exchange in three forest biomes, Global Change Biology, 13, 776-787, 2007.

Angstrom, A.: Solar and terrestrial radiation. Report to the international commission for solar research on actinometric investigations of solar and atmospheric radiation, Q J Roy Meteor Soc, 50, 121-126, 1924.

Boland, J., Scott, L., and Luther, M.: Modelling the diffuse fraction of global solar radiation on a horizontal surface, Environmetrics, 12, 103-116, 2001.

Chen, R. S., Ersi, K., Yang, J. P., Lu, S. H., and Zhao, W. Z.: Validation of five global radiation models with measured daily data in China, Energ Convers Manage, 45, 1759-1769, 2004.

Farquhar, G. D. and Roderick, M. L.: Atmospheric science: Pinatubo, diffuse light, and the carbon cycle, Science, 299, 1997-1998, 2003.

Gu, L. H., Baldocchi, D., Verma, S. B., Black, T. A., Vesala, T., Falge, E. M., and Dowty, P. R.: Advantages of diffuse radiation for terrestrial ecosystem productivity, J Geophys Res-Atmos, 107, ACL 2-1-ACL 2-23, 2002.

Gu, L. H., Baldocchi, D. D., Wofsy, S. C., Munger, J. W., Michalsky, J. J., Urbanski, S. P., and Boden, T. A.: Response of a deciduous forest to the Mount Pinatubo eruption: Enhanced photosynthesis, Science, 299, 2035-2038, 2003.

He, H. L., Liu, M., Xiao, X. M., Ren, X. L., Zhang, L., Sun, X. M., Yang, Y. H., Li, Y. N., Zhao, L., Shi, P. L., Du, M. Y., Ma, Y. M., Ma, M. G., Zhang, Y., and Yu, G. R.: Large-scale estimation and uncertainty analysis of gross primary production in Tibetan alpine grasslands, Journal of Geophysical Research-Biogeosciences, 119, 466-486, 2014.

Hijmans, R. J., Cameron, S. E., Parra, J. L., Jones, P. G., and Jarvis, A.: Very high resolution interpolated climate surfaces for global land areas, Int J Climatol, 25, 1965-1978, 2005.

Hutchinson, M.: Interpolating mean rainfall using thin plate smoothing splines, International Journal of Geographical Information Systems, 9, 385-403, 1995.

Hutchinson, M. F.: ANUSPLIN Version 4.2 User Guide, Center for Resource and Environmental Studies, the Australian National University, Canberra, 2001.

Jacovides, C. P., Tymvios, F. S., Assimakopoulos, V. D., and Kaltsounides, N. A.: The dependence of global and diffuse PAR radiation components on sky conditions at Athens, Greece, Agricultural and Forest Meteorology, 143, 277-287, 2007.

Kanniah, K. D., Beringer, J., North, P., and Hutley, L.: Control of atmospheric particles on diffuse radiation and terrestrial plant productivity: A review, Prog Phys Geog, 36, 209-237, 2012.

Lauret, P., Boland, J., and Ridley, B.: Derivation of a Solar Diffuse Fraction Model in a Bayesian Framework, Case Studies in Business, Industry and Government Statistics, 3, 108-122, 2010.

Liu, B. Y. H. and Jordan, R. C.: The Interrelationship and Characteristic Distribution of Direct, Diffuse and Total Solar Radiation, Sol Energy, 4, 1-19, 1960.

Mercado, L. M., Bellouin, N., Sitch, S., Boucher, O., Huntingford, C., Wild, M., and Cox, P. M.: Impact of changes in diffuse radiation on the global land carbon sink, Nature, 458, 1014-1017, 2009.

Page, J. K.: The estimation of monthly mean values of daily total short wave radiation on vertical and inclined surfaces from sunshine records for latitudes 40 N-40 S, 1961, 378-390.

Reindl, D. T., Beckman, W. A., and Duffie, J. A.: Diffuse Fraction Correlations, Sol Energy, 45, 1-7, 1990.

Ren, X., He, H., Zhang, L., Ge, R., Feng, A., Yu, G., and Zhang, L.: Net ecosystem production of alpine grasslands in the Three-river Headwaters Region during 2001-2010 (in Chinese), Research of Environmental Sciences, 30, 51-58, 2017a.

