Response to the reviewers and the editor

essd-2023-178

Title: An integrated and homogenized global surface solar radiation dataset and its reconstruction based on a convolutional neural network approach

Journal: Earth System Science Data

Dear authors,

Thanks for your efforts to improve the manuscript. However, several remaining concerns and minor suggestions need to be addressed first. Kindly make the necessary revisions accordingly, and we look forward to reviewing your revised paper.

Sincerely,

Jing Wei, Editor

Response to the Editor：

Dear Dr Wei,

Thank you for your letter and for the reviewer’s comments concerning our manuscript entitled “An Integrated and Homogenized Global Surface Solar Radiation Dataset and its Reconstruction Based on a Convolutional Neural Network Approach” (essd-2023-178).

We have revised the manuscript and responded to the second round of comments carefully which we hope will meet with approval. The “error estimation and source of error” would be applicable to the first half of this manuscript, but not to the reconstructed dataset. We cannot estimate the reconstruction uncertainty range because we did not adopt an ensemble reconstruction under different parameters (not applicable to the AI or similar approaches). Also, a little strange to see that there was much different judgment in the “originality” and “uniqueness” of the manuscript in reviewer #1’s two rounds of comments.

Moreover, as suggested by Polina Shvedko from the editorial office, we have combined the manuscript and the supplement into one file.

The main corrections in the paper and the responses to the reviewer’s comments are as follows.

Qingxiang Li

2023-08-30

Response to the Reviewer's Comments

Reviewer's comments:

Reviewer #1:

I appreciate the authors' responses to my comments. However, I still have several queries regarding the manuscript and its corresponding responses:

1. In alignment with the review criteria outlined in this guide (https://www.earth-system-science-data.net/peer_review/review_criteria.html), it is imperative to furnish "error estimates and sources of error." in the data files (Item 2)

Response: Thank you for your comments.

The "error estimation and source of error" is applicable to the first half of this manuscript (data homogenized and gridded dataset), but not to the reconstructed dataset. We cannot estimate its uncertainties because we did not develop an ensemble reconstruction under different parameters.

The sources of error in the observational dataset can be divided into three types: (1) station error, the uncertainties of individual station anomalies; Including measurement errors (which are not the focus of the considerations in this manuscript) and errors due to homogenization. The errors due to homogenization adjustment are always approximately normally distributed (Jones et al., 2008, see their Figure 5; also see Figure S9 in the SM and below) and therefore have limited impacts on the global average SSR change (Figure S5 a, b). (2) sampling error, the uncertainties in a grid box mean caused by estimating the mean from a small number of point values (Jones et al., 1997); and (3) bias error. It generally refers to systematic errors such as urbanization together, which has not been discussed here. However, even the sum of the above errors is much smaller than the errors due to limited data coverage (Li, et al., 2010, see their Figure 5). So, the focus of this study is to eliminate this kind of error through the CNN reconstruction.

We have added the above description to the manuscript (**Pages 18-19, Lines 484-494**).

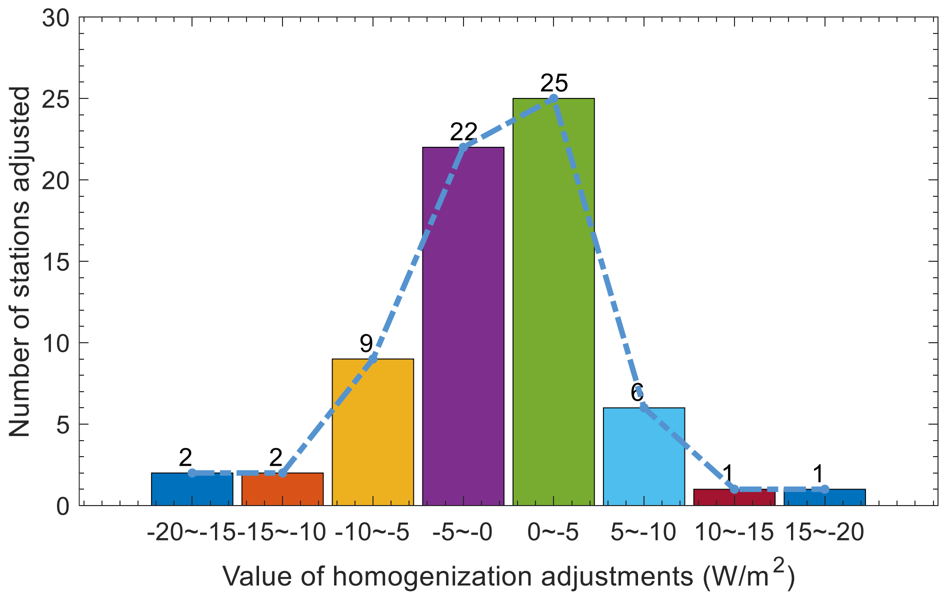

Figure S9 Distribution of annual SSR homogenization adjustments.

