Manuscript: ESSD-2025-376

Comment by Anonymous Referee #1

Huang et al. contribute to understanding the limitations of hydrological datasets (ground-, satellite-, and reanalysis-based) in capturing the relationship between monthly variations in soil moisture (SM) and the difference between precipitation (P), evapotranspiration (ET), and runoff (R) at a pixel scale around the world. Additionally, the manuscript's results contribute to identifying the most suitable datasets for different geographical and ecological regions, which is important for reducing uncertainty in ecological, climatological, and hydrological studies using the evaluated datasets.

Response: Thank you for your encouraging evaluation.

Overall, I found the paper well written and organized, and suitable for publication in the ESSD journal, but I have some comments that should be addressed before publication consideration. Particularly, some work is required to improve the clarity of the methods and results sections: (i) Explain how lateral flows and water table depth may potentially bias the proposed water balance at pixel scale, leading to the low water balance consistency reported in the manuscript; (ii) provide a clearer explanation of the linear relationship between SM, P, ET, and R ($P - ET - R)s = k \Delta SMs$) at the monthly scale, including the potential limitations of assuming a linear relationship.

Response: Thank you for your suggestions. In this revision, we have (1) quantified the potential impact of lateral flows from rivers and groundwater, and (2) clarified the rationale for using a linear regression model based on our water balance assumption. Additionally, we include supplementary results on water balance consistency using terrestrial water storage from GRACE, extend the introduction on the discrepancy among *ET*, *R*, and *SM* datasets, and quantify the influence of urbanization by incorporating the global artificial impervious area. Detailed responses are provided below.

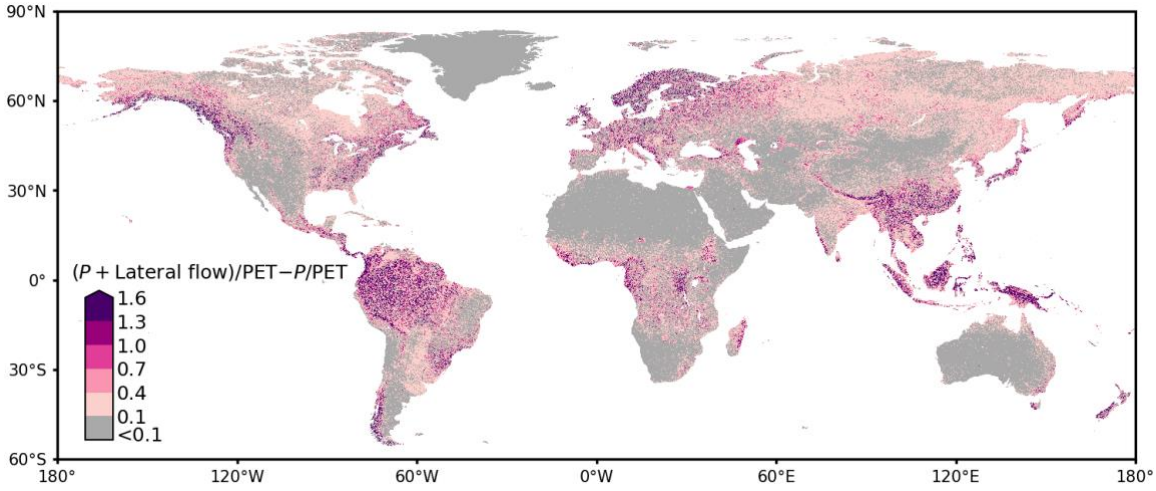
Major comments:

Line 191: The proposed water balance equation does not include some fluxes that may strongly affect hydrological dynamics at the pixel scale and may contribute to the low water balance consistency reported in the manuscript. For example, lateral fluxes (both inputs and outputs) can significantly influence variations in soil moisture (SM) and runoff (R) at the pixel scale, particularly in low-elevation areas and along river channels (e.g., Fan et al., 2013; Miguez-Macho and Fan, 2025; Nobre et al., 2011). Similarly, SM dynamics are strongly influenced by water table depth (WTD). Therefore, the authors should explain how excluding lateral flows and

WTD could bias the results. In this regard, I also suggest examining whether and how the runoff datasets capture lateral flows and groundwater dynamics at the pixel scale.

Response: We thank the reviewer for raising this interesting aspect. To quantify the potential influence of lateral flows from rivers and groundwater on regional water balance, we include published data from Miguez-Macho & Fan (2025) as one of the predictors in the attribution models. The data provide two indices, including *P*/PET and (*P* + lateral flow)/PET where the lateral flow is the total subsidies by rivers and groundwater, and the groundwater flow is determined by water table dynamics. Therefore, the difference in (*P* + lateral flow)/PET and *P*/PET for each grid cell was calculated to indicate the influence of lateral flows on regional water balance.

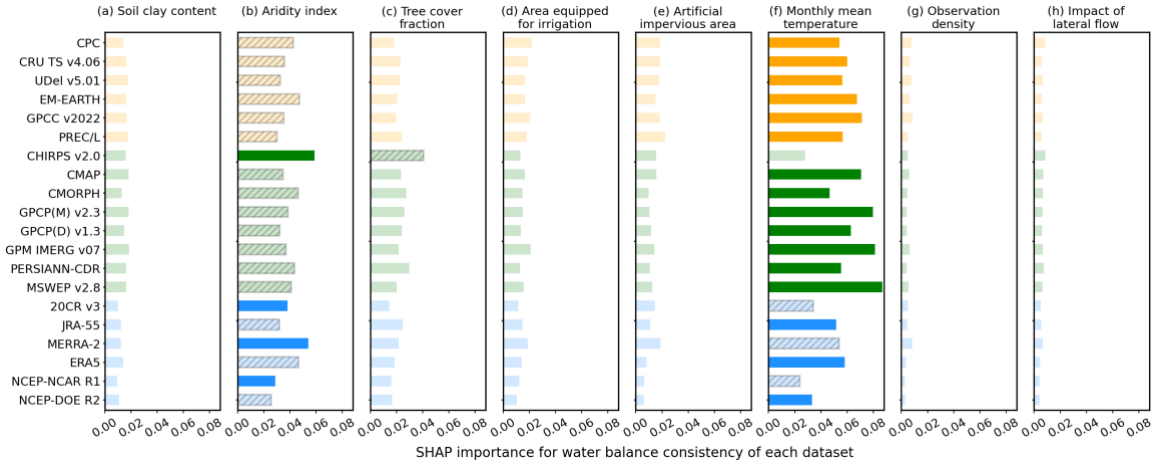
In this revision, we show the resampled 0.25-degree map of lateral flow impact (i.e., (*P* + lateral flow)/PET - *P*/PET) in the new Fig. S9. By considering it to be a predictor in our explainable machine learning method (see lines 286−289), we further quantify the relative role of lateral flow impact on the performance of each dataset. Since the lateral flow can be directly regulated by topography, the topography factor is not considered in this revision. The updated results across global grid cells indicate that lateral flow plays a relatively minor role in the performance of the considered datasets in terms of water balance consistency (Figs. S17−S20).



