Response to Editor

Comments to the Author:

Dear authors,

three reviewers have given feedback on your manuscript. The reviewers give generally very positive feedbacks and state they were intrigued by the analysis and results. All find that it is a timely and valuable contribution to the field of global hydrology. The paper is well structured and written. The reviewers have also given constructive feedback and criticism and you have addressed several of those comments in your response.

I agree with the assessment of the reviewers on the merit and novelty of the presented analysis. I would however like to emphasize one point: All of the reviewers comment, in one way or the other, on the fact that the results hinge upon the correctness of the CDR dataset. In your response you emphasize how carefully the CDR dataset was developed and validated, and also your own efforts to validate e.g. the standard deviation of E. I appreciate this. However, some of the standard variations in the dataset are not yet validated. I agree with reviewer #2 (René Orth) that a cross-validation would be desirable to learn whether the observed variance patterns are a property of the CDR dataset or hold with other datasets. At the very least, and since the main message of the manuscript is a call for investigation into the causes of the observed hydroclimatic variability, the discussion should more than now acknowledge to that fact that any efforts towards validation of those patterns are equally warranted.

Please submit the revised manuscript, with changes highlighted, together with a point by point response to all of the reviewers comments.

I thank both the authors and reviewers for the constructive discussion and look forward to the revised manuscript,

Anke Hildebrandt.

Response: We thank the editor for the evaluation and comment on the manuscript. As suggested by the editor and reviewers, we have carefully read and revised the manuscript accordingly as well as conducted a point-by-point response to all the comments.

The main comment here is a further cross-validation of the CDR data results based on atmospheric reanalysis (e.g., the state-of-the-art ERA5 dataset). As suggested by both editor and R2, in this response we report a comparison of the CDR (P, E, Q and ΔS) with the same from the recently released ERA5. We found P to be similar in both CDR and ERA5, but we found E and Q to be generally **much** higher in ERA5 compared to CDR (please see details in response to R2C3). As a consequence, in ERA5 we found that the sum of E and Q regularly exceeded P by large amounts. For example, in the Amazon, E and Q exceeded P by up to 1000 mm each and every year. So over a 27 year period, the predicted decline in storage in the Amazon region embedded in ERA5 approached 27000 mm (27 m)! This represents a major problem in the mass balance (or a lack of mass balance) in the ERA5 reanalysis and is physically not plausible. In contrast, over ice covered regions (e.g., Greenland), the hydrologic balance implied a continuing gain in storage of roughly similar magnitudes (i.e., 27 m in 27 years). Again, this is also physically not plausible.

Though the ERA5 is the state-of-the-art atmospheric reanalysis, we concluded that there was a major problem with the hydrologic (mass) balance and that the "atmospheric-centric" ERA5 database was not yet suitable for use in hydrologic studies.

As suggested by the editor, we also added the statement about the importance towards further improvement and validation of the patterns obtained in this manuscript in the revised manuscript.

Another important point raised by the reviewers (R2, R3) were (divergent) criticisms of the summary sections of the original manuscript. After carefully looking at comments from R2 and R3 and the structure and content of the original manuscript, we concluded that the underlying problem was that the original Discussion and Conclusions were repetitive and generally not well formulated. In response, we decided to combine the original sections (sections 5 and 6) into a new single section 5 (Discussion and Conclusions), and have streamlined the text accordingly by integrating the comments by reviewers. We believe that this has made the summary section more concise and that this change has substantially improved the manuscript.

We sincerely appreciate both the editor and reviewers for constructive suggestions and comments on the manuscript.

Response to Referee #1 (Anonymous)

In the following we use R1C1 (etc) to refer to comment 1 (C1) by referee 1 (R1).

R1C1: This is an excellent paper with major implications to our understanding of long term water balance and their climatic and landscape controls.

Response: We thank the anonymous reviewer for the evaluation and positive comment on the manuscript.

R1C2: This kind of work could not have been even just a few years ago, but as more and more reanalysis data become available the ability to do this kind of work and learn from it improves (given the caveat that this is ultimately model generated data, but the best we have).

I have no problems with the analyses that have been done, and the presentation. The authors use monthly data but the analysis is about inter-annual variability, although they do use the monthly data to estimate the storage capacity. I would like to see a categorical statement about this, I found it confusing. This means they only have 28 years of data (28 numbers) - they need to make an assessment/statement about the implications of this for their estimates of the various statistics, given potential non-stationarities etc.

Response: In this initial investigation, we use the CDR (monthly database) and as the reviewer has noted this is an entirely new field of research since global hydrologic reanalysis data has not previously been available. We chose to focus on the inter-annual variability to establish links directly with important earlier work on this topic (e.g., Koster & Suarez, 1999). We plan to extend this work to a seasonal time scale in future research. To eliminate the potential confusion, we made a statement as the reviewer suggested in the revised version of manuscript:

(Lines 100-101): "*In this study we focus on the inter-annual variability and the monthly water cycle variables (P, E, Q and ΔS) are aggregated to annual totals.*". Also, another statement about the limitations of 27-year study period has be added in the revision (Lines 457-460): "*The CDR is one of the first dedicated hydrologic reanalysis databases and includes data for a 27-year period. Accordingly, we could only examine hydrologic variability over this relatively short period. Further, we expect future improvements and modifications as the hydrologic community seeks to further develop and refine these new reanalysis databases.*". Thanks.

R1C3: The main issue that I have with the paper is that (as the authors themselves admit) is the preliminary nature of the discussion and conclusions. The results, to say the least, are quite interesting and intriguing. Without further analysis, one can only speculate. The dependence on storage capacity and temperature are potential clues. This is a concern for me - one solution is to delay the paper until further analysis is done to elucidate these results. It seems the main route to explanations is to use the monthly data that they already have, to see if there is an extension of the variances and especially cross-covariances into the seasonal regime. In other words, I am speculating if the causes of the inter-annual variability lie in the intra-annual variability of the fluxes and the storage, and in the role of vegetation (and soils) buffering the variability in the climate.

Response: We agree with R1 about the likely importance of the seasonal (i.e. intra-annual) cycle to further explain these results. However, given the new approach developed in this manuscript we deliberately chose to publish the somewhat simpler inter-annual results first.

Please also see R1C2.

R1C4: For now there is a decision to be made - I am comfortable with going ahead with publication of the current paper (in spite of its preliminary nature) in view of the fact publication of the paper may trigger follow-on research by other research groups as well.

Response: We appreciate the comments of the reviewer.

Response to Referee #2 (Dr René Orth)

R2C1: Review of Dongqin and Roderick "Inter-annual variability of the global terrestrial cycle" This study investigates the propagation of precipitation variability into the water cycle, i.e. into variations of runoff, evapotranspiration, and of storage changes. The authors show that this is mostly controlled by temperature (in wet regions), long-term aridity (in transitional regions), and by soil water storage capacity (in dry regions). Further, the results illustrate that the corresponding partitioning is different from the partitioning of mean precipitation into the means of these water cycle variables.

Recommendation: I think the paper requires major revisions.

The analysis is very interesting and provides new and fundamental insights into large- scale land surface hydrology. Related variability analyses are still not commonly done due to a lack of reliable data and underlying theory. This study can foster theory development in this area, and it underlines the importance of continuous improvement of the just-emerging global hydrological re-analysis datasets. Therefore I would be happy to see it published in HESS, but after some general revisions.

Response: We thank R2 for the evaluation and helpful comments on the manuscript.

R2C2: (1) Next to the consideration of the soil water storage capacity and the mean temperature to explain variations in the partitioning of precipitation variability, I am missing the inclusion of vegetation type as an explanatory variable. It might have strong implications on evapotranspiration variability, and therefore also on runoff and storage variabilities.

Response: We agree with Dr René Orth that the inter-annual variability might be related to the other factors, e.g., vegetation type. However, given the fact that this is a new approach and the research is exploratory, we focused on relating the inter-annual variability with the most general hydrologic factors (i.e., the air temperature as a surrogate for snow/ice and water storage capacity). We expect to extend the current work to a more complete analysis (e.g., relation to vegetation) in future research and we hope others will follow by examining factors like vegetation since this will require the effort of many scientists.

R2C3: (2) I agree with the authors that comprehensive hydrological reanalysis datasets are lacking, and the CDR dataset is an important contribution in that respect. Further, I appreciate the effort they make to validate the applicability of the dataset in the context of this study. However, also the CDR dataset is (necessarily) based on a model and hence it is not clear that the reported relationships are operating in nature, and not only in this model. To address this issue, I would like to see the key analyses from this study repeated with the state-of-the-art ERA5 reanalysis, which should be superior to ERA-Interim also in terms of land surface representation.

Response: As suggested by both R2 and the editor, we have compared the CDR (P, E, Q and ΔS) with the same from the recently released ERA5. For this comparison, we use the same 1984-2010 period. We downloaded monthly P, E and Q (denoted as total runoff and calculated by ERA5 as surface plus sub-surface runoff) from the ERA5 website. The water storage change (ΔS) is not included in the ERA5 database, and we calculated it using mass balance for each individual month during 1984-2010. We then conducted further analysis and found P to be similar in both CDR and ERA5 (Fig. R1). However, we found E and (especially) Q to be generally **much** higher in ERA5 compared to CDR (Figs. R2-R3). This has important consequences for the change in storage as described below.

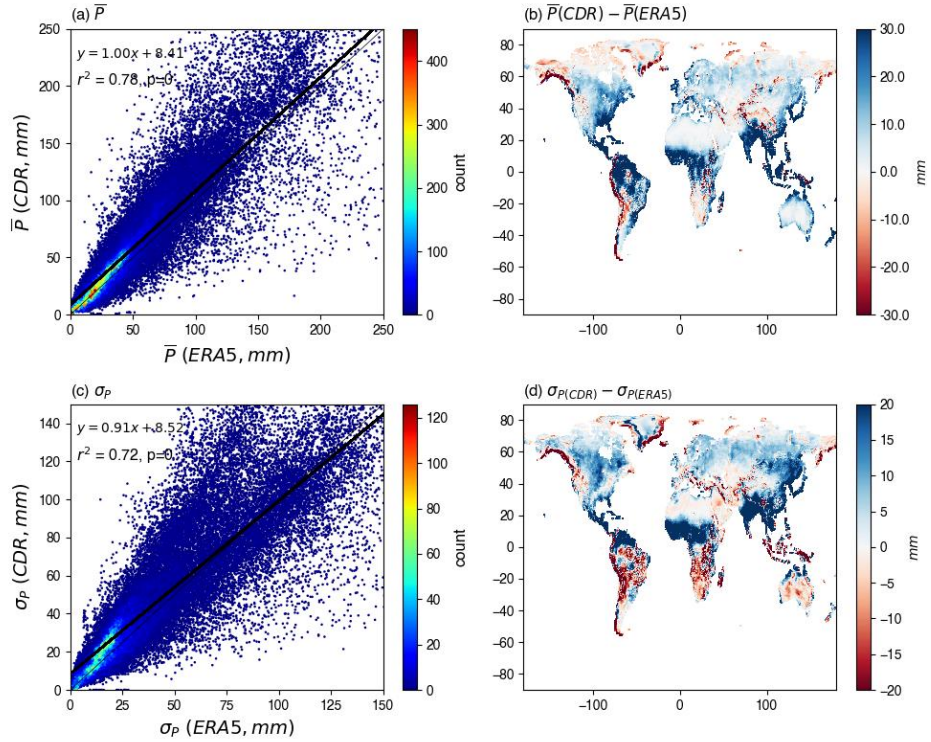

Figure R1. Comparison of monthly precipitation P between ERA5 and CDR databases. Top panels (a) (b) show comparison of the mean monthly ($\bar{P}$) while bottom panels (c) (d) show comparison of the standard deviation (σ_P) of monthly P.

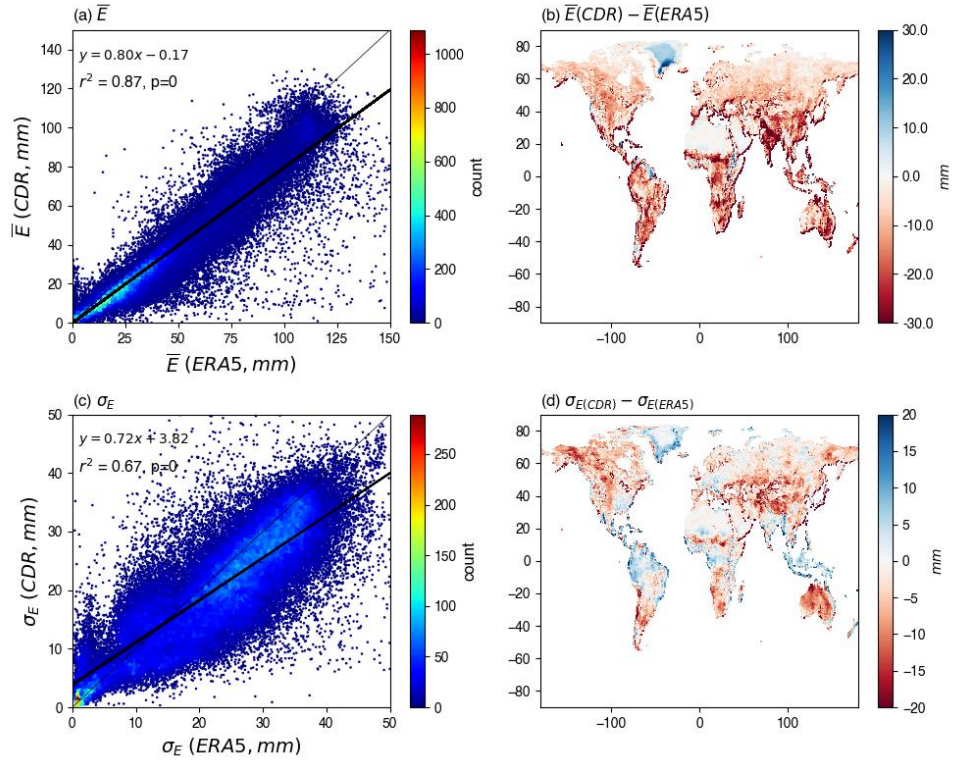

Figure R2. The same as Fig. R1 but using monthly evapotranspiration *E* from ERA5 and CDR databases.