Ren, X., He, H., Zhang, L., Ge, R., Zeng, N., Li, P., and Yu, G.: Effects of Diffuse Radiation on Estimation of Gross Primary Production of Alpine Grasslands on the Tibetan Plateau (in Chinese), Research of Environmental Sciences, 30, 1898-1907, 2017b.

Ren, X., He, H., Zhang, L., Su, W., and Yu, G.: Monthly diffuse photosynthetically active radiation dataset of China (1981-2010), China Scientific Data, 2, 81-87, 2017c.

Ren, X. L., He, H. L., Zhang, L., and Yu, G. R.: Estimation of diffuse photosynthetically active radiation and the spatiotemporal variation analysis in China from 1981 to 2010, Journal of Geographical Sciences, 24, 579-592, 2014.

Ren, X. L., He, H. L., Zhang, L., Zhou, L., Yu, G. R., and Fan, J. W.: Spatiotemporal variability analysis of diffuse radiation in China during 1981–2010, Ann. Geophys., 31, 277-289, 2013.

Shi, G. Y., Hayasaka, T., Ohmura, A., Chen, Z. H., Wang, B., Zhao, J. Q., Che, H. Z., and Xu, L.: Data quality assessment and the long-term trend of ground solar radiation in China, J Appl Meteorol Clim, 47, 1006-1016, 2008.

Spitters, C. J. T., Toussaint, H. A. J. M., and Goudriaan, J.: Separating the Diffuse and Direct Component of Global Radiation and Its Implications for Modeling Canopy Photosynthesis .1. Components of Incoming Radiation, Agricultural and Forest Meteorology, 38, 217-229, 1986.

Wild, M.: Global dimming and brightening: A review, J Geophys Res-Atmos, 114, D00D16, 2009.

Wild, M., Gilgen, H., Roesch, A., Ohmura, A., Long, C. N., Dutton, E. G., Forgan, B., Kallis, A., Russak, V., and Tsvetkov, A.: From dimming to brightening: Decadal changes in solar radiation at Earth's surface, Science, 308, 847-850, 2005.

Zeng, N., Ren, X., He, H., Zhang, L., Li, P., Li, Z., and Zhang, L.: Aboveground biomass of grasslands in the Three-river Headwaters Region based on neural network (in Chinese), Research of Environmental Sciences, 30, 59-66, 2017.

Zhang, M., Yu, G. R., Zhuang, J., Gentry, R., Fu, Y. L., Sun, X. M., Zhang, L. M., Wen, X. F., Wang, Q. F., Han, S. J., Yan, J. H., Zhang, Y. P., Wang, Y. F., and Li, Y. N.: Effects of cloudiness change on net ecosystem exchange, light use efficiency, and water use efficiency in typical ecosystems of China, Agricultural and Forest Meteorology, 151, 803-816, 2011.

Zhang, Q., Chen, J. M., Ju, W. M., Wang, H. M., Qiu, F., Yang, F. T., Fan, W. L., Huang, Q., Wang, Y. P., Feng, Y. K., Wang, X. J., and Zhang, F. M.: Improving the ability of the photochemical reflectance index to track canopy light use efficiency through differentiating sunlit and shaded leaves, Remote Sens Environ, 194, 1-15, 2017.

Zhao, J.: Atlas for Physical Geography of China (in Chinese), Higher Education Press, Beijing, 1997.

Zhu, X. D., He, H. L., Liu, M., Yu, G. R., Sun, X. M., and Gao, Y. H.: Spatio-temporal variation of photosynthetically active radiation in China in recent 50 years, Journal of Geographical Sciences, 20, 803-817, 2010.

Earth Syst. Sci. Data Discuss., https://doi.org/10.5194/essd-2018-4
Manuscript under review for journal Earth Syst. Sci. Data
Discussion started: 28 March 2018

