Peer Review File

Precipitation Observing Network Gaps Limit Climate Change Impact Assessment

Corresponding Author: Professor Chiyuan Miao

This file contains all reviewer reports in order by version, followed by all author rebuttals in order by version.

Attachments originally included by the reviewers as part of their assessment can be found at the end of this file.

Version 1:

Reviewer comments:

Referee #1

(Remarks to the Author)
The manuscript "Global Gaps in Precipitation Monitoring Networks Hinder Climate Change Impact Assessment" by Su et al. describes and discusses a lasting challenge in hydrology, the lack of observational networks with sufficient spatial and temporal coverage. Furthermore, they report a robust analysis identifying the priority level for siting new gauges based on precipitation change and socio-economic scenarios. The methods are robust, and the findings should aid local and international organizations/governments in deploying new gauges following their priority level. I have a few minor comments/suggestions for the authors.

L191-194. The second-highest long-term record continental density is smaller by a factor of 10 compared to the first (0.2 vs 1.5). A sentence explicitly stating so could further stress how scarce historical gauge data is and why it is important to act now to have sufficient observations with long-term records in the near future.

L483. (...) from ref. -> from Wang et al.

L485. (...) from ref. -> from Wang and Sun

L486. If the population/GDP datasets had a higher resolution than 1 degree, why were they not spatially aggregated/averaged rather than interpolated?

L497. What was the rationale for setting a 2.5% threshold?

L557 and Supplementary Text 4. We developed a metric, Absolute Error (AE), to quantify the trends disagreement (...) -> We adjusted the Absolute Error (AE) metric to quantify the trend disagreement (...)

Supplementary Table 1. Add a column with the date of last access.

(Remarks on code availability)
There are two R scripts provided, both coded in a tidy fashion and well documented.

Referee #2

(Remarks to the Author)
This work provides an important and timely evaluation of global precipitation gauge distribution and its implications for climate projections and water deficiency assessments. The study addresses a key challenge in climate science—ensuring the spatial and temporal completeness of precipitation observations, which is critical for accurate modeling and risk assessments. The authors do a great job in presenting a global overview, with clear geographical insights into gauge

density and regions where expansion is most needed. The integration of emission scenarios and socioeconomic projections adds an extra layer of depth and relevance to the analysis. To further improve the representation and quality of this work, a few suggestions are listed below for authors to consider.

1. Methodology could be further clarified: For instance, this work relies on the "distribution of 216,059 internationally exchanged precipitation gauges" but does not clarify how these were selected or whether any biases might exist in the dataset. Including a brief mention of the methodology for data selection or inclusion criteria could help readers understand the robustness of the dataset. Would be great to check through the methodology and SI to provide other details that might be helpful for readers to follow the method applied.

2. More elaborations are needed to those 'high-need' areas. While this work identifies regions like India, China, and the United States as high-need areas, a little more detail on why these regions specifically need more gauges (e.g., socioeconomic vulnerabilities, rapid urbanization, or climate sensitivity) would add context to the finding.
With those information, it will help to better justify the importance and emergence of this study.

3. The results section presents a wealth of valuable data, but the extensive listing of numbers across different regions feels somewhat overwhelming and detracts from the key takeaways. While the data is crucial, the presentation could be more engaging by highlighting the broader trends or implications first, followed by specific numbers to support the narrative.
One suggestion for writing is to keep on asking the 'why and so what' questions—that's usually what help to engage readers.
4. The figures are generally visually appealing and effectively display the data. Improvements could be made: 1) in fig. 1, provide the name of the 4 regions chosen; also, provide the number of each region; maybe provide the distribution for each region as well. The fonts in fig.3 are different with other figures, and too large…
4. It is unclear what does 'for the priority level for siting new gauges' (PSNG) mean?
5. The conclusions could be strengthened. The section could be more impactful if the main conclusions are highlighted more clearly in a narrative format, rather than presenting a series of statistics. For instance, instead of just listing numbers, it could provide a concise synthesis of what these gaps in the precipitation network mean for global climate monitoring, different climate impacts analysis, particularly concerning for which region, which type of climate impact etc. Some discussions based on existing literature would be helpful to provide the context.
While the future work section raises valid points about the need for new gauges and data-sharing, it could be strengthened by offering more concrete, actionable, and region-specific recommendations based on underlying drivers and consequences.
For example, instead of just noting that "many cities have their own observing gauges that are not shared internationally," it could suggest specific strategies for improving data sharing, such as developing a global data-sharing platform or incentivizing local authorities to share data in ** region, but this may not be practical in ** regions, explain why and provide recommendations for those regions…
The mention of challenges (e.g., uneven distribution of station elevations, limited data in remote areas) is important but could be connected back to the main findings more directly. The reader should be reminded that addressing these challenges is crucial for closing the global data gaps identified earlier in the conclusion. Also, it might be helpful to clarify how these future directions directly link to improving global precipitation monitoring, reinforcing the study's broader relevance.
6. Comments on codes: As there is no complete input data, I cannot actually run the code. But as far as I can tell, there seems to be no logic issue and should work.

Overall, it is a great work with valuable insights, hope my suggestions would be helpful for the author team to further improve the manuscript.

(Remarks on code availability)
As there is no complete input data, I cannot actually run the code. But as far as I can tell, there seems to be no logic issue and should work.

Version 2:

Reviewer comments:

Referee #1

(Remarks to the Author)
The authors have appropriately and extensively addressed all the comments/suggestions raised during the review round. I have no further comments and would gladly recommend the manuscript for publication.

(Remarks on code availability)
With the added sample data the scripts provided are fully reproducible.

Referee #2

(Remarks to the Author)
The authors have satisfactorily addressed all of my concerns, and I recommend the manuscript for publication. This study represents a timely and important contribution to the field.

(Remarks on code availability)
Yes, the code includes a readme file and sample data, I'm able to run the code and reproduce the major results.

A DETAILED LIST OF RESPONSES
TO THE EDITOR

Dear Professor Miao

Your manuscript, "Global Gaps in Precipitation Monitoring Networks Hinder Climate Change Impact Assessment", has now been seen by 2 referees, whose comments are attached below. While they find your work of potential interest, as indeed do we, they have raised substantial concerns on your data and methodological transparency that first need to be addressed before we can consider the paper further for possible publication in Nature.

In view of the additional data and analysis that are required to address these concerns, we appreciate that the necessary revisions will probably take some time. But let me assure you that we will nevertheless be happy to look at a revised manuscript (unless, of course, something similar has by then been accepted at Nature or appeared elsewhere). We hope to receive your revised paper within four to six months. If you cannot complete the revisions within this time frame, please let us know when you would anticipate being able to submit a revised manuscript.

Please note also that we are committed to providing a fair and constructive peer-review process; do not hesitate to contact us if there are specific requests from the reviewers that you believe are technically impossible or unlikely to yield a meaningful outcome. I should stress, however, that we would be reluctant to trouble our referees again unless we thought their comments and any editorial issues had been responded to in full.

Response: We would like to thank the editors and the two anonymous reviewers, whose constructive comments have helped improve the manuscript. In the following pages, we provide detailed answers to each of the comments. Reviewer's comments are reproduced in **black** font, our responses are provided in **blue** font, and **underlined text** indicates revisions in the main text. All changes in the main text and the Supplementary Information are provided in track changes format for easy reference.

In summary, the main changes we have made to the manuscript are as follows:

(1) We have thoroughly revised the Methods, Results and Discussion, and Conclusions and future work sections to enhance clarify, accuracy, readability and scientific rigor in our revised manuscript (in response to all referees);

(2) We updated the code and corresponding data to allow readers to easily repeat the experiments (in response to the comments raised by the referee #2);

(3) We further augmented the station datasets, and updated all relevant results described in Results and Discussion, and Conclusions and future work sections (in response to all

referees);

(4) We clarified how we defined the urban area threshold in identified urban regions when mapping physiographical regions in the Supplementary Information (in response to the comments raised by the referee #1).

COMMENTS and RESPONSES

Reviewer #1

General comments

The manuscript "Global Gaps in Precipitation Monitoring Networks Hinder Climate Change Impact Assessment" by Su et al. describes and discusses a lasting challenge in hydrology, the lack of observational networks with sufficient spatial and temporal coverage. Furthermore, they report a robust analysis identifying the priority level for siting new gauges based on precipitation change and socio-economic scenarios. The methods are robust, and the findings should aid local and international organizations/governments in deploying new gauges following their priority level. I have a few minor comments/suggestions for the authors.

Response: Thank you very much for this positive assessment. We have made substantial revisions according to your suggestions, which have been very valuable in improving the manuscript. Below is a point-by-point response to your comments.

Minor Comments

L191-194. The second-highest long-term record continental density is smaller by a factor of 10 compared to the first (0.2 vs 1.5). A sentence explicitly stating so could further stress how scarce historical gauge data is and why it is important to act now to have sufficient observations with long-term records in the near future.

Response: We thank the reviewer for this insightful observation. We agree that explicitly highlighting the order-of-magnitude difference in station density powerfully underscores the scarcity of long-term historical gauge data. As suggested, we have revised the text in the manuscript:

"European countries have the highest densities of all stations (2.4 stations per 1000 km^2), followed by North America (1.1 stations per 1000 km^2). For LR stations, European again has the highest density (1.3 stations per 1000 km^2), exceeding second-place Oceania (0.2 stations per 1000 km^2) by nearly an order of magnitude (Supplementary Table 2). This severe shortage of long-term observations underscores the challenge to the track water cycle and predict future weather events more accurately, especially in Africa (where the total and LR station densities are 0.09 and 0.02 stations per 1000 km^2 respectively)."

Fig 1, and Supplementary Figs. 2–3 are also presented here (Figs. R1–3) for the reviewer's convenience.

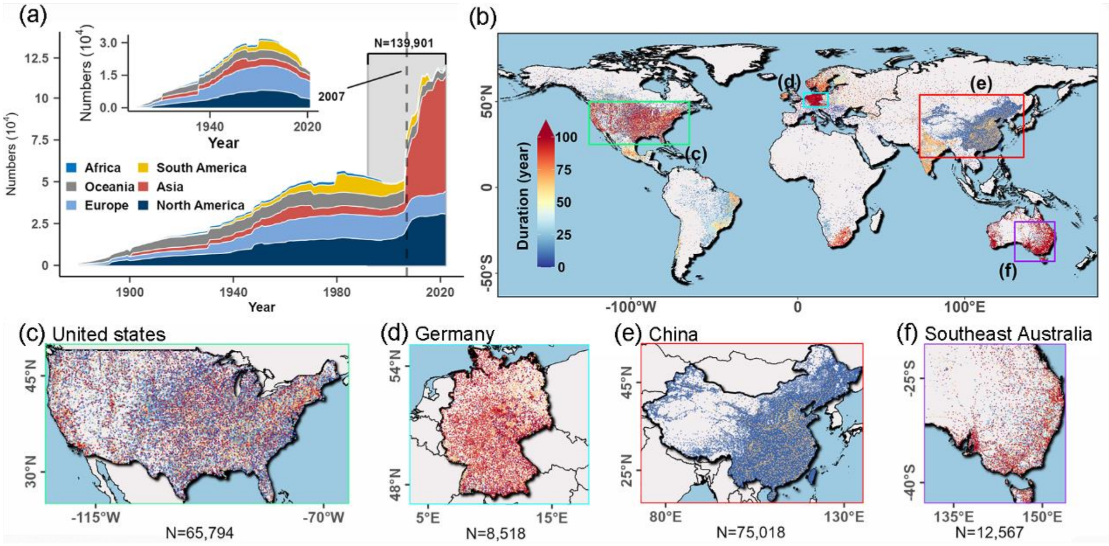

Figure R1 | Collected daily precipitation gauge records from 1900 to 2022 (221,483 gauges). (a) Yearly count of stations by continent. The stacked area plot inset presents the yearly count of Long-term Record (LR) stations (38,203 gauges) meeting specific criteria (see Methods). (b) Map of stations record lengths, with (c-f) focusing on four regions with notable precipitation gauge densities.