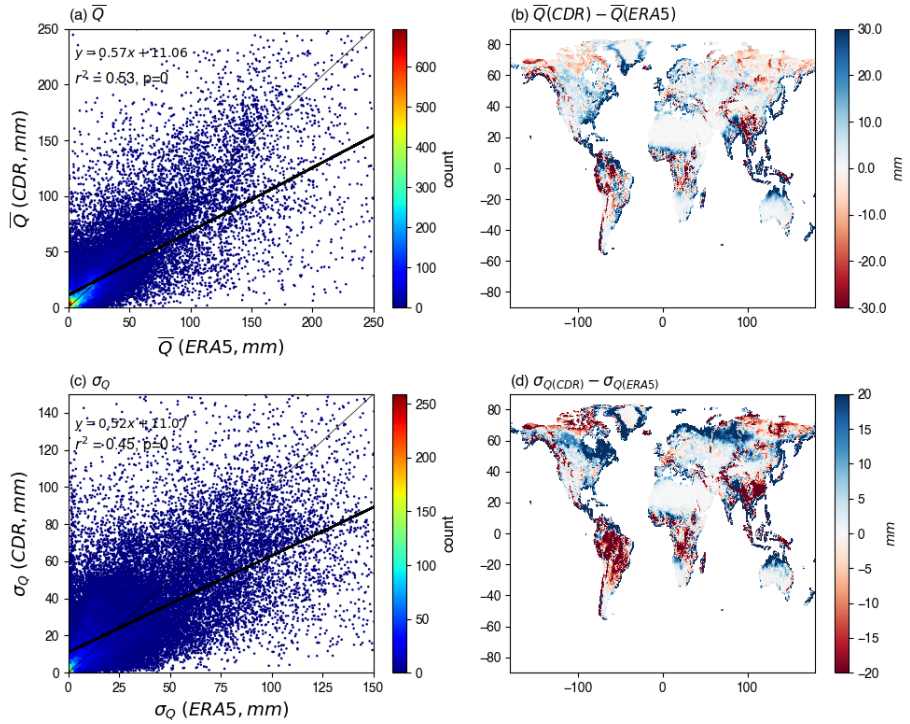

Figure R3. The same as Fig. R1 but using monthly runoff *Q* from ERA5 and CDR databases.

While the comparison with *P* (CDR vs ERA5 is reasonable, i.e., slope of the regression in Fig. R1a = 1.0), we find that *E* from ERA5 is on average 25% larger (i.e. slope is 0.8, see Fig. R2a) than *E* in CDR. Further, *Q* from ERA5 is on average 75% larger (i.e., slope is 0.57, see Fig. R3a) than *Q* in CDR. Now we know that in CDR, the mass balance was enforced. The obvious implication from these regressions is that in ERA5 the sum of *E* and *Q* must substantially exceed *P*.

To further evaluate ERA5, we then integrated the monthly data to annual totals. Visually, the results visually show similar global spatial patterns of long-term mean *P*, *E* and *Q* in the ERA5 database (see the Fig. R4a-c) to those in the CDR database (see Fig. 1 in the revised manuscript). However, as noted above, the long-term mean annual water storage change (ΔS, Fig. R4d) implied by ERA5 showed evidence of a major problem with the local hydrology. In particular, most regions of the earth surface show very large negative values for ΔS, e.g., in the Amazon long term mean annual ΔS is around -1000 mm. The implication is that over the 27-year period (1984-2010), the annual storage change in ERA5 over the Amazon region is -1000 mm every year and this equal 27 meters of storage change over the full period. This occurs in ERA5 because the sum of long-term mean annual *E* and *Q* is substantially greater than *P* in the Amazon. This is physically not plausible. The same problem holds for many other warm regions. In contrast, over the ice covered regions (e.g., Greenland), the hydrologic balance implied a continuing gain in storage. Again, this is physically not plausible.

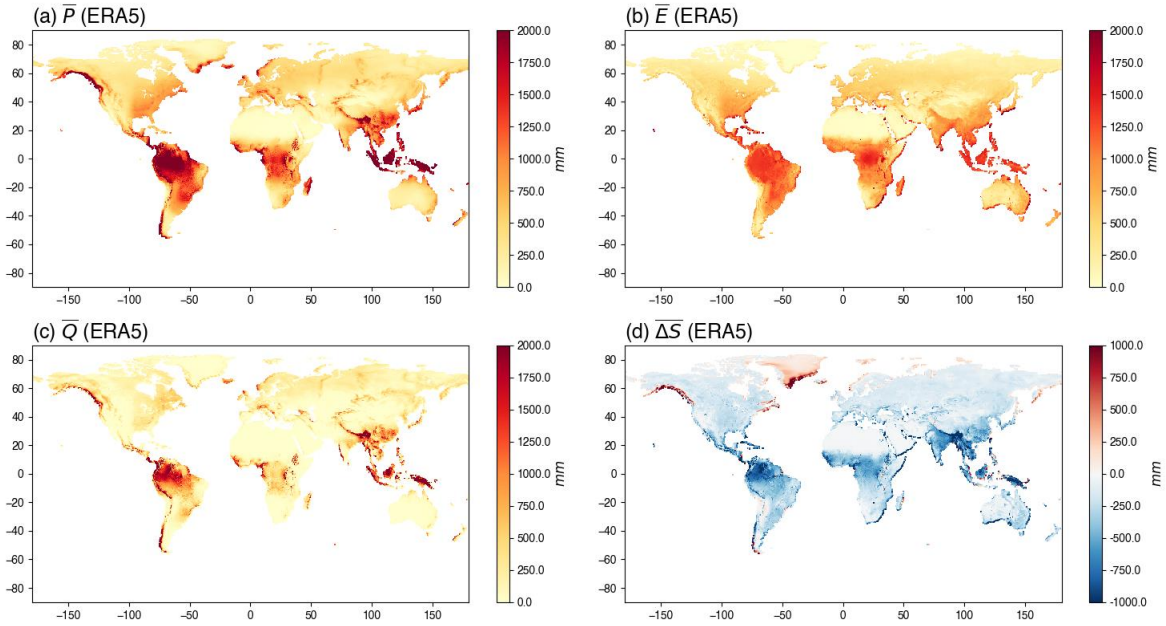

Figure R4. Mean annual (1984-2010) (a) *P*, (b) *E*, (c) *Q* and (d) ΔS in the ERA5 database.

Though the ERA5 is the state-of-the-art atmospheric reanalysis, we concluded that there was a major problem with the hydrologic (mass) balance and that the "atmospheric-centric" ERA5 database was not yet suitable for use in hydrologic studies.

Returning to the suitability of the CDR database and its relation to the real world, there is ample evidence that it is suitable for the analysis conducted here including:

(i) The enforcement of basic hydrologic concepts (mass balance).

(ii) The numerous tests of CDR reported in the original Zhang et al 2018 HESS publication (that are summarized on lines 134-139 of the HESSD manuscript). Those tests include a (successful) comparison of CDR runoff to observations of monthly runoff at 165 medium size basins and 862 small basins. In fact, the assessment of CDR in the original paper was quite comprehensive as you would expect.

(iii) We have augmented those extensive original tests by independently comparing monthly *E* with FLUXNET tower data at 32 sites which confirmed that the CDR captured the general seasonal cycle in both *P* and *E* at those 32 sites (Fig. S3, S4, S5, Table S1 in the revised manuscript). We also used the same FLUXNET data to compare the variability in *P* with variability in *E* (Fig. S6 in the revised manuscript).

(iv) We further compared CDR *E* with two gridded *E* databases that are not included in the source databases of CDR (LandFluxEval, MPI, see lines 159-166 in the revised manuscript and Fig. S7, S8) and the comparison was satisfactory.

(v) We compared how the standard deviation for *E* and the mean for *E* are related in the CDR (Fig. 4 in the revised manuscript) and compared that with the same relations in LandFluxEval and MPI (Fig. S10 in the revised manuscript). Those two comparisons were satisfactory.

(vi) The mean water cycle (*P*, *E*, *Q*) in CDR was shown to be consistent with the long-standing Budyko framework (Fig. 2 in the revised manuscript).

(vii) The CDR data were consistent with the Koster & Suarez (1999) theory in the limit of sites that have limited water storage (Fig. 5 in the revised manuscript).

That is a very comprehensive assessment.

Further, we readily acknowledge that the CDR database is the first hydrologic reanalysis and we expect more 'hydrologic-centered' databases to compare it to in the near future. For that reason we chose to only investigate the most general factors that we believe will stand the test of time and we have also described the study as an initial exploratory survey at several places in the manuscript.

R2C4: (3) I appreciate the idea of investigating the influence of the soil water storage capacity and the mean temperature on the variability partitioning. However, I think parts of the conclusions drawn by the authors from Figures 8-10 are not supported by the data. For example, I cannot see in Figure 10 that the temperature influence is particularly strong in very wet regions. Rather, to me it seems to be strong in moderately wet and dry regions (Fig 10b,d,f,h,j,l,n,p). Further, also the aridity limit of 6 which the authors suggest in their interpretation of the results in Figure 9, is arbitrary and not supported by the actual results. Storage capacity is obviously having an influence already for aridity values above 2-3 (Fig. 9b,c,f,j,k). Overall, in these Figures there are many interesting patterns but the authors focus only on few sub-plots and limit their interpretation to these. Therefore, I suggest to either show less information/sub-plots there, or to develop explanations also for patterns emerging within other sub-plots.

Response: We accept that Fig. 10 (Fig. 8 in the revised manuscript) is hard to interpret. On reading the reviewers comments and going over the manuscript we realize the problem was that we did not explicitly indicate the relevant panels (i.e., a, b, c, ….) and the text was not well-formulated. This was an oversight correctly identified by the reviewer. In general, the data in Fig. 10 was not particularly revealing (i.e., a negative result) but we actually focused the discussion to the first and third columns but we did not identify them properly. In response, we replaced the original text with the following (lines 307-314):

"To understand the potential role of snow/ice in modifying the variance partitioning, we repeat the previous analysis (Fig. 7) but here we use the mean annual air temperature ($\overline{T_a}$) to colour the grid-cells to (crudely) indicate the presence of snow/ice (Fig. 8). The results are complex and not easy to simply understand. The most important difference revealed by this analysis is in the hydrologic partitioning between cold (first column) and hot (third column) conditions in wet environments ($\overline{E_o}/\bar{P} \leq 0.5$). In particular, when $\overline{T_a}$ is high, σ_P^2 is almost completely partitioned into σ_Q^2 in wet environments (e.g., $\overline{E_o}/\bar{P} \leq 0.5$, Fig. 8g). In contrast, when $\overline{T_a}$ is low in a wet environment ($\overline{E_o}/\bar{P} \leq 0.5$ in first column of Fig. 8), there are substantial variations in the hydrologic partitioning. That result reinforces the complexity of variance partitioning in the presence of snow/ice."

R2C5: (4) The paper contains (too) many figures, which is diluting the main message(s), I feel. For example, Figures 1 and 2 could be merged, Figure 5 could be moved to the supplementary material, Figure 13 could be merged into Figure 8. The authors might have further ideas to reduce the amount of figures. Moreover, I do not really understand the difference between Figures 7 and 8, and why both are needed.

I do not wish to remain anonymous - René Orth.

Response: We respect the reviewer's opinion that we have too many figures – this is always a hard balance to get right to everyone's satisfaction. We have moved the original Fig. 1 and Fig. 5 to the supporting material as suggested. There are now 12 figures in the revised manuscript with another 12 in the supporting material. However, we do not think the original Fig. 13 (Fig. 11 in the revision) should be merged into original Fig. 8 (Fig. 6 in the revision) since the two figures belong to different sections (original Fig. 8 for the relation between variance partitioning and aridity section, original Fig. 13 for the case study section). Original Fig. 7 (Fig.5 in the revision) is a direct link to previous work while original Fig. 8 is the variance partitioning in the CDR database. Hence while these two figures are similar, they make separate independent contributions to the manuscript.

Specific comments:

R2C6: line 8: Equation 2 not introduced yet line 13: It should be 'variabilities'.

Response: We have deleted the text 'Eq. 2' and changed 'the variability…' to 'that variability…' to make the text clear to understand in the revised version of manuscript. Thanks.

R2C7: line 15: Some word is missing towards the end of the line

Response: We have checked line 15 in the original manuscript and did not find missing words?

R2C8: lines 35-39: Orth & Destouni (2018) might be relevant in this context and could be cited.

Response: The reference has now been cited in the revised manuscript.

R2C9: line 37: Not sure I get the point here.

Response: We mean that droughts and floods are typical extremes but that hydrologic variability encompasses more than just droughts and floods, i.e., hydrologic variability occurs across all time-space scales.

R2C10: lines 106-118: Please clarify that what you are determining here is actually not the soil water storage capacity, but rather the active range within which the soil moisture varies.

Response: Yes, exactly. We have modified the text and state the calculation to make this explicit in Lines 108-110 in the revised manuscript: "*For the storage, the active range of the monthly water storage variation was used to approximate the water storage capacity (S_{max}).*".

R2C11: lines 157-163: I would recommend to replace the LandFluxEVAL and the Jung et al. datasets with more recent gridded ET datasets such as the Jung et al. 2019 dataset and the GLEAM dataset (Martens et al. 2017).

Response: The reason we chose the LandFluxEVAL and MPI databases is that they are among the most widely used and validated *E* data that were also **not used** to develop the CDR database. We do not think adding a comparison to the latest GLEAM database would be as useful since an earlier version of GLEAM (v2a) was actually an input to the data assimilation scheme used to construct the CDR (see Table 1 in Zhang et al., 2018, HESS). Instead, the more appropriate approach would be to revise the CDR data assimilation but incorporating the latest GLEAM database but that is well beyond the scope of this work. (Also see R2C3 for similar comments about ERA.) We could replace the MPI we used with the updated database (Jung et al., 2019) but we do not see how that would alter the results.

R2C12: line 180: Gudmundsson et al. (2016) might be relevant in this context and could be cited.

Response: The reference has been cited in the revised manuscript. Thanks.

R2C13: line 181: What is meant by seasonality here? I thought you are considering annual data? In general, I think the considered temporal and spatial scales and resolution need to be more clearly stated and motivated at the beginning of the manuscript. Also, the role of these decisions on the results could be discussed.