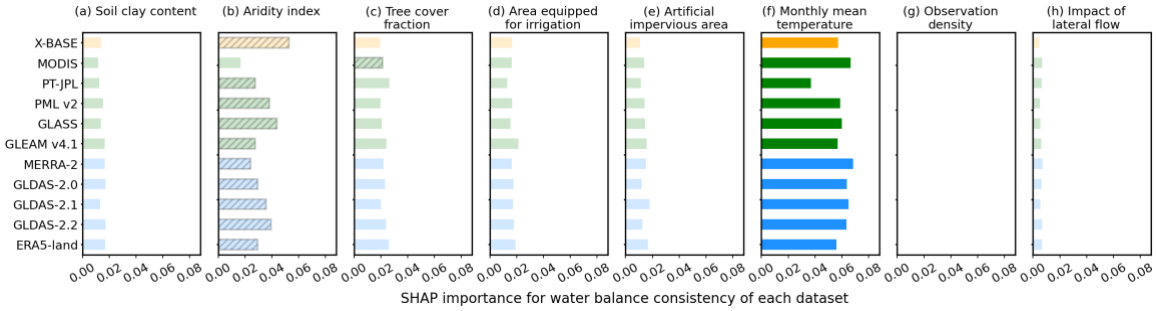
*"**Fig. S9.** Maps showing the potential impact of lateral flow from rivers and groundwater on regional water cycles. The impact is quantified by using the published indices from Miguez-Macho & Fan (2025), including P/PET and (P + lateral flow)/PET where the lateral flow is the total subsidies by rivers and groundwater, and the PET is potential evapotranspiration."*

In lines 286−289:

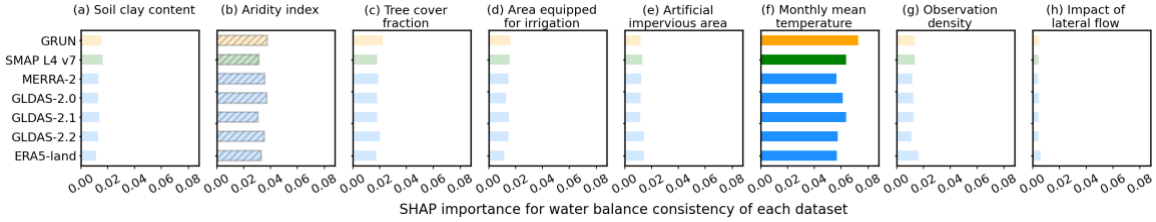
"The global impact of lateral flow has been evaluated by Miguez-Macho and Fan (2025), where the differences of (P + lateral flow)/PET and P/PET (with PET as the potential evapotranspiration) represent the influence of subsidies by rivers and groundwater on regional water cycles (Fig. S9)."



*"**Fig. S17.** Importance of (a) soil clay content, (b) aridity index, (c) tree cover fraction, (d) area equipped for irrigation, (e) artificial impervious area, (f) monthly mean temperature, (g) observation density, and (h) impact of lateral flow to water balance consistency of each P dataset. The importance is quantified by global averaged absolute SHAP values (Methods). Bars with dark color and hatch, respectively, indicate the first and second important factors for the water balance consistency of each P dataset."*

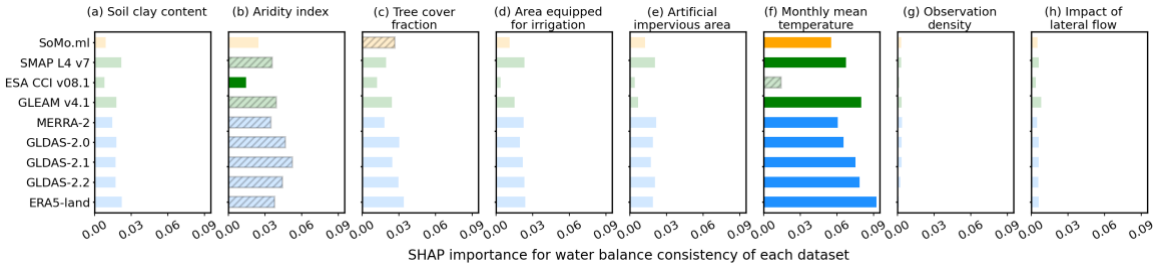


*"**Fig. S18.** Importance of (a) soil clay content, (b) aridity index, (c) tree cover fraction, (d) area equipped for irrigation, (e) artificial impervious area, (f) monthly mean temperature, (g) observation density, and (h) impact of lateral flow to water balance consistency of each ET dataset. The importance is quantified by global averaged absolute SHAP values (Methods). Bars with dark color and hatch, respectively, indicate the first and second important factors for the water balance consistency of each ET dataset."*



*"**Fig. S19.** Importance of (a) soil clay content, (b) aridity index, (c) tree cover fraction, (d) area equipped for irrigation, (e) artificial impervious area, (f) monthly mean temperature, (g) observation density, and (h) impact of lateral flow to water balance consistency of each*

R dataset. The importance is quantified by global averaged absolute SHAP values (Methods). Bars with dark color and hatch, respectively, indicate the first and second important factors for the water balance consistency of each R dataset."



*"**Fig. S20.** Importance of (a) soil clay content, (b) aridity index, (c) tree cover fraction, (d) area equipped for irrigation, (e) artificial impervious area, (f) monthly mean temperature, (g) observation density, and (h) impact of lateral flow to water balance consistency of each SM dataset. The importance is quantified by global averaged absolute SHAP values (Methods). Bars with dark color and hatch, respectively, indicate the first and second important factors for the water balance consistency of each SM dataset."*

Line 191: The linear regression between SM and P–ET–R may also introduce bias into your results. Because your analysis is performed at a monthly scale, the hydrological response of each water balance component may occur at different rates due to, e.g., seasonality (dry vs wet season or summer vs winter) or soil saturation. Therefore, I encourage the authors to provide a more detailed explanation of why the linear assumption is appropriate for the analysis, as well as its limitations.