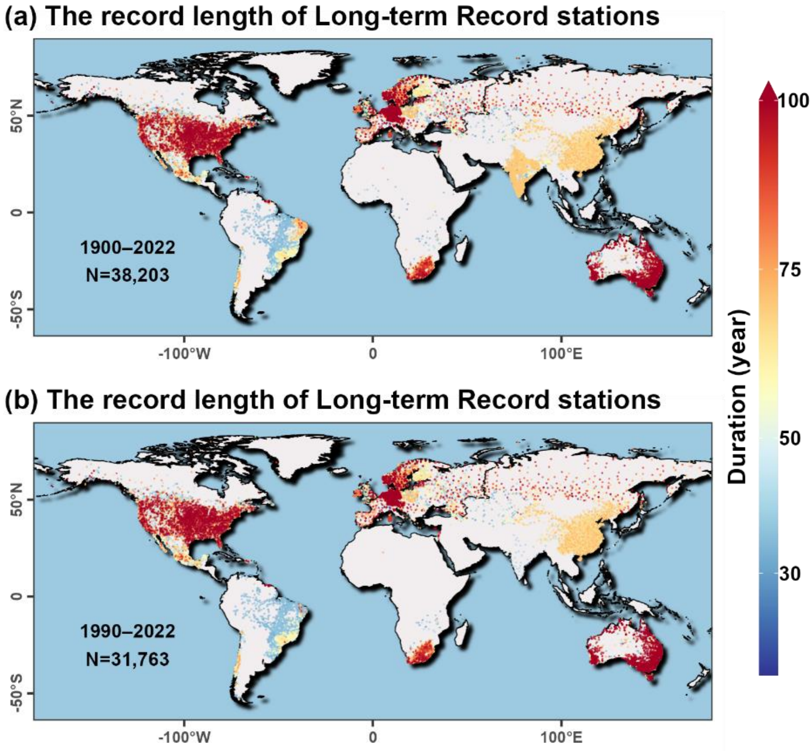

Figure R2 | The record length of Long-term Record stations (meeting specific criteria, see Method). (a) Map of stations record lengths from 1900 to 2022. (b) Map of stations record lengths from 1990 to 2022.

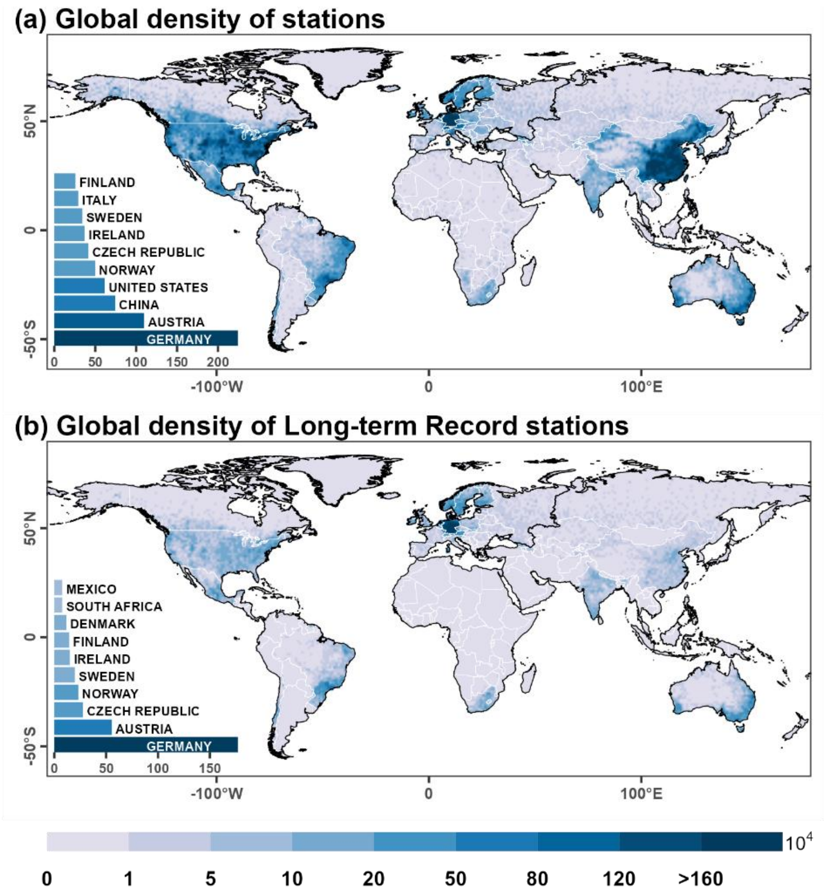

Figure R3 | Collected daily precipitation gauge density from 1900 to 2022. (a) Station density (total N = 221,483 gauges, see Method). (b) Long-term Record station density (N = 38,203 gauges). The unit is station numbers per area (stations per km^2). The inset plots show the top 10 countries by station density, with areas larger than 50,000 km^2. Gauge density is based on a 1° × 1° grid for the period 1900–2022.

L483. (...) from ref. -> from Wang et al.

Response: Done.

L485. (...) from ref. -> from Wang and Sun

Response: Done.

L486. If the population/GDP datasets had a higher resolution than 1 degree, why were they not spatially aggregated/averaged rather than interpolated?

Response: We thank you for raising this important methodological point. We apologize for the lack of clarity in our original description. The global population dataset used in our study has an original resolution of approximately 30 arc-seconds, but its spatial extent is inconsistent with other datasets. To maintain consistency with other datasets in our analysis, we initially applied an interpolation method to resample the data to a uniform 1-degree grid.

We have now reprocessed the population and GDP datasets using a spatial averaging (aggregation) method, which is indeed more appropriate for this purpose. We have replaced all datasets in our final analysis with those generated by spatial averaging and have updated all corresponding figures, results, and discussions in the revised manuscript accordingly.

L497. What was the rationale for setting a 2.5% threshold?

Response: Thank you for the question. The rationale for setting the threshold at 2.5% is as follows. When aggregating the original 250 m physiography data to a 1-degree grid, we typically assigned the dominant class within each cell. We used a set of 4 objective measures (detailed further below) to judge whether this approach would result in an adequate representation of urban areas. We found that because urban pixels are spatially sparse compared to natural land cover classes, simply aggregating on the basis of dominant land class would lead urban areas to be underrepresented. To preserve urban representation, we introduced an override rule: if the urban coverage within a 1-degree grid cell exceeded a certain threshold, the cell would be classified as urban, regardless of the dominant class. To determine this threshold objectively, we used a global urban boundary dataset (2018), filtered for large urban agglomerations (>100 km^2), and compared the agreement between different urban classification thresholds and the reference boundaries. The 2.5% threshold yielded the best balance between the detection of 1-degree grid cells with large urban agglomerations and false alarms. We have added a clarification of this procedure and the performance metrics considered in the Supplementary Information, as follow:

"Supplementary Text 2. Urban area classification

The physiographic classes were aggregated to a 1° × 1° resolution by assigning the dominant class within each grid cell. This simple approach, would however, lead to underrepresentation of urban areas because the occurrence urban pixels is spatially sparse compared to natural land cover classes. To preserve urban representation during aggregation, we therefore applied a special threshold to identify grid cells with a large urban component relative to other grid cells and classified any grid cell with an urban area-fraction exceeding this threshold as urban. The threshold was selected to optimize the identification of major urban agglomerations, using the 2018 Global Urban Boundary dataset**[Error! Reference source not found.]**, and considering only urban areas larger than 100 km^2.

To determine the area-fraction threshold for reclassifying a grid cell as "urban", multiple thresholds were tested and evaluated through a per-pixel accuracy assessment. Performance was comprehensively assessed using four metrics[0,0]: the balanced accuracy, F1, commission errors and omission errors scores. Among these, balanced accuracy and the F1-score are overall accuracy measure, while commission and omission errors scores specifically quantify the two types of possible classification mistakes. All metrics are derived from the confusion matrix, which includes true positive (*TP*), true negative (*TN*), false positive (*FP*) and false negative (*FN*) counts.

The formulae for these scores are as follows: Balanced accuracy is given by $\frac{1}{2}(\frac{TP}{(TP+FN)}+\frac{TN}{(TN+FP)})$, representing the average accuracy across classes. The F1-score is given by $\frac{2\times TP}{(2\times TP+FP+FN)}$, the harmonic mean of precision and recall that considers both false negatives and false positives, which evaluates the correct identification of the positive class. Commission errors is given by $\frac{FP}{TP+FP}$, reflecting the rate of false alarms, and omission errors is given by $1-\frac{TP}{TP+FN}$, reflecting the rate of missed detections.

The 1% and 2.5% thresholds were initially considered due to their high balanced accuracy (both exceeding 0.8) and moderate F1-score (both exceeding 0.5). However, the 1% threshold was subsequently rejected because of its substantial commission errors rate (>0.5), which corresponds to a high false alarm rate in urban classification. World Meteorological Organization standards indicate that urban precipitation monitoring requires a high gauge density (Supplementary Table 3), and thus excessive classification false alarms would overestimate urban area gauge scarcity, potentially leading to high cost if used to guide the placement of new gauges. Ultimately, a threshold of 2.5% was selected based on its high balanced accuracy, moderate F1-score, and acceptable levels of commission and omission errors, indicating that it effectively captures the spatial pattern of major urban agglomerations (Supplementary Fig. 28). Accordingly, any 1° grid cell with urban coverage exceeding 2.5% was classified as urban, overriding the dominant physiographic class of that cell."

Supplementary Fig. 28 is presented here (Fig. R4) to facilitate your review.

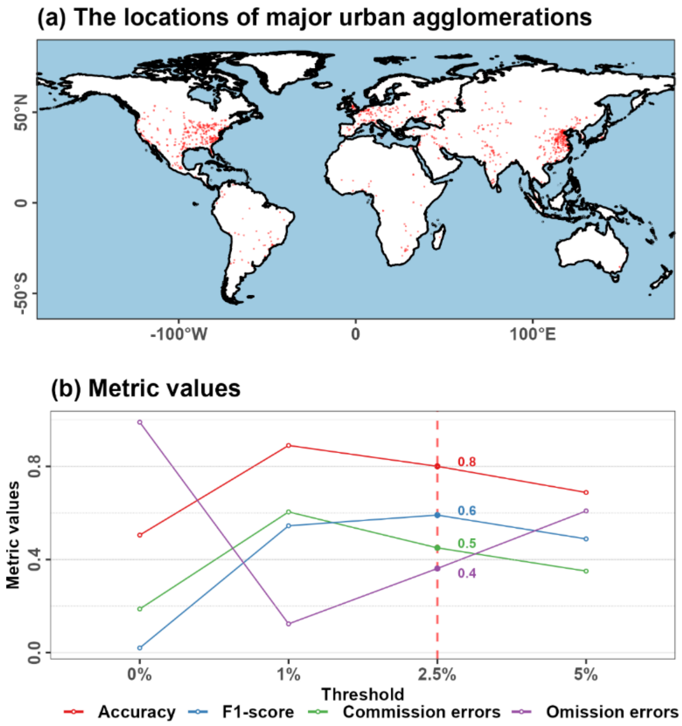

Figure R4 | Urban region classification by different thresholds. (a) The locations of major urban agglomerations in 2018. (b) The performance of different thresholds to identify the urban region by four metrics.