Response: Yes, we are using annual data. But we know that differences of the intra-year seasonal timing (phase) of precipitation and E_o do have an effect on the annual water balance (as per the seminal work by Chris Milly in the early 1990s.). To make this more clear, we have added a statement in in the revised manuscript (Lines 100-101): "*In this study we focus on the inter-annual variability and the monthly water cycle variables (P, E, Q and ΔS) to annual totals.*"

Given the initial stage for this type of research and our plan to include the seasonal variations in future work (also see R1C2 and R1C3), a statement has been added in the revised manuscript (Lines 505-508): "*That result demonstrates that deeper understanding of the process-level interactions that are embedded within each of the three covariance terms (e.g., the role of seasonal vegetation variation) will be needed to develop process-based understanding of variability in the water cycle in these biologically productive regions (0.5<$\overline{E_o}/\bar{P}$ <1.5).*".

R2C14: line 252/253: I could not find this discussion in section 5!? Would be important to explain these discrepancies, though.

Response: Thanks for pointing this oversight out. The underlying scientific issue here is that the original Koster and Suarez (1999) work assumed negligible water storage change. In that sense the original results of Koster and Suarez (1999) can be seen as an upper limit and any variance in storage can only reduce the partitioning of variability in *P* to variability in *E* under dry conditions (Fig. 7). We have added a short discussion on this in the revised manuscript (Lines 488-492): "*This result explains the overestimation of σ_E/σ_P by the empirical theory of Koster and Suarez (1999) which implicitly assumed no inter-annual change in storage. The Koster and Suarez empirical theory is perhaps better described as an upper limit that is based on minimal storage capacity, and that any increase in storage capacity would promote the partitioning of σ_P^2 to $\sigma_{\Delta S}^2$ particularly under dry conditions (Figs. 10-12).*".

R2C15: line 327 & 333: 'leaving very limited variance' - not really true given your statement in lines 385-387

Response:

> We show the P, E, Q and ΔS time series along with the relevant variances and covariances in Fig. 12. Starting with the two dry sites, at the site with low storage capacity (Site 1), the time series shows that E closely follows P leaving annual Q and ΔS close to zero (Fig. 12a). The variance of P (σ_P^2 = 206.9 mm^2) is small and almost completely partitioned into the variance of E (σ_E^2 = 196.9 mm^2), leaving very limited variance for Q, ΔS and all three covariance components (Fig. 12b). At the site with high storage capacity (Site 2), E, Q and ΔS do not simply follow P (Fig. 12c). As a consequence, the variance of P (σ_P^2 = 2798.0 mm^2) is shared between E (σ_E^2 = 1150.2 mm^2), ΔS ($\sigma_{\Delta S}^2$ = 800.5 mm^2) and their covariance component ($2cov(E, \Delta S)$ = 538.4 mm^2, Fig. 12d). Switching now to the remaining wet and hot site (Site 3), Q closely follows P, with ΔS close to zero and E showing little inter-annual variation (Fig. 12e). The variance of P (σ_P^2 = 57374.4 mm^2) is relatively large and almost completely partitioned into the variance of Q (σ_Q^2 = 57296.4 mm^2), leaving very limited variance for E and ΔS and the three covariance components (Fig. 12f). We also examined numerous other sites with similar extreme conditions as the three case study sites and found the same basic patterns as reported above.

The text here refers to the site-based case studies (line 327 – Fig. 12a (Fig. 10 in the revised manuscript) – Site 1; line 333 – Fig. 12 f – Site 3) while the later text (lines 385-387) refers to the general pattern across all grid-boxes, i.e., Fig. 4 (Fig. 3 in the revised manuscript). We have corrected this misunderstanding by rewriting lines 385-387 (lines 470-478 in revised manuscript) to indicate the relevant figures as follows:

"With that in mind, we were surprised that the inter-annual variability of water storage change ($\sigma^2_{\Delta S}$) is typically larger than the inter-annual variability of evapotranspiration (σ^2_E) (cf. Fig. 3b and 3d). The consequence is that $\sigma^2_{\Delta S}$ is more important than σ^2_E for understanding inter-annual variability of global water cycle. A second important generalisation is that unlike the variance components which are all positive, the three covariance components in the theory (Eq. 2) can be both positive and negative. We report results here showing both large positive and negative values for the three covariance terms (Fig. 3efg). This was especially prevalent in biologically productive regions ($0.5<\overline{E_o}/\bar{P}<1.5$, Fig. 3eg)."

R2C16: lines 403-405: I cannot see this from Figure 8.

Response: Agreed. That was our mistake. The reference to Fig. 8 (Fig. 6 in the revised manuscript) should be to Fig. 4 (Fig. 3 in the revised manuscript, global pattern of water cycle variability) and we have revised that in the revision.

R2C17: Section 5: Overall a bit lengthy with too much summarizing, I think. Could be shorter, and more concise.

Response: Both R2 & R3 (see R3C4) had divergent views about the summary sections of our original manuscript.

After looking at both comments (R2, R3) and the structure of the original manuscript, we concluded that the original Discussion and Conclusions sections were repetitive and not well formulated.

In response, we have combined the original sections into a single section 5 (Discussion and Conclusions) and have streamlined the text accordingly. We believe that this has substantially improved the manuscript.

R2C18: Figure 3: Why are there data points outside the physically plausible range?

Response: We assume you mean points with *E* exceeding *P*? This is possible in for example, regions with run-on, or irrigation. We have further investigated those points and also find that some of them come from the parts of Greenland that had not been masked out (Fig. 1).

R2C19: Figure 4: Many values seem to be cut at 10 as this is the end of the color bar. You could use log scale here for the color bar.

Response: Yes, the scale for *P* in Fig. 4a (new Fig. 3a in the revised manuscript) is saturated with the maximum value of the color bar 10,000. The reason we chose 10,000 as the limit was to show the patterns for both the relatively high (e.g., σ^2_P, σ^2_Q and $\sigma^2_{\Delta S}$) and low variabilities (e.g., σ^2_E, 2cov(E, ΔS)) while keeping the same scale for all panels. We have tried to modify this figure by using a log scale (see Fig. R5) to mitigate saturation, but it made the spatial patterns very difficult to distinguish compared with Fig. 3 in the revised manuscript (original Fig. 4) especially for the covariance panels (Fig. R5e-g). Therefore, we thought it better to keep the original legend in Fig. 3.

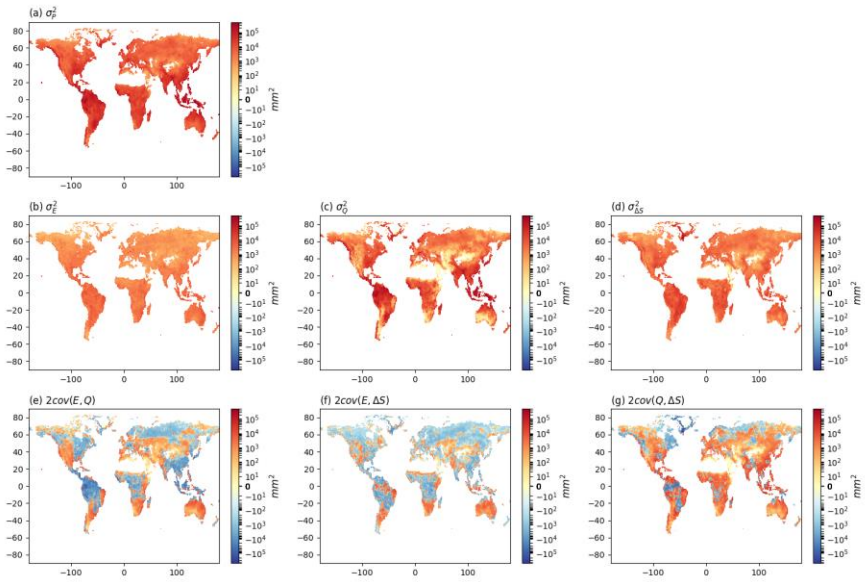

Figure R5. Water cycle variances (σ_P^2, σ_E^2, σ_Q^2, $\sigma_{\Delta S}^2$) and covariances ($cov(E,Q)$, $cov(E,\Delta S)$, $cov(Q,\Delta S)$). Note that we have multiplied the covariances by two (see Eq. 2).

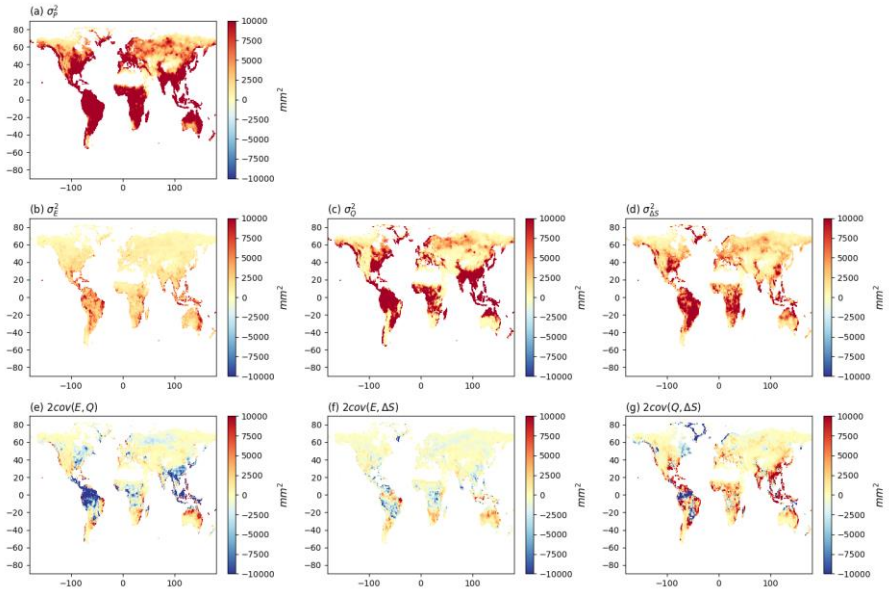

Figure 3 (original Figure 4). Water cycle variances (σ_P^2, σ_E^2, σ_Q^2, $\sigma_{\Delta S}^2$) and covariances ($cov(E,Q)$, $cov(E,\Delta S)$, $cov(Q,\Delta S)$). Note that we have multiplied the covariances by two (see Eq. 2).

R2C20: References:

Gudmundsson, L., P. Greve, and S. I. Seneviratne, 2016: The sensitivity of water avail- ability to changes in the aridity index and other factorsâA˘TA˘A probabilistic analysis in the Budyko space, Geophys. Res. Lett. 43 (13), 6985-6994.

Jung, M., S. Koirala, U. Weber, K. Ichii, F. Gans, G. Camps-Valls, D. Papale, C. Schwalm, G. Tramontana, and M. Reichstein, 2019: The FLUXCOM ensemble of global land-atmosphere energy fluxes. Scientific Data, 6 (74).

Martens, B., D. G. Miralles, H. Lievens, R. van der Schalie, R. A. M. de Jeu, D. Fernández-Prieto, H. E. Beck, W. A. Dorigo, and N. E. C. Verhoest, 2017: GLEAM v3: satellite-based land evaporation and root-zone soil moisture, Geosci. Model Dev. 10, 1903–1925.

Orth, R., and G. Destouni, 2018: Drought reduces blue-water fluxes more strongly than green-water fluxes in Europe. Nature Communications, 9, 3602, doi: 10.1038/s41467- 018-06013-7

Response: We appreciate Dr René Orth for listing all the reference mentioned above in the comments, and we have read and cite these reference accordingly in the revised manuscript. Thanks.

Response to Referee #3 (Anonymous)

R3C1: This study tries to partition the inter-annual variability in precipitation (P), i.e., the source term in terrestrial water cycle, into variabilities in three sink terms in terrestrial water cycle (ET, Q, ΔS), and then to relate the partitioning of variabilities to various factors like temperature, aridity, and storage capacity. I think this type of study at global scale is rather new, if not first of its kind at global scale, and thus very interesting to the hydrology community. This is the case mostly because there has been a lack of "hydrologic reanalysis" (CDR) for such kind of analysis in the first place. At the same time, this effort couldn't fully answer many of the questions set forth at the beginning, leaving perhaps "more questions than answers" (as phrased by another referee). The authors have done a solid amount of thorough analysis and experiments toward the questions of interest and these analyses are also well designed too.

Overall I consider this manuscript of good quality, both scientifically and technically, and thus publishable in HESS with several concerns addressed.

Response: We agree that this is a first-of-its-kind study and thank the referee for the encouraging positive comments on the manuscript.

R3C2: My primary concern is there is a lack of general "signal-to-noise" discussions to better inform readers to what extent the findings are significant signals from the underlying data (CDR, Zhang et al., 2018) and how much of it could be due to data uncertainties (or possible artifacts due to how the data is produced). For example, the ET products that went into the CDR (satellite products, reanalysis, etc.) share some similarity in their production methods (e.g., Penman-Monteith or Priestley-Taylor type of schemes). Such similarity may limit the variability of ET in CDR. Of course, the plants do apply a strong filter on the inter-annual variability based on their survival need. Such uncertainty analysis may be difficult but I think some qualitative and general assessment would be very beneficial.

Response: The CDR uses a formal data assimilation scheme based on mass balance that weights the various inputs, and thereby produces uncertainty estimates for each variable (P, E, Q, ΔS). The original paper (Zhang et al., 2018 HESS) includes a formal assessment of the sensitivity of P, E, Q over large regions (continents, basins) using the coefficient of variation (see original Figures 2, 3, 4, 5, 6, 7 in Zheng et al., 2018 HESS). We actually followed from that work and used those uncertainty estimates (lines 124-132 in the revised manuscript) to identify and mask out regions where the uncertainty was large relative to the magnitude of the fluxes. This screening procedure removed most grid-boxes from the Himalayas, Sahara Desert and Greenland (see Fig. S2 in the revised manuscript).

Secondly, while it is true that some of the products might share similarity in producing, for example, E (Penman-Monteith, Priestley-Taylor as the examples noted by the reviewer) the data assimilation is a comprehensive approach that includes all available estimates of P, E, Q and ΔS at each grid box. With mass balance enforced, the CDR estimates represent a composite product that is designed to avoid bias of the type described by the reviewer as much as possible by using all available estimates of the hydrologic fluxes. As we have described in a response to Reviewer 2 (see R2C3), the CDR has been extensively validated in the original publication.