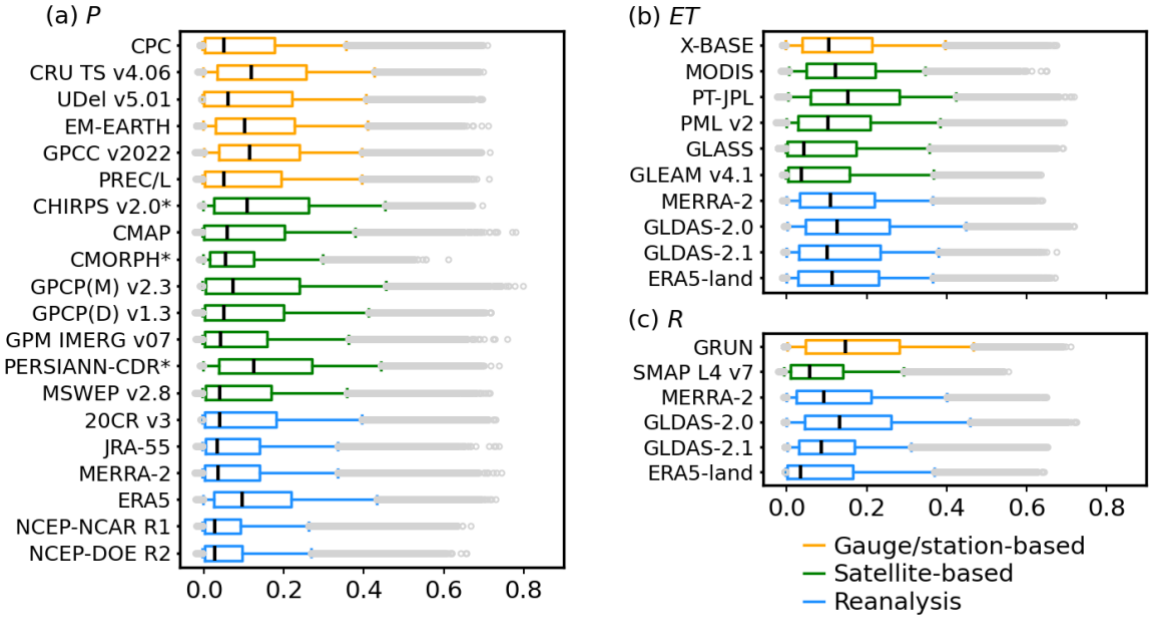
Response: We appreciate the reviewer's insight. Linear regression is appropriate under the water balance assumption of this study, where changes in soil water content are driven by accumulated precipitation, evapotranspiration, and runoff, expressed as $P–ET–R=\Delta SM$. Unconsidered water processes may influence our water balance assumption, leading to a nonlinear response of ΔSM to $P–ET–R$. To test the potential influence and bias, we 1) quantify the relative importance of later flow impact in the attribution models, and 2) evaluate whether the use of terrestrial water storage change (ΔTWS) instead of ΔSM can benefit higher R^2, since ΔTWS, in theory, integrates the changes of glacier, snow, and surface water storage.

First, the impact of later flow on the dataset performance is relatively low (updated Figs. S17−S20), supporting our water balance assumption. Second, using ΔTWS from the GRACE and its Follow-On mission (GRACE-FO) to form the water balance as $P–ET–R=\Delta TWS$ yields similar ranking results as using ΔSM (added Fig. S3). This also supports using SM as the water balance assumption is sufficient for our study purposes, and therefore the linear regression on top of it is appropriate. In this revision, we clarify the motivation for using linear regression in lines 203−205:

"Under our water balance assumption, we build a linear regression model in each grid cell of each considered combination of hydrological datasets, considering all available months, and assess its adjusted R^2 score:",

and introduce the use of GRACE data in lines 242−248 as well as new Text S3.

"In addition, unconsidered water variables, like glacier, snow, and surface water storage, might introduce bias into our water balance assumption, leading to a nonlinear response of ΔSM to P–ET–R. We thereby used terrestrial water storage from GRACE instead of SM in equation (1) to evaluate the performance of the P, ET, and R datasets, based on their combinations with GRACE data (Text S3). In this case, the number of combinations is decreased by one order of magnitude (933 remained), but ranking results are similar to using ΔSM (Fig. S3)."



*"**Fig. S3.** Performance of the considered datasets based on R^2 scores measuring water balance consistency through P−ET−R=ΔTWS. Colors indicate the type of each dataset. Each box shows the median value, as well as the 5th, 25th, 75th, and 95th percentiles of the global pattern of water balance consistency derived from monthly data. Asterisks (*) following the name of P dataset indicate its limited spatial coverage of 50°S−50°N or 60°S−60°N."*

"***Text S3. Performance calculations with the use of terrestrial water storage from GRACE***

In this case, the terrestrial water storage (TWS) at 0.25 degree resolution from GRACE and its Follow-On mission (GRACE-FO) is provided by the Center for Space Research mascon product (Save et al., 2016). We calculated the change in TWS (ΔTWS) as the difference between the TWS anomaly of a given month and that of the previous month. Then, ΔTWS was used with P, ET, and R datasets to form combinations. Besides the exclusion rules

detailed in Methods, we further consider the combinations with water balance components from GLDAS-2.2 to be not considered. For each of the remaining 933 independent combinations, we build a linear regression model in each grid cell:

$$(\boldsymbol{P} - \boldsymbol{ET} - \boldsymbol{R})s = k \cdot \boldsymbol{\Delta TWS}s \quad (S1)$$

where s is the spatial index (grid cell) and k is the proportionality factor. Similar to the processing steps in Methods, the adjusted R^2 score of each linear model was calculated for each independent combination with ΔTWS. Finally, the overall performance for each P, ET, or R dataset in each grid cell was obtained by averaging R^2 across all combinations of datasets containing the respective dataset."

Line 205: The coefficient of determination (R2) of the linear regression model quantifies how well P-ET-R explains the variability of SM. However, you can include a bias metric (e.g., mean water balance error = i=1m(P-ET-R-SM)) to further examine the consistency of hydrological datasets.

Response: We appreciate the suggestion of using the mean water balance error to further examine water balance consistency. However, the units of soil moisture are not consistent across datasets, where the volumetric content is not easily converted to mm/day which is the unit of the other considered variables. Therefore, we will still focus on using the linear regression model.

Minor comments:

Lines 47 – 68: You should provide further information about the general advantages and disadvantages of ground-based, satellite, and reanalysis datasets to characterize ET, runoff, and soil moisture as you did for precipitation.

Response: We extend the introduction accordingly in lines 66−81.

"With the developing observation networks and data synthesis (Dorigo et al., 2011; Pastorello et al., 2020; Do et al., 2018), machine-learning algorithms present an alternative opportunity instead of interpolation to produce seamless observation-based datasets globally for evapotranspiration (ET), runoff (R), and soil moisture (SM) datasets (Nelson et al., 2024; Ghiggi et al., 2019; O and Orth, 2021). Although Penman-Monteith and the simpler Priestley-Taylor models are still the key physical algorithms to estimate ET through remote sensing, the relevant products tend to leverage recent advances in satellite data and climate reanalysis (Fisher et al., 2008; Miralles et al., 2025; Zhang et al., 2019). Differently, satellite-based SM datasets follow different technical roadmaps, such as merging retrievals from various sensors (Gruber et al., 2019) or assimilating radiometer observations into land surface modeling (Reichle et al., 2019). In this way, the latter additionally provides an SM-constrained R dataset (Reichle et al., 2019). At the same time, there are updated parametrizations for the land surface model in reanalysis to better describe the soil water balance and hydrological cycle (Hirschi et al., 2025; Muñoz-

Sabater et al., 2021). It has been documented that those technical discrepancies could cause datasets' performance in terms of agreement with observations, while the influence of environmental factors remains unclear (Markonis et al., 2024; Tang et al., 2024).”

Lines 72, 237 and 253: I encourage authors to use another expression instead of the term “water variables” to avoid confusion.

Response: We use water balance components instead of water variables.

Line 89: Please clarify that R2 corresponds to the coefficient of determination.

Response: We clarify accordingly.

“For each combination, we evaluate adjusted R^2 as the performance of linear regression of temporal changes in $P-ET-R$ against changes in SM (ΔSM) to determine its water balance consistency since R^2 corresponds to the coefficient of determination.”

