A DETAILED LIST OF RESPONSES
TO REVIEWER #2

The objective of the manuscript is to present a new gridded precipitation dataset across mainland China using the best interpolation scheme among the 8 tested. Reliable precipitation data are important to ensure water safety and guarantee water availability and quality. Hence, efforts in creating reliable datasets are quite valuable.

Response: We would like to thank you for your constructive comments on our manuscript. Your insightful review has enhanced our paper considerably. We have updated the dataset to 2022 (https://doi.org/10.6084/m9.figshare.21432123.v3). Below is a point-by-point response to your comments.

However, the manuscript in its current form lacks a critical discussion on the limitation of the gridded data available and on the selected interpolation scheme. The Authors provide a list of gridded precipitation datasets available (Lines 71-104). However, a critical review of such datasets is missing. They mentioned the sensitivity to interpolation algorithms, but it is too vague. The Authors do not discuss why the scheme considered the optimal (even though it is not an optimal scheme but rather the best, based on some metrics, among the few schemes tested) leads to better goodness of fit metrics. Is such a result expected? Why is such a combination better than the others? It is simply chance? Can this scheme be transferred to other regions?

Response: Many thanks for the insightful comments. We have added Table 1 for a summary of the current daily gridded precipitation datasets over China:

Table 1 Gauge-based gridded precipitation datasets for China

Name	Spatial resolution	Domain	Temporal resolution	Time period	Reference	Number of stations	Interpolation method
1 km monthly temperature and precipitation dataset for China from 1901 to 2017	1 km	China	Monthly	1901 to the present	Peng et al., 2019	~700	Bilinear interpolation
HRLT	1 km	China	Daily	1961–2019	Qin et al., 2022	~700	Machine learning, the generalized additive model, and thin plate spline
CMFD	0.1° × 0.1°	China	Three hours	1979 to the present	He et al.,2020	~700	Thin plate spline
EA05	0.5° × 0.5°	East Asia	Daily	1978–2003	Xie et al., 2007	~1,700	Optimal interpolation
CN05.1	0.25° × 0.25°	China	Daily	1961 to the present	Wu and Gao, 2013	~2,400	Angular distance weight
CMA V2.0	0.5° × 0.5°	China	Daily	1961–2019	Zhao et al., 2014	~2,400	Thin plate spline
CGDPA	0.25° × 0.25°, 0.5° × 0.5°	China	Daily	2008–2015	Shen et al., 2010	~2,400	Optimal interpolation

And instead of the phrase "optimal scheme" used in the original text, we have revised to use "the interpolation scheme with better performance among selected metrics".

In addition, we also have discussed the main reasons for the differences among various gauge-based precipitation datasets in section 4.2. The reasons include the density of gauges involved and whether or not the interpolation scheme fully considers the impact of topography and boundary effects. Considering the spatiotemporal consistency of the daily gauge observations, the differences in interpolation performance among the eight interpolation schemes are mainly driven by whether the interpolation scheme fully considers the impact of topography and boundary effects.

The overall interpolation strategy was to combine the daily climatology field (*Cd*) with the field of the ratio between daily precipitation and daily climatology (*P/Cd*). With respect to *Cd*, the PRISM-type daily climatology field incorporates topographic features, proximity to coastlines, and several measures of terrain complexity, which goes beyond the climate–elevation relationships that the ANUSPLIN-type daily climatology field considers. As for *P/Cd,* we selected the four alternative interpolation methods (angular-distance weighting (ADW), inverse distance weighting (IDW), thin plate spline (TPS), and triangulation-based nearest neighbor interpolation (TNNI)) to consider the balance between local data fidelity and global fitting smoothness in addition to the popularity, authority, and simplicity of the interpolation methods. Specifically, the ADW and IDW methods were chosen due to their high local data fidelity. Both are local interpolation methods (Liszka, 1984). Unlike the IDW method, the ADW method assigns a tiny weight to far-distant gauge observations to promote global fitting smoothness. This impacts the local accuracy of interpolation. The TPS and TNNI methods, on the other hand, are chosen for their high global fitting smoothness. Both TPS and TNNI are global interpolation methods (Liszka, 1984). The TPS method is based on a mathematical model for surface estimation that fits a minimum-curvature surface through all input points, while TNNI constructs a Delaunay triangulation of three station locations. So TNNI tends to assign more weights to maintain local data fidelity but has weaker fitting smoothness. To sum up, the combination of PRISM-type *Cd* and IDW-type *P/Cd* yields the best performance among the selected schemes. This is not simply due to chance. This best-performing interpolation scheme could be applied in other regions, but further validation would be needed to confirm whether it is the best-performing interpolation scheme there. We have added relevant discussion on the best-performing scheme in the Section 4.1 as follows:

"Scheme 4 had better performance than the other schemes because it considers the impact of topography more deeply and holds an appropriate balance between local data fidelity and global fitting smoothness. The overall interpolation strategy was to combine the daily climatology field (*Cd*) with the field of the ratio between daily precipitation and daily climatology (*P/Cd*). With respect to *Cd*, the PRISM-type daily climatology field incorporates topographic features, proximity to coastlines, and several measures of terrain complexity, which goes beyond the climate–elevation relationships that the ANUSPLIN-type daily climatology field considers. As for *P/Cd,* we selected the four alternative interpolation methods (angular-distance weighting (ADW), inverse distance weighting (IDW), thin plate spline (TPS), and triangulation-based nearest neighbor interpolation (TNNI)) to consider the balance between local data fidelity and global fitting smoothness in addition to the popularity, authority, and simplicity of the interpolation methods. Specifically, the ADW and IDW methods were chosen due to their high local data fidelity. Both are local interpolation methods (Liszka, 1984). Unlike the IDW method, the ADW method assigns a tiny weight to far-distant gauge observations to promote global fitting smoothness. This impacts the local accuracy of interpolation. The TPS and TNNI methods, on the other hand, were chosen for their high global fitting smoothness. Both TPS and TNNI are global interpolation methods (Liszka, 1984). The TPS method is based on a mathematical model for surface estimation that fits a minimum-curvature surface through all input points, while TNNI constructs a Delaunay triangulation of three stations locations. So TNNI tends to assign more weights to maintain local data fidelity but has weaker fitting smoothness. To sum up, the combination of PRISM-type *Cd* and IDW-type *P/Cd* yielded the best performance among the selected schemes. This was not simply due to chance. This best-performing interpolation scheme could be applied in other regions, but further validation would be needed to confirm whether it is the best-performing interpolation scheme there."

Point-by-point comments:

Abstract: I suggest the Authors revise the abstract. The primary objective of the paper (the new gridded data) and the temporal coverage (from when to when) should be better highlighted. Moreover, it should be clearer why the interpolation method selected is the best among the ones tested and how it addresses the limitations of currently available products. RMSE and other metrics as presented are not enough to judge the goodness of the method. How does this perform compared to the others? Why does it perform better?

Response: Many thanks for your insightful suggestions. We have revised the abstract as follows: “High-quality, freely accessible, long-term precipitation estimates with fine spatiotemporal resolution play essential roles in hydrologic, climatic, and numerical modeling applications. However, the existing daily gridded precipitation datasets over China either are constructed with insufficient gauge observations or neglect topographic effects and boundary effects on interpolation. Using daily observations from 2,839 gauges located across China and nearby regions from 1961 to the present, this study compared eight different interpolation schemes that adjusted the climatology based on a monthly precipitation constraint and topographic characteristic correction, using an algorithm that combined the daily climatology field with a precipitation ratio field. Results from these eight interpolation schemes were validated using 45,992 high-density daily gauge observations from 2015 to 2019 from China. Of these eight schemes, the one with the best performance merges the Parameter-elevation Regression on Independent Slopes Model (PRISM) in the daily climatology field and interpolates station observations into the ratio field using an inverse distance weighting method. This scheme had median values of 0.78 for the correlation coefficient, 8.8 mm/d for the root-mean-square deviation, and 0.69 for the Kling-Gupta efficiency for comparisons between the 45,992 high-density gauge observations and the best interpolation scheme for the 0.1° latitude × longitude grid cells from 2015 to 2019. This scheme had the best overall performance, as it fully considers topographic effects in the daily climatology field and it balances local data fidelity and global fitting smoothness in the interpolation of the precipitation ratio field. Therefore, this scheme was used to construct a new long-term, gauge-based gridded precipitation dataset for the Chinese mainland (called CHM_PR, as a member of the China Hydro-Meteorology dataset) with spatial resolutions of 0.5°, 0.25°, and 0.1° from 1961 to the present. This precipitation dataset is expected to facilitate the advancement of drought monitoring, flood forecasting, and hydrological modeling. Free access to the dataset can be found at https://doi.org/10.6084/m9.figshare.21432123.v3 (Han and Miao, 2022).”

Lines 80-81: what does the following sentence mean? “Through a fusion of remote sensing products and reanalysis datasets into in situ station data”. Remote sensing products and reanalysis data generated gauged precipitation dataset? Or gauged data were combined with remote sensing products and reanalysis data?

Response: Thank you for pointing this out. We are sorry for causing this confusion. The meaning of the sentence is the second option you described. It means gauged data were combined with remote sensing products and reanalysis data. We meant to use the phrase "a fusion of something. into *in-situ* station data" to express that the *in-situ* station observations are the backbone of the CMFD as He et al. (2020) mentioned in their paper. We have revised the sentence for better understanding: "Through a fusion of remote sensing products, reanalysis datasets, and *in-situ* station data, the China Meteorological Forcing Dataset (CMFD) has been produced to serve as a high-resolution (three hours, 0.1° × 0.1°) input forcing dataset for hydrological and ecosystem models beginning in 1979 (He et al., 2020)."

Section 2.3 and 2.4: Which method did the Authors use to re-grid the data? Where the raw data can be found?

Response: We used bilinear interpolation to regrid the data. We have added relevant descriptions of the regridding method into two sections as follows:

(In section 2.3) "We resampled the SRTM-DEM into 0.05° × 0.05° grid cells using the bilinear interpolation method."

(In Section 2.4) "The original spatial resolution is 0.04° × 0.04° for the monthly climatology of PRISM between 1961 and 1990; we used bilinear interpolation to regrid the spatial resolution into 0.05° × 0.05° grid cells for adjustment based on climatology."

The raw SRTM-DEM data can be found at this link: https://cmr.earthdata.nasa.gov/search/concepts/C1214622194-SCIOPS. We have updated the link in the main text. And the raw monthly climatology from PRISM can be found here: https://prism.oregonstate.edu/

Line 173: is it possible to eliminate interpolation errors?

Response: Thanks for your question. The interpolation errors cannot be eliminated entirely but just reduced as much as possible. The word "eliminate" we used here is inappropriate and is misleading. We have revised the expression as follows: "To avoid this and reduce introduced errors, the overall strategy for establishing a daily gridded precipitation dataset is to construct a relatively continuous daily climatology field (Shen et al., 2010)."

Line 200: in the 30-year mean daily precipitation, was there any trend in the data or inhomogeneity?

Response: Thanks for the question. We calculated the trend in the 30-year mean daily precipitation. About two-thirds of stations have no significant trend for the 30-year mean daily precipitation.

As for inhomogeneity, we have previously tested the homogeneity of the gauge-based raw monthly precipitation series using the software package RHtestsV4 (Wang, published online July 2013). RHtestsV4 recommends testing the monthly series first before testing the corresponding daily series because daily series are much noisier and thus more difficult to test for changepoints. In RHtestsV4, two types of changepoint are detected: 1) Type-1 changepoints, which can be detected as significant at the nominal level even without metadata support (and if there is no significant changepoint identified, the time series being tested can be declared to be homogeneous); and 2) Type-0 changepoints, which can be significant only if they are supported by reliable metadata. In this study, we test for the existence of a Type-1 changepoint. Results show that, out of all 2,839 gauges, the monthly precipitation series between 1961 and 2022 is homogeneous for 2,133 gauges. Therefore, we ignore the impact of inhomogeneity in this version of dataset.

Lines 245 - 325: Four interpolation methods to construct the field of ratio. Still missing how they differ, why those have been chosen, and why they provide different results.

Response: Thanks for the comments. The four interpolation methods (angular-distance weighting (ADW), inverse distance weighting (IDW), thin plate spline (TPS), and triangulation-based nearest neighbor interpolation (TNNI)) for the field of ratio were selected based on three main principles: 1) Popularity—These four interpolation methods are widely used in generating daily gridded precipitation for various disciplines, such as atmospheric sciences (Ahrens, 2006), hydrological modelling (Ly et al., 2013), environmental management (Li and Heap, 2011), and civil engineering (Zhou et al., 2007). 2) Authority—Internationally, most of the currently prevailing meteorological datasets adopt one of these four interpolation methods. For example, the Climatic Research Unit gridded Time Series (CRU TS) is developed using TNNI (Harris et al., 2014); Global land-surface precipitation data products of the Global Precipitation Climatology Centre (GPCC) are built based on ADW (Becker et al., 2013); and the China Meteorological Forcing Dataset (CMFD) is constructed using TPS (He et al., 2020). 3) Simplicity—Previous studies have demonstrated that the IDW method is a simple but efficient interpolation method (Ahrens, 2006). Statistical interpolation methods such as multiple linear regression, optimal interpolation, or kriging can perform better, but only if data density is sufficient (Eischeid et al., 2000).

Interpolation methods or interpolation functions are expected to be "smooth" (continuous and once differentiable), to produce values that will pass through the specified points (e.g., gauges), and to meet the user's intuitive expectations about the phenomenon under investigation (Shepard, 1968). Hence, there is a trade-off between local data fidelity and global fitting smoothness. To find the most appropriate interpolation method, we selected the four alternative interpolation methods to consider the balance between local data fidelity and global fitting smoothness in addition to the popularity, authority, and simplicity of each interpolation method. The ADW and IDW methods were chosen due to their high local data fidelity. Both are local interpolation methods (Liszka, 1984). However, unlike the IDW method, the ADW method assigns a tiny weight to far-distant gauge observations to promote global fitting smoothness. The TPS and TNNI methods, on the other hand, were chosen for their high global fitting smoothness. Both TPS and TNNI are global interpolation methods (Liszka, 1984). The TPS method is based on a mathematical model for surface estimation that fits a minimum-curvature surface through all input points, while TNNI constructs a Delaunay triangulation of three station locations. So TNNI tends to assign more weights to maintain local data fidelity.

Section 4.1 (starting line 369). My suggestion is to revise the term "optimal" for a scheme since there is no optimal scheme but simply the scheme having better metrics compared to the other schemes tested. The question of why such a combination of methods leads to better goodness of fit metrics is not answered. Why is such a combination better compared to the others? It is simply chance? Can this combination be transferred to other regions? Since the schemes perform differently depending on the topography (369-372), how do these differences affect the overall performance of the scheme? Are the metrics' values listed (lines 375-380) average over the 45k stations used for verification?

Response:

Many thanks for your constructive suggestions. We have revised the phrase "optimal interpolation scheme" to "best-performing interpolation scheme among the selected metrics" in the manuscript.

We have discussed the main reasons for the differences among various gauge-based precipitation datasets in section 4.2. These reasons include the density of gauges involved and whether or not the interpolation scheme fully considers the impact of topography and boundary effects. Considering the spatiotemporal consistency of the daily gauge observations, the differences in interpolation performance among the eight interpolation schemes is mainly driven by whether the interpolation scheme fully considers the impact of topography and boundary effects.

The overall interpolation strategy was to combine the daily climatology field (*Cd*) with the field of the ratio between daily precipitation and daily climatology (*P/Cd*). With respect to *Cd*, the PRISM-type daily climatology field incorporates topographic features, proximity to coastlines, and several measures of terrain complexity, which goes beyond the climate–elevation relationships that the ANUSPLIN-type daily climatology field considers. As for *P/Cd,* we selected the four alternative interpolation methods (angular-distance weighting (ADW), inverse distance weighting (IDW), thin plate spline (TPS), and triangulation-based nearest neighbor interpolation (TNNI)) to consider the balance between local data fidelity and global fitting smoothness in addition to the popularity, authority and simplicity of the interpolation methods. Specifically, the ADW and IDW methods were chosen due to their high local data fidelity. Both are local interpolation methods (Liszka, 1984). Unlike the IDW method, the ADW method assigns a tiny weight to far-distant gauge observations to promote global fitting smoothness. This impacts the local accuracy of interpolation. The TPS and TNNI methods, on the other hand, were chosen for their high global fitting smoothness. Both TPS and TNNI are global interpolation methods (Liszka, 1984). The TPS method is based on a mathematical model for surface estimation that fits a minimum-curvature surface through all input points, while TNNI constructs a Delaunay triangulation of three station locations. So TNNI tends to assign more weights to maintain local data fidelity but has weaker fitting smoothness. To sum up, the combination of PRISM-type *Cd* and IDW-type *P/Cd* yielded the best performance among the selected schemes. This was not simply due to chance. This best-performing interpolation scheme could be applied in other regions, but further validation would be needed to confirm whether it is the best-performing interpolation scheme there.

And for the metrics' value in Lines 375-380, no, the metrics' values here are the median values over the ~45,000 stations used for verification.

Lines 479: Optimal interpolation scheme. Again, there is no optimal but the best among the ones tested

Response: Thanks for the suggestion. We have revised the term "Optimal interpolation scheme" in this sentence as follows:

"The median CC, RMSE, and KGE values for the interpolation scheme that performed the best among the selected metrics (in comparison with the high-density gauge observations used for validation) were 0.78, 8.8 mm/d, and 0.69, respectively."

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