In that context, our goal was not to assess the CDR, but rather to use it for this "first-of-a-kind" study on the sources and sinks of inter-annual hydrologic variability. We have added words at the end of the manuscript that we expect further improvement and validation of obtained patterns (Lines 459-460): "*Further, we expect future improvements and modifications as the hydrologic community seeks to further develop and refine these new reanalysis databases.".*

R3C3: Also, at the scale of the CDR (0.5 degree), I would say the partitioning is more complicated than just a result of several factors. The horizontal transport of water, seasonality, local water use, etc., can add a lot of noise. I wouldn't say it is not possible to do it at 0.5 degree, but it would probably be less noisy at a slightly coarser scale. Also, there could be much more controlling factors for the partitioning than being investigated, e.g., land cover/land use, LAI, topography.

Response: We agree with the reviewer that the partitioning is complex and could be related to the other factors, e.g., land cover/land use, LAI and horizontal transport of water due to topography, etc. In this first-of-a-kind analysis we chose to focus on the zero'th order physical factors (storage capacity, snow/ice) at the CDR data resolution (0.5 degree), but we fully expect more detailed analysis to follow, e.g., vegetation plant-based variables as discussed by the reviewer. We have added new text in the last paragraph of section 4.5 that speculates on the important role of vegetation processes that addresses this comment by R3. We have also emphasized that again in the final concluding paragraph of the manuscript.

R3C4: Finally, given that this study does tend to raise more questions than answers, I feel the authors should provide some more insights on what we can do from the analysis and findings in this study. What can we do with the numbers concluded here? Validating models? Improving single models like Budyko? Hydrologic/water risk analysis? Climate system behavior/sensitivity and hydrologic impacts of climate changes? And how can we improve our understanding in the future? What kind of new data at what scales would be critical to answering such questions? I feel this paper is incomplete without offering some of such insights.

Response: Please also see R2C17.

In further response, we have modified the final paragraph to set out a rough guideline for future research (lines 511-515): "*The hydrologic data needed to understand hydrologic variability are only now becoming available. With those data we can begin to develop a process-based understanding of hydrologic variability that can be used for a variety of purposes, e.g., deeper understanding of hydro-climatic behaviour, hydrologic risk analysis, climate change assessments and hydrologic sensitivity studies are just a few applications that spring to mind.*".

Inter-annual variability of the global terrestrial water cycle

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Abstract:

Variability of the terrestrial water cycle, i.e., precipitation (P), evapotranspiration (E), runoff (Q) and water storage change (ΔS) is the key to understanding hydro-climate extremes. However, a comprehensive global assessment for the partitioning of variability in P between E, Q and ΔS is still not available. In this study, we use the recently released global monthly hydrologic reanalysis product known as the Climate Data Record (CDR) to conduct an initial investigation of the inter-annual variability of the global terrestrial water cycle. We first examine global patterns in partitioning the long-term mean $\bar{P}$ between the various sinks $\bar{E}$, $\bar{Q}$ and $\overline{\Delta S}$ and confirm the well-known patterns with $\bar{P}$ partitioned between $\bar{E}$ and $\bar{Q}$ according to the aridity index. In a new analysis based on the concept of variability source and sinks ~~(Eq. 2)~~ we then examine how variability in the precipitation σ_P^2 (the source) is partitioned between the three variability sinks σ_E^2, σ_Q^2 and $\sigma_{\Delta S}^2$ along with the three relevant covariance terms, and how that partitioning varies with the aridity index. We find that the partitioning of inter-annual variability does not simply follow the mean state partitioning. Instead we find that ~~, with~~ σ_P^2 is mostly partitioned between σ_Q^2, $\sigma_{\Delta S}^2$ and the associated covariances. We also find that the magnitude of the covariance components can be large and often negative, indicating that ~~e~~ variability in the sinks (e.g., σ_Q^2, $\sigma_{\Delta S}^2$) can, and regularly does, exceed variability in the source (σ_P^2). Further investigations under extreme conditions revealed that in extremely dry environments the variance partitioning is closely related to the water storage capacity. With limited storage capacity the partitioning of ~~-~~σ_P^2 is mostly to σ_E^2, but as the storage capacity increases the partitioning of σ_P^2 is increasingly shared between σ_E^2, $\sigma_{\Delta S}^2$ and the covariance between those variables. In other environments (i.e., extremely wet and semi-arid/semi-humid) the variance partitioning proved to be extremely complex and a synthesis ~~was~~ has not been developed. We anticipate that a major scientific effort will be needed to develop a synthesis of hydrologic variability.

1. Introduction

In describing the terrestrial branch of the water cycle, the precipitation (P) is partitioned into evapotranspiration (E), runoff (Q) and change in water storage (ΔS). With averages taken over many years, $\overline{\Delta S}$ is usually assumed to be zero and it has long been recognized that the partitioning of the long-term mean annual precipitation ($\bar{P}$) between $\bar{E}$ and $\bar{Q}$ was jointly determined by the availability of both water ($\bar{P}$) and energy (represented by the net radiation expressed as an equivalent depth of water and denoted $\overline{E_o}$) ~~fluxes~~. Using data from a large number of watersheds, Budyko (1974) developed an empirical relation relating the evapotranspiration ratio ($\bar{E}/\bar{P}$) to the aridity index ($\overline{E_o}/\bar{P}$). The resultant empirical relation and other Budyko-type forms (e.g., Fu, 1981; Choudhury, 1999; Yang et al., 2008, Roderick and Farquhar, 2011; Sposito, 2017) that partition P between E and Q have proven to be extremely useful in both understanding and characterising the long-term mean annual hydrological conditions in a given region.

However, the long-term mean annual hydrologic fluxes rarely occur in any given year. Instead, society must (routinely) deal with variability around the long-term mean. The classic hydro-climate extremes are droughts and floods but the key point here is that hydrologic variability is expressed on a full spectrum of time and space scales. To accommodate that perspective, we need to extend our thinking beyond the long-term mean to ask how the variability of P is partitioned into the variability of E, Q and ΔS (e.g., Orth and Destouni, 2018).~~?~~

Early research on hydrologic variability focussed on extending the Budyko curve. In particular, Koster and Suarez (1999) used the Budyko curve to investigate ~~analyse~~ inter-annual variability in the water cycle. In their framework, the evapotranspiration standard deviation ratio (defined as the ratio of standard deviation for E to P, σ_E/σ_P) was (also) estimated using the aridity index ($\overline{E_o}/\bar{P}$). The classic Koster and Suarez framework has been widely applied and extended in subsequent investigations of the variability in both E and Q, using catchment observations, reanalysis data and model outputs (e.g., McMahon et al., 2011; Wang and Alimohammadi 2012; Sankarasubramanian and Vogel, 2002; Zeng and Cai, 2015). However, typical applications of the Koster and Suarez framework have previously been at regional scales and there is still no comprehensive global assessment for ~~the~~ partitioning the ~~of~~ variability of P into the variability of E, Q and ΔS. One reason for the lack of a global comprehensive assessment is the absence of gridded global hydrologic data. Interestingly, the atmospheric science

community have long used a combination of observations and model outputs to construct gridded global ~~-~~scale atmospheric re-analyses and such products have become central to atmospheric research. Those atmospheric products also contain estimates of some of the key water cycle variables (e.g., *P*, *E*), such as in the widely used interim ECMWF Re-Analysis (ERA-Interim; Dee et al. 2011). However, the central aim of atmospheric re-analysis is to estimate atmospheric variables, which, understandably, ignores many of the nuances of soil water infiltration, vegetation water uptake, runoff generation and many other processes of central importance in hydrology.

Hydrologists have only recently accepted the challenge of developing their own re-analysis type products with perhaps the first serious hydrologic re-analysis being published as recently as a few years ago (Rodell et al., 2015). More recently, the Princeton University group has extended this early work by making available a gridded global terrestrial hydrologic re-analysis product known as the Climate Data Record (CDR) (Zhang et al., 2018). Briefly, the CDR was constructed by synthesizing multiple in-situ observations, satellite remote sensing products, and land surface model outputs to provide *gridded* estimates of global land precipitation *P*, evapotranspiration *E*, runoff *Q* and total water storage change ΔS (0.5° × 0.5°, monthly, 1984-2010). In developing the CDR, the authors adopted local water budget closure as the fundamental hydrologic principle. That approach presented one important difficulty. Global observations of ΔS start with the GRACE satellite mission from 2002. Hence before 2002 there is no direct observational constraint on ΔS and the authors made the further assumption that the mean annual ΔS over the full 1984-2010 period was zero at every grid-box. That is incorrect in some regions (e.g. Scanlon et al., 2018) and represents an observational problem that cannot be overcome. However, our interest is in the year-to-year variability and for that application, the assumption of no change in the mean annual ΔS over the full 1984-2010 period is unlikely to lead to major problems since we are not looking for subtle changes over time~~the full time series~~. With that caveat in mind, the aim of this study is to use this new 27-year gridded hydrologic re-analysis product to conduct an initial investigation of the inter-annual variability of the terrestrial branch of the global water cycle.

The paper is structured as follows. We begin in Section 2 by describing the various climate and hydrologic databases including a further assessment of the suitability of the CDR database for this initial variability study. In Section 3, we examine relationships between the mean and variability in the four water cycle variables (*P*, *E*, *Q*

and ΔS). In Section 4, we first relate the variability to the classical aridity index and then use those results to evaluate the theory of Koster and Suarez (1999). Subsequently we examine how the variance of P is partitioned into the variances (and relevant covariances) of E, Q and ΔS and undertake an initial survey that investigates some of the factors controlling the variance partitioning. We conclude ~~finalise~~ the paper with a discussion summarising what we have learnt about water cycle variability over land by using the CDR database.

2. Methods and Data

2.1 Methods

The water balance is defined by,

$$P(t) = E(t) + Q(t) + \Delta S(t) \quad (1)$$

with P the precipitation, E the evapotranspiration, Q the runoff and ΔS the total water storage change in time step t. By the usual variance law, we have,

$$\sigma_P^2 = \sigma_E^2 + \sigma_Q^2 + \sigma_{\Delta S}^2 + 2cov(E,Q) + 2cov(E,\Delta S) + 2cov(Q,\Delta S) \quad (2)$$

that includes all relevant variances (denoted σ^2) and covariances (denoted cov). Eq. (1) is the familiar hydrologic mass balance equation. In that context, Eq. (2) can be thought of as the hydrologic variance balance equation.

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2.2 Hydrologic and Climatic Data

We use the recently released global land hydrologic re-analysis known here as the Climate Data Record (CDR) (Zhang et al., 2018). This product includes global precipitation P, evapotranspiration E, runoff Q and water storage change ΔS (0.5° × 0.5°, monthly, 1984-2010). In this study we focus on the inter-annual variability and the monthly water cycle variables (P, E, Q and ΔS) are aggregated to annual totals. The CDR does not report additional radiation ~~ve~~ variables and we use the NASA/GEWEX Surface Radiation Budget (SRB) Release-3.0 (monthly, 1984-2007, 1° × 1°) database (Stackhouse et al., 2011) to calculate E_o (defined as the net radiation expressed as an equivalent depth of liquid water, Budyko, 1974). We then calculate the aridity index ($\overline{E_o}/\bar{P}$) using P from the CDR and E_o from the SRB databases (see Fig. S1a in the Supplementary Material).

On general grounds, we anticipate that two important factors likely to influence ~~control~~ the partitioning of hydrologic variability were the water storage capacity and the presence of ice/snow at the surface. For the storage,

the active range of the monthly water storage variation was used to approximately ~~we estimate~~represent the water storage capacity (S_{max}) ~~in this study using the monthly ΔS data in CDR database~~. In more detail, t~~T~~he water storage $S(t)$ at each time step t (monthly here) was first calculated from the accumulation of $\Delta S(t)$, i.e., $S(t) = S(t\text{-}1) + \Delta S(t)$ where we assumed zero storage at the beginning of the study period (i.e., $S(0) = 0$). With the resulting time series available, S_{max} was estimated as the difference between the maximum and minimum $S(t)$ during the study period at each grid-box (see Fig. S1b in the Supplementary Material). The estimated S_{max} shows a large range from 0 to 1000 mm with the majority of values from 50 to 600 mm (Fig. S1b), which generally agrees with global rooting depth estimates assuming that water occupies from 10 to 30% of the soil volume at field capacity (Jackson et al., 1996; Wang-Erlandsson et al., 2016; Yang et al., 2016). To characterise snow/ice cover, and to distinguish extremely hot and cold regions, we also make use of a gridded global land air temperature dataset from the Climatic Research Unit (CRU TS4.01 database, monthly, 1901-2016, 0.5° × 0.5°) (Harris et al., 2014). (see Fig. S1c in the Supplementary Material).

2.3 Spatial Mask to Define Study Extent

The CDR database provides an estimate of the uncertainty (± 1σ) for each of the hydrologic variables (P, E, Q, ΔS) in each month. We use those uncertainty estimates to identify and remove regions with high relative uncertainty in the CDR data. The relative uncertainty is calculated as the ratio of root mean square of the uncertainty (± 1σ) to the mean annual P, E and Q at each grid-box following the procedure used by Milly and Dunne (2002a). Note that the long term mean ΔS is zero by construction in the CDR database, and for that reason we did not use ΔS to calculate the relative uncertainty. Grid-boxes with a relative uncertainty (in P, E and Q) of more than ~~0.1~~ 10% are deemed to have high relative uncertainty (Milly and Dunne, 2002a) and were excluded from the study extent. The excluded grid-boxes were mostly in the Himalayan region, the Sahara Desert and in Greenland. The final spatial mask is shown in ~~Fig. 1~~Fig. S2 and this has been applied throughout this study.

2.4 Further Evaluation of CDR Data for Variability Analysis

In the original work, the CDR database was validated by comparison with independent observations including (i) mean seasonal cycle of Q from 26 large basins (see Fig. 8 in Zhang et al., 2018), (ii) mean seasonal cycle of ΔS from 12 large basins (Fig. 10 in Zhang et al., 2018), (iii) monthly runoff from 165 medium size basins and a

further 862 small basins (Fig. 14 in Zhang et al., 2018), (iv) summer *E* from 47 flux towers (Fig. 16 in Zhang et al., 2018). Those evaluations did not directly address variability in various water cycle elements. With our focus on the variability we decided to conduct further validations of the CDR database beyond those described in the original work. In particular, we focussed on further independent assessments of *E* and we use monthly (as opposed to summer) observations of *E* from FLUXNET to evaluate the variability in *E*. We also compare the CDR with two other gridded global *E* products that were not used to develop the CDR including the LandFluxEval database (1° × 1°, monthly, 1989-2005) (Mueller et al., 2013) and the Max Planck Institute database (MPI, 0.5° × 0.5°, monthly, 1982-2011) (Jung et al., 2010) ~~product~~.