References:

2. Li, X. et al. Mapping global urban boundaries from the global artificial impervious area (GAIA) data. *Environ. Res. Lett*, **15**, 094044 (2020).

3. Swaminathan, S., & Tantri, B. R. Confusion matrix-based performance evaluation metrics. *Afr J Biomed Res*, **27**, 4023–4031 (2024).

4. Corbane, C. et al. Automated global delineation of human settlements from 40 years of Landsat satellite data archives. *Big Earth Data*, **3**, 140–169 (2019).

L557 and Supplementary Text 4. We developed a metric, Absolute Error (AE), to quantify the trends disagreement (...) -> We adjusted the Absolute Error (AE) metric to quantify the trend disagreement (...)

Response: Done.

Supplementary Table 1. Add a column with the date of last access.

Response: As suggested by the reviewer, we have added a column indicating the date of last access for each dataset in Supplementary Table 1. As follow:

Supplementary Table 1 | Detailed information on global daily precipitation gauges, along with approximate gauge numbers by source.

Dataset	Coverage	Station numbers	Link	Accessed date
GHCNd[0]	Global	122,047	https://www.ncei.noaa.gov/maps/daily/	2025.11.01
ECA&D	Europe and the Mediterranean	15,086	https://www.ecad.eu//dailydata/index.php	2025.11.01
SACA&D	Southeast Asia	1356	https://sacad.database.bmkg.go.id/dailydata/datadictionary.php	2022.10.19
LACA&D	Latin America	15,085	https://lacad.ciifen.org/	2022.12.07
HPD[0]	United States, and several U.S. territories in the Caribbean and Pacific	2008	https://www.ncei.noaa.gov/maps/hourly/?layers=0001	2025.11.01
GSOD[0]	Global	16,906	https://www.ncei.noaa.gov/metadata/geoportal/rest/metadata/item/gov.noaa.ncdc:C00516/html	2025.11.01
SWIS	Switzerland	802	https://www.meteoswiss.admin.ch/home/measurement-and-forecasting-systems/land-based-stations/data-availability.html	2025.11.01
SCAL	Southern Africa	156	https://sasscal.org/oadc-open-access-data-center/	2025.11.01
GTS	Global	8241	https://ftp.cpc.ncep.noaa.gov/cadb_v2/	2025.11.01
CDC	Germany	5661	https://www.dwd.de/EN/climate_environment/cdc/cdc_node_en.html	2025.11.01
KORA	Republic of Korea	140	https://data.kma.go.kr/tmeta/stn/selectStnList.do?pgmNo=123	2025.11.01
China	China	79,900	https://data.cma.cn/en/#/home	2025.11.01
India	India	74	https://dsp.imdpune.gov.in/	2025.11.21

Brazil	Brazil	9034	https://doi.org/10.3389/feart.2020.00092	2025.11.21
Colombia	Colombia	713	https://dev.socrata.com/foundry/www.datos.gov.co/s54a-sgyg	2025.11.21

References:

26. Menne, M. J., Durre, I., Vose, R. S., Gleason, B. E. & Houston, T. G. An Overview of the Global Historical Climatology Network-Daily Database. *J. Atmos. Ocean. Technol*. **29**, 897–910 (2012).
27. Lawrimore, J. H. *et al*. Quality Control and Processing of Cooperative Observer Program Hourly Precipitation Data. *J. Hydrometeorol*. **21**, 1811–1825 (2020).
28. Lavigne, T. & Liu, C. Validity of Global Fog-Day Trends Indicated by the Global Surface Summary of the Day (GSOD) Data Set. *J. Geophys. Res. Atmos*. **127**, e2021JD035881 (2022).

Referee #1 (Remarks on code availability): There are two R scripts provided, both coded in a tidy fashion and well documented.

Response: We sincerely thank the reviewer for their positive assessment of our code and documentation. We have now updated the code and corresponding data to facilitate easy execution and verification of the analysis scripts. The complete code can be accessed via the following link: https://github.com/JJiaSu/Global-Gaps-in-Precipitation-Monitoring-Networks-Hinder-Climate-Change-Impact-Assessment

Reviewer #2 comments

General comments

This work provides an important and timely evaluation of global precipitation gauge distribution and its implications for climate projections and water deficiency assessments. The study addresses a key challenge in climate science—ensuring the spatial and temporal completeness of precipitation observations, which is critical for accurate modeling and risk assessments. The authors do a great job in presenting a global overview, with clear geographical insights into gauge density and regions where expansion is most needed. The integration of emission scenarios and socioeconomic projections adds an extra layer of depth and relevance to the analysis. To further improve the representation and quality of this work, a few suggestions are listed below for authors to consider.

Response: We are deeply grateful for the thorough and constructive feedback, which has fundamentally strengthened our manuscript. All requested revisions have been rigorously implemented as follows:

1. We have supplemented the precipitation station datasets for Brazil and India, where our previous data coverage was limited after 1990. This update has increased the total number of gauges from 216,059 to 221,483, and the number of Long-term Record stations from 35,872 to 38,203. All related descriptions in our manuscripts have been revised accordingly.

2. We have thoroughly revised the Methods, Results and Discussion, and Summary and future work sections corresponding to your suggestion. Throughout the revision, we consistently applied the "why and so what" framework to strengthen the narrative, thereby improving the manuscript's clarity, accuracy, readability and scientific rigor.

3. We have reorganized the structure of the Methods and Results sections to make it easier to follow. For instance, the analytical timeline has been reframed into historical and future periods, and the PSNG scenario based solely on historical and future precipitation has been moved to the supplementary materials;

4. We updated the code and corresponding data to allow readers to easily repeat the experiments;

5. We have incorporated an attribution analysis in the priority area result, to better justify the underlying reason for high-priority.

Our response to each point is given below.

Minor Comments

1. Methodology could be further clarified: For instance, this work relies on the "distribution of 216,059 internationally exchanged precipitation gauges" but does not clarify how these were selected or whether any biases might exist in the dataset. Including a brief mention of the methodology for data selection or inclusion criteria could help readers understand the robustness of the dataset. Would be great to check through the methodology and SI to provide other details that might be helpful for readers to follow the method applied.

Response: In response to the reviewer's comment, we have reorganized the Methodology section and added corresponding descriptions in the Supplementary Information to enhance clarity and reproducibility.

Specifically, to improve spatial representation in regions with limited post-1990 records, we have incorporated additional gauges from Brazil and India. This addition increased the total number of gauges from 216,059 to 221,483 and the number of Long-term Record stations from 35,872 to 38,203. We have also clarified that the initial dataset was quality-controlled by the original data providers. We also detail the pre-processing steps applied to ensure consistency and reliability, including station location verification, unit and format standardization, data quality assessment with source labelling, station relocation and intra-source merging, multi-source merging with deduplication, and final selection of long-term record stations. These procedures are detailed in the Supplementary Information to facilitate a deeper understanding of the data curation process and support transparency and reproducibility. The revised description of the procedures is as follows:

"**Supplementary Text 1. Preprocessing the observed data**

We compiled data from multiple contributors, totaling 245,368 stations (Supplementary Table 1). All datasets had been quality controlled by their respective providers prior to being shared[Error! Reference source not found.]. Following the quality control guidelines of each source, we conducted a systematic pre-processing procedure to integrate records and eliminate duplicate records, as outlined below:

Step 1: Station location check

Station coordinates were verified to ensure they fell within reasonable geographic ranges and records with invalid coordinates (*e.g.*, longitude labeled as NA) were removed.

Step 2: Unit and format standardization

Based on each dataset's documentation, we converted the observations and metadata to standardized units and formats. Precipitation was converted to mm, geographic coordinates to decimal degrees, elevation to meters, and dates to YYYYMMDD format.

Step 3: Data quality assessment and source labeling

We performed dataset-specific quality checks, removing records marked as low quality or lacking measurement information. Records prior to 1900 were also excluded. For each station, we calculated the maximum record length and missing data rate, and labeled all records by their source.

Step 4: Station relocation and intra-source merging
Within each dataset, station relocations were identified, and the latest recorded location was retained as the final position. If two stations shared the same final location, the record with the longer observation period and lower missing rate was kept.

Step 5: Multi-source merging and removal of duplicate records
All datasets were merged into a unified database. Stations with geographic coordinates within approximately 0.001° of each other across different sources were considered duplicates. We identified 16,409 such duplicate groups. Among these “duplicate” records, a decision on which to retain was made by first giving preference to records from national meteorological archives, and then considering whether the alternative record or records could provide a longer timeline and lower missing data rate. This process yielded 221,483 unique stations, of which 7.4% records were selected from duplicate sets. Each station was assigned a unique ID.

Step 6: Selection of Long-term Record stations
We focused on the period 1900–2022, recalculating record length and missing rate for each station. Stations with over 30 years of data and a missing rate below 10% were classified as “Long-term Record” (LR) stations, yielding 38,203 LR stations.”

We have also comprehensively restructured the Methodology section to improve clarity and flow. Specifically, we introduced a dedicated “Input Data” subsection to provide a detailed overview of all datasets employed in our study. Furthermore, the original “Identifying priorities for siting new gauges” subsection has been reorganized into two distinct parts: “Information for prioritizing new gauge siting”, and “Multicriteria incorporation algorithm”. The former explains the three types of information used to identify priority areas, and the latter details how this information is integrated to derive the priority areas for siting new gauges (PSNG in our manuscript). Additionally, the analysis timeline has been reframed into historical and future periods. The PSNG scenario based solely on historical and future precipitation has been discussed as the precipitation effect on PSNG, and its corresponding results are now provided in the supplementary materials, adhering to the “less is more” principle. This reorganization eliminates redundancy and presents a more coherent Methodology section, enhancing readability and helping readers better grasp the methodological framework.

2. More elaborations are needed to those ‘high-need’ areas. While this work identifies regions like India, China, and the United States as high-need areas, a little more detail on why these regions specifically need more gauges (e.g., socioeconomic vulnerabilities, rapid urbanization, or climate sensitivity) would add context to the

finding. With those information, it will help to better justify the importance and emergence of this study.