Figures and captions

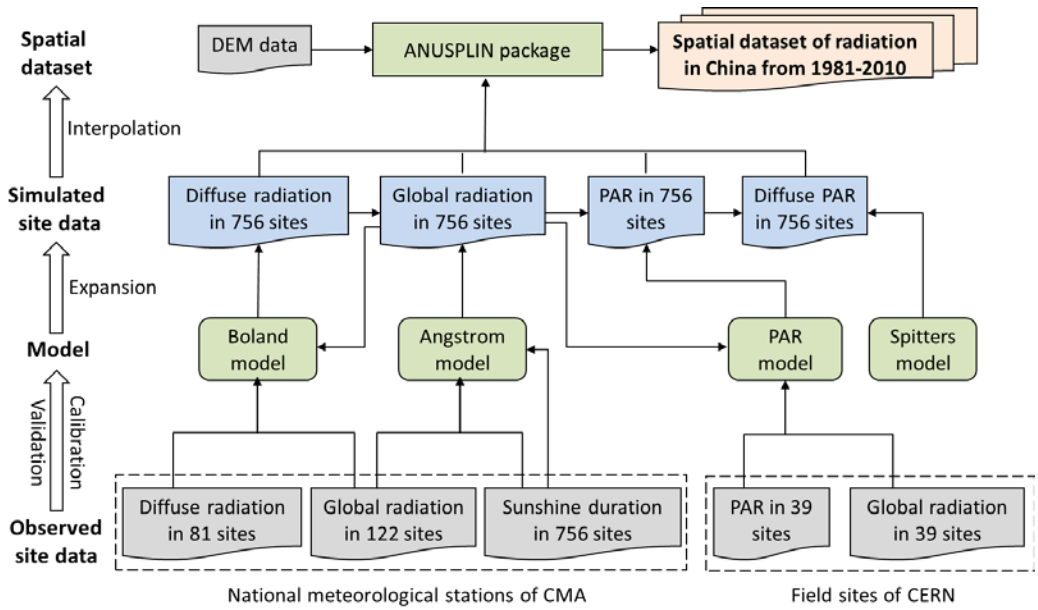

Figure 1. The schematic workflow of the radiation dataset production.

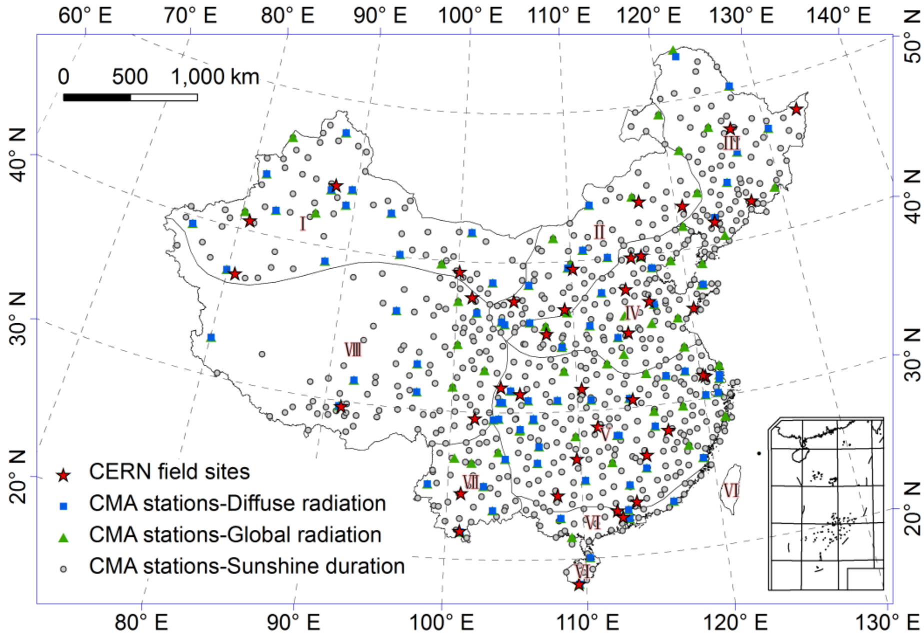

Figure 2. Distribution of the meteorological stations of China Meteorology Administration (CMA) that measured sunshine duration, global radiation, diffuse radiation, and the field sites of Chinese Ecosystem Research Network (CERN) that measured global radiation and PAR (I: Northwest China; II: Inner Mongolia; III: Northeast China; IV: North China; V: Central China; VI: South China; VII: Southwest China; VIII: Qinghai-Tibet Plateau).