For the comparison to FLUXNET observations (Baldocchi et al., 2001; Agarwal et al., 2010) we identified 32 flux tower sites (site locations are shown in ~~Fig. S2~~Fig. S3 and details are shown in Table S1) having at least three years of continuous (monthly) measurements using the FluxnetLSM R package (v1.0) (Ukkola et al. 2017). The monthly totals and annual climatology of *P* and *E* from CDR generally follow FLUXNET observations, with high correlations and reasonable Root Mean Square Error (Figs. ~~S4~~-S5~~S3-S4~~, Table S1). Comparison of the point-based FLUXNET (~ 100 m – 1 km scale) with the grid-based CDR (~ 50 km scale) is problematic since the CDR represents an area that is at least 2500 times larger than the area represented by the individual FLUXNET towers and we anticipate that the CDR record would be "smoothed" relative to the FLUXNET record. With that in mind, we chose to compare the ratio of the standard deviation of *E* to *P* between the CDR and FLUXNET databases and this normalised comparison of the hydrologic variability proved encouraging (~~Fig. S5~~Fig. S6).

The comparison of *E* between the CDR and the LandFluxEval and MPI databases also proved encouraging. ~~As a further evaluation, we compare gridded *E* data in the CDR database against two other global *E* databases (including i.e., LandFluxEVAL (1° × 1°, monthly, 1989-2005) (Mueller et al., 2013) and Max Planck Institute (MPI), 0.5° × 0.5°, monthly, 1982-2011) (Jung et al., 2010) that were not used to construct the CDR database.~~ We found that the monthly mean *E* from the CDR database is slightly underestimated compared with LandFluxEVAL database (~~Fig. S6~~Fig. S7a), but agrees closely with the MPI database (~~Fig. S7~~Fig. S8a). In terms of variability, the standard deviations of monthly *E* from the CDR are in very close agreement with the LandFluxEVAL database (Fig. S7c) but there was a bias and scaling offset for the comparison with the MPI database (Fig. S8c).

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~~slightly different than those in the MPI database (Fig. S7~~Fig. S8c) ~~but were in very close agreement with the LandFluxEVAL database (Fig. S6~~Fig. S7c). ~~W~~In summary, ~~w~~e concluded that while the ~~the~~ CDR database was unlikely to be perfect, it was nevertheless suitable ~~suitable~~ for an initial exploratory survey ~~investigation~~ of ~~the~~ inter-annual variability in the terrestrial branch of the global water cycle.

3. Mean and Variability of Water Cycle Components

3.1 Mean Annual *P*, *E*, *Q* and the Budyko Curve

The global pattern of mean annual *P*, *E*, *Q* using the CDR data (1984-2007) is shown in ~~Fig. 2~~Fig. 1. The mean annual *P* ($\bar{P}$) is prominent in tropical regions, southern China, eastern and western North America (~~Fig. 2~~Fig. 1a). The magnitude of mean annual *E* ($\bar{E}$) more or less follows the pattern of $\bar{P}$ in the tropics (~~Fig. 2~~Fig. 1b) while the mean annual *Q* ($\bar{Q}$) is particularly prominent in the Amazon, South and Southeast Asia, tropical parts of west Africa and in some other coastal regions at higher latitudes (~~Fig. 2~~Fig. 1c).

We relate the grid-box level ratio of $\bar{E}$ to $\bar{P}$ in the CDR database to the classical Budyko (1974) curve using the aridity index ($\overline{E_o}/\bar{P}$) (~~Fig. 3~~Fig. 2a). As noted previously, in the CDR database, $\overline{\Delta S}$ is forced to be zero and this enforced steady state (i.e., $\bar{P} = \bar{E} + \bar{Q}$) allowed us to also predict the ratio of $\bar{Q}$ to $\bar{P}$ using the same Budyko curve (~~Fig. 3~~Fig. 2b). The Budyko curves follow the overall trend in the CDR data, which agrees with previous studies showing that the ~~dominant effect of~~ aridity index can be used to predict ~~on~~ water availability (e.g., Gudmundsson et al., 2016). However, there is substantial scatter due to, for example, regional variations related to seasonality, water storage change and the physics of runoff generation (Milly, 1994a, b). With that caveat in mind, t~~T~~he overall patterns are as expected with $\bar{E}$ following $\bar{P}$ in dry environments ($\overline{E_o}/\bar{P} > 1.0$) while $\bar{E}$ follows $\overline{E_o}$ in wet environments ($\overline{E_o}/\bar{P} \leq 1.0$) (~~Fig. 3~~Fig. 2).

3.2 Inter-annual Variability in *P*, *E*, *Q* and ΔS

We use the variance balance equation (Eq. 2) to partition the inter-annual σ_P^2 into separate components due to σ_E^2, σ_Q^2, $\sigma_{\Delta S}^2$ along with the three covariance components ($2cov(E,Q)$, $2cov(E,\Delta S)$, $2cov(Q,\Delta S)$) (~~Fig. 4~~Fig. 3). The spatial pattern of σ_P^2 (~~Fig. 4~~Fig. 3a) is very similar to that of $\bar{P}$ (~~Fig. 2~~Fig. 1a), which implies that the σ_P^2 is positively correlated with $\bar{P}$. In contrast the partitioning of σ_P^2 to the various components is very different from

the partitioning of $\bar{P}$ (cf. ~~Fig. 2~~Fig. 1 and ~~4~~3). First we note that while the overall spatial pattern of σ_E^2 more or less follows σ_P^2, the overall magnitude of σ_E^2 is much smaller than σ_P^2 and σ_Q^2 in most regions, and in fact σ_E^2 is also generally smaller than $\sigma_{\Delta S}^2$. The prominence of $\sigma_{\Delta S}^2$ (compared to σ_E^2) surprised us. The three covariance components ($cov(E,Q)$, $cov(E,\Delta S)$, $cov(Q,\Delta S)$) are also important in some regions. In more detail, the $cov(E,Q)$ term is prominent in regions where σ_Q^2 is large and is mostly negative in those regions (~~Fig. 4~~Fig. 3e), indicating that years with lower E are associated with higher Q and vice-versa. There are also a few regions with prominent positive values for $cov(E,Q)$ (e.g., the seasonal hydroclimates of northern Australia) indicating that in those regions, years with a higher E are associated with higher Q. The $cov(E,\Delta S)$ term (~~Fig. 4~~Fig. 3f) has a similar spatial pattern to the $cov(E,Q)$ term (~~Fig. 4~~Fig. 3e) but with a smaller overall magnitude. Finally, the $cov(Q,\Delta S)$ term shows a more complex spatial pattern, with both prominent positive and negative values (~~Fig. 4~~Fig. 3g) in regions where σ_Q^2 (~~Fig. 4~~Fig. 3c) and $\sigma_{\Delta S}^2$ (~~Fig. 4~~Fig. 3d) are both large.

These results show that the spatial patterns in variability are not simply a reflection of patterns in the long-term mean state. On the contrary, we find that of the three primary variance terms, the overall magnitude of (inter-annual) σ_E^2 is the smallest implying the least (inter-annual) variability in E. This is very different from the conclusions based on spatial patterns in the mean P, E and Q (see ~~previous~~ section 3.1). Further, while σ_Q^2 more or less follows σ_P^2 as expected, we were surprised by the magnitude of $\sigma_{\Delta S}^2$ which, in general, substantially exceeds the magnitude of σ_E^2. Further, the magnitude of the covariance terms can be important, especially in regions with high σ_Q^2. However, unlike the variances, the covariance can be both positive and negative and this introduces additional complexity. For example, with a negative covariance it is possible for the variance in Q (σ_Q^2) to exceed the variance in P (σ_P^2). To examine that in more detail we calculated the equivalent frequency distribution for each of the plots in ~~Fig. 4~~Fig. 3. The results (~~Fig. 5~~Fig. S9) further emphasise that in general, σ_E^2 is the smallest of the variances (~~Fig. 5~~Fig. S9b). We also note that the frequency distributions for the covariances (~~Fig. 5~~Fig. S9efg) are not symmetrical. In summary, it is clear that spatial patterns in the inter-annual variability of the water cycle (~~Fig. 4~~Fig. 3) do not simply follow the spatial patterns for the inter-annual mean (~~Fig. 2~~Fig. 1).

3.3 Relation Between Variability and the Mean State for *P*, *E*, *Q*

Differences in the spatial patterns of the mean (~~Fig. 2~~Fig. 1) and inter-annual variability (~~Fig. 4~~Fig. 3) in the global water cycle led us to further investigate the relation between the mean and the variability for each separate component. Here we relate the standard deviation (σ_P, σ_E, σ_Q) instead of the variance to the mean of each water balance flux (~~Fig. 6~~Fig. 4) since the standard deviation has the same physical units as the mean making the results more comparable. As inferred previously, we find σ_P to be positively correlated with $\bar{P}$ but with substantial scatter (~~Fig. 6~~Fig. 4a). The same result more or less holds for the relation between σ_Q and $\bar{Q}$ (~~Fig. 6~~Fig. 4c). In contrast the relation between σ_E and $\bar{E}$ is very different (~~Fig. 6~~Fig. 4b). In particular, σ_E is a small fraction of $\bar{E}$ and this complements the earlier finding (~~Fig. 6~~Fig. 4b) that the inter-annual variability for E is generally smaller than for the other physical variables~~,~~ (*P*, *Q* ~~or~~ and ΔS). (The same result was also found using both LandFluxEVAL and MPI databases, see ~~Fig. S8~~Fig. S10 in the Supplementary Material.) Importantly, unlike *P* and *Q*, *E* is constrained by both water and energy availability (Budyko, 1974) and the limited inter-annual variability in *E* presumably reflects limited inter-annual variability in the available (radiant) energy (E_o). This is something that could be investigated in a future study.

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4. Relating the Variability of Water Cycle Components ~~*P, E, Q and ΔS*~~ to Aridity

In the previous section, we investigated spatial patterns of the mean and the variability in the global water cycle. In this section, we extend that by investigating the partitioning of σ_P^2 to the three primary physical terms (σ_E^2, σ_Q^2, $\sigma_{\Delta S}^2$) along with the three relevant covariances. For that, we begin by comparing the Koster and Suarez (1999) theory against the CDR data and then investigate how the partitioning of the variance is related to the aridity index $\overline{E_o}/\bar{P}$ (see Fig. S1a in the Supplementary Material). Following that, we investigate variance partitioning in relation to both our estimate of the storage capacity S_{max} (see Fig. S1b in the Supplementary Material) as well as the mean annual air temperature $\overline{T_a}$ (see Fig. S1c in the Supplementary Material) that we use as a surrogate for snow/ice cover. We finalise this section by examining the partitioning of variance at three selected study sites that represent extremely dry/wet, high/low water storage capacity and the hot/cold spectrums.

4.1 Comparison with the Koster and Suarez (1999) Theory

We first evaluate the classical empirical curve of Koster and Suarez (1999) by relating ratios σ_E/σ_P and σ_E/σ_P to the aridity index (~~Fig. 7~~Fig. 5). The ratio σ_E/σ_P in the CDR database is generally overestimated by the empirical

Koster and Suarez curve, especially in dry environments (e.g., $\overline{E_o}/\bar{P} > 3$) (Fig. 5a). The inference here is that the Koster and Suarez theory predicts σ_E/σ_P to approach unity in dry environments while the equivalent value in the CDR data is occasionally unity but is generally smaller. With σ_E/σ_P generally overestimated by the Koster and Suarez theory we expect, and find, that σ_Q/σ_P is generally underestimated by the same theory (~~Fig. 7~~Fig. 5b). The same overestimation was found based on the other two independent databases for *E* (LandFluxEVAL and MPI) (~~Fig. S9~~Fig. S11). This overestimation is discussed further in section 5.

4.2 Relating Inter-annual Variability to Aridity

Here we examine how the fraction of the total variance in precipitation accounted for by the three primary variance terms along with the three covariance terms varies with the aridity index ($\overline{E_o}/\bar{P}$) (~~Fig. 8~~Fig. 6). (Also see ~~Fig. S10~~Fig. S12 for the spatial maps.) The ratio $\sigma_{\bar{E}}^2/\sigma_P^2$ is close to zero in extremely wet regions and has an upper limit noted previously (~~Fig. 7~~Fig. 5a) that approaches unity in extremely dry regions (~~Fig. 8~~Fig. 6a). The ratio σ_Q^2/σ_P^2 is close to zero in extremely dry regions but approaches unity in extremely wet regions but with substantial scatter (~~Fig. 8~~Fig. 6b). The ratio $\sigma_{\Delta S}^2/\sigma_P^2$ is close to zero in both extremely dry/wet regions (~~Fig. 8~~Fig. 6c) and ~~but~~ shows the largest range at an intermediate aridity index ($\overline{E_o}/\bar{P} \sim 1.0$).

The covariance ratios are all small in extremely dry (e.g., $\overline{E_o}/\bar{P} \geq 6.0$) environments and generally show the largest range in semi-arid and semi-humid environments. The peak magnitudes for the three covariance components consistently occur when $\overline{E_o}/\bar{P}$ is close to 1.0 which is the threshold often used to separate wet and dry environments.

4.3 Further Investigations on the Factors Controlling Partitioning of the Variance

Results in t~~T~~he previous section ~~results (Sections 4.1 and 4.2) have~~ demonstrated that spatial variation in the partitioning of σ_P^2 into $\sigma_{\bar{E}}^2$, σ_Q^2, $\sigma_{\Delta S}^2$ and the three covariance components is complex (Fig. 6). To help further understand inter-annual variability of the terrestrial water cycle, we conduct further investigations in this section using two factors likely to have a major influence on the variance partitioning of σ_P^2. The first is the storage capacity $S_{\max}$ (see Fig. S1b in the Supplementary Material). The second is the mean annual air temperature $\overline{T_a}$ (see Fig. S1c in the Supplementary Material) which is used here as a surrogate for snow/ice presence.