Response: Thank you for this suggestion. We have revised the "Priority areas under historical period" results section to offer further elaboration. For example, we now emphasize that monsoon regions in South America and Africa are categorized as high priority due to their characteristically high precipitation variability and critically low inter-station redundancy, which collectively exacerbate monitoring gaps and climate risks. We have revised the text as follows:

"Globally, approximately 25% of land areas are identified as high priority for siting new gauges (PSNG score of 7 to 8) based on historical precipitation information from 1900 to 2022 (Fig. 3a, Supplementary Fig. 8). This includes extensive parts of Africa (38.7% of the continent's land area), South America (32.3%) and Europe (33.6%). High priority arises in these regions for different reasons. High priority in low-latitude regions is often due to a combination of highly variable daily precipitation and low inter-station redundancy. For example, in central Africa and northern South America, the key mechanisms producing high variability are often associated with their monsoon regimes, including a strong land-ocean thermal contrast[0] and the annual movement of active convective zones (*e.g.*, the South Atlantic and Intertropical Convergence Zones). Also, variability in these regions can be further modulated by slow changes in the Atlantic Meridional Overturning Circulation[0,0]. High priority in high-latitude regions, including northern Europe, is driven primarily by Arctic Amplification, rapid sea ice retreat, annual snow fraction changes[0,Error! Reference source not found.] in a warming climate, and compounded in Europe by the influence of the North Atlantic Oscillation[0]. Additional gauges in these northern areas would enhance the understanding of the global water cycle, as the sparse network of available stations complicates model bias evaluation[Error! Reference source not found.] and inhibits the ability to understand how warming and precipitation changes are reshaping the hydrology of many cold regions[0,0]. In contrast, Asia (20.7%) exhibits substantial inter-station redundancy, leading to low priority despite high precipitation variability associated with the Asian monsoon[0]."

Additionally, we have included an in-depth analysis of the contributing factors (climate sensitivity and socioeconomic vulnerability) behind each high-priority country across scenarios, based on the normalized contribution of each factor (*GD* [gauge density] and *MIMR* [historical precipitation spatial variability], *AE* [future precipitation trends], population density and GDP) to the national PSNG. This analysis is included in both the "Multicriteria incorporation algorithm" section of the main manuscript and the "Supplementary Text 8. Multicriteria incorporation algorithm" section, as follow:

Changes to the Methodology section in the main text are as follows:
"To better understanding factors leading to high PSNG, we decompose the PSNG into contributions from its factors in each country (Supplemental Text 8 Eq. (23))."

Additional detail is now provided in Supplemental Text 8 as follows:

"PSNG in each country is decomposed into contributions from *GD*, *MIMR*, *AE*, population density and GDP by computing the relative contribution from each factor in each country. The relative contribution $C_{relative}^{j,i}$ for factor *j* normalized by the PSNG score of country *i* is given by:

$$C_{relative}^{j,i} = \frac{C_{absolute}^{j,i}}{PSNG_i} \times 100\% = \frac{W_j \times F_{j,i}}{PSNG_i} \times 100\% \quad (23)$$

where $C_{absolute}^{j,i}$ is the absolute contribution of factor in *j* in country *i*, W_j is the weight assigned to factor *j*, $F_{j,i}$ represents the value of factor, and $PSNG_i$ is the PSNG score of country *i*."

Historical results show priorities for 1900–2022, while SSP1-2.6 and SSP5-8.5 represent priorities under a future low and very high emissions scenarios respectively for 2025–2100. For instance, the analysis reveals that India's high PSNG level is largely driven by socioeconomic vulnerabilities, whereas China's high level is influenced by a combination of climate sensitivity and socioeconomic pressures. To provide additional context, we have also included a ranked list of the top 15 countries based on the proportion of land area classified under PSNG levels 7–8, offering a clearer global perspective, as follows:

"Under the SSP5-8.5 scenario, precipitation dynamics and socio-economic pressures converge to elevate the PSNG in both low- and mid-latitude regions (Supplementary Figs. 20–21). Low-latitude areas in Africa and South America exhibit the most extensive coverage of high PSNG land area, with 54.9% and 39.3% of their respective continental areas classified as high priority, corresponding to increases of 16.3% and 7.0% respectively compared to the historical period (Supplementary Fig. 8). These areas are particularly sensitive to precipitation variability governed by monsoon systems and convective activity[0-0]. In contrast, across Europe, Asia and North America, socio-economic factors dominantly amplify PSNG, with high priority area expansions reaching 43.6%, 31.4% and 14.4%, respectively. This pattern is generally evident in high-population or high-GDP nations. For instance, when socio-economic dimensions are incorporated, France (population 66.7 million in 2025), Turkey (87.7 million), India (1463.8 million), Pakistan (255.2 million), Mexico (131.9 million), Iran (92.4 million) and China (1416.1 million) experience a notable transition from low categories (PSNG based on precipitation information alone, Fig. 3) to high values under both low- and high-emission scenarios (Supplementary Figs. 22–23)."

To facilitate your review, we have included Fig. 3 and Supplementary Figs. 8, 20–23 in this response document as Figs. R5–R10.

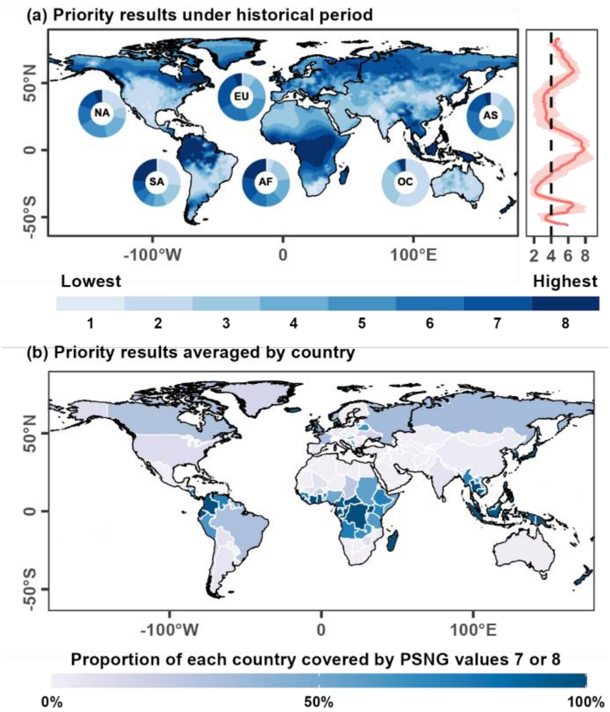

Figure R5 | Global priority for siting new gauges (PSNG) under historical period (1900–2022). (a) The inset pie charts show the relative proportion of each PSNG level across continents. The red line on the right represents the mean PSNG by latitude, with shading for the mean ± one standard deviation. Continental abbreviations are as follows: AS = Asia, EU = Europe, AF = Africa, OC = Oceania, NA = North America, SA = South America. (b) Proportion of each country covered by PSNG levels 7–8.

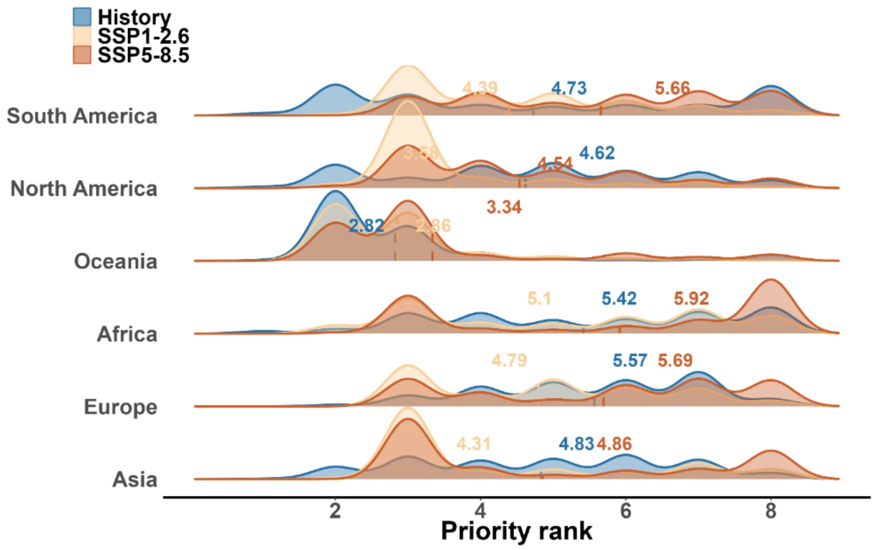

Figure R6 | Density distribution of priority for siting new gauges. Historical results show priorities for 1900–2022, while SSP1-2.6 and SSP5-8.5 represent priorities under future low- and high-emission scenarios for 2025–2100. Colored numbers indicate the mean priority rank for each continent and scenario.

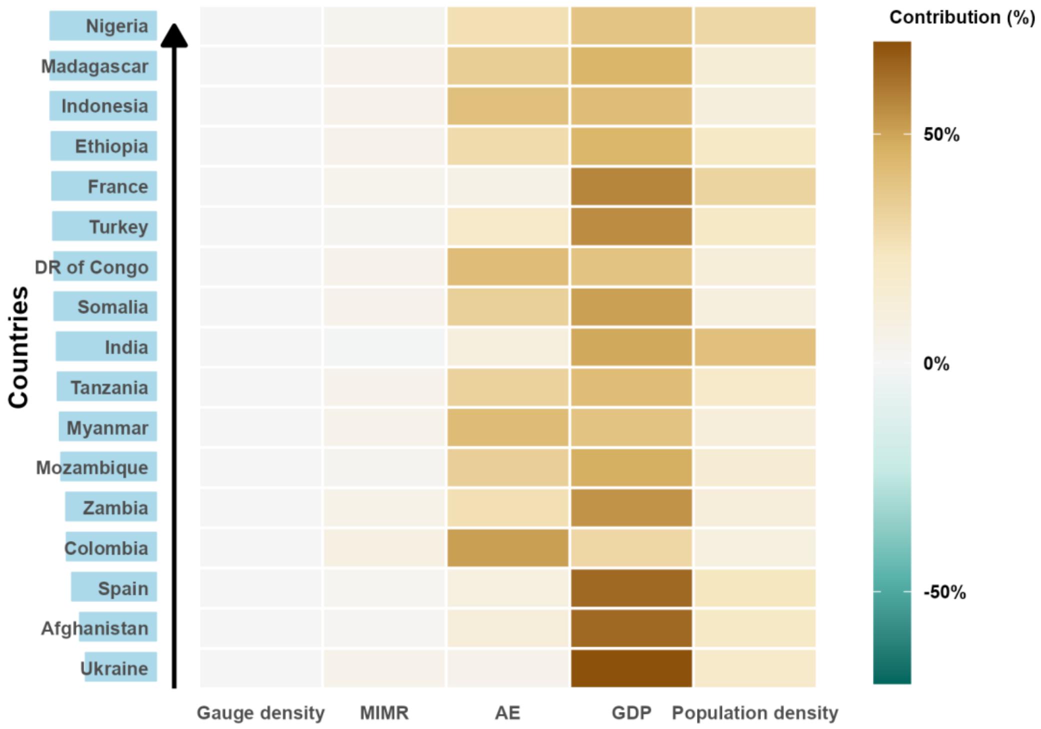

Figure R7 | Factors contributing to future PSNG under SSP5-8.5 scenario. The bar plot showing the top 15 largest countries (over 500,000 km^2) ranked by the proportion of their area classified as high priority (PSNG scores 7–8, the blue length indicates the proportion).