Earth Syst. Sci. Data Discuss., https://doi.org/10.5194/essd-2018-4
Manuscript under review for journal Earth Syst. Sci. Data
Discussion started: 28 March 2018

Open Access Earth System Science Data Discussions

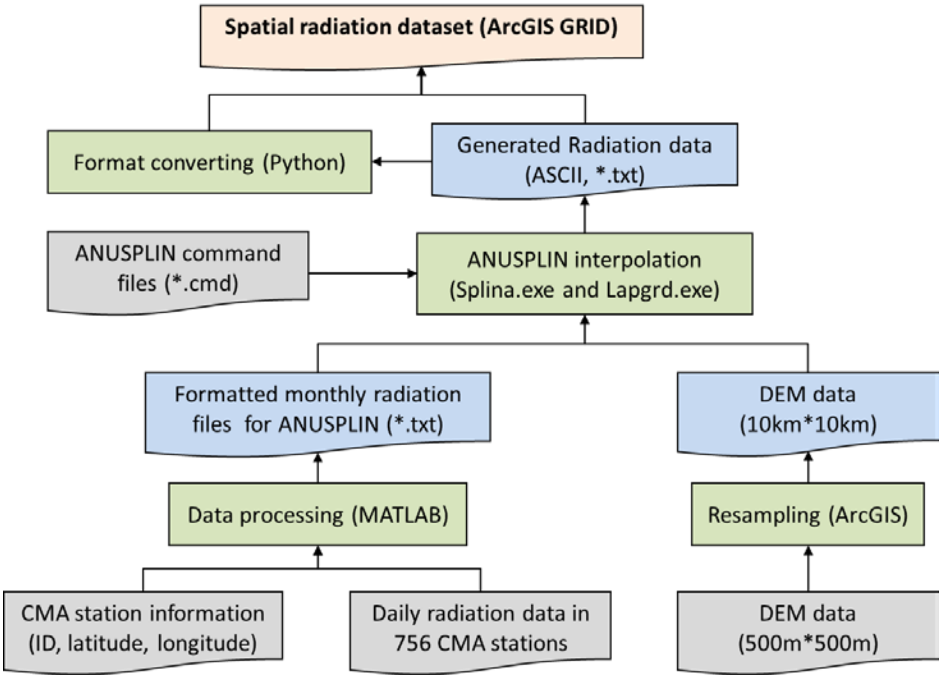

Figure 3. The workflow of the generation of radiation dataset.

