A DETAILED LIST OF THE RESPONSES TO REVIEWER #1

Anonymous Reviewer #1 comments

General comments:

This study introduces a new precipitation dataset, CHM_PRE V2, for China, demonstrating notable accuracy improvements over its predecessor, CHM_PRE V1, as well as several other existing precipitation datasets. The work represents a valuable contribution to the field, particularly for researchers seeking high-quality precipitation data in China, and is well-suited for publication in ESSD. My comments are as below. Hope those can help the authors further improve the manuscript.

Response: Thank you very much for the positive comments. We have made substantial revisions according to your suggestions, which have been very valuable in improving the manuscript. We hope these changes meet your expectations.

Specific comments:

1. My only concern is about a terminology used in this manuscript. The phrase "interpolation considering spatiotemporal and physical correlations" appears to introduce a new term for a method that has been widely used in prior research. While the authors aim to highlight the integration of spatial, temporal, and physical factors in their interpolation approach, the study does not explicitly quantify real correlation coefficients or provide a transparent framework for how these correlations are incorporated; instead, it employs a black-box approach where the spatiotemporal and physical correlations are not directly tangible.

For precipitation estimation, precipitation can be treated as a predictand, with various predictors such as static variables (latitude, longitude, elevation, slope) and dynamic variables (gridded precipitation datasets, soil moisture, precipitation climatology) as outlined in Table 1. Categorizing them strictly into spatial, temporal, and physical correlations (as done in Table 1 and elsewhere in the manuscript) may not accurately reflect their complex interdependencies. Many variables exhibit overlapping spatial, temporal, and physical correlations simultaneously. In addition, classifying GLDAS and satellite precipitation under "physical correlation" does not make sense, as it essentially implies that "precipitation correlates with precipitation". Your approach looks more like merging multiple sources of precipitation data.

Additionally, the physical correlation of NDVI on a daily scale is questionable and warrants further justification. Vegetation does not show immediate response to precipitation. Furthermore, the importance analysis based on these correlation classifications may not be reliable. For instance, if additional features are added to a specific category, I think this could artificially inflate the perceived importance of that category (e.g., Figure 5d).

Given these concerns, I recommend that the authors avoid introducing a new term that may not accurately describe the method's nature, especially given the extensive body of research on precipitation estimation. The authors approach of using new predictors (i.e., Table 1) can benefit accuracy improvement, while this falls within the feature engineering field which can be clarified in the manuscript.

Response: Thank you for your insightful comments. In the latest manuscript, we have removed the previous, imprecise description of "spatiotemporal and physical correlations." The term "spatial correlation" has been updated to "spatial autocorrelation" to more accurately express the dependence of precipitation at a location on surrounding areas. Additionally, "temporal and physical correlations" have been revised to "precipitation-related covariates." We have modified all relevant parts of the manuscript accordingly.
Regarding the relative importance of covariates to precipitation retrieval (Figure 5(c)), as you rightly pointed out, the importance analysis results may not be sufficiently reliable. To maintain the rigor of the manuscript, we have removed this part from the revised version. The major revisions are as follows:

"An upgraded high-precision gridded precipitation dataset for the Chinese mainland considering spatial autocorrelation and covariates" (Title)

"Precipitation is a critical driver of the water cycle, profoundly influencing water resources, agricultural productivity, and natural disasters. However, existing gridded precipitation datasets exhibit markable deficiencies in capturing the spatial autocorrelation and associated environmental and climatic influences—here referred to collectively as precipitation-related covariates—which limits their accuracy, particularly in regions with sparse meteorological stations. To address these challenges, this study proposes a completely new gridded precipitation generation scheme that integrates long-term daily observations from 3,746 gauges with 11 key precipitation-related covariates." (Lines 12–17)