4.3.1 Relating Inter-annual Variability to Storage Capacity

We first relate the partitioning of σ_P^2 to water storage capacity (S_{max}) by repeating ~~Fig. 8~~Fig. 6 but instead we use a logarithmic scale for the x-axis and we distinguish S_{max} via the background colour (~~Fig. 9~~Fig. 7). To eliminate the possible overlap of grid-cells in the colouring process, all the grid-cells over land are further separated using different latitude ranges (as shown in the four columns of ~~Fig. 9~~Fig. 7), i.e., 90N-60N, 60N-30N, 30N-0 and 0-90S. We find that S_{max} is relatively high in wet environments ($\overline{E_o}/\bar{P} \leq 1.0$, Fig. 7a) but shows no obvious relation to ~~with~~ the partitioning of σ_P^2. However, in dry environments ($\overline{E_o}/\bar{P} > 1.0$) the ratio σ_E^2/σ_P^2 apparently decreases with the increase of S_{max} (~~Fig. 9~~Fig. 7a-d). That relation is particularly obvious in extremely dry environments ($\overline{E_o}/\bar{P} \geq 6.0$) at equatorial latitudes where there is an upper limit of σ_E^2/σ_P^2 close to 1.0 when S_{max} is small (blue grid-cells in ~~Fig. 9~~Fig. 7c). The interpretation for those extremely dry environments is that when S_{max} is small, σ_P^2 is almost completely partitioned into σ_E^2 (~~Fig. 9~~Fig. 7bc) with the other variance and covariance components close to zero. While for those same extremely dry environments, as S_{max} increases, the partitioning of σ_P^2 is shared between σ_E^2 and $\sigma_{\Delta S}^2$ and their covariance (~~Fig. 9~~Fig. 7cks) while ~~ith~~ σ_Q^2 and its covariance components remain close to zero (~~Fig. 9~~Fig. 7gow). However, at polar latitudes in the northern hemisphere (panels in the first and second columns of ~~Fig. 9~~Fig. 7) there are variations that could not be easily associated with variations in S_{max} which led us to further investigate the role of snow/ice on the variance partitioning in the following section.

4.3.2 Relating Inter-annual Variability to Mean Air Temperature

To understand the potential role of snow/ice in modifying the variance partitioning, we repeat the previous analysis (~~Fig. 9~~Fig. 7) but here we use the mean annual air temperature ($\overline{T_a}$) to colour the grid-cells to (crudely) indicate ~~identify~~ the presence of snow/ice (~~Fig. 10~~Fig. 8). The results are complex and not easy to simply understand. The most important difference revealed by this analysis is in the hydrologic partitioning between cold (first column) and hot (third column) conditions in wet environments ($\overline{E_o}/\bar{P} \leq 0.5$). In particular, when $\overline{T_a}$ is high, σ_P^2 is almost completely partitioned into σ_Q^2 in wet environments (e.g., $\overline{E_o}/\bar{P} \leq 0.5$, Fig. 8g). In contrast, when $\overline{T_a}$ is low in a wet environment ($\overline{E_o}/\bar{P} \leq 0.5$ in first column of Fig. 8), there are substantial variations in the hydrologic partitioning. That result reinforces the complexity of variance partitioning in the presence of snow/ice.

~~Most of the variations at polar latitudes in the northern hemisphere (panels in the first and second columns of Fig. 10Fig. 8) is associated with low air temperature (e.g., $\overline{T_a}$ < 0 °C in blue colour), making the results associated with high air temperature (e.g., $\overline{T_a}$ > 10 °C in the third and fourth columns of Fig. 8green-yellow-red colours) relatively more compactshow less scatters. That pattern is particularly obvious in extremely wet environment ($\overline{E_o}/\bar{P} \leq 0.5$), where the ratio σ_Q^2/σ_P^2 is close to 1.0 when $\overline{T_a}$ is high (e.g., $\overline{E_o}/\bar{P} \leq 0.5$ and $\overline{T_a}$ > 10 °C, with green-yellow-red grid-cells on the panels in the second row of Fig. 10Fig. 8gh) but shows lots of scatters when $\overline{T_a}$ is low (e.g., $\overline{T_a}$ < 0 °C, Fig. 8ef)with the other variance-covariance components close to zero. This indicates that in extremely wet environment, when $\overline{T_a}$ is high, σ_P^2 is almost completely partitioned into σ_Q^2 (e.g., $\overline{E_o}/\bar{P} \leq 0.5$ and $\overline{T_a}$ > 10 °C in the third and fourth columns of Fig. 8). However, when $\overline{T_a}$ is low in extremely wet environment, there are substantial variations in all variance-covariance components (e.g., $\overline{E_o}/\bar{P} \leq 0.5$ and $\overline{T_a}$ < 0 °C, see the blue grid-cells on the panels in the first and second columns column of Fig. 10Fig. 8). That result indicates the complexity of variance partitioning associated with the presence of snow/ice.~~

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4.4 Case Studies

The previous results (Section 4.3) have demonstrated that the partitioning of σ_P^2 is ~~predominantly~~ influenced by the water storage capacity (S_{max}) in extremely dry environments ($\overline{E_o}/\bar{P} \geq 6.0$) and that the presence of snow/ice is important (as indicated by mean air temperature ($\overline{T_a}$)) in extremely wet environments ($\overline{E_o}/\bar{P} \leq 0.5$). In this section, we examine, in greater detail, several sites to gain deeper understanding of the partitioning of σ_P^2. For that purpose, we selected three sites based on extreme values for the three explanatory parameters, i.e., $\overline{E_o}/\bar{P}$ (Fig. S1a), S_{max} (Fig. S1b) and $\overline{T_a}$ (Fig. S1c). The criteria to select three climate sites are as follows, Site 1: dry ($\overline{E_o}/\bar{P} \geq 6.0$) and small S_{max} ($S_{max} \approx 0$), Site 2: dry ($\overline{E_o}/\bar{P} \geq 6.0$) and relatively large S_{max} ($S_{max} \gg 0$) and Site 3: wet ($\overline{E_o}/\bar{P} \leq 0.5$) and hot ($\overline{T_a} > 25$ °C). For each of the three classes, ~~sites,~~ we use a representative grid-cell (~~Fig. 11~~Fig. 9) to show the original time series (~~Fig. 12~~Fig. 10) and the partitioning of the variability (~~Fig. 13~~Fig. 11).

We show the P, E, Q and ΔS time series along with the relevant variances and covariances in ~~Fig. 12~~Fig. 10. Starting with the two dry sites, at the site with low storage capacity (Site 1), the time series shows that E closely follows P leaving annual Q and ΔS close to zero (~~Fig. 12~~Fig. 10a). The variance of P (σ_P^2 = 206.9 mm^2) is small and almost completely partitioned into the variance of E (σ_E^2 = 196.9 mm^2), leaving very limited variance for Q, ΔS and all three covariance components (~~Fig. 12~~Fig. 10b). At the dry site with larger ~~high~~ storage capacity (Site

2), E, Q and ΔS do not simply follow P (~~Fig. 12~~Fig. 10c). As a consequence, the variance of P (σ_P^2 = 2798.0 mm^2) is shared between E (σ_E^2 = 1150.2 mm^2), ΔS ($\sigma_{\Delta S}^2$ = 800.5 mm^2) and their covariance component ($2cov(E, \Delta S)$ = 538.4 mm^2, ~~Fig. 12~~Fig. 10d). Switching now to the remaining wet and hot site (Site 3), we note that Q closely follows P, with ΔS close to zero and E showing little inter-annual variation (~~Fig. 12~~Fig. 10e). The variance of P (σ_P^2 = 57374.4 mm^2) is relatively large and almost completely partitioned into the variance of Q (σ_Q^2 = 57296.4 mm^2), leaving very limited variance for E and ΔS and the three covariance components (~~Fig. 12~~Fig. 10f). We also examined numerous other sites with similar extreme conditions as the three case study sites and found the same basic patterns as reported above.

To put the data from the three case study sites into a broader variability context we position the site data onto a backdrop of original ~~Fig. 8~~Fig. 6. As noted previously, at Site 1, the ratio σ_E^2/σ_P^2 is very close to unity (~~Fig. 13~~Fig. 11a), and under this extreme condition, we have the following approximation,

$$\sigma_P^2 \approx \sigma_E^2 \quad \text{(Site 1, dry and } S_{\max} \approx 0) \tag{3}$$

In contrast, for Site 2 with the same aridity index but higher $S_{\max}$, we have,

$$\sigma_P^2 \approx \sigma_E^2 + \sigma_{\Delta S}^2 + 2cov(E, \Delta S) \quad \text{(Site 2, dry and } S_{\max} \gg 0) \tag{4}$$

Finally, at Site 3, we have,

$$\sigma_P^2 \approx \sigma_Q^2 \quad \text{(Site 3, wet and hot)} \tag{5}$$

4.5 Synthesis

The above simple examples demonstrate that aridity $\overline{E_o}/\bar{P}$, storage capacity $S_{\max}$ and to a lesser extent, air temperature $\overline{T_a}$, all play some role ~~roles~~ in the partitioning of σ_P^2 to the various components. Our synthesis of the results for the partitioning of σ_P^2 is summarised in ~~Fig. 14~~Fig. 12. In dry environments with ~~and~~low storage capacity ($S_{\max} \approx 0$) ~~environments~~ we have minimal runoff and expect that σ_P^2 is more or less completely partitioned into σ_E^2 (~~Fig. 14~~Fig. 12a). In those environments, (inter-annual) variations in storage $\sigma_{\Delta S}^2$ play a limited role in setting the overall variability. However, in dry environments with larger storage capacity (~~and~~ $S_{\max} \gg 0$) ~~environments~~, σ_E^2 is only a small fraction of σ_P^2 (Fig. 12a) leaving most of the overall variance in σ_P^2 to be partitioned ~~attributed~~ to $\sigma_{\Delta S}^2$ and the covariance between E and ΔS (~~Fig. 14~~Fig. 12c and ~~Fig. 14~~Fig. 12e). This emphasises ~~implies~~ the hydrological importance of water storage capacity in buffering variations of the water cycle under dry conditions.

Under extremely wet conditions, the largest ~~huge~~ difference in variance partitioning is not due to differences in storage capacity but is instead related to differences in mean air temperature.~~occurs between the hot and cold conditions instead of water storage capacity conditions in dry conditions~~environments~~.~~ In wet and hot environments, we have maximum runoff and find ~~expect~~ that σ_P^2 is more or less completely partitioned into σ_Q^2 (~~Fig. 14~~Fig. 12b) while the partitioning to ~~, and the variations in evapotranspiration~~ σ_E^2 and ~~storage~~ $\sigma_{\Delta S}^2$ is small. ~~play a limited role in setting the overall variability.~~ However, in wet and cold environments, the variance partitioning shows great complexity with σ_P^2 being partitioned into all possible components. ~~, with σ_Q^2/σ_P^2 and $\sigma_{\Delta S}^2/\sigma_P^2$ vary a lot caused by snow/ice melting.~~ We suggest that this emphasises ~~This signifies~~ the hydrological importance of thermal processes (melting/freezing) under extremely cold conditions.

However, t~~T~~he most complex patterns to interpret are those for semi-arid to semi-humid environments (i.e., $\overline{E_o}/\bar{P}$ ~1.0). Despite a multitude of attempts over an extended period we were unable to develop a simple useful synthesis to summarise the partitioning of variability in those environments. We found ~~In those environments,~~ that the three covariance terms all play important roles and we also found that simple environmental gradients (e.g., dry/wet, high/low storage capacity, hot/cold) could not easily explain the observed patterns. We anticipate that vegetation related processes (e.g., phenology, rooting depth, gas exchange characteristics, disturbance, etc.) may prove to be important in explaining hydrologic variability in these biologically productive regions that support most of human population. This result implies that a ~~A~~ major scientific effort will be needed to develop a synthesis of ~~iscover~~ the controlling factors for variability of the water cycle in these environments.

5. Discussion and Conclusions

~~In this study, we have used a recently released global gridded hydrologic re-analysis product, i.e., the Climate Data Record (CDR) to conduct an initial investigation of inter-annual variability in the terrestrial branch of the global water cycle. To the best of our knowledge, the results in our manuscript present the first attempt to gain a global overview of the magnitude for various terms (Eq. 2) that document variability in the water cycle. Our results demonstrate that the global patterns of inter-annual variability in the water cycle do not simply follow those of the long-term mean. In particular, with the variance calculations, the annual anomalies are squared and hence do not cancel out (like they do when calculating the mean). Hence we were initially surprised that the inter-~~

annual variability of water storage change ($\sigma^2_{\Delta S}$) is typically larger than the inter-annual variability of evapotranspiration (σ^2_E). Moreover, the covariance components are also prominent and can be negative, which means that it is possible for the variability in the sinks (e.g., σ^2_Q, $\sigma^2_{\Delta S}$) can actually exceed the variability in the source (σ^2_P) (Eq. 2).

Our further analysis based on six climate end members, dry/wet, high/low water storage capacity and hot/cold offered some further general insights about hydrologic variability. For example, under extremely dry (water-limited) conditions, with limited storage capacity (S_{max}) we found that E follows P and σ^2_E follows σ^2_P, with σ^2_Q and $\sigma^2_{\Delta S}$ approaching zero. However, as S_{max} increases, the partitioning of σ^2_P progressively shifts to a balance between σ^2_E, $\sigma^2_{\Delta S}$ and cov (E, ΔS) (Fig. 12Figs. 10-12-14). Under extremely wet (energy-limited) and hot environments (i.e., no snow/ice impact) we found the inter-annual variations in P mostly be partitioned to inter-annual variations in Q (with both σ^2_E and $\sigma^2_{\Delta S}$ approaching zero). However, in wet environments that were cold, we expected thermal processes (freeze/melt) to play a critical role in the hydrologic variability. Our results confirm that, with the finding that hydrologic partitioning of variability was highly (spatially) variable under extremely cold conditions (Figs. 10-1212-14) and we were unable to provide any useful simplifications to summarise the data. These results highlight a key point that while the long-term mean state is not especially sensitive to variations in hydrologic water storage or phase, the long-term variability is very sensitive to those same variations.

The most complex results were found in semi-arid/semi-humid ($0.5<\overline{E_o}/\overline{P}<1.5$) environments, where all three covariances (Eq. 2) were found to play critical roles in the overall partitioning of variability (Figs. 3 and Fig. S94-5). In many regions, the (absolute) magnitudes of the covariances were actually larger than the variances of the water balance components E, Q and ΔS (e.g., Fig. 8Fig. 6). That result demonstrates that deeper understanding of the process-level interactions that are embedded within each of the three covariance terms is still needed to help understand variability in the water cycle in these biologically productive regions ($0.5<\overline{E_o}/\overline{P}<1.5$).