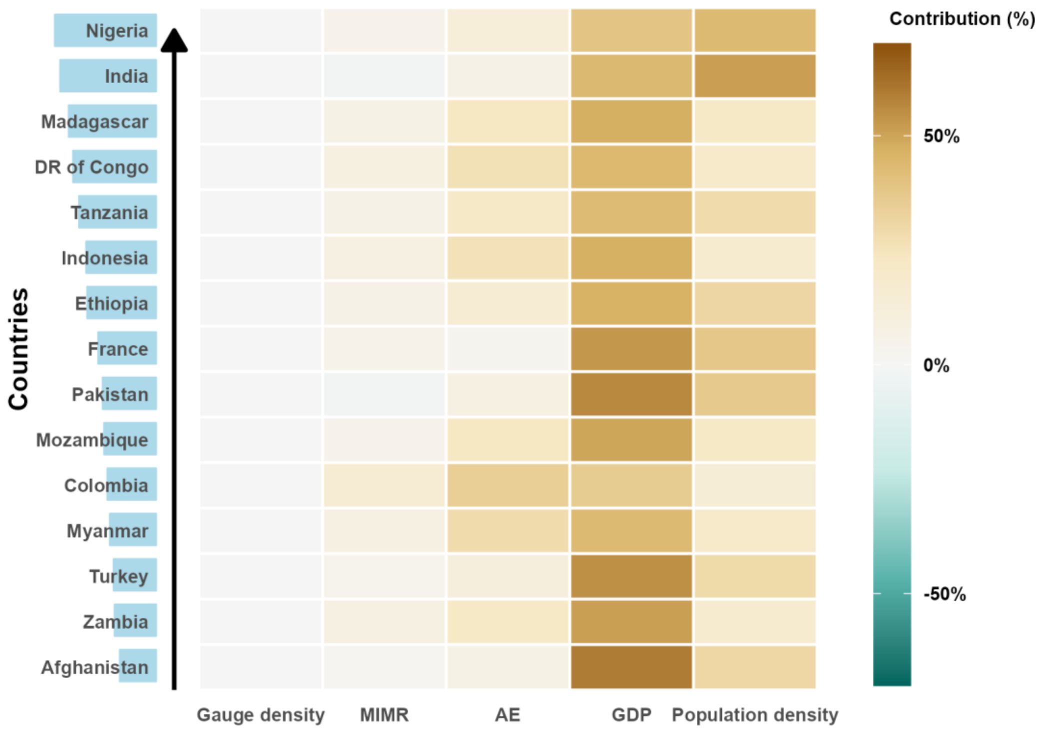

Figure R8 | Factors contributing to future PSNG under SSP1-2.6 scenario. The bar plot showing the top 15 largest countries (over 500,000 km^2) ranked by the proportion of their area classified as high priority (PSNG scores 7–8, the blue length indicates the proportion).

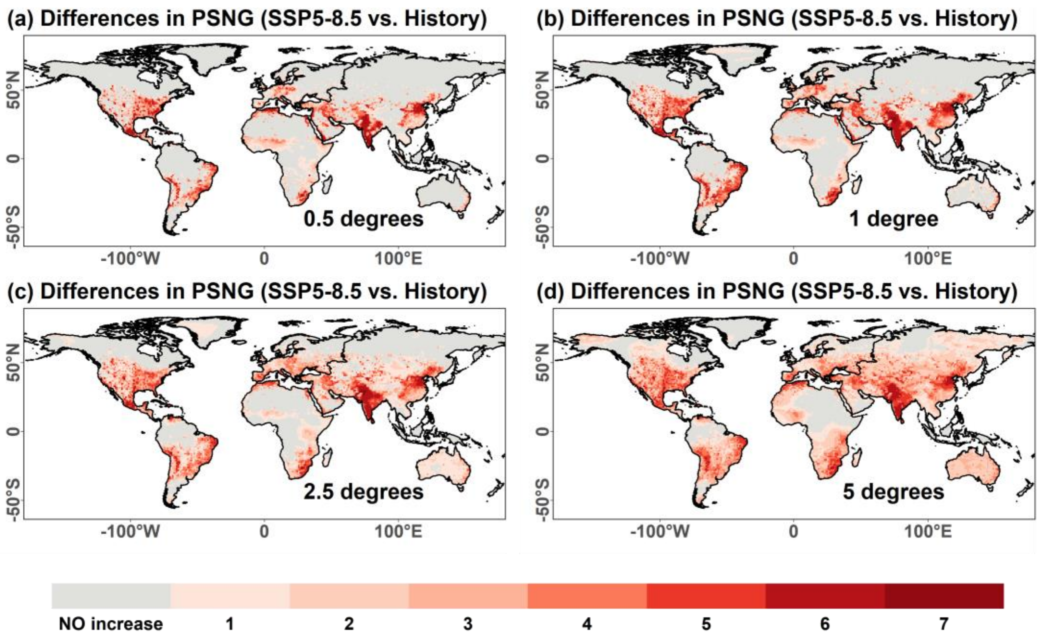

Figure R9 | Differences in PSNG between future SSP5-8.5 and historical periods when aggregating data at (a) 0.5°, (b) 1°, (c) 2.5°, and (d) 5° resolution.

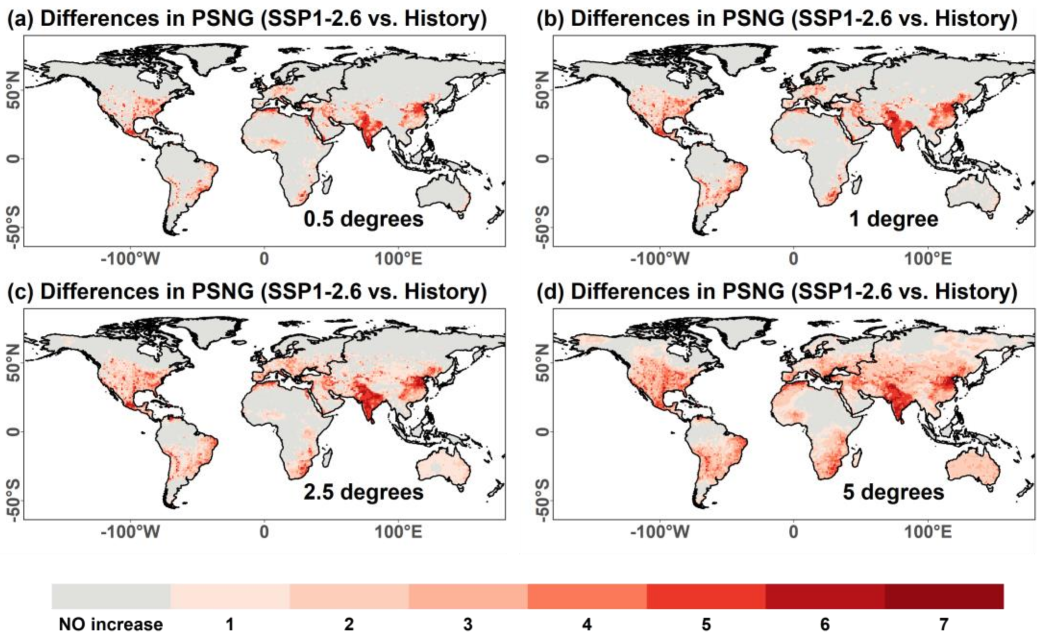

Figure R10 | Differences in PSNG between future SSP1-2.6 and historical periods when aggregating data at (a) 0.5°, (b) 1°, (c) 2.5°, and (d) 5° resolution.

References:

62. Rodríguez-Fonseca, B. *et al*. Variability and predictability of west African droughts: a review on the role of sea surface temperature anomalies. *J. Climate.* **28**, 4034–4060 (2015).
63. Mohtadi, M., Prange, M., & Steinke, S. Palaeoclimatic insights into forcing and response of monsoon rainfall. *Nature*. **533**, 191–199 (2016).
64. Mulitza, S., Chiessi, C. M., Schefuß, E., Lippold, J., Wichmann, D., Antz, B. *et al*. Synchronous and proportional deglacial changes in Atlantic meridional overturning and northeast Brazilian precipitation. *Paleoceanography*. **32**, 622–633 (2017).
65. Bintanja, R., & Andry, O. Towards a rain-dominated arctic. *Nat. Clim. Change.* **7**, 263–267 (2017).
66. McCrystall, M. R. *et al*. New climate models reveal faster and larger increases in arctic precipitation than previously projected. *Nat. Commun.* **12**, 6765 (2021).
67. Liu, Q., Bader, J., Jungclaus, J.H. et al. More extreme summertime North Atlantic Oscillation under climate change. Commun Earth Environ **6**, 474 (2025).
68. Serreze, M. C., Barrett, A. P., & Lo, F. Northern high-latitude precipitation as depicted by atmospheric reanalyses and satellite retrievals. *Mon. Weather Rev.* **133**, 3407–3430 (2005).
69. Rawlins, M. A., & Karmalkar, A. V. Regime shifts in arctic terrestrial hydrology manifested from impacts of climate warming. *The Cryosph.* **18**, 1033–1052 (2024).
70. Bring, A. *et al*. Arctic terrestrial hydrology: a synthesis of processes, regional effects, and research challenges. *J. Geophys. Res. Biogeosci*. **121**, 621–649 (2016).

3. The results section presents a wealth of valuable data, but the extensive listing of numbers across different regions feels somewhat overwhelming and detracts from the key takeaways. While the data is crucial, the presentation could be more engaging by highlighting the broader trends or implications first, followed by specific numbers to support the narrative. One suggestion for writing is to keep on asking the 'why and so what' questions—that's usually what help to engage readers.

Response: Thank you for highlighting the importance of narrative focus in the Results section. In response, we have thoroughly rewritten this section to highlight broader trends and implications, while using specific data as supporting evidence. Guided by the suggestion to continually ask "why" and "so what," we have reframed the presentation to enhance engagement and clarity.

For example, in the "Spatial and temporal characteristics of global gauge records" subsection, we first address why the total number of stations increased slightly, attributing this primarily to the introduction of WMO-standard non-recording precipitation gauges and China's deployment of automatic rain gauges. We then explore the so-what implication: the total station count reflects potential monitoring capacity, noting, for instance, that despite the large number of stations in China with relatively short records, the recent surge in station numbers indicates significant promise for future climate observation.

Similarly, for the decline in Long-term Record stations, we explain why this occurred, citing limited international data sharing, the dissolution of the Soviet Union, and 20th-century economic disruptions. The so-what insight emphasizes that these stations serve as a direct measure of long-term data availability and that their decline undermines effective monitoring of climate change over time, a concern that warrants attention from both researchers and policymakers. By structuring the text around these guiding questions, we have replaced exhaustive listings with a more compelling, interpretative narrative that highlights key drivers and consequences without sacrificing analytical rigor. The revised text is as follows:

"A slight increase in the total number of stations occurred in 1983 following the global rollout of automatic precipitation gauges in 1982 that occurred after the WMO introduced standard non-recording precipitation gauge measurements in 1981[0,0]. Asia saw a notable surge in station numbers that was largely driven by China's sustained efforts to deploy automatic rain gauges beginning in that period[0]. Consequently, Asia had nearly 70,000 precipitation gauges by 2022, comprising roughly 57.2% of the global total and representing the largest share of any region (Supplementary Table 2). While Asia's stations have relatively short record lengths (Fig. 1, Supplementary Fig. 1), they hold significant potential for future climate monitoring if they continue to operate. North America also experienced a sharp rise in gauge numbers in the 2000s, reaching over 30,000 by 2022 (25.6% of global total, ranked second). In contrast, the consistent decline in the total number of stations across most other continents does not bode well for long term data availability, pointing to a heightened risk of future observational scarcity.