"In summary, a key limitation of existing datasets is that they tend to focus on either spatial autocorrelation or a limited set of precipitation-related covariates, but rarely incorporate multiple types of information simultaneously. However, precipitation is influenced not only by spatial autocorrelation—that is, the dependence of precipitation at a given location on surrounding areas (Chen et al., 2010, 2016; Fan et al., 2021; Huff and Shipp, 1969; Tang et al., 2020)—but also by a wide array of covariates, such as elevation, land surface conditions, atmospheric parameters, and recent precipitation events (Adler et al., 2008; Ham et al., 2023; Ravuri et al., 2021; Trucco et al., 2023). This lack of comprehensive consideration for multiple covariates constrains the accuracy of these datasets, particularly in regions with sparse meteorological stations, such as western China (Jiang et al., 2023). Moreover, existing methods tend to generate excessive minor precipitation, leading to an overestimation of precipitation events, which will have considerable impacts on hydrologic modelling (Dong et al., 2020; Kang et al., 2024; Wei et al., 2022).
To address the aforementioned issues, this study introduces a new high-precision, long-term daily gridded precipitation dataset for the Chinese mainland (a member of the China Hydro-Meteorology datasets, hereinafter called CHM_PRE V2). Building on CHM_PRE V1, CHM_PRE V2 integrates precipitation gauges, remote sensing observations, reanalysis data, and various precipitation-related factors. Through the use of advanced spatial interpolation and machine learning algorithms, our method captures spatial autocorrelation while jointly modelling multiple covariates to enhance precipitation accuracy." (Lines 58–73)

“2 Data

The CHM_PRE V2 dataset was developed using extensive precipitation gauge observations, supplemented with a diverse array of ancillary datasets that serve as precipitation covariates. These covariates include satellite-derived products, land surface model outputs, and various geophysical and meteorological variables, aiming to enhance the characterization of precipitation, particularly in regions with sparse observational coverage. This integration of multi-source information is designed to improve the spatial continuity and accuracy of the precipitation estimates across the Chinese mainland. **Figure 1** illustrates details of the various datasets utilized in CHM_PRE V2 construction, including dataset names, original spatial and temporal resolutions, and coverage periods. In total, 16 datasets from 11 distinct categories were incorporated. These datasets collectively provide critical information on land surface properties, atmospheric conditions, and recent precipitation patterns that influence precipitation generation and distribution. In addition, the CHM_PRE V2 dataset is designed to represent precipitation characteristics across the Chinese mainland, excluding Taiwan, Hong Kong, Macau, and other Chinese islands. In the following sections, we will provide a detailed introduction to the data sources employed in the construction of the CHM_PRE V2 dataset.

2.1 Spatial autocorrelation data

CHM_PRE V2 incorporates comprehensive daily precipitation gauge data to support spatial autocorrelation modelling. The primary daily precipitation gauge data sourced from the China Meteorological Administration (CMA; http://data.cma.cn, last access: January 2024) spans the entire Chinese mainland, encompassing records from 2,816 stations between 1960 and 2023. Daily precipitation is defined as the cumulative precipitation recorded between 20:00 on one day and 20:00 on the following day (local time in Beijing), with all data subjected to rigorous quality control (Zhang et al., 2020). To mitigate the limit of boundary effects (Ahrens, 2006), additional precipitation gauges near the Chinese mainland were obtained from the Global Historical Climatology Network-Daily Version 3 (GHCND) dataset. The GHCND is a reliable and globally comprehensive climate dataset, and maintained by the National Climatic Data Center (NCDC) of the National Oceanic and Atmospheric Administration (NOAA) (Durre et al., 2008, 2010; Menne et al., 2012). The GHCND dataset was sourced from NOAA (https://www.ncei.noaa.gov/products/land-based-station/global-historical-climatology-network-daily) on September 11, 2024.

To ensure data quality, only stations with more than 70% effective days (over 255 days) in a year were retained for dataset construction. **Figure 2(a)** illustrates the spatial distribution of both CMA and GHCND stations, while **Figure 2(b)** shows their annual availability. Over time, the number of available CMA stations increased from 1,992 in 1960 to 2,767 in 2023, improving spatial coverage considerably. In contrast, the number of accessible GHCND stations in the region declined from 674 in 1960 to 264 in 2023.

2.2 Precipitation-related covariate data

The Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) dataset was utilized to characterize the influence of elevation on precipitation and to generate slope data. In this study, we used the SRTM DEM V4 acquired from the Consortium for Spatial Information, Consultative Group for International Agricultural Research (CGIAR-CSI, https://srtm.csi.cgiar.org/) on August 8, 2024, with a spatial resolution of 3 arc-seconds (approximately 90 meters near the equator). The SRTM DEM V4 was generated based on

National Aeronautics and Space Administration (NASA) SRTM DEM V1, and has undergone post-processing of the NASA data to "fill in" the no data voids, such as water bodies (lakes and rivers), areas with snow cover and in mountainous regions (e.g., the Himalayas), resulting in seamless elevation for the globe.