This study should be viewed as an initial investigation of the inter-annual variability in the global land water cycle. We managed to obtain some syntheses based on the availability of current data, and we expect that with the improvement of hydrologic databases over the coming years some of the detailed spatial patterns may change. However, even from this initial investigation, some general principles do already appear clear. One general finding is that the global pattern in the partitioning of inter-annual variability in the water cycle is not simply a reflection

~~of patterns in the partitioning of the long-term mean. For example, while the inter-annual water storage change is often (safely) assumed to be negligible in terms of the long-term mean state, it is clear that storage variations are central to understanding inter-annual variability of global water cycle. A second generalisation is that the covariance components (Eq. 2) can be relatively large and are negative in some regions. The consequence is that variability in the sinks (e.g., σ_E^2, $\sigma_{\Delta S}^2$) can, and do, exceed the variability in the source (σ_P^2), especially in biologically productive regions (Fig. 4Fig. 3).~~

~~The syntheses of the long-term mean water cycle originated in 1970s (Budyko, 1974), and it took several decades for those general principles to become widely adopted in the hydrologic community. It remains a challenge to develop a synthesis of hydro-climatic variability in the terrestrial branch of the water cycle, and major intellectual efforts will be needed to develop generally applicable principles.~~

~~6. Conclusions~~

Importantly, hydrologists have long been interested in hydrologic variability~~aware that the water storage effects were going to be important for understanding water cycle variability (e.g., Milly and Dunne, 2002b; Zhang et al., 2008; Donohue et al., 2010; Wang and Alimohammadi, 2012)~~, but without readily available databases it has been difficult to quantify water cycle variability~~. in a consistent way.~~ For example, we are not aware of maps showing global spatial patterns in variance for any terms of the water balance (except for *P*). In this study, we describe an initial investigation of the inter-annual variability of the terrestrial branch in the global water cycle that uses the recently released global monthly Climate Data Record (CDR) database for *P*, *E*, *Q* and ΔS. ~~We start by investigating the partitioning of *P* in the water cycle in terms of long-term mean and then extend that to the inter-annual variability.~~ The CDR is one of the first dedicated hydrologic reanalysis databases and includes data for a 27-year period. Accordingly, we could only examine hydrologic variability over this relatively short period. Further, we expect future improvements and modifications as the hydrologic community seeks to further develop and refine these new reanalysis databases. With those caveats in mind, we started this analysis –by first investigating the partitioning of *P* in the water cycle in terms of long-term mean and then extended ~~that~~ to the inter-annual variability using a theoretical variance balance equation (Eq. 2). Despite the ~~From this~~ initial nature of this investigation we have been able to establish some useful general principles.

The mean annual P is mostly partitioned into mean annual E and Q, as is well known, and the results using the CDR were generally consistent with the earlier ~~previous~~ Budyko framework ~~work~~ (Fig. 2). Having established that, the first general finding is that the spatial pattern in the partitioning of inter-annual variability in the water cycle is not simply a reflection of the spatial pattern in the partitioning of the long-term mean. In particular, with the variance calculations, the annual anomalies are squared and hence the storage anomalies do not cancel out like they do when calculating the mean. With that in mind, w~~W~~e were ~~initially~~ surprised that the inter-annual variability of water storage change ($\sigma^2_{\Delta S}$) is typically larger than the inter-annual variability of evapotranspiration (σ^2_E) (cf. Fig. 3b and 3d). The consequence is that $\sigma^2_{\Delta S}$ is more important than σ^2_E for understanding inter-annual variability of global water cycle. A second important generalisation is that unlike the variance components which are all positive, the three covariance components in the theory (Eq. 2) can be both positive and negative. We report results here showing both large positive and negative values for the three covariance terms ~~can be relatively large and are negative in some regions~~ (Fig. 3efg). ~~The consequence is that variability in the sinks (e.g., σ^2_Q, $\sigma^2_{\Delta S}$) can, and do, exceed the variability in the source (σ^2_P)~~This was especially ~~, especially~~ prevalent in biologically productive regions (0.5≤$\overline{E_o}/\bar{P}$≤1.5, Fig. 3eg). When examining the mean state, we are accustomed to think that P sets a limit to E, Q and ΔS, as per the mass balance (Eq. 1). But the same thinking does not extend to the variance balance since the covariance terms on the right hand side of Eq. 2 can be both large and negative leading to circumstances where the variability in the sinks (σ^2_E, σ^2_Q, $\sigma^2_{\Delta S}$) could actually exceed variability in the source (σ^2_P).

Our initial attempt to develop deeper understanding of variance partitioning was based on a series of case studies located in extreme environments (wet/dry vs hot/cold vs high/low water storage capacity). The results offered some further insights about hydrologic variability. For example, under extremely dry (water-limited) environments, with limited storage capacity (S_{max}) we found that E follows P and σ^2_E follows σ^2_P, with σ^2_Q and $\sigma^2_{\Delta S}$ both approaching zero. However, as S_{max} increases, the partitioning of σ^2_P progressively shifts to a balance between σ^2_E, $\sigma^2_{\Delta S}$ and cov(E, ΔS) (Figs. 10-12). This result explains the overestimation of σ_E/σ_P by the empirical theory of Koster and Suarez (1999) which implicitly assumed no inter-annual change in storage.~~negligible storage variation.~~ The Koster and Suarez ~~at~~ empirical theory is perhaps better described as an upper limit that is based on minimal storage capacity, and that any increase in storage capacity would promote the partitioning of σ^2_P to $\sigma^2_{\Delta S}$ particularly under dry conditions (Figs. 10-12).

In ~~Under~~ extremely wet/hot environments (i.e., no snow/ice presence~~impact~~) we found σ_P^2 to be mostly partitioned to σ_Q^2 (with both σ_E^2 and $\sigma_{\Delta S}^2$ approaching zero, Fig. 10). In contrast, in ~~under~~ extremely wet/cold environments, ~~conditions,~~ the partitioning of σ_P^2 was highly (spatially) variable presumably because of ~~the~~ spatial variability in the all-important thermal processes (freeze/melt). ~~These results highlight a key point that while the long-term mean state is not especially sensitive to variations in either water storage or physical phase (liquid/solid), the overall hydrologic variability is expected to be sensitive to those same variations.~~

The most complex results were found in mesic biologically productive environments ($0.5<\overline{E_o}/\bar{P}<1.5$), where all three covariance terms (Eq. 2) were found to be relatively large and therefore they all played critical roles in the overall partitioning of variability (Fig. 6). As noted above, in ~~In~~ many of these regions, the (absolute) magnitudes of the covariances were actually larger than the variances of the water balance components E, Q and ΔS (e.g., Fig. 3). That result demonstrates that deeper understanding of the process-level interactions that are embedded within each of the three covariance terms (e.g., ~~for instance,~~ the role of seasonal vegetation variation) will be needed to develop process-based understanding of variability in the water cycle in these biologically productive regions ($0.5<\overline{E_o}/\bar{P}<1.5$).

The syntheses of the long-term mean water cycle originated in 1970s (Budyko, 1974), and it took several decades for those general principles to become widely adopted in the hydrologic community. The hydrologic data needed to understand hydrologic variability are only now becoming available. With those data we can begin to develop a process-based understanding of hydrologic variability that can be used for a variety of purposes, e.g., deeper understanding of ~~such as hydrologic water risk analysis,~~ hydro-climatic behaviour, hydrologic risk analysis, climate change assessments and hydrologic sensitivity studies are just a few applications that spring to mind. The initial results presented here show that a major ~~. Major~~ intellectual efforts will be needed ~~are still needed~~ to develop a general understanding of hydrologic variability.

~~. We start by investigating the partitioning of P in the water cycle in terms of long-term mean and then extend that to the inter-annual variability. While the mean annual P is mostly partitioned into mean annual E and Q, as is well known. However, we find that the variance of P (σ_P^2) is mostly partitioned into the variance of Q (σ_Q^2) and variance of ΔS ($\sigma_{\Delta S}^2$). This result indicates that the global patterns of inter-annual variability in the water cycle do not simply follow the long-term mean. A second general finding is that the covariance components are important~~

~~and can be negative in some regions, indicating the variability in the sinks (e.g., σ_Q^2, $\sigma_{\Delta S}^2$) can, and do, exceed the variability in the source (σ_P^2). Our attempts to develop deeper understanding of variance partitioning led to some syntheses in extreme environments (wet/dry vs hot/cold). In particular, we find that in extremely dry environments (either hot/cold) the partitioning of σ_P^2 is closely related to the water storage capacity. With limited storage capacity, the partitioning of σ_P^2 is mostly to σ_E^2 but as the storage capacity increases, the partitioning of σ_P^2 is increasingly shared between σ_E^2 and $\sigma_{\Delta S}^2$ and the covariance between those variables (Fig. 14Fig. 12). In contrast, in extremely wet environments, there are large divergences in the variance partitioning between hot and cold conditions. In hot conditions, σ_P^2 is mostly partitioned to σ_Q^2 but under cold conditions, σ_P^2 is partitioned to all available variability sinks (Fig. 14Fig. 12). However, in biologically productive semi-arid/semi humid ($0.5<\overline{E_o}/\bar{P}<1.5$) environments, we found the variance partitioning to be very complex and that partitioning was not obviously associated with simple environmental factors. A general understanding of hydro-climatic variability remains a major intellectual challenge and we anticipate major efforts will be needed to synthesise general principles that cover the full spectrum of hydrologic variability.~~

Acknowledgements

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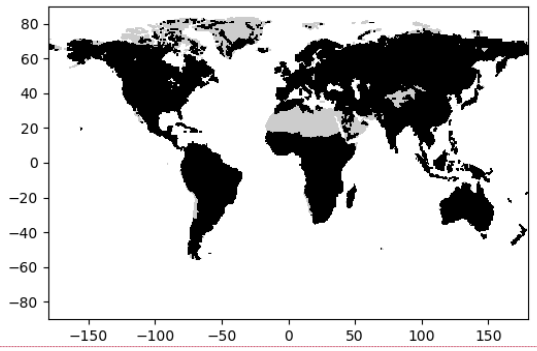
List of Figures:



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~~Figure 1. Spatial mask used in this study. Grey areas (Himalayan region, Sahara Desert, Greenland) have been masked out of the CDR database.~~

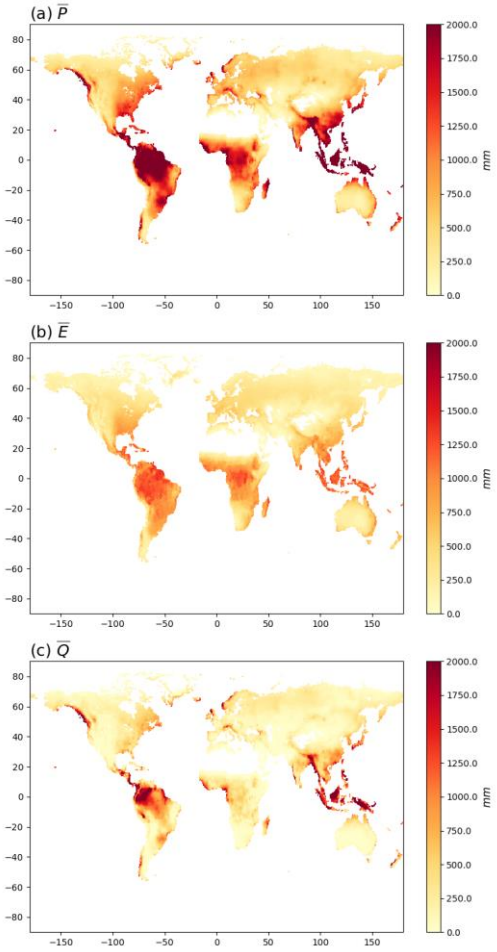

Figure 12. Mean annual (1984-2010) (a) *P*, (b) *E* and (c) *Q*. Note that the mean annual ΔS in the CDR database is zero by construction and is not shown.

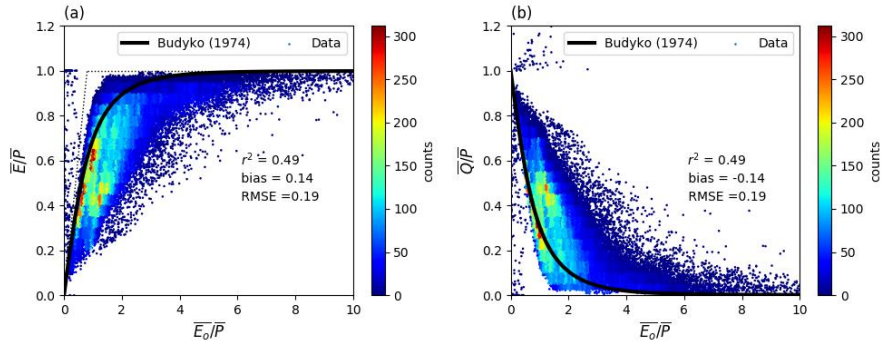

Figure 2~~3~~. Relationship of mean annual (a) evapotranspiration ($\overline{E}/\overline{P}$) and (b) runoff ($\overline{Q}/\overline{P}$) ratios to the aridity index ($\overline{E_o}/\overline{P}$) from the CDR and SRB databases. For comparison, the Budyko (1974) curve is shown on the left panel (~~Fig. 3~~Fig. 2a). The curve on the right panel (~~Fig. 3~~Fig. 2b) is calculated assuming a steady state ($\overline{Q}/\overline{P} = 1 - \overline{E}/\overline{P}$).