Although LR stations make up only a much smaller fraction of all stations, their proportion provides a clearer indicator of current long-term data availability. Since the 1980s, the number of LR stations has generally declined, primarily due to limited data sharing[0], the dissolution of the Soviet Union[0], and 20th-century economic conflicts[0], all of which restricted data accessibility and usability. By 2022, only 16,491 (13.8%) of 119,731 operating stations were LR stations. Europe had the largest share (49.8%, 8,205 stations), while North America (23.6%, 3,892 stations) and Asia (15.9%, 2,623 stations) mainly accounted for the remaining LR stations (Supplementary Table 2). The global scarcity of LR stations that has developed since the 1980s, and similar trends in river gauge availability[0], limits the effectiveness of long-term climate change monitoring and should be a serious concern for policymakers and researchers."

To facilitate your review, we have included Fig. 1 and Supplementary Fig. 1 in this response document as Figs. R1, R11.

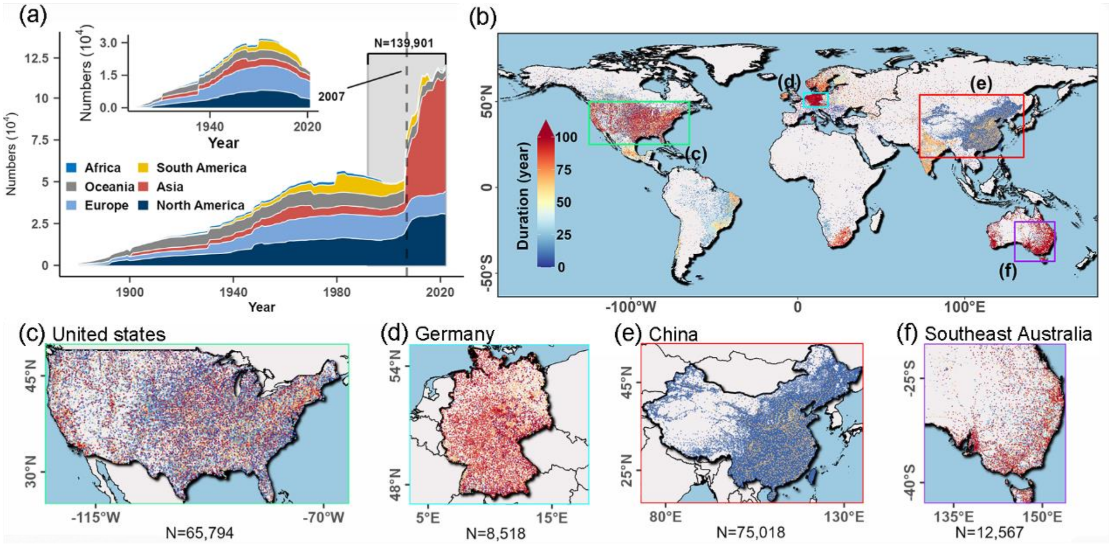

Figure R1 | Collected daily precipitation gauge records from 1900 to 2022 (221,483 gauges). (a) Yearly count of stations by continent. The stacked area plot inset presents the yearly count of Long-term Record (LR) stations (38,203 gauges) meeting specific criteria (see Methods). (b) Map of stations record lengths, with (c-f) focusing on four regions with notable precipitation gauge densities; the bottom numbers indicate the station numbers within four regions.

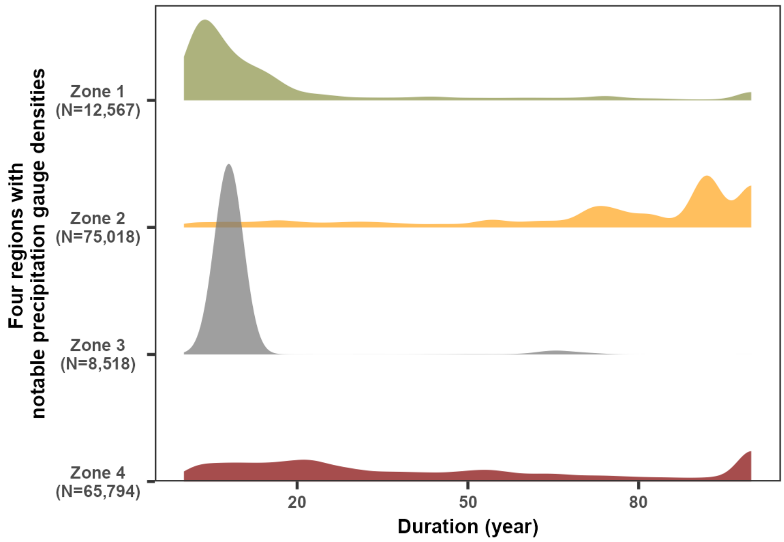

Figure R11 | The density distribution of stations' record length from 1900 to 2022 in four zones with notable precipitation gauge densities. Four zones are consistent with the representations in Figure 1, Zone 1–4 indicate United states, Germany, China and Southeast Australia.

References:

34. Hannah, D. M. *et al*. Large-scale river flow archives: importance, current status and future needs. *Hydrol. Process*. **25**, 1191–1200 (2011).

35. Zandler, H., Haag, I., & Samimi, C. Evaluation needs and temporal performance differences of gridded precipitation products in peripheral mountain regions. *Sci*

Rep. **9**, 15118 (2019).
36. Riggs, R. M. *et al*. Extending global river gauge records using satellite observations. *Environ. Res. Lett.* **18**, 064027 (2023).
52. Brandsma, T. Comparison of automatic and manual precipitation networks in the Netherlands. Technical report. (2014).
53. Aart Overeem. Climatology of extreme rainfall from rain gauges and weather radar. Wageningen University, the Netherlands. (2009).
54. Reporter. Promoting Meteorological Reform and Opening up, Focusing on Strengthening the Infrastructure Construction of Grassroots Stations. China Meteorological News. 2008–01–03 (001).

4. The figures are generally visually appealing and effectively display the data. Improvements could be made: 1) in fig. 1, provide the name of the 4 regions chosen; also, provide the number of each region; maybe provide the distribution for each region as well. The fonts in fig.3 are different with other figures, and too large…

Response: Thank you for these constructive comments, which have helped us improve the clarity and consistency of our figures.

In direct response to the point on Figure 1, we have now added the names, precise geographic descriptors, and station numbers for each of the four key regions examined in our study. To provide further depth, we have also included detailed record length distributions for these regions in the Supplementary Information (Supplementary Fig. 1), offering readers a comprehensive view of data temporal coverage and supporting robust interpretation of regional monitoring capabilities.

Regarding Figure 3, we have revised the figure to harmonize the typography with all other figures in the manuscript, ensuring visual cohesion and improving readability across the document. The revised figures as below:

To facilitate your review, we have included Fig. 1, Supplementary Fig. 1 and Fig. 3 in this response document as Figs. R1, R11 and R5.

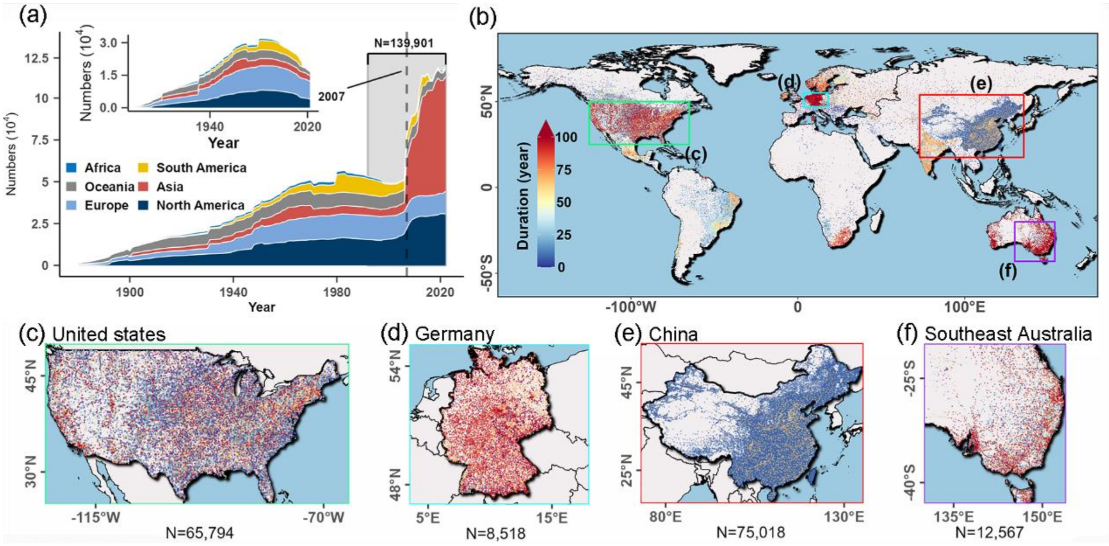

Figure R1 | Collected daily precipitation gauge records from 1900 to 2022 (221,483 gauges). (a) Yearly count of stations by continent. The stacked area plot inset presents the yearly count of Long-term Record (LR) stations (38,203 gauges) meeting specific criteria (see Methods). (b) Map of stations record lengths, with (c-f) focusing on four regions with notable precipitation gauge densities; the bottom numbers indicate the station numbers within four regions.

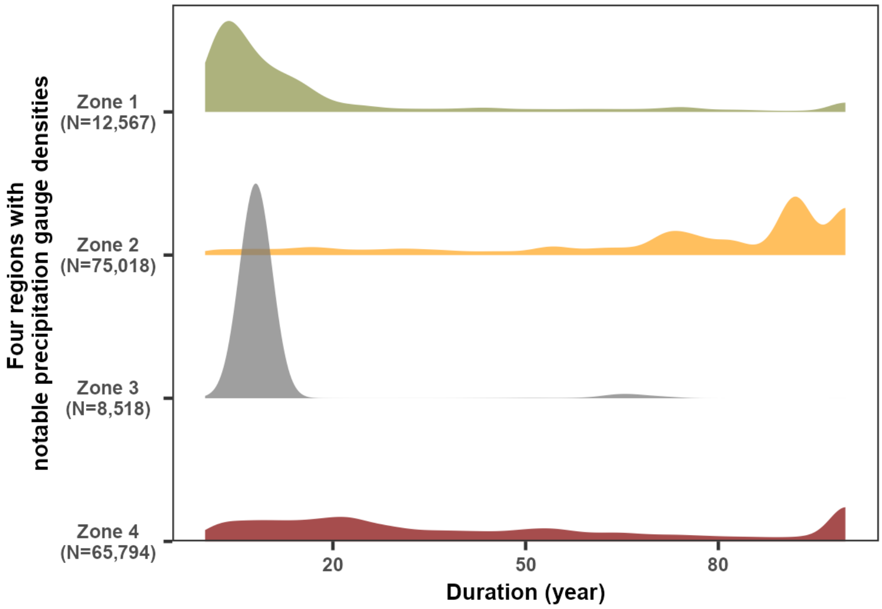

Figure R11 | The density distribution of stations' record length from 1900 to 2022 in four zones with notable precipitation gauge densities. Four zones are consistent with the representations in Figure 1, Zone 1–4 indicate United states, Germany, China and Southeast Australia.