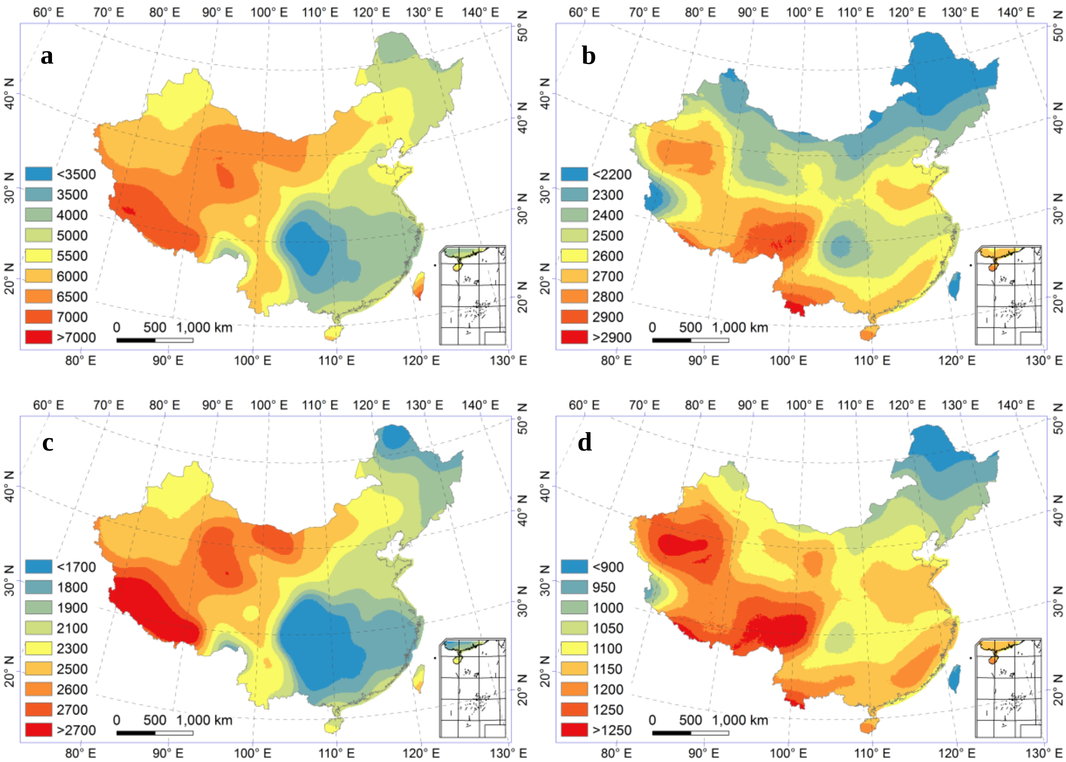

Figure 4. Spatial pattern of global radiation (a), diffuse radiation (b), PAR (c), and diffuse PAR (d) in China for 1981-2010. Units are in MJ m^{-2} yr^{-1}.

Earth Syst. Sci. Data Discuss., https://doi.org/10.5194/essd-2018-4
Manuscript under review for journal Earth Syst. Sci. Data
Discussion started: 28 March 2018

Open Access Earth System Science Data Discussions

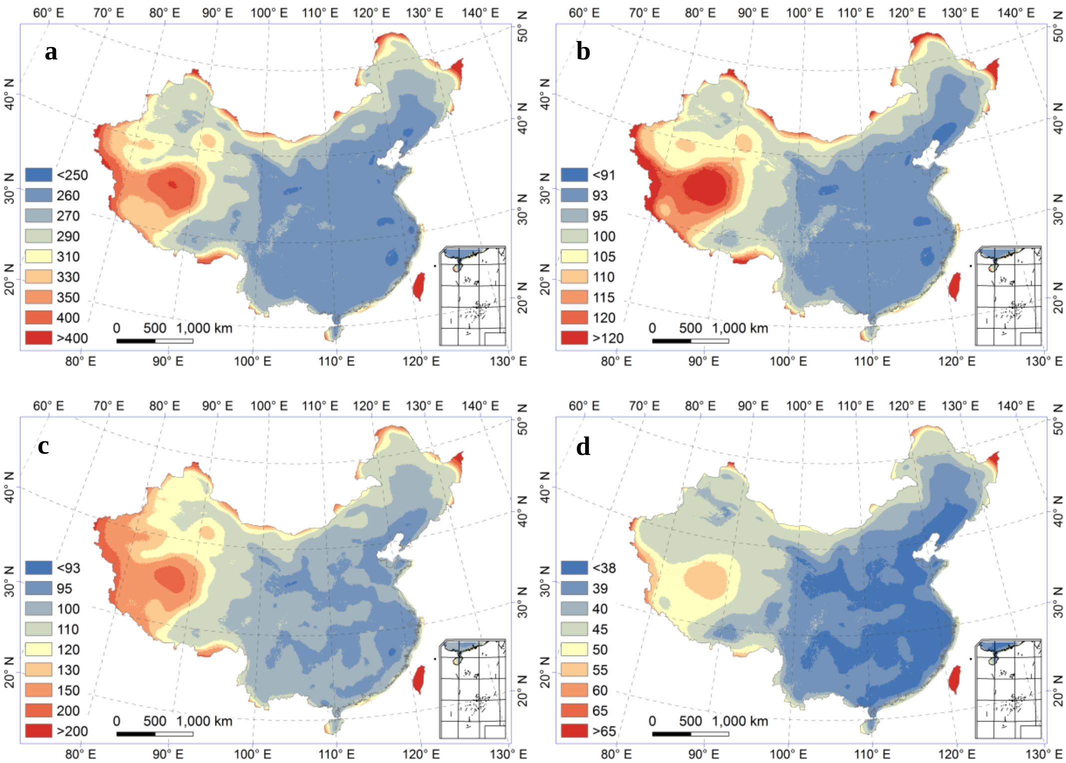

Figure 5. Spatial pattern of prediction standard errors of global radiation (a), diffuse radiation (b), PAR (c), and diffuse PAR (d) in China during 1981–2010. Units are in MJ m^{-2} yr^{-1}.

Tables

Table 1. Global radiation, diffuse radiation, PAR, diffuse PAR in China for each year. Units are in MJ m^{-2} yr^{-1}.