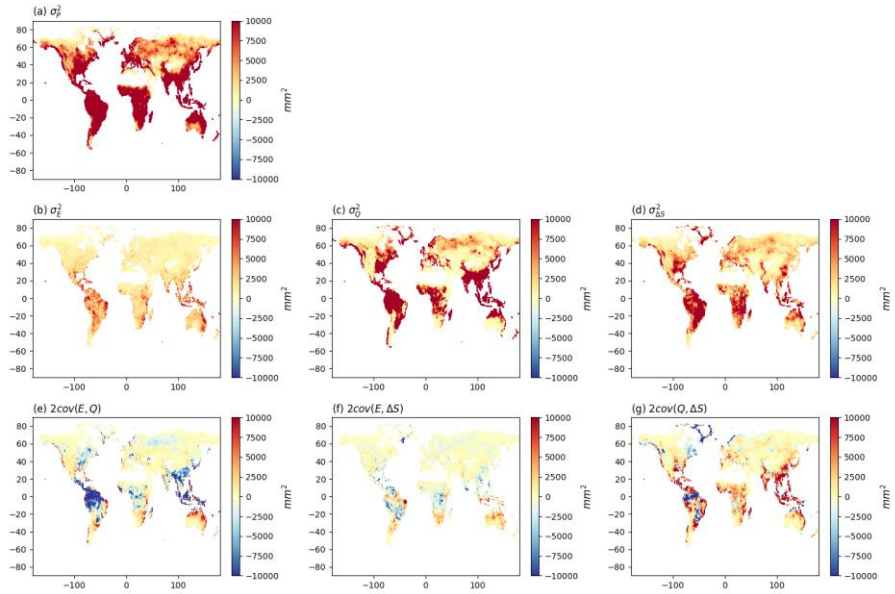

Figure 34. Water cycle variances (σ_P^2, σ_E^2, σ_Q^2, $\sigma_{\Delta S}^2$) and covariances ($cov(E,Q)$, $cov(E,\Delta S)$, $cov(Q,\Delta S)$). Note that we have multiplied the covariances by two (see Eq. 2).

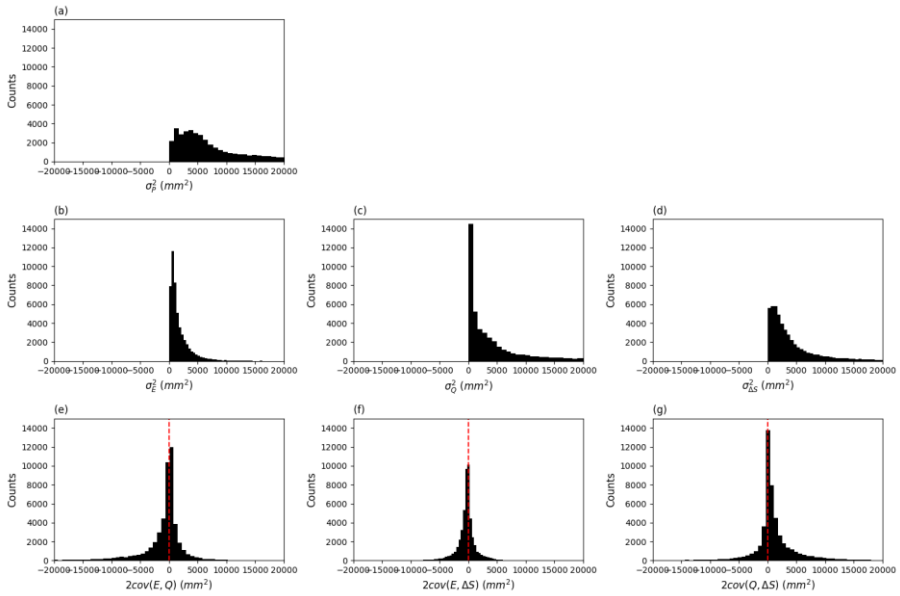

Figure 5. Distribution of water cycle variances (σ_P^2, σ_E^2, σ_Q^2, $\sigma_{\Delta S}^2$) and covariances ($cov(E,Q)$, $cov(E,\Delta S)$, $cov(Q,\Delta S)$). Note that we have multiplied the covariances by two (see Eq. 2).

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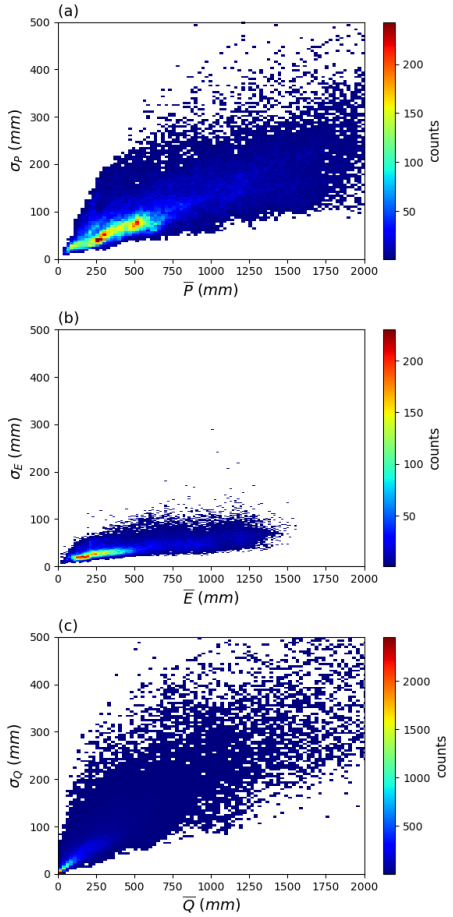


Figure 46. Relation between inter-annual mean and standard deviation for (a) *P*, (b) *E* and (c) *Q* from the CDR database. Note that the mean annual ΔS is zero by construction and is not shown.

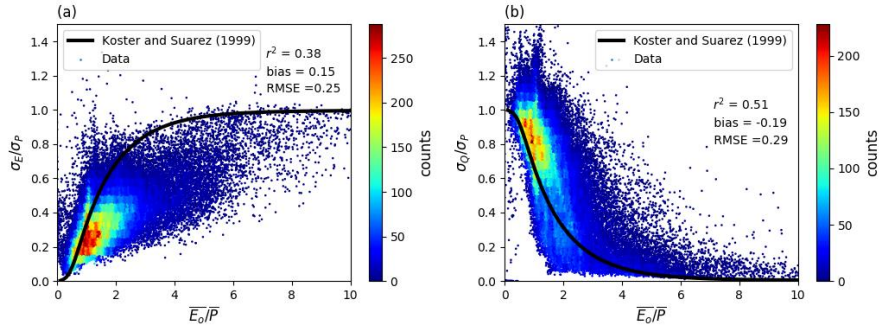


Figure 5~~7~~. Relationship of inter-annual standard deviation of (a) evapotranspiration (σ_E/σ_P) and (b) runoff (σ_Q/σ_P) ratios to aridity ($\overline{E_o}/\overline{P}$). The curves represent the semi-empirical relations from Koster and Suarez (1999).

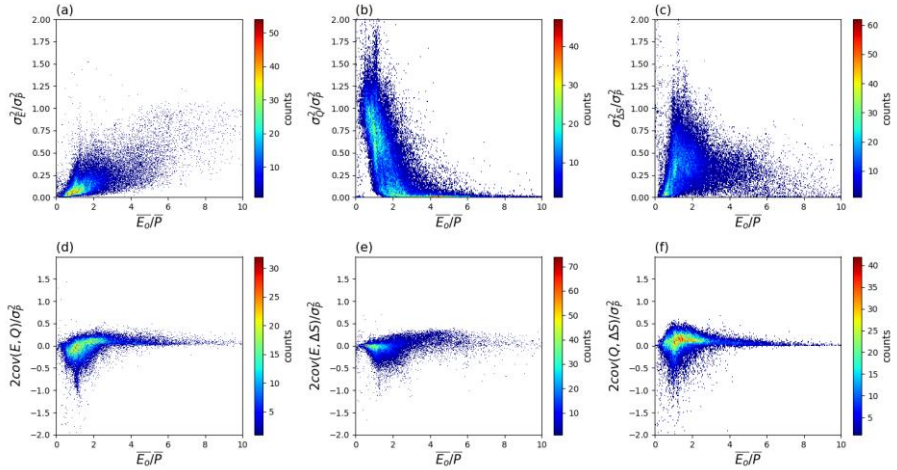


Figure ~~6~~8. Relation between water cycle variances-covariances (see ~~Fig. 4~~Fig. 3b-g) as a fraction of the variance of *P* (σ_P^2) and the aridity index ($\overline{E_o}/\overline{P}$) coloured by density. Note that we have multiplied the covariance components by two (see Eq. 2).

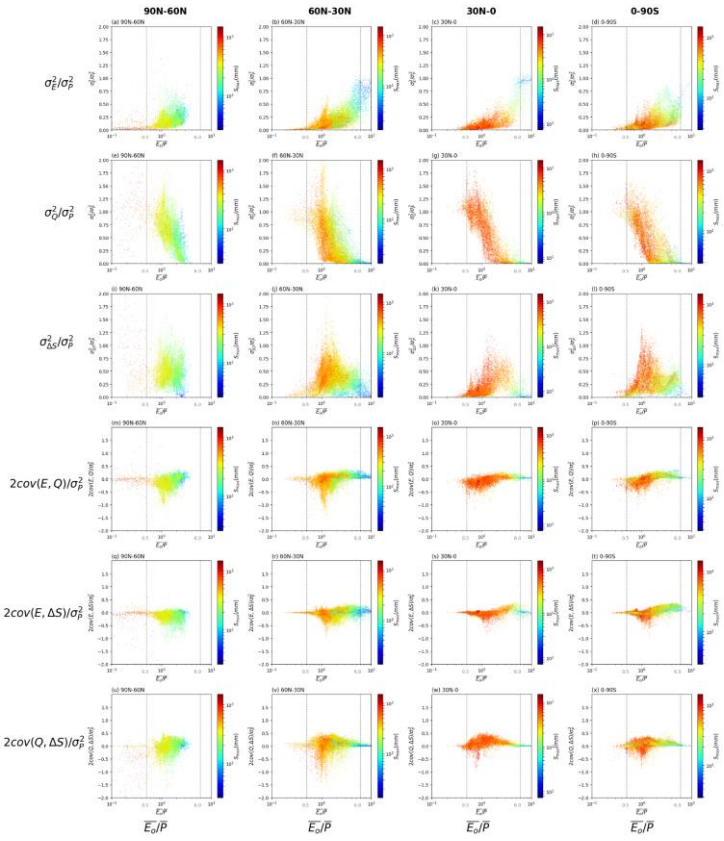


Figure 7~~9~~. Relation between water cycle variances-covariances (see ~~Fig. 4~~Fig. 3b-g) as a fraction of the variance for *P* (σ_P^2) and the aridity index ($\overline{E_o}/\overline{P}$) for grid-cells over different latitude ranges (i.e., 90N-60N, 60N-30N, 30N-0 and 0-90S). The colours relate to the water storage capacity S_{max}. Note that we have multiplied the covariances by two (see Eq. 2). The vertical grey dashed lines represent thresholds used to separate extremely dry ($\overline{E_o}/\overline{P} \geq 6.0$) and wet ($\overline{E_o}/\overline{P} \leq 0.5$) environments. Note the use of a logarithmic x-axis and scale bar for S_{max}.

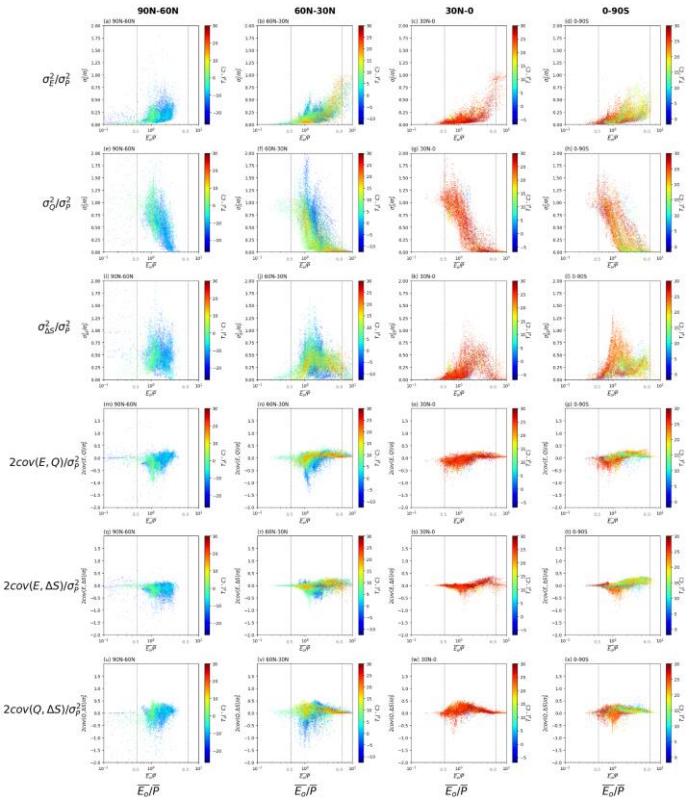


Figure 8~~10~~. Relation between water cycle variances-covariances (see ~~Fig. 4~~Fig. 3b-g) as a fraction of the variance for *P* (σ_P^2) and the aridity index ($\overline{E_o}/\overline{P}$) for grid-cells over different latitude ranges (i.e., 90N-60N, 60N-30N, 30N-0 and 0-90S). The colours relate to the mean air temperature ($\overline{T_a}$). Note that we have multiplied the covariances by two (see Eq. 2). The vertical grey dashed lines represent thresholds used to separate extremely dry ($\overline{E_o}/\overline{P} \geq 6.0$) and wet ($\overline{E_o}/\overline{P} \leq 0.5$) environments.

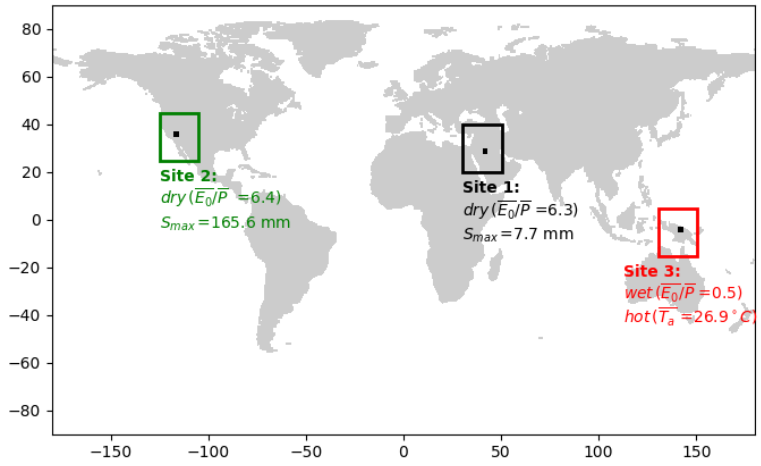