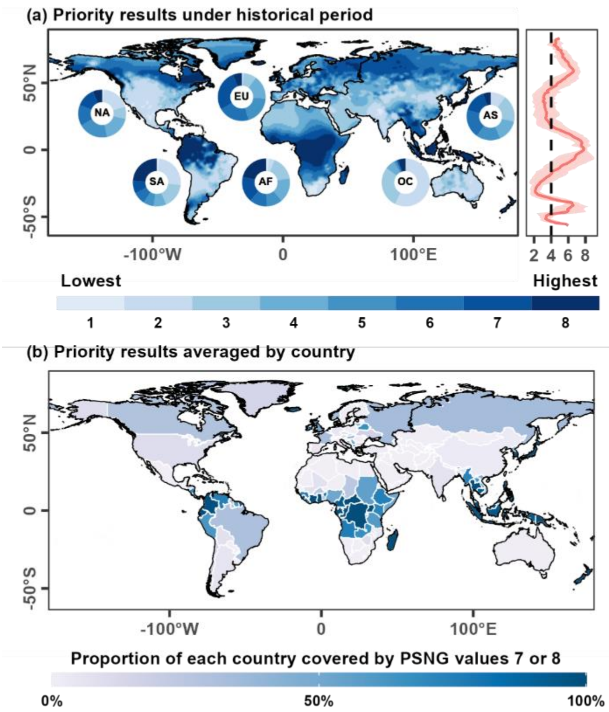

Figure R5 | Global priority for siting new gauges (PSNG) under historical period (1900–2022). (a) The inset pie charts show the relative proportion of each PSNG level across continents. The red line on the right represents the mean PSNG by latitude, with shading for the mean ± one standard deviation. Continental abbreviations are as follows: AS = Asia, EU = Europe, AF = Africa, OC = Oceania, NA = North America, SA = South America. (b) Proportion of each country covered by PSNG levels 7–8.

4. It is unclear what does 'for the priority level for siting new gauges' (PSNG) mean?

Response: Thank you for raising this point; we apologize for any lack of clarity in our original description. The term "priority areas for siting new gauges" (PSNG) refers to geographic regions where additional precipitation monitoring stations are most critically needed to address gaps in observational coverage and enhance the accuracy of hydroclimatic data. For readability, we use the historical PSNG as an example. Historical PSNG is calculated by combining two key factors: precipitation spatial variability and existing gauge density (*GD*). Areas with high precipitation variability (high precipitation information and low redundancy relative to their neighbors, defined as maximum information minimum redundancy, *MIMR*) and low *GD* result in a high PSNG score. We finally estimate PSNG by weighting two factors, and we ensure robustness based on two structurally different types of weighting analysis – Entropy Weight Method (EWM) and a Principal Component Analysis (PCA), in both cases, of suitably normalized variables. Both approaches produce similar weights for *MIMR* and *GD*, with PCA assigning weights of 0.95 to *MIMR* and 0.05 to *GD*, and EWM evaluating weights of 0.99 to *MIMR* and 0.01 to *GD*. Thus, we combine them to produce a single PSNG value, resulting in weights of 0.97 for *MIMR* and 0.03 for *GD*. The resulting PSNG scores are re-expressed on a scale from 1 to 8, corresponding to low priority (precipitation variation is well monitored with the existing observing network) to high priority (precipitation variation is inadequately monitored with the existing observing network) for additional stations. There is good correspondence during the historical period between areas with low PSNG and those that meet WMO observing station density standards, and vice-versa (Supplementary Fig. 6). Accounting for future projection uncertainty and socio-economic further alters these scores.

The motivation for using these two techniques to calculate PSNG is as follows. First, the Entropy Weight Method (EWM) is adopted to objectively quantify the relative information content of each factor (*e.g.*, *GD* and *MIMR*), factors showing greater spatial differentiation across grid cells exhibit lower entropy and are thus assigned higher weights. Second, Principal Component Analysis (PCA) is used to account for the correlation structure between factors and to mitigate potential redundancy (multicollinearity). PCA transforms the original variables into orthogonal components; by incorporating all components weighted by their explained-variance ratios, the resulting PCA-based weights reflect each factor's contribution to the total variance. Finally, averaging the EWM- and PCA-derived weights balances dispersion-driven information content with variance-structure considerations, yielding a more robust composite weighting scheme for PSNG.

This is now explained in the main text as follows:

"Assessing current gauge density and precipitation spatial variability offers a benchmark for identifying priority areas for siting new gauges, expressed as PSNG values ranging from 1 (lowest priority) to 8 (highest priority) (see Methods). High PSNG indicates a combination of high precipitation spatial variability and low gauge density, implying insufficient monitoring. Precipitation spatial variability is derived from daily precipitation records from LR stations using an entropy method that evaluates the information content of precipitation observations and its redundancy relative to neighboring stations. PSNG is determined from gauge density and spatial variability using two weighting methods: the Entropy Weight Method (dispersion-based information content) and Principal Component Analysis (variance-structure considerations). During the historical period, there is good correspondence between areas with low PSNG and those that meet WMO observing station density standards, and vice-versa (Fig. 3a, Supplementary Fig. 6)."

Future PSNG is calculated by combining information about precipitation variability with information about projection uncertainty (*AE*) and socio-economic development (population density and GDP). It follows the same weighting framework as historical PSNG, but incorporates these additional factors. Projection uncertainty (*AE*) is evaluated by considering uncertainties in CMIP6-based precipitation trend projections. Such uncertainty can be reduced, at least in part, by closing observational gaps in measurement networks, as this would permit the development of improved emergent constraints on projected precipitation change. Furthermore, socio-economic conditions representing where citizens have high need and where countries can support the constructing new stations or maintaining existing equipment. This information is now presented in the text as follows:

"Future precipitation projections suggest that PSNG will shift to higher values as climate warming increases the spatial variability of precipitation[0,0,0], reducing the mutual information shared amongst existing stations, a change quantified by analyzing the uncertainty in CMIP6-based precipitation trend projections."

and

"Beyond precipitation, future socio-economic conditions further affect PSNG by altering the relative prosperity of difference regions, and thus their ability to install and maintain stations, and by increasing the need for denser gauge networks in highly populated regions."

We also revised the Methodology section ("Multicriteria incorporation algorithm") in the main text as follows:

"We used averaged weights driven by PCA and EWM methods as the robust final weight of factors (*GD* and *MIMR*, *AE*, population density and GDP) due to this synthesis, dispersion-based information content (from EWM) with variance-structure considerations (from PCA), and the weights obtained from PCA and EWM were similar (see Supplementary Fig. 34, further details of PSNG and weights comparisons provided in the Supplementary Text 8)."

Additional detail is now provided in Supplemental Text 8 as follows:

"To identify the priority areas for siting new gauges (denoted as PSNG) score, we applied two objective weighting methods. First, we used Principal Component Analysis (PCA) to account for the correlation structure between factors and to mitigate potential redundancy (multicollinearity). PCA transforms the original variables into orthogonal components; by incorporating all principal components weighted by their explained-variance ratios, the resulting PCA-based weights reflect each factor's contribution to the total variance. Second, the Entropy Weight Method (EWM) is adopted to objectively quantify the relative information content of each factor (*e.g.*, *GD* and *MIMR*), factors showing greater spatial differentiation across grid cells exhibit lower entropy and are thus assigned higher weights. Both methods determine weights from the data structure without relying on subjective assumptions can be sensitivity assessment across alternative relative weightings. Finally, averaging the EWM- and PCA-derived weights balances dispersion-driven information content with variance-structure considerations, yielding a more robust composite weighting scheme for PSNG.

Historical PSNG. For PSNG when considering precipitation characteristics under historical periods, we combine *GD* and *MIMR* into a single priority level for siting new gauges score. The weights obtained from PCA and EWM were similar, with PCA assigning weights of 0.95 to *MIMR* and 0.05 to *GD*, EWM evaluating weights of 0.99 to *MIMR* and 0.01 to *GD* (the consistent spatial patterns of PSNG generated from each see Supplementary Fig. 34). The final weights for *MIMR* (0.97) and *GD* (0.03) were determined by averaging the weights from PCA and EWM, taking into account the various advantages and limitations of the two methods."

To facilitate your review, we have included Fig. 3 and Supplementary Figs. 6, 34 in this response document as Figs. R5, R12 and R13.

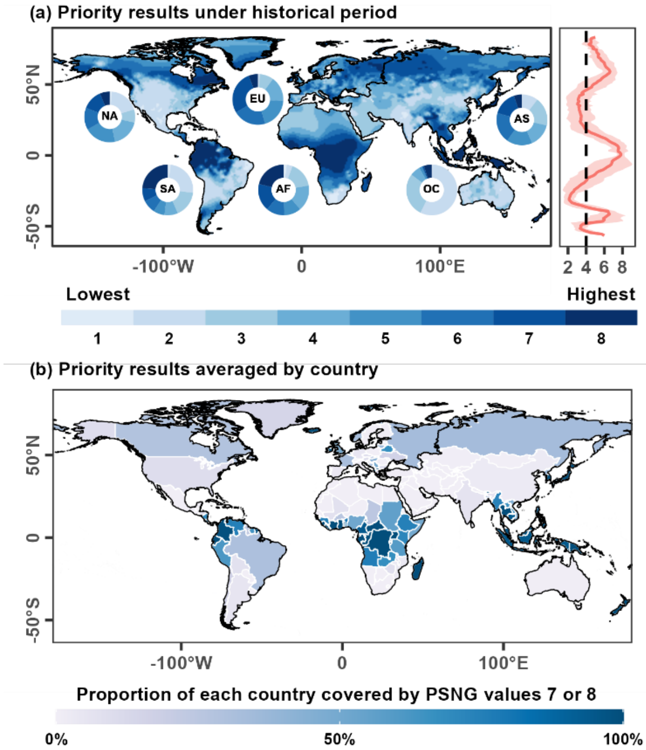

Figure R5 | Global priority for siting new gauges (PSNG) under historical period (1900–2022). (a) The inset pie charts show the relative proportion of each PSNG level across continents. The red line on the right represents the mean PSNG by latitude, with shading for the mean ± one standard deviation. Continental abbreviations are as follows: AS = Asia, EU = Europe, AF = Africa, OC = Oceania, NA = North America, SA = South America. (b) Proportion of each country covered by PSNG levels 7–8.

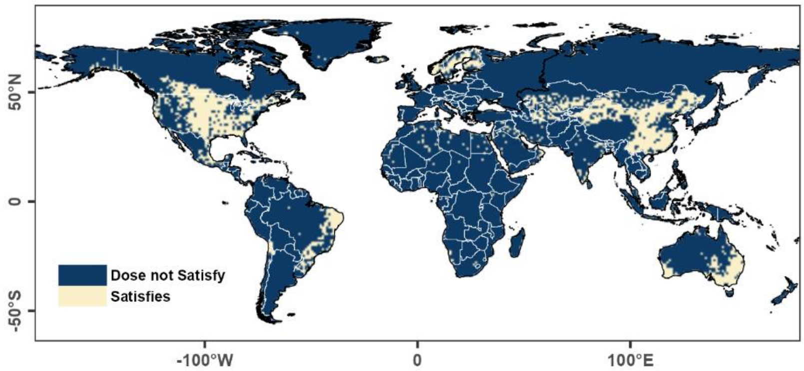

Figure R12 | Global assessment of station density (1900–2022) compliance with WMO standards.