Year	Global radiation	Diffuse radiation	PAR	Diffuse PAR
1981	5329.7	2472.4	2185.9	1104.8
1982	5280.6	2494.7	2168.5	1113.6
1983	5281.8	2490.1	2169.9	1112.4
1984	5290.4	2461.8	2173.3	1101.3
1985	5228.4	2465.4	2149.0	1101.7
1986	5386.8	2449.1	2206.5	1095.3
1987	5323.0	2454.7	2183.2	1097.2
1988	5287.1	2453.6	2170.3	1097.0
1989	5202.2	2450.4	2138.4	1095.8
1990	5274.7	2445.2	2165.7	1093.6
1991	5223.2	2471.2	2147.2	1104.3
1992	5198.6	2510.5	2138.5	1120.3
1993	5190.8	2485.8	2135.6	1110.7
1994	5286.0	2479.1	2170.8	1108.2
1995	5289.4	2476.7	2171.5	1106.9
1996	5218.4	2480.1	2145.9	1108.8
1997	5330.5	2475.4	2185.7	1106.2
1998	5222.5	2486.2	2146.9	1111.0
1999	5274.2	2480.5	2165.8	1108.7
2000	5287.2	2480.3	2170.8	1108.6
2001	5296.7	2483.6	2173.7	1109.6
2002	5232.5	2489.0	2150.2	1111.8
2003	5222.6	2495.2	2148.2	1114.8
2004	5374.8	2478.9	2203.2	1107.7
2005	5253.9	2481.8	2158.7	1108.4
2006	5281.9	2490.6	2169.6	1112.2
2007	5295.1	2473.9	2174.1	1106.1
2008	5238.2	2492.4	2153.7	1113.2
2009	5293.3	2478.7	2173.3	1108.1
2010	5204.8	2482.1	2140.5	1109.4
Mean	5270.0	2477.0	2164.5	1106.9

Earth Syst. Sci. Data Discuss., https://doi.org/10.5194/essd-2018-4
Manuscript under review for journal Earth Syst. Sci. Data
Discussion started: 28 March 2018

Table 2. Calibration and validation of Angstrom, Boland, and PAR model in different regions across China. *R* and *RMSE* is correlation coefficient and root mean square error, respectively.

Model	Estimated values and validation of parameters	Northwest China	Inner Mongolia	Northeast China	North China	Central China	South China	Southwest China	Qinghai-Tibet Plateau
Angstrom model	*a*	0.22	0.18	0.20	0.17	0.15	0.17	0.19	0.20
	b	0.52	0.57	0.52	0.53	0.55	0.53	0.55	0.55
	Site expansion-*R*	0.96	0.95	0.94	0.94	0.93	0.91	0.88	0.87
	Site expansion-*RMSE* (MJ m^{-2} d^{-1})	2.11	2.38	2.60	2.45	2.88	2.96	3.08	3.58
	Time expansion-*R*	0.96	0.95	0.94	0.94	0.93	0.90	0.88	0.81
	Time expansion *RMSE* (MJ m^{-2} d^{-1})	2.17	2.41	2.52	2.49	2.74	2.97	2.95	4.08
Boland model	*c*	-4.26	-3.51	-3.38	-4.14	-4.32	-4.02	-3.98	-3.38
	d	7.57	6.54	6.43	7.62	8.11	7.96	7.59	6.34
	Site expansion-*R*	0.84	0.83	0.85	0.90	0.92	0.82	0.86	0.77
	Site expansion-*RMSE* (MJ m^{-2} d^{-1})	2.02	1.96	1.79	1.54	1.43	1.66	1.70	2.35
	Time expansion-*R*	0.83	0.80	0.86	0.89	0.91	0.83	0.86	0.76
	Time expansion *RMSE* (MJ m^{-2} d^{-1})	1.99	1.90	1.75	1.53	1.49	1.66	1.69	2.25
PAR model	*e*	0.39	0.38	0.35	0.35	0.36	0.38	0.36	0.40
	f	-0.06	-0.06	-0.06	-0.07	-0.07	-0.02	-0.04	-0.03
	Site expansion-*R*	0.99	0.99	0.97	0.98	0.98	0.98	0.92	0.98
	Site expansion-*RMSE* (mol m^{-2} d^{-1})	2.29	2.49	3.41	2.96	2.89	3.29	4.15	2.58
	Time expansion-*R*	0.99	0.99	0.97	0.98	0.98	0.99	0.97	0.99
	Time expansion *RMSE* (mol m^{-2} d^{-1})	2.15	2.31	3.17	2.83	2.85	2.76	3.54	2.40