Lines 128 – 135: Soil moisture estimates were obtained from different depth profiles (< 2 cm, 0-50 cm, 0 – 100 cm, and > 100 cm). How well correlated are the variations in SM among these depth profiles? Do you consider extracting total water storage from GRACE https://grace.jpl.nasa.gov/mission/grace/?

Response: We did not correlate the variations in *SM* among these profiles because this is beyond the scope of our study. Instead, we highlight that the *SM* datasets with different depths have distinct performance in terms of water balance consistency, because the *SM* variations below 50cm in many regions are relevant to *R* and *ET* for water balance consistency. In this revision, we also consider adding a supplement of using water balance consistency with ΔTWS from GRACE, to investigate whether the water variations below 2m can benefit water balance consistency (new Fig. S3). However, we find that using GRACE data results in a lower R^2 than using *SM* datasets. It is likely because GRACE data is originally provided at 3-degree resolution, and products at finer resolutions rely on the downscaling models.

Line 124: Could you explain using linear interpolation in the dataset resampling process? Did you consider using bilinear interpolation?

Response: We used the interpolation function from the xarray package, where the parameter was set as “linear”. The interpolation was applied in both dimensions of latitude and longitude; therefore, we used bilinear interpolation. We clarify accordingly in lines 138−139.

Line 229: An additional factor that may influence your analysis is the urban area fraction. Did you examine its effect on dataset's performance?

Response: Thank you for your suggestion. In this revision, we include the global artificial impervious area as one of the predictors in the attribution models to quantify urban influence, as it directly reflects surface changes associated with urbanization that impede the natural infiltration of water into the soil. Please see lines 272−273. However, the results indicate that the urban influence is not the dominant factor of dataset performance in terms of water balance consistency (Figs. S17−20).

> In lines 272−273:
>
> "*Global artificial impervious area from Gong et al. (2019) was also averaged among the available periods for each independent combination.*"

Line 245: Please specify for which period you extract tree cover data.

Response: The tree cover data we used differs across combinations because the available period for each independent combination is not consistent. In other words, we calculated 8,294 tree cover maps first, and then averaged them as one map for model input. Please find the relevant description in lines 254−257.

Line 313-320: Recently, Vargas Godoy et al., (2025) provide a global performance of several global precipitation datasets, identifying the best product at different spatial scales. Your manuscript and Vargas Godoy's results agree that IMERG and MSWEP are the best products around the world. However, I am curious about the high R2 that you reported for PERSIANN-CDR (Fig. 1) due to Vargas Godoy et al. (2025), and several regional analyses suggest that PERSIANN-CDR exhibits a low accuracy compared to ground observations. Thus, I suggest providing a potential explanation for its high performance.

Response: Thank you for your insight. First, our results are not fully comparable to Vargas Godoy et al. (2025), which identified the representativeness of *P* datasets across different regions in terms of their similarity to one another. Although Vargas Godoy et al. (2025) did not identify PERSIANN-CDR as the representative *P* dataset in most global regions, their analysis revealed close genealogical relationships between PERSIANN-CDR and IMERG or MSWEP. This could support our result on similar medians of 50ºS−50ºN among PERSIANN-CDR, IMERG, and MSWEP. Second, PERSIANN-CDR exhibits lower accuracy compared to some ground observations, but it also has relatively high performance in other regions, such as tropical regions (Sun et al., 2018). In this revision, additional interpretation is added in lines 435−438.

"For the medians of 50°S−50°N, several P datasets like PERSIANN-CDR, GPM IMERG v07, and MSWEP v2.8 are also comparable, which might be related to their close genealogical relationships (Markonis et al., 2024; Vargas Godoy et al., 2025)."

Lines 440 – 442: Interestingly, reanalysis products show the best performance in terms of SM. Could you extend your explanation about these results and the potential reasons behind the lower performance of satellite-based products?

Response: Yes, please see lines 471−473 in the revised manuscript.

"In contrast, low penetration depths (~2–5 cm) of microwave sensors limit the ability of ESA CCI v08.1 to capture deeper-layer SM variations (Hirschi et al., 2025)."

Lines 445-450: Why is the lowest consistency observed at the annual scale?

Response: It is because the seasonal variability is removed at the annual scale. Please see lines 477−480 in the discussion.

"Dataset performance varied significantly across time scales, with the highest correspondence at the monthly scale, where seasonal variability is well-captured and synoptic weather variability is mitigated. This explains the markedly lower water balance consistency observed at the annual scale for all datasets, where seasonal signals are strongly smoothed."

Technical corrections:

Please check whether the figure colors are suitable for color-blind readers.

Response: We appreciate your considerate suggestion. We have avoided using a color combination of red and green in the figures.

References

Fan, Y., Li, H., and Miguez-Macho, G.: Global Patterns of Groundwater Table Depth, Science, 339, 940–943, https://doi.org/10.1126/science.1229881, 2013.

Miguez-Macho, G. and Fan, Y.: A global humidity index with lateral hydrologic flows, Nature, 644, 413–419, https://doi.org/10.1038/s41586-025-09359-3, 2025.

Nobre, A. D., Cuartas, L. A., Hodnett, M., Rennó, C. D., Rodrigues, G., Silveira, A., Waterloo, M., and Saleska, S.: Height Above the Nearest Drainage – a hydrologically relevant new terrain model, Journal of Hydrology, 404, 13–29, https://doi.org/10.1016/j.jhydrol.2011.03.051, 2011.

Vargas Godoy, M. R., Markonis, Y., Thomson, J. R., Ballarin, A. S., Perri, S., Miao, C., Sun, Q., Hanel, M., Papalexiou, S. M., Kummerow, C., Oki, T., and Molini, A.: Which Precipitation Dataset to Choose for Hydrological Studies of the Terrestrial Water Cycle?, Bulletin of the American Meteorological Society, BAMS-D-24-0306.1, https://doi.org/10.1175/BAMS-D-24-0306.1, 2025.

Comment by Anonymous Referee #2

My review comments are structured as follows: **Overall Assessment**, **Major Strengths**, and **Recommendations for Improvement**.

I. Overall Assessment

This paper presents a systematic evaluation of the water balance consistency of 47 state-of-the-art hydrological datasets (precipitation, evapotranspiration, runoff, and soil moisture) using 8,294 independent combinations. The methodology is rigorous, the data coverage is extensive, and the study holds significant scientific and practical value. It reveals a widespread lack of water balance consistency in current global hydrological datasets and provides an in-depth analysis of the spatial patterns, influencing factors, and temporal trends. The manuscript is well-structured, the methods are transparent, and the results are credible. I recommend **acceptance after minor revisions**.

II. Major Strengths

1.High Novelty: This is the first study to systematically assess the consistency of multi-source, multi-variable hydrological datasets from a water balance perspective, filling a critical gap in the current literature.

2.Methodological Rigor:

a.The use of independent dataset combinations effectively avoids spurious consistency arising from the use of the same model or forcing data.

b.The use of adjusted R^2 as the consistency metric mitigates errors introduced by unit inconsistencies between variables.

c.The application of SHAP for factor attribution enhances the interpretability of the results.