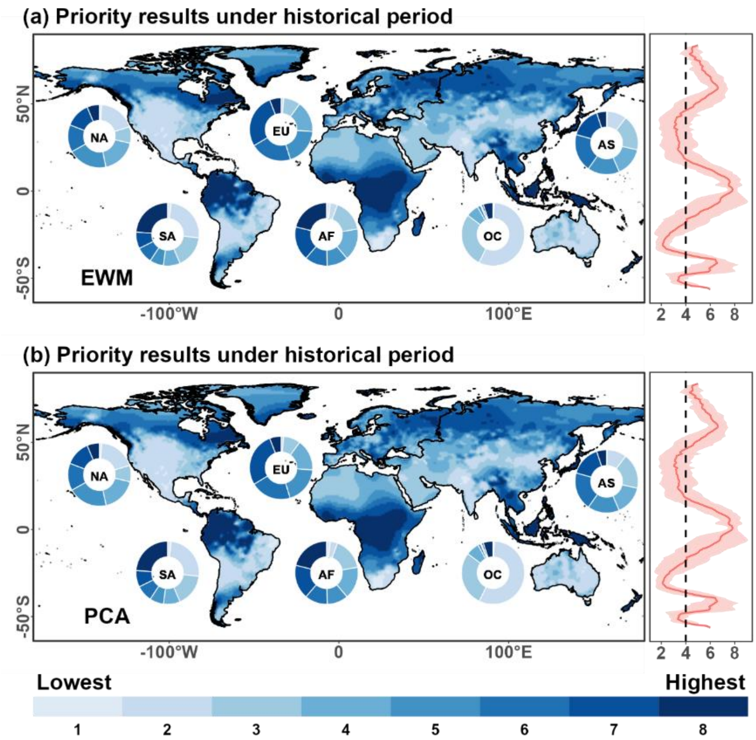

Figure R13 | Global priority for siting new gauges under historical period from 1900–2022 when aggregating the data at 1 degree based on (a) EWM, (b) PCA. The red line plot shows mean PSNG by latitude, with shaded area indicating ± one standard deviation.

References:

7. Ham, Y. G. *et al*. Anthropogenic fingerprints in daily precipitation revealed by deep learning. *Nature*. **622**, 301–307 (2023).

72. Gu, L. *et al*. Large anomalies in future extreme precipitation sensitivity driven by atmospheric dynamics. *Nat Commun*. **14**, 3197 (2023).

73. Le, P.V.V. *et al*. Climate-driven changes in the predictability of seasonal precipitation. *Nat Commun*. **14**, 3822 (2023).

5. The conclusions could be strengthened. The section could be more impactful if the main conclusions are highlighted more clearly in a narrative format, rather than presenting a series of statistics. For instance, instead of just listing numbers, it could provide a concise synthesis of what these gaps in the precipitation network mean for global climate monitoring, different climate impacts analysis, particularly concerning for which region, which type of climate impact etc. Some discussions based on existing literature would be helpful to provide the context.

While the future work section raises valid points about the need for new gauges and data-sharing, it could be strengthened by offering more concrete, actionable, and region-specific recommendations based on underlying drivers and consequences.
For example, instead of just noting that "many cities have their own observing gauges that are not shared internationally," it could suggest specific strategies for improving data sharing, such as developing a global data-sharing platform or incentivizing local authorities to share data in ** region, but this may not be practical in ** regions, explain why and provide recommendations for those regions…

The mention of challenges (e.g., uneven distribution of station elevations, limited data in remote areas) is important but could be connected back to the main findings more directly. The reader should be reminded that addressing these challenges is crucial for closing the global data gaps identified earlier in the conclusion. Also, it might be helpful to clarify how these future directions directly link to improving global precipitation monitoring, reinforcing the study's broader relevance.

Response: Thank you for your insightful comments and constructive suggestions for strengthening our Conclusions section. We appreciate the detailed examples provided, which have been invaluable in enhancing the impact and clarity of our manuscript. In direct response to the feedback, we have thoroughly revised the Conclusions to provide a more narrative-driven synthesis, clearly highlight the main findings, and offer concrete, region-specific recommendations. Specifically, we have:

1. Provided a concise synthesis of the implications of precipitation network gaps for global climate monitoring and climate impact assessments, with a focus on vulnerable regions, such as Central Africa and Southern Asia, and specific climate impacts, such as drought and floods.

2. Incorporated discussions based on existing literature to contextualize our findings, particularly regarding socio-economic vulnerabilities and climate sensitivity in regions such as tropical Africa, and urban areas.

3. Developed actionable recommendations tailored to regional contexts, such as advocating for international data-sharing platforms in data-rich regions, while proposing low-cost sensor deployments and international funding mechanisms for data-

poor regions (e.g., in developing countries).

4. Directly linked challenges like uneven station elevation distribution and limited remote area coverage back to our core findings (e.g., Qinghai-Tibet Plateau), emphasizing that addressing these issues is essential for closing the global data gaps identified in our study (e.g., Asian water tower).

The text has been revised as follows:

"**Summary and future work**

Our findings highlight critical gaps in the global precipitation observation network, including gaps in monsoon affected regions and low- and mid-latitude areas due to precipitation variability and socio-economic vulnerabilities, and that reflect regional disparities that undermine climate resilience monitoring. For instance, across tropical Africa, the sparse distribution of stations limits the accuracy of drought and food security early warning systems, especially for severe drought conditions[0] and limits the ability to provide comprehensive drought assessments[0], which could be mitigated with new gauges and enhanced data sharing. Alternatively, at the physiographic scale, gauge density in urban regions falls below WMO standards, which limits the reliability of urban water security and agricultural early warning systems because available gauges are insufficient to capture fine-scale extreme precipitation events amid rapid urbanization and increased flooding[0]. Increasing evidence of a pronounced urban-rural disparity in extreme precipitation[0,0] further elevates societal risk, collectively heightening vulnerability, resulting in high-priority areas in urban regions. Therefore, targeted investment in station deployment is not only a scientific priority but also an urgent social imperative. This study provides insight into where those investments are most urgently needed.

While this study provides valuable insights, some challenges remain unexplored. First, tailored strategies are essential for regions with poor data sharing or sparse stations. For instance, developed countries with existing infrastructure could establish collaborative data-sharing platforms that are led by national governments, supported by provincial agencies, and facilitated by international organizations to integrate diverse datasets into public databases with appropriate licenses, as demonstrated by Canada's DataMart service and the provincial Pacific Climate Data Set (PCDS), which archives and disseminates data from a broad range of observing networks in British Columbia. Funding and training in deploying, managing and curating data from low-cost sensor networks provided by international organizations could help developing nations to improve their monitoring and data sharing capabilities. Secondly, the global station distribution is geographically biased towards lower elevations, with high-altitude regions like the Qinghai-Tibet Plateau, where orographic effects are critical, very heavily under-represented (representative errors in elevation estimation at the grid level are shown in Supplementary Fig. 27). Addressing this bias would improve hydrometeorological in headwater regions for rivers that provide much of the world's surface freshwater and would enhance understanding of pivotal systems like the Asian water tower[0]. Finally, although satellite and reanalysis data provide valuable coverage in data-sparse regions, they cannot substitute for ground-based rain gauges, which are essential for validation. This is exemplified in Africa, where the scarcity of rain gauge data makes it impossible to evaluate the accuracy of satellite-based precipitation products.

Our study also underscores that gaps in the in-situ monitoring network fundamentally hinder water cycle and climate change assessment. Therefore, fostering global cooperation to enhance data sharing and establish new stations in the priority regions identified here is imperative to addressing this critical challenge."

To facilitate your review, we have included Supplementary Fig. 27 in this response document as Fig. R14.

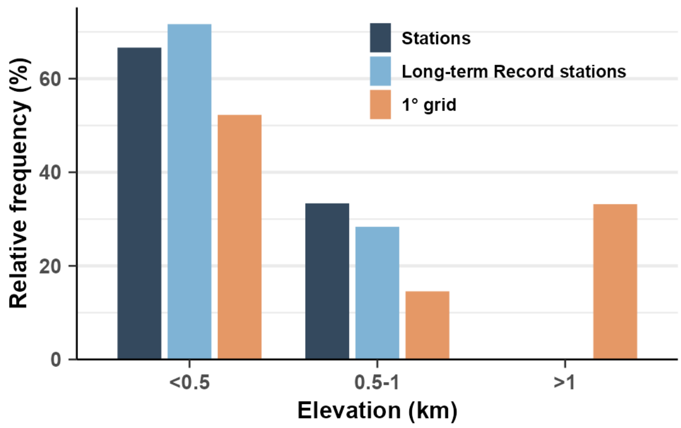

Figure R14 | Relative frequency of stations, Long-term Record stations and the global grid cell (1° × 1°) under different elevation bands.

References:

74. Masih, I., Maskey, S., Mussá, F. E. F., & Trambauer, P. A review of droughts on the African continent: a geospatial and long-term perspective. *Hydrol. Earth Syst. Sci*. **18**, 3635–3649 (2014).
75. Huang, S. *et al*. Widespread global exacerbation of extreme drought induced by urbanization. *Nat. Cities*. **1**, 597–609 (2024).
76. Rentschler, J. *et al*. Global evidence of rapid urban growth in flood zones since 1985. *Nature*. **622**, 87–92 (2023).
77. Liu, S., Han, Y., Wang, P., Zhang, G., Wang, B., & Wang, Y. More heavy precipitation in world urban regions captured through a two-way subgrid land-atmosphere coupling framework in the NCAR CESM2. *Geophys. Res. Lett*. 51, e2024GL108747. (2024).
78. Su, J., Miao, C., Hu, J., Wu, Y., & Ji, J. Widening urban–rural precipitation

differences in China: regionally varied intensification since 2000. *Earth's Future*. **13**, e2025EF006657 (2025).
79. Zhang, Q. *et al*. Oceanic climate changes threaten the sustainability of Asia's water tower. *Nature*. **615**, 87–93 (2023).

6. Comments on codes: As there is no complete input data, I cannot actually run the code. But as far as I can tell, there seems to be no logic issue and should work.

Overall, it is a great work with valuable insights, hope my suggestions would be helpful for the author team to further improve the manuscript.

Response: Thank you very much for this positive assessment and constructive feedback, which has fundamentally strengthened our manuscript. We have updated the code and corresponding data to facilitate easy execution and verification of the analysis scripts, which can be found at https://github.com/JJiaSu/Global-Gaps-in-Precipitation-Monitoring-Networks-Hinder-Climate-Change-Impact-Assessment

Referee #2 (Remarks on code availability):
As there is no complete input data, I cannot actually run the code. But as far as I can tell, there seems to be no logic issue and should work.

Response: Thank you very much for this positive assessment. We have updated the code and corresponding data to facilitate easy execution and verification of the analysis scripts, which can be found at https://github.com/JJiaSu/Global-Gaps-in-Precipitation-Monitoring-Networks-Hinder-Climate-Change-Impact-Assessment

COMMENTS and RESPONSES

Reviewer #1

General comments

The authors have appropriately and extensively addressed all the comments/suggestions raised during the review round. I have no further comments and would gladly recommend the manuscript for publication.

Response: Thank you for your positive assessment and for recommending the manuscript for publication.

Referee #1 (Remarks on code availability):
With the added sample data the scripts provided are fully reproducible.

Response: Thanks.

Reviewer #2 comments

General comments

The authors have satisfactorily addressed all of my concerns, and I recommend the manuscript for publication. This study represents a timely and important contribution to the field.

Response: We sincerely thank you for your positive evaluation and for recommending the manuscript for publication. We appreciate your view that the study is timely and important.

Referee #2 (Remarks on code availability):
Yes, the code includes a readme file and sample data, I'm able to run the code and reproduce the major results.

Response: Thank you.