To enhance the spatial and temporal detail of precipitation estimation, two satellite-based precipitation products—the Global Satellite Mapping of Precipitation (GSMaP) and the Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN-CDR) dataset—were incorporated as covariates. GSMaP V8 data spans from 1998 to the present with 0.1° spatial and 1-hour temporal resolution (Kubota et al., 2020). We acquired the GSMaP data from Japan Aerospace Exploration Agency (JAXA; https://sharaku.eorc.jaxa.jp) on September 9, 2024, and used the data from 1998 to 2023. PERSIANN-CDR data spans from 1983 to the present (Ashouri et al., 2015), and the data from 1983 to 1997 was used for the retrieval.

The precipitation and soil moisture from the Global Land Data Assimilation System Noah Land Surface Model (GLDAS NOAH) (Rodell et al., 2004) were also used for the retrieval. The data spans from 1960 to 1999 and the data spans from 2000 to 2023 were acquired from the GLDAS Noah L4 V2.0 and GLDAS Noah L4 V2.1 datasets. The NOAA Climate Data Record (CDR) of AVHRR Normalized Difference Vegetation Index (NDVI) (Vermote and NOAA CDR Program, 2019) was utilized to depict the vegetation characteristics, and the data from 1981 to 2023 was used.

In addition to spatial and environmental variables, precipitation temporal features were also introduced as covariates. Two types of temporal indicators were constructed: (1) the cumulative precipitation of the current month and year, representing broader-scale precipitation conditions; and (2) daily lagged precipitation values from the previous five days, capturing short-term fluctuations. Each of these five recent days was treated as a separate variable. For example, the variable named "1st-day prior Prec." refers to precipitation one day before the current date, while "5th-day prior Prec." corresponds to five days prior." (Lines 79–135)