3.Comprehensive Data Coverage: The inclusion of gauge-based, satellite-based, and reanalysis products ensures broad spatiotemporal coverage and strong representativeness.

4.Insightful and Actionable Results:

a.Clearly identifies the strengths and weaknesses of different data sources across various regions and climatic conditions.

b.Highlights the significant impact of soil moisture data depth on consistency.

c.Reveals an improvement in dataset consistency in mid-to-high latitude regions of the Northern Hemisphere in recent decades.

Response: We would like to express our gratitude to your encouraging evaluation, and for the time and effort you devoted to reviewing our work.

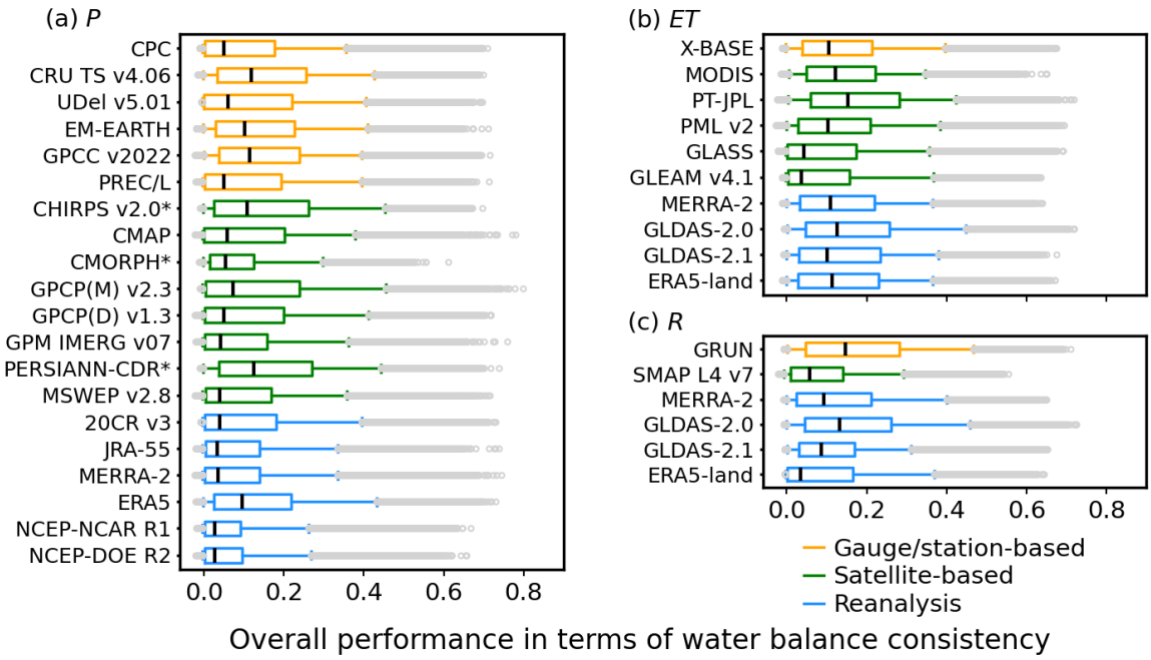
III. Recommendations for Improvement

1. Clarifications in the Methods Section

Handling Soil Moisture Depth Differences: While the manuscript states that ΔSM represents "change," the response of soil moisture at different depths to P-ET-R varies. It would be beneficial to clarify if any normalization or sensitivity analysis was performed for ΔSM across different depths.

Response: We thank the reviewer for raising this point. We did not apply normalization or sensitivity analysis for Δ*SM* across different depths. However, we found the *SM* datasets with simulations of deep soil layers generally performed better in most global regions. Please find the relevant text in lines 362−364 and lines 470−473. Additionally, using terrestrial water storage changes from GRACE, which integrates deeper soil moisture and groundwater availability, is not beneficial for improving water balance consistency (new Fig. S3).

> In lines 362−364:
>
> "*This is because they only represent the surface layers instead of the entire soil column (Fig. 1e). Meanwhile, the SM datasets with simulations of deep soil layers generally performed better in most global regions, such as the reanalysis and GLDAS-2 products (Fig. 2d and Fig. S16d).*"
>
> In lines 470−473:
>
> "*For SM, reanalysis datasets perform best, likely because they are constrained by physical laws and consider deeper soil moisture variability (Table S4 and Fig. S16). In contrast, low penetration depths (~2–5 cm) of microwave sensors limit the ability of ESA CCI v08.1 to capture deeper-layer SM variations (Hirschi et al., 2025).*"



*"**Fig. S3.** Performance of the considered datasets based on R^2 scores measuring water balance consistency through $P-ET-R=\Delta TWS$. Colors indicate the type of each dataset. Each box shows the median value, as well as the 5th, 25th, 75th, and 95th percentiles of the global pattern of water balance consistency derived from monthly data. Asterisks (*) following the name of P dataset indicate its limited spatial coverage of 50°S−50°N or 60°S−60°N."*

Temporal Scale Analysis: The significant differences in consistency between daily and annual scales warrant further discussion of the underlying physical mechanisms (e.g., high noise at daily scales, strong smoothing effects at annual scales).

Response: Thank you for your suggestions. We have clarified accordingly in lines 477−483.

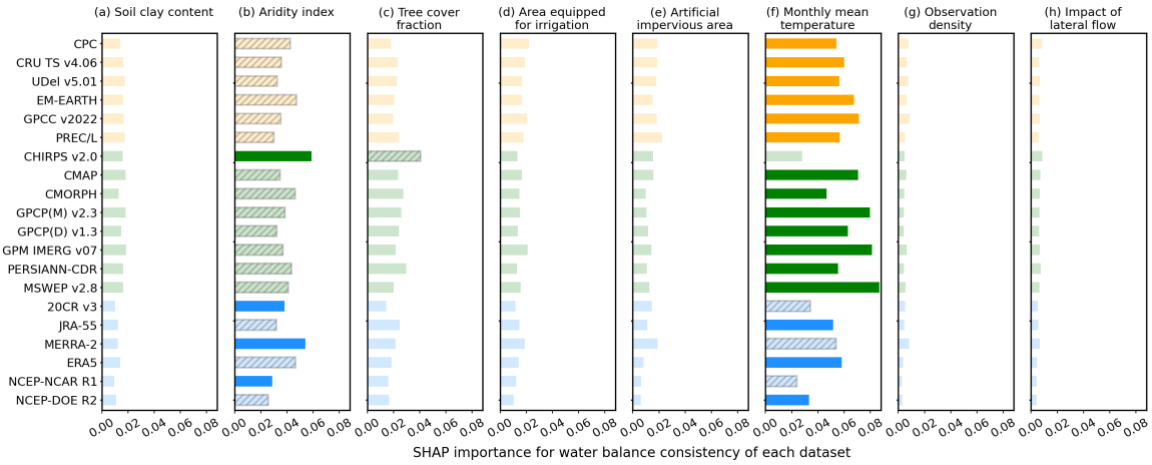
"Dataset performance varied significantly across time scales, with the highest correspondence at the monthly scale, where seasonal variability is well-captured and synoptic weather variability is mitigated. This explains the markedly lower water balance consistency observed at the annual scale for all datasets, where seasonal signals are strongly smoothed. At a daily time scale, the variability of the involved variables is high, including more extreme values and high noise, and apparently under-constrained by available observations (Maurer and Hidalgo, 2008; Fisher et al., 2008)."