(The histogram is based on adjustments from all 66 stations adjusted in this paper)

Page 82, Lines 1111-1113

Reference:

Jones, P. D., Lister, D. H., and Li, Q.: Urbanization effects in large-scale temperature records, with an emphasis on China, *Journal of Geophysical Research*, 113, 10.1029/2008jd009916, 2008.

Jones, P. D., Osborn, T. J., and Briffa, K. R.: Estimating Sampling Errors in Large-Scale Temperature Averages, *Journal of Climate*, 10, 2548-2568, 1997.

Li, Q., Dong, W., Li, W., Gao, X., Jones, P., Kennedy, J., and Parker, D.: Assessment of the uncertainties in temperature change in China during the last century, *Chinese Science Bulletin*, 55, 1974-1982, 10.1007/s11434-010-3209-1, 2010.

2. A comparative analysis with CERES in the response letter reveals a substantially amplified annual variability in the proposed dataset post-2000. Could you offer plausible explanations for this disparity?

In addition, the overall trend of ERA is negative after 2004, which is completely different from the positive trend of SSRIHGrid, while CERES is stable correspondingly. Any explanations about this point? CERES has been widely consdiered as the benchmark for SSR reanalysis and GCM assessment, while here the proposed dataset shows clear difference in variablity and trend.

Response: Thanks for your question.

It is generally believed that the most reliable benchmark data is still *in situ* observation data for local SSR change in a certain station. CERES has been considered as the benchmark for SSR reanalysis and GCM assessment because of its comprehensive coverage (Wild, M., 2009). However, note that CERES SSRs are also largely a modelled product since satellites can only accurately measure the TOA fluxes, but not at the surface, since the atmosphere perturbs the surface signal received at the satellite sensor (Wild, M., 2016; 2020). And the difference in the SSR trends since 2000 from *in situ* observations and satellites (including CERES) has been extensively discussed in the previous studies (Wild, M., 2012).

We have also got the same comparison result between the *in situ* and ERA5 SSR in the previous paper (Jiao et al., 2022). In this manuscript, we may not give the exact reasons why these are different, but the *in situ* observed SSRs before and after reconstruction show highly consistent long-term /short-term trends, which suggests that our reconstruction does not bring much inhomogeneity into the global mean SSR series.

Reference:

Jiao, B., Li, Q., Sun, W., and Wild, M.: Uncertainties in the global and continental surface solar radiation variations: inter-comparison of in-situ observations, reanalyses, and model simulations, *Climate Dynamics*, 1-18, doi:10.1007/s00382-022-06222-3, 2022.

Wild, M.: Global dimming and brightening: A review, *Journal of Geophysical Research*, 114, 10.1029/2008jd011470, 2009.

Wild, M.: Enlightening global dimming and brightening, *Bulletin of the American Meteorological Society*, 93, 27-37, doi:10.1175/BAMS-D-11-00074.1, 2012.

Wild, M.: Decadal changes in radiative fluxes at land and ocean surfaces and their relevance for global warming, *WIREs Climate Change*, 7, 91-107, https://doi.org/10.1002/wcc.372, 2016.

Wild, M.: The global energy balance as represented in CMIP6 climate models, *Climate Dynamics*, 55, 553-577, 10.1007/s00382-020-05282-7, 2020.

3. Could you elucidate how the uncertainties pertaining to the trends are quantified, both in Table S3 and within the manuscript itself? Additionally, I noted the absence of any significance test and result statements, such as p-values.

Response: Thanks for your question.

There are two ways to show the uncertainties pertaining to the trends: the first is by giving p values as you suggest, and the second is to give the trends and their 95% confidence ranges. In this manuscript, we use the second way.

To make it clearer, we added some annotations in the revised manuscript (**Table S3 & S4, Pages 45-46, Lines 924-931**).

Table S3 Trends and their 95% confidence ranges in various data sources global SSR change (units: W/m^2 per decade). * Indicate trends that are significant at the 5% level.

Type	1955-1991	1991-2018	1955-2018
$SSRI_{grid}$	-1.995 ± 0.251*	0.999 ± 0.504*	-0.494 ± 0.228*
$SSRIH_{grid}$	-1.776 ± 0.230*	0.851 ± 0.410*	-0.554 ± 0.197*
$SSRIH_{20CR}$	-1.276 ± 0.205*	0.697 ± 0.359*	-0.434 ± 0.148*
ERA5	-1.162 ± 0.319*	0.653 ± 0.350*	-0.180 ± 0.176*

Table S4 Trends and their 95% confidence ranges in continental and hemispheric $SSRIH_{20CR}$ change (Units: W/m^2 per decade). * Indicate trends that are significant at the 5% level.

Continental	Time period /Trend	Time period /Trend
North America	1955-1973	1973-2018
	-3.588 ± 1.290*	1.074 ± 0.278*
South America	1955-1990	1990-2018
	-0.408 ± 0.619	0.049 ± 0.768
Europe	1963-1978	1978-2018
	-2.180 ± 1.866*	1.081 ± 0.312*
Africa	1955-1991	1991-2018
	-1.506 ± 0.496*	0.340 ± 0.998
Asia	1955-1990	1990-2018
	-1.633 ± 0.473*	0.435 ± 0.505
North Hemisphere	1955-1991	1991-2018
	-1.457 ± 0.246*	0.887 ± 0.415*
South Hemisphere	1955-1991	1991-2018
	-0.708 ± 0.330*	-0.076 ± 0.656*

4. Referring to Line 29: the trend of SSRIH20CR is nearly 28% lower than SSRIHgrid, which is hard to be considered as 'slightly smaller'. In addition, any explanations about such trend difference? There are similar issues for the brighting period.

Response: Thank you for pointing out this problem in the manuscript.

We have changed 'slightly smaller' to 'smaller' (**Page 2, Line 29**).

As can be seen in Figure 8, the larger differences in $SSRIH_{20CR}$ and $SSRIH_{grid}$ variations mainly appeared during the 1950s-60s and in the 2010s, which coincided with the years with relatively few stations. This phenomenon shows the reconstruction in this manuscript reduces errors /uncertainties due to limited coverage, especially for the 1950s-60s and 2010s.

Could I deduce that the CNN enhancement has led to the mitigation of anomalies in the proposed dataset from SSRIHgrid to SSRIH20CR? If this is indeed the case, has the smoothing effect extended to realistic anomalies or extremes?

Response: Thanks for your question.

The CNN approach learns relatively realistic SSR trends (relationships not only in time but also in space) from a large amount of data (Teuwen, J., et al., 2020). When we use these implicit relationships (CNN models) to fill in the missing data, it attempts to restore the true SSR trends, rather than determining the SSR trends. The values already in the $SSRIH_{grid}$ remain unchanged in the $SSRIH_{20CR}$ when we use CNN to reconstruct SSR. Therefore, the CNN enhancement has not led to the mitigation of anomalies in the proposed dataset from $SSRIH_{grid}$ to $SSRIH_{20CR}$. However, when more grid SSR series are applied to the calculation of global average SSR, it may result in a visual smoothing effect.

It has been proven that the lack of a fully sampled global temperature benchmark dataset has led to a certain degree of underestimation of warming relative to the pre-industrial period (Gulev et al., 2021; Sun, et al., 2021; 2022). Similarly, in this manuscript, we consider that the errors /uncertainties due to limited data coverage in the $SSRIH_{20CR}$ have been eliminated through reconstruction by CNN, instead of the smoothing effect extended to realistic anomalies or extremes. Therefore, a more homogeneous and comprehensive global long-term SSR climatic dataset ($SSRIH_{20CR}$) can eliminate the errors due to limited coverage and provide a better benchmark for observational constraints on the global surface energy balance /budget.

Reference:

Gulev, S. K., Thorne, P. W., J. Ahn, F. J. D., Domingues, C. M., Gerland, S., Gong, D., Kaufman, D. S., Nnamchi, H. C., Quaas, J., Rivera, J. A., Sathyendranath, S., Smith, S. L., Trewin, B., Shuckmann, K. v., and Vose, R. S.: In: Climate Change 2021: The Physical Science Basis., Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change, in, edited by: [Masson-Delmotte, V., Zhai, P., Pirani, A., Connors, S. L., Péan, C., Berger, S., Caud, N., Chen, Y., Goldfarb, L., Gomis, M. I., Huang, M., Leitzell, K., Lonnoy, E., Matthews, J. B. R., Maycock, T. K., Waterfield, T., Yelekçi, O., Yu, R., and (eds.)], B. Z., Cambridge University Press. 2021., 287–422. Cambridge University Press, 2021.

Sun, W., Li, Q., Huang, B., Cheng, J., Song, Z., Li, H., Dong, W., Zhai, P., and Jones, P.: The Assessment of Global Surface Temperature Change from 1850s: The C-LSAT2.0 Ensemble and the CMST-Interim Datasets, *Advances in Atmospheric Sciences*, 38, 875-888, 10.1007/s00376-021-1012-3, 2021.

Sun, W., Yang, Y., Chao, L., Dong, W., Huang, B., Jones, P., and Li, Q.: Description of the China global Merged Surface Temperature version 2.0, *Earth System Science Data*, 14, 1677-1693, 10.5194/essd-14-1677-2022, 2022.

Teuwen, J. and Moriakov, N.: Chapter 20 - Convolutional neural networks, in: Handbook of Medical Image Computing and Computer Assisted Intervention, edited by: Zhou, S. K., Rueckert, D., and Fichtinger, G., Academic Press, 481-501, https://doi.org/10.1016/B978-0-12-816176-0.00025-9, 2020.