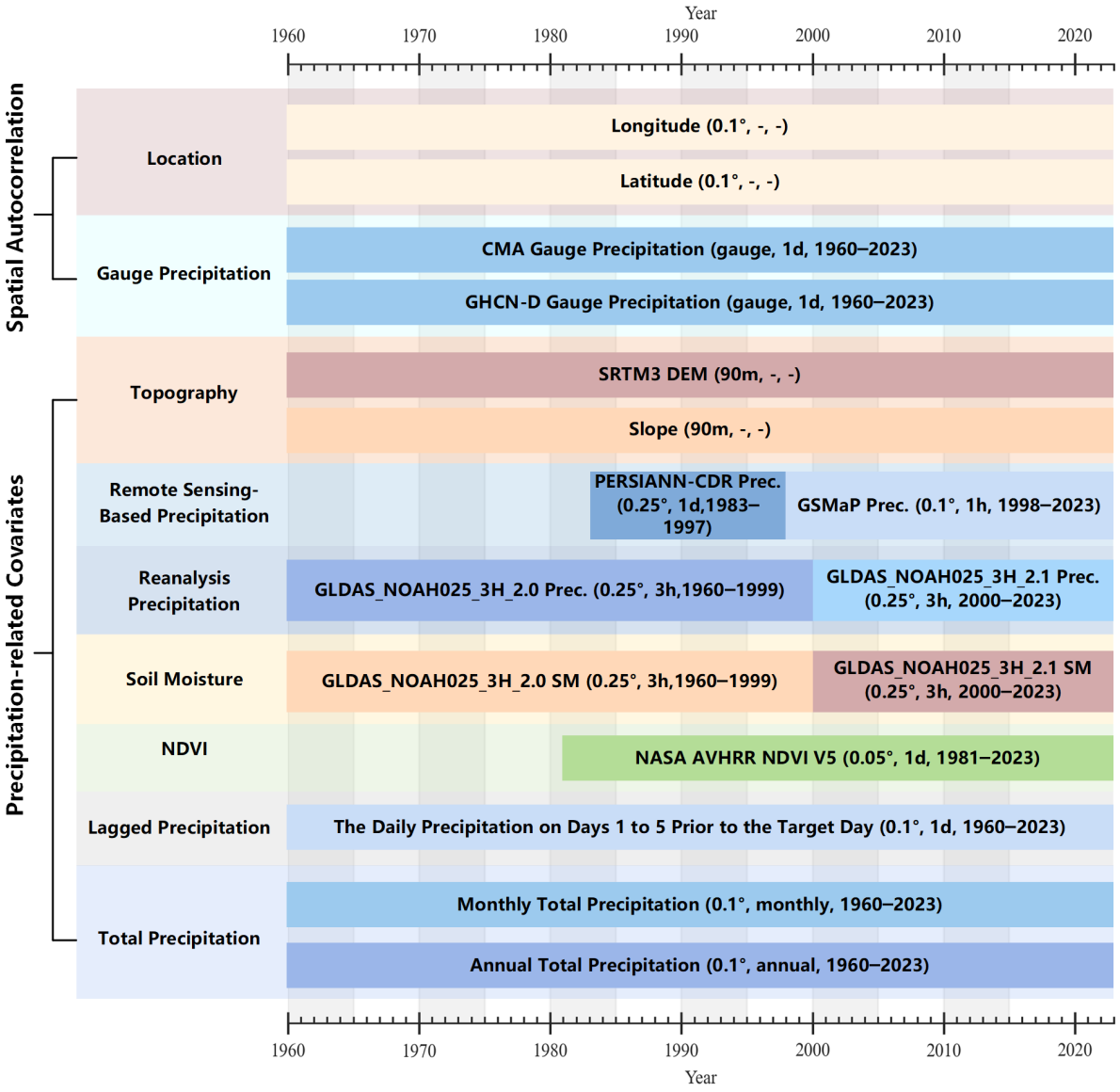


Figure 1. The data used for precipitation retrieval.

Thank you again for your thoughtful comments and support, which have helped us significantly improve the rigor of our manuscript.

2. About the title, the two words "new upgraded" seems repeated.

Response: According to your suggestion, we have revised the title to "An upgraded high-precision gridded precipitation dataset for the Chinese mainland considering spatial autocorrelation and covariates."

3. There are three versions of datasets published at https://zenodo.org/records/14634575. What's the difference among them?

Response: We appreciate your careful comment. In fact, there are no substantive differences among the multiple versions of the dataset on Zenodo. Zenodo requires the creation of a new version whenever any file within a dataset is modified. During the data upload process, we

updated the content of the documentation file (in PDF format), which necessitated the creation of multiple dataset versions. To help users better understand the differences among these versions, we have added corresponding explanations on Zenodo. Furthermore, we have updated the dataset link provided in the manuscript (https://doi.org/10.5281/zenodo.14632156) to one that will always resolve to the latest version of the dataset.

4. Line 23 and 25: I suppose those improvements use CHM_PRE V1 as a benchmark. Please specify this.

Response: We apologize for not making this point clear in the previous manuscript. In this study, we compared CHM_PRE V2 with five existing gridded precipitation datasets and calculated the improvement ratio of CHM_PRE V2 relative to the best-performing dataset among them. Our previous CHM_PRE V1 dataset did not always outperform the other datasets across all evaluation metrics. For example, in terms of the false alarm ratio (FAR) metric, GSMaP performed slightly better than CHM_PRE V1 (**Table S7**). Therefore, the comparison was not always based on CHM_PRE V1 as the benchmark. To clarify this point, we have revised the corresponding description as follows:

"Specifically, it achieves a mean absolute error of 1.48 mm/day and a Kling-Gupta efficiency of 0.88, representing improvements of 12.84% and 12.86%, respectively, compared to the previously optimal dataset. Regarding precipitation event detection, CHM_PRE V2 achieved a Heidke skill score of 0.68 and a false alarm ratio of 0.24, surpassing the previously optimal dataset by 17.24% and 29.17%, respectively." (Lines 23–27)

Table S7. Precipitation event accuracy of different datasets validated by high-density gauge data. The bolded numbers in the column represent the optimal accuracy values for that metric.

Dataset Name	HSS	F1 Score	Accuracy	POD	FAR
CHM_PRE V2	**0.68**	**0.80**	**0.85**	0.84	**0.24**
CHM_PRE V1	0.58	0.75	0.79	**0.93**	0.37
GSMaP	0.50	0.67	0.78	0.65	0.31
IMERG	0.39	0.62	0.71	0.69	0.43
PERSIANN-CDR	0.21	0.54	0.59	0.70	0.55
GLDAS	0.29	0.54	0.68	0.55	0.47

5. Please introduce the methodological difference between V2 and V1 datasets in the abstract.

Response: According to your suggestion, we have rewritten the abstract to highlight the methodological difference of CHM-PRE V2 compared to V1, as follows:

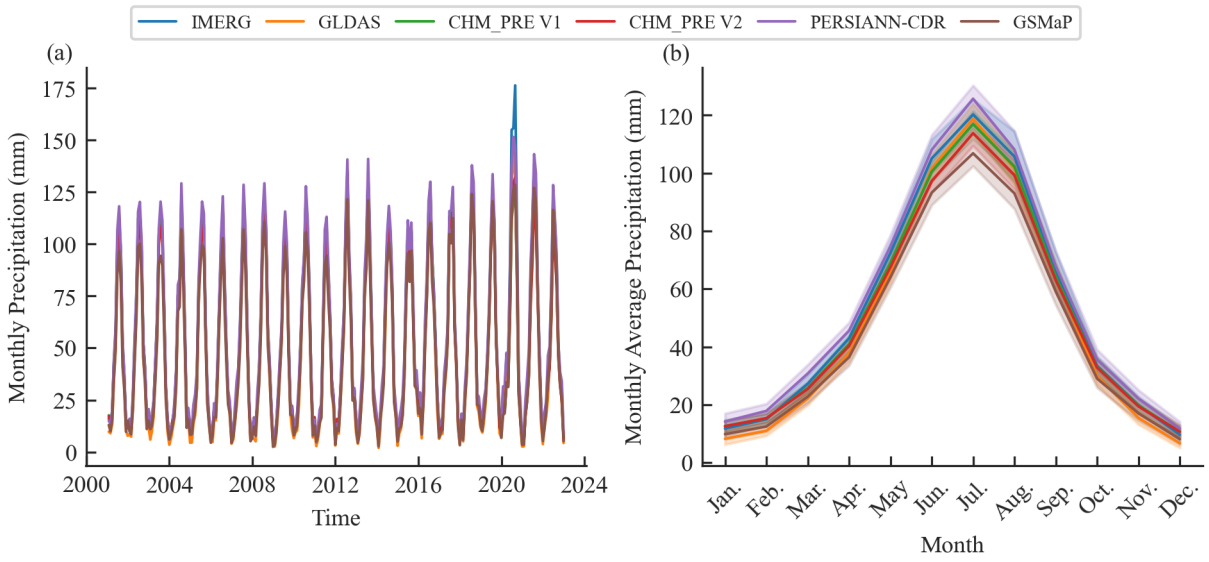
"Building upon the improved inverse distance weighting interpolation method used in our previous dataset CHM_PRE V1, we integrated a machine learning algorithm—light gradient boosting machine (LGBM)—to incorporate precipitation-related covariates in a data-driven manner. This integration allows for a more comprehensive characterization of precipitation

patterns, jointly capturing spatial autocorrelation and covariate-based variability.” (Lines 17–21)

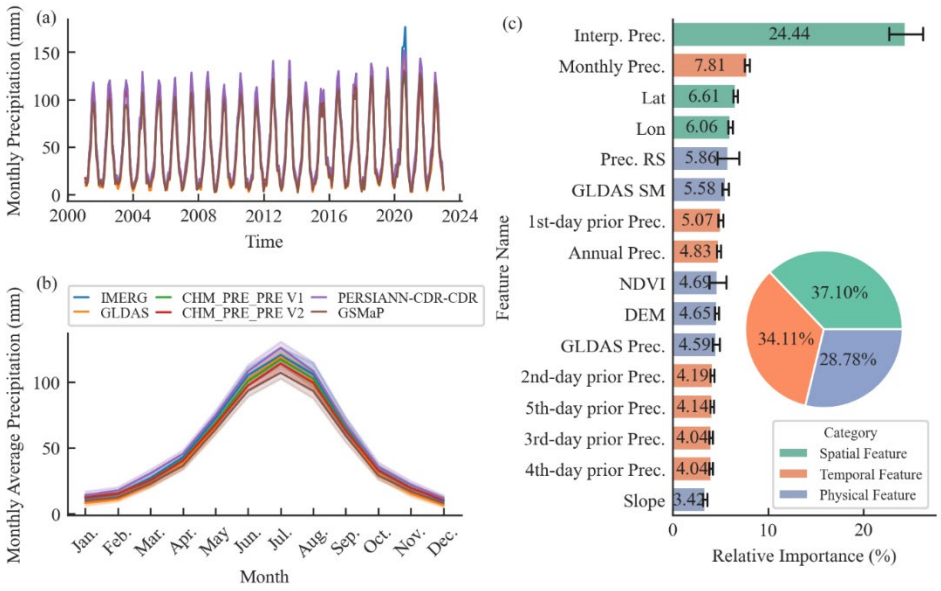
6. Line 26: What do the three numbers represent?

Response: We apologize for not clearly conveying this point in the previous manuscript. The original sentence — “Feature importance analysis revealed that spatiotemporal and physical correlations contributed 37.10%, 34.11%, and 28.78% to precipitation retrieval, underscoring the necessity of incorporating temporal and physical correlations.” — referred to the relative contributions of spatial, temporal, and physical correlations to precipitation retrieval (previously shown in Figure 5(c)). However, as you pointed out in Comment 1, the results of this importance analysis may not be sufficiently reliable. To ensure the rigor of the manuscript, we have removed this part in the latest manuscript (latest Figure 5).

Thanks again for your valuable comments.



Latest Figure 5. (a) time series of monthly precipitation; (b) multi-year mean monthly precipitation from 2001 to 2020.



Previous Figure 5. (a) time series of monthly precipitation; (b) multi-year mean monthly precipitation from 2001 to 2020; (c) feature importance of precipitation retrieval. In the figure, precipitation is abbreviated as "Prec.," interpolation-based precipitation is denoted as "Interp. Prec.," while remote sensing and soil moisture are represented by "RS" and "SM," respectively; "1st-day prior Prec." to "5th-day prior Prec." means the precipitation from the 1st day ago to 5th day ago.

7. Line 51: What interpolation method?

Response: In response to your suggestion, we have made the following revisions to improve the clarity of the manuscript:

"Our previous study developed a gridded precipitation dataset for the Chinese mainland (a member of the China Hydro-Meteorology datasets, hereinafter called CHM_PRE V1) based on inverse-distance weighting interpolation method and parameter-elevation regression on independent slopes model (PRISM) (Daly et al., 1994, 2002), using data from 2,839 gauges. The CHM_PRE V1 demonstrates overall high accuracy across the Chinese mainland (Han et al., 2023), and has received widespread attention and extensive use, benefiting a large number of hydro-meteorological related studies (Hu et al., 2024; Wan and Zhou, 2024; Yin et al., 2025)." (Lines 50–55)

8. Line 60: "are" should be "is". Besides, putting "historical precipitation data" in this sentence is weird.

Response: We have thoroughly rewritten these sentences and the results are as follows

"In summary, a key limitation of existing datasets is that they tend to focus on either spatial autocorrelation or a limited set of precipitation-related covariates, but rarely incorporate multiple types of information simultaneously. However, precipitation is influenced not only by spatial autocorrelation—that is, the dependence of precipitation at a given location on surrounding areas (Chen et al., 2010, 2016; Fan et al., 2021; Huff and Shipp, 1969; Tang et al.,

2020)—but also by a wide array of covariates, such as elevation, land surface conditions, atmospheric parameters, and recent precipitation events (Adler et al., 2008; Ham et al., 2023; Ravuri et al., 2021; Trucco et al., 2023).” (Lines 57–62)

9. Line 95: I think the station data cannot be freely accessed from this website ...
Response: Thank you very much for this valuable feedback. We obtained the precipitation gauge data from the China Meteorological Administration in January 2024. To better clarify this point, we have corrected the corresponding description in the manuscript:

“The primary daily precipitation gauge data sourced from the China Meteorological Administration (CMA; http://data.cma.cn, last access: January 2024) spans the entire Chinese mainland, encompassing records from 2,816 stations between 1960 and 2023.” (Lines 95–97)

10. Line 222-223: This does not seem to be solid reason for selecting LGBM.
Response: Thank you for your helpful comment. Our previous research (Hu et al., 2023) has demonstrated that the LGBM method achieves a higher accuracy compared to other commonly used machine learning methods (such as Random Forest and Support Vector Machine). Therefore, we adopted the LGBM method as the retrieval method in this study. Following your suggestion, we have provided a more detailed explanation of the reason for choosing the LGBM method. The corresponding revisions are as follows:

“LGBM demonstrates exceptional accuracy and generalization, making it widely applicable to various tasks such as classification, regression, and ranking (Bian et al., 2023; Jiang et al., 2024; Zhang et al., 2024). Hu et al. (2023) applied LGBM to the retrieval of suspended sediment concentration in the lower Yellow River and found that LGBM outperformed methods such as partial least squares regression, support vector regression, and random forest in terms of retrieval accuracy. Consequently, we employed the LGBM method to integrate all these variables for precipitation retrieval, effectively accounting for the spatiotemporal and physical correlations of precipitation.” (Lines 238–243)

11. Section 3.3: The description of data training is unclear to me. I recommend that the users use a few bullet points to explain what are the inputs and outputs of CHM_PRE production. For example, after reading Section 3.3 and looking at Table 1, I am still not sure what are samples you used in model training.
Response: We apologize for not clearly describing the modeling process in the previous manuscript. In the latest manuscript, we have thoroughly rewritten Section 3.3 and added **Table S3** in the supplementary materials to better illustrate the modeling process and the modeling variables. We hope that the revised Section 3.3 meets your expectations. The corresponding revisions are as follows:

“Except spatial autocorrelation, precipitation is influenced by a range of meteorological factors that vary over space and time. However, most existing gridded precipitation datasets tend to model these aspects in isolation, often focusing solely on spatial autocorrelation or meteorological inputs, which may constrain the accuracy and generalizability of the datasets,

especially in regions with sparse gauge coverage. To address this limitation, we propose a novel framework that integrates multiple precipitation covariates into a unified machine learning-based retrieval system, thereby enhancing the fidelity of precipitation estimates. To model spatial autocorrelation, we employed gridded precipitation data derived from gauge-based interpolation in Section 3.2, along with geographic coordinates (longitude and latitude). Precipitation covariates were drawn from various sources, including topographic features (elevation and slope), satellite-derived precipitation estimates, reanalysis-based precipitation products, soil moisture, and the normalized difference vegetation index (NDVI). Recent daily precipitation records and aggregate precipitation metrics were also incorporated to capture the temporal variability and underlying climatological patterns. The details of the retrieval data can be found in **Figure 1**.

To synthesize these spatial and covariate-based features, we employed a machine learning regression framework using the light gradient boosting machine (LGBM) algorithm. This model enables the flexible representation of complex nonlinear relationships between precipitation and its associated covariates, surpassing the limitations of conventional linear regression models. While linear regression models are the most commonly used response models, they are limited by their inability to capture nonlinear relationships and their relatively weak fitting capacity (Breiman, 2001; Chen and Guestrin, 2016; Yang et al., 2021). Machine learning-based models, in contrast, offer significant improvements in fitting performance and are more effective in representing nonlinear relationships (Guo et al., 2024; Hu et al., 2023). Among numerous machine learning-based models, LGBM, developed by Microsoft (Ke et al., 2017), is renowned for its high precision and high generalizability. Fundamentally, it employs a series of decision tree models for iterative training, progressively minimizing errors (or residuals) to ultimately generate predictions through a weighted summation. Unlike traditional gradient-boosted decision tree (GBDT) methods, LGBM utilizes a histogram-based technique for data binning, rather than processing each individual data record. This method iterates, calculates gains, and splits data accordingly (Zhang and Gong, 2020). Gradient-based one-side sampling is employed to sample the dataset, assigning greater weights to data points with larger gradients during gain computation. Under equivalent sampling rates, this method often outperforms random sampling (Candido et al., 2021). Owing to these features, LGBM demonstrates exceptional accuracy and generalization, making it widely applicable to various tasks such as classification, regression, and ranking (Bian et al., 2023; Jiang et al., 2024; Zhang et al., 2024). Hu et al. (2023) applied LGBM to the retrieval of suspended sediment concentration in the lower Yellow River and found that LGBM outperformed methods such as partial least squares regression, support vector regression, and random forest in terms of retrieval accuracy. Consequently, we employed the LGBM method to integrate all these variables for precipitation retrieval, effectively accounting for the spatiotemporal and physical correlations of precipitation.

In the precipitation retrieval process, we employed a two-stage strategy: precipitation event classification and precipitation value retrieval. Sixteen variables were used as independent variables in the retrieval process, and all of them are listed in **Table S3** in the supplementary materials. For the precipitation event classification model, the variable indicating whether a precipitation event occurred was used as the dependent variable, while the precipitation value was used as the dependent variable in the precipitation value retrieval model. For the

convenience of updating and maintaining data every year in the future, we constructed separate models for each year. That is, for each year, the same independent variables were used to develop two different models based on the LGBM method, with precipitation event and precipitation amount as the dependent variables, respectively. One model is used for precipitation event classification, and the other for precipitation value retrieval. From 1960 to 2023, a total of 64 years, 128 different models were generated. Specifically, for a given year, all variables required for retrieval were consolidated and split into training and validation sets at a ratio of 8:2. The training set was utilized to develop a precipitation event classification model based on the LGBM method, while the validation set was used for hyperparameter optimization. Then, the established classification model was applied to all samples to determine whether each sample was a precipitation event. Samples identified as precipitation events were used to train a precipitation value reversal model based on the LGBM method, while non-precipitation samples were excluded from the retrieval process. This approach effectively removed the majority of non-precipitation samples, simplifying the capture of precipitation characteristics and enhancing the accuracy of the reversal model. Additionally, this strategy notably improved the discrimination of precipitation events and mitigated the overestimation of precipitation events commonly associated with traditional interpolation-based methods. Upon completing the retrieval process, the trained precipitation value retrieval models were used to generate the final gridded daily precipitation for the entire Chinese mainland from 1960 to 2023." (Lines 213–262)

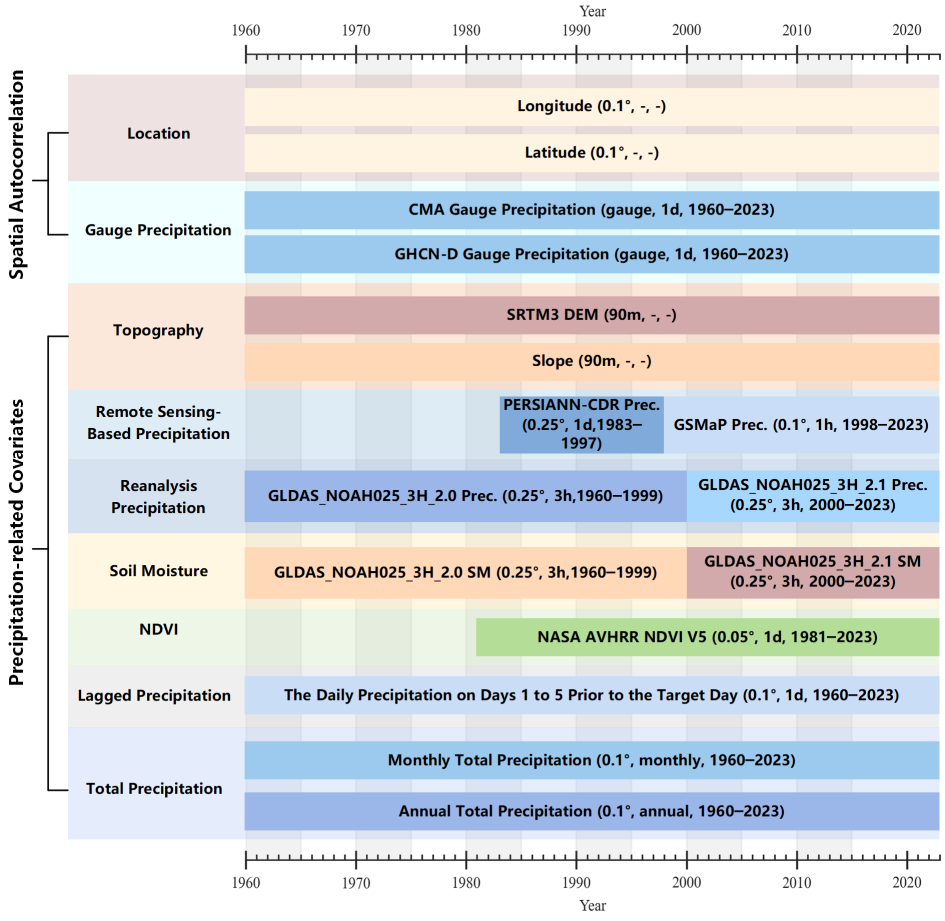


Figure 1. The data used for precipitation retrieval.

Table S3. The variables used in the precipitation retrieval.

Variable Type	Variable Name	Description
Spatial autocorrelation variables	Lat	Latitude of the grid center
	Lon	Longitude of the grid center
	Interp. Prec.	Gridded precipitation based on gauge interpolation
Precipitation-related covariates	DEM	Average elevation of the grid
	Slope	Average slope of the grid
	GLDAS Prec.	Precipitation of the grid from GLDAS
	Prec. RS	Satellite-derived precipitation of the grid
	GLDAS SM	Soil moisture of the grid from GLDAS
	NDVI	NDVI of the grid
	Annual Prec.	Annual total precipitation of the grid
	Monthly Prec.	Monthly total precipitation of the grid
	1st-day prior Prec.	Daily precipitation one day before the current date
	2nd-day prior Prec.	Daily precipitation two day before the current date
	3rd-day prior Prec.	Daily precipitation three day before the current date
	4th-day prior Prec.	Daily precipitation four day before the current date
	5th-day prior Prec.	Daily precipitation five day before the current date

Thank you again for your valuable comments, which have greatly helped us improve the quality of the manuscript.

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In order to make the review of our revision more convenient, we have marked all changes using the "Track Changes" function in Microsoft Word, and have uploaded the "tracked changes" version as Supplementary Material.