2. Deepening the Results and Discussion

Root Causes of Low Consistency: Beyond the mentioned observational errors and model structures, could factors like surface-groundwater exchange or human activities (e.g., irrigation, reservoir regulation) also contribute? Expanding the discussion on this point would be valuable.

Response: In this revision, we also considered the potential influence of urbanization and lateral flow, which we found to have relatively low importance for dataset performance in terms of water balance consistency (see updated Figs. S17−S20). Please find the modified text in lines 398−399.

"At the same time, factors like irrigation, urbanization, and lateral flow play relatively minor roles (Figs. S17−S20)."



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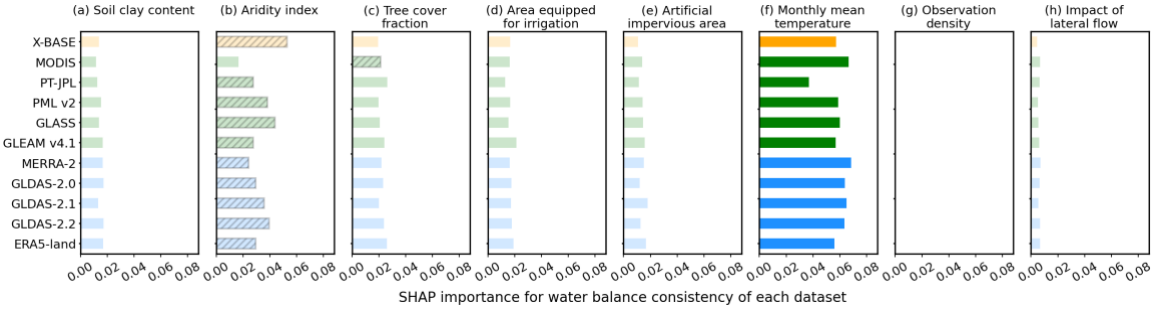

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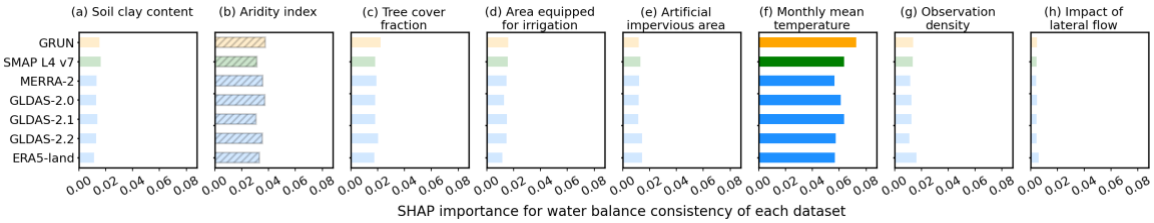
(Methods). Bars with dark color and hatch, respectively, indicate the first and second important factors for the water balance consistency of each ET dataset."



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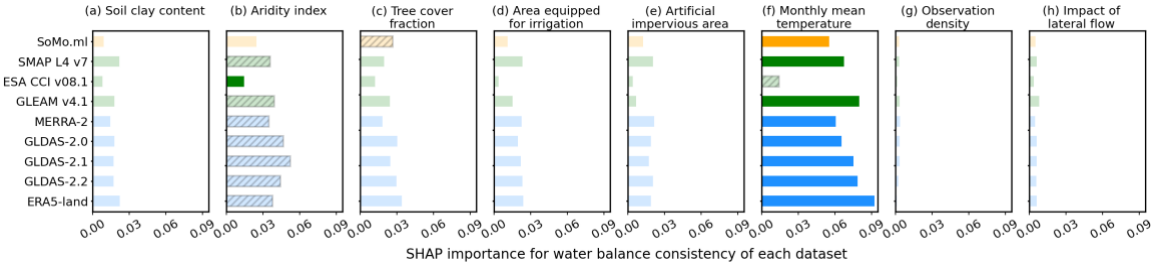


*"**Fig. S20.** Importance of (a) soil clay content, (b) aridity index, (c) tree cover fraction, (d) area equipped for irrigation, (e) artificial impervious area, (f) monthly mean temperature, (g) observation density, and (h) impact of lateral flow to water balance consistency of each SM dataset. The importance is quantified by global averaged absolute SHAP values (Methods). Bars with dark color and hatch, respectively, indicate the first and second important factors for the water balance consistency of each SM dataset."*

Mechanisms Behind Spatial Consistency Patterns: For instance, is the low consistency in high-latitude regions linked to insufficient representation of processes like snowpack and permafrost? Further interpretation in the context of existing literature is recommended.

Response: We have added accordingly:

"Limitations in representing snowpack and permafrost processes, along with difficulties in satellite retrievals over snow- and ice-covered high-latitude regions, also contribute to this issue (Hirschi et al., 2025; Muñoz-Sabater et al., 2021)."

3. Figures and Presentation

Figure 1: The meaning of the asterisk * and dashed lines in the boxplots should be explicitly stated in the figure caption.

Response: We have stated in the figure caption at the end, as follows:

*"Median results for performing the analysis with daily and annual data are indicated through crosses (×) and pluses (+), respectively (Text S1−S2). Asterisks (*) following the name of P dataset indicate its limited spatial coverage omitting high-latitude regions with typically low performance, and dashed line in each box indicates median of only 50°S−50°N. * of SM dataset indicates that the dataset does not consider the entire soil column."*

Figure 2: The grey areas, indicating "multiple datasets show similar performance or low consistency," would benefit from having the specific thresholds for "similar" and "low" defined in the caption or figure.

Response: We specify the thresholds in the caption of Figure 2:

Gray color indicates that multiple datasets show similar water balance consistency (with R^2 scores varying by less than 5%) or low water balance consistency (with all R^2 scores below 0.2).

Supplementary Material: Briefly mentioning the names of the best/worst performing datasets from Figures S13–S28 in the main text would help readers quickly grasp key findings.

Response: In section 3.1, we mention the best-performing *P* datasets in lines 347−348, the best-performing *ET* datasets in lines 355−356, the best-performing *R* datasets in lines 359−360, and the worst (best) performing *SM* datasets in line 361 (line 364).

4. Language and Formatting

Some sentences are quite long; breaking them up would improve readability.

Terminology should be checked for consistency (e.g., unified use of "gauge-based" vs. "station-based").

Response: We have broken the long sentences accordingly. However, we continue to use the terms gauge-based and station-based together because the in situ measurements differ by variable: *P* and *R* are derived from rain gauges and river gauges, respectively, whereas *ET* is measured at flux stations.

IV. Recommendation

Recommendation: Minor Revision

This manuscript makes a pioneering contribution to the evaluation of hydrological datasets. It is scientifically sound, its conclusions are robust, and it provides crucial insights for hydrological model development, data fusion, and climate change research. I recommend acceptance after the authors address the points above.

Response: Thank you for your encouraging evaluation.

Comment by Anonymous Referee #3

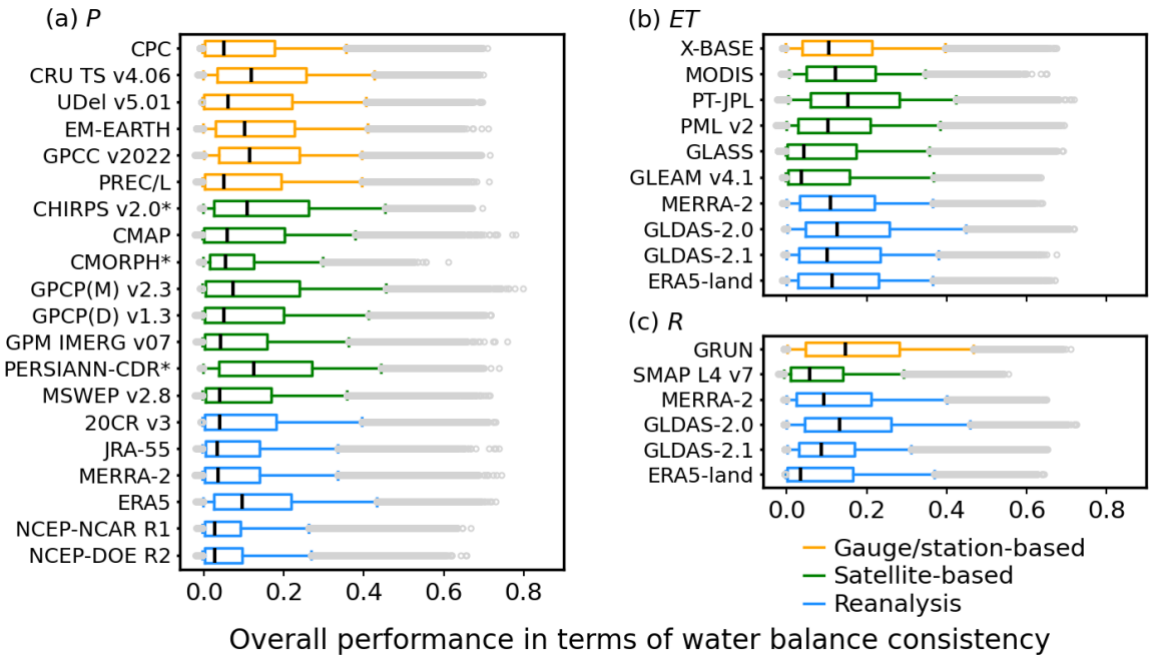
This study comprehensively evaluates the water balance consistencies among many state-of-the-art geospatial datasets on P, ET, and R. While it represents lots of work, clearly demonstrating the power of big data geospatial analysis, and the manuscript is generally well-written, there are several major concerns that should be addressed.

Response: Thank you for your encouraging comments, which have been invaluable for improving the quality of this manuscript.

1. The method for evaluating the water balance inconsistencies may need better justifications or some back-up analyses. While delta_SM is a reasonable proxy for the storage changes, it is still insufficient to capture those mass changes related to lakes/reservoirs/snow/glaciers, or those from underground. Therefore, the authors may need to explore the use of GRACE data to support their methods. I am afraid that some of the major conclusions for the high-latitude changes may be compromised if using GRACE.

Response: We agree with the reviewer's concerns, especially regarding the misrepresentation of snow and glacier changes in high-latitude regions using *SM* datasets. Therefore, we include supplementary results on water balance consistency using terrestrial water storage from GRACE in this revision. Please see the new Text S3 for detailed calculations through $P-ET-R=\Delta TWS$, where the number of independent combinations becomes less sufficient with a decrease by one order of magnitude from ~8,000 to ~900. Our results show that using ΔTWS from the GRACE has similar ranking results as using ΔSM (new Fig. S3), which supports the use of *SM* in the water balance assumption is sufficient for our study purposes. The relevant text can be found in lines 245−248:

"We thereby used terrestrial water storage from GRACE instead of SM in equation (1) to evaluate the performance of the P, ET, and R datasets, based on their combinations with GRACE data (Text S3). In this case, the number of combinations is decreased by one order of magnitude (933 remained), but ranking results are similar to using ΔSM (Fig. S3)."



*"**Fig. S3.** Performance of the considered datasets based on R^2 scores measuring water balance consistency through $P-ET-R=\Delta TWS$. Colors indicate the type of each dataset. Each box shows the median value, as well as the 5th, 25th, 75th, and 95th percentiles of the global pattern of water balance consistency derived from monthly data. Asterisks (*) following the name of P dataset indicate its limited spatial coverage of 50°S–50°N or 60°S–60°N."*

"***Text S3. Performance calculations with the use of terrestrial water storage from GRACE***

In this case, the terrestrial water storage (TWS) at 0.25 degree resolution from GRACE and its Follow-On mission (GRACE-FO) is provided by the Center for Space Research mascon product (Save et al., 2016). We calculated the change in TWS (ΔTWS) as the difference between the TWS anomaly of a given month and that of the previous month. Then, ΔTWS was used with P, ET, and R datasets to form combinations. Besides the exclusion rules detailed in Methods, we further consider the combinations with water balance components from GLDAS-2.2 to be not considered. For each of the remaining 933 independent combinations, we build a linear regression model in each grid cell:

$$(\boldsymbol{P}-\boldsymbol{ET}-\boldsymbol{R})s = k\cdot\boldsymbol{\Delta TWS}s \qquad (S1)$$

where s is the spatial index (grid cell) and k is the proportionality factor. Similar to the processing steps in Methods, the adjusted R^2 score of each linear model was calculated for each independent combination with ΔTWS. Finally, the overall performance for each P, ET, or R dataset in each grid cell was obtained by averaging R^2 across all combinations of datasets containing the respective dataset."

2. There are many useful insights regarding the performance of different datasets, however, it seems this study dos not directly contribute a new dataset itself? According to my understanding, ESSD's scope is more data-centered. In this regard, can the authors clarify what are the new datasets they may be able to contribute to the community?

Response: Please note that ESSD features different types of contributions, and this is a review article rather than a data description paper (please see also https://www.earth-system-science-data.net/about/manuscript_types.html). As a review article, it is not necessary to describe a new dataset which is typically done by data description papers. Therefore our study meets the requirements for articles in ESSD.

3. The authors seem to overlook several past studies working on the similar topic (e.g., https://link.springer.com/chapter/10.1007/978-3-319-32449-4_4 and relevant citing references)

Response: The suggested paper has been added to support the introduction of water balance closure (lines 42−46).

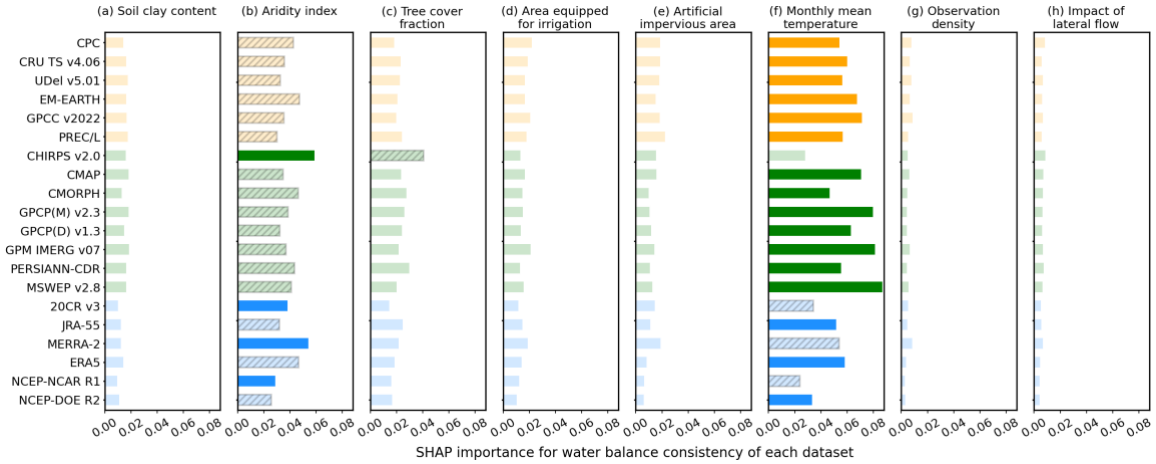
4. Although water balance closure is indeed important, there are occasions where water balance is violated because of the unobserved loss/addition of water. For most cases, it points to the error of datasets, but for some occasional cases, they may point toward new hydrological insights. Authors may need to briefly discuss the limitation of their assumption on 'water balance consistency is directly associated with good dataset performance'.

Response: We thank the reviewer for raising this valid point. In this revision, we identify potential bias in lines 242−245 when adding additional calculations using GRACE data.

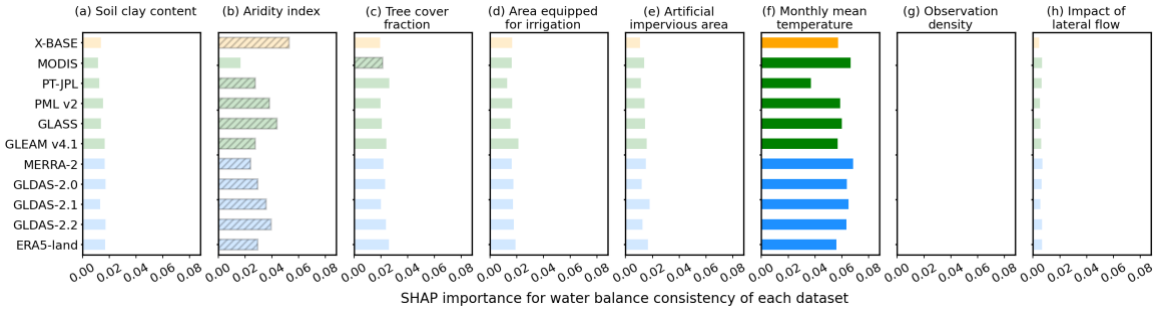
"In addition, unconsidered water variables, like glacier, snow, and surface water storage, might introduce bias into our water balance assumption, leading to a nonlinear response of ΔSM to P–ET–R."

Further, we also considered the potential influence of urbanization and lateral flow, which we found to have relatively low importance for dataset performance in terms of water balance consistency (see updated Figs. S17−S20). Please find the modified text in lines 398−399.

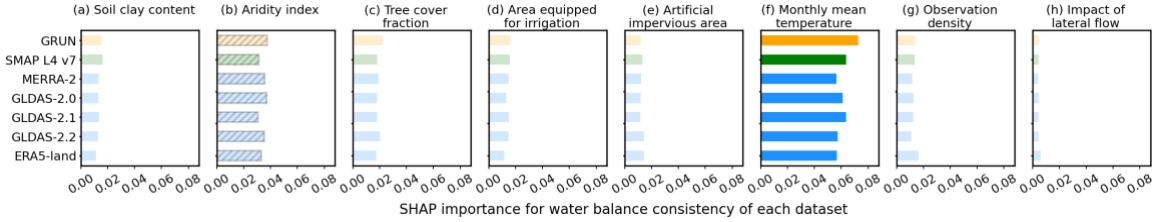
"At the same time, factors like irrigation, urbanization, and lateral flow play relatively minor roles (Figs. S17−S20)."



*"**Fig. S17.** Importance of (a) soil clay content, (b) aridity index, (c) tree cover fraction, (d) area equipped for irrigation, (e) artificial impervious area, (f) monthly mean temperature, (g) observation density, and (h) impact of lateral flow to water balance consistency of each P dataset. The importance is quantified by global averaged absolute SHAP values (Methods). Bars with dark color and hatch, respectively, indicate the first and second important factors for the water balance consistency of each P dataset."*

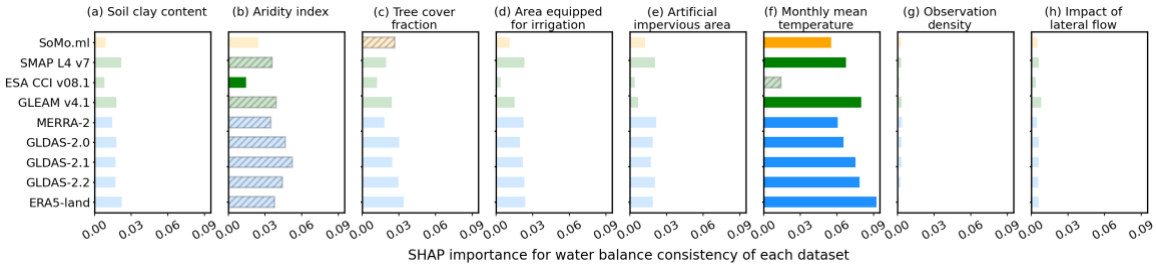


*"**Fig. S18.** Importance of (a) soil clay content, (b) aridity index, (c) tree cover fraction, (d) area equipped for irrigation, (e) artificial impervious area, (f) monthly mean temperature, (g) observation density, and (h) impact of lateral flow to water balance consistency of each ET dataset. The importance is quantified by global averaged absolute SHAP values (Methods). Bars with dark color and hatch, respectively, indicate the first and second important factors for the water balance consistency of each ET dataset."*



*"**Fig. S19.** Importance of (a) soil clay content, (b) aridity index, (c) tree cover fraction, (d) area equipped for irrigation, (e) artificial impervious area, (f) monthly mean temperature, (g) observation density, and (h) impact of lateral flow to water balance consistency of each*

R dataset. The importance is quantified by global averaged absolute SHAP values (Methods). Bars with dark color and hatch, respectively, indicate the first and second important factors for the water balance consistency of each R dataset."



*"**Fig. S20.** Importance of (a) soil clay content, (b) aridity index, (c) tree cover fraction, (d) area equipped for irrigation, (e) artificial impervious area, (f) monthly mean temperature, (g) observation density, and (h) impact of lateral flow to water balance consistency of each SM dataset. The importance is quantified by global averaged absolute SHAP values (Methods). Bars with dark color and hatch, respectively, indicate the first and second important factors for the water balance consistency of each SM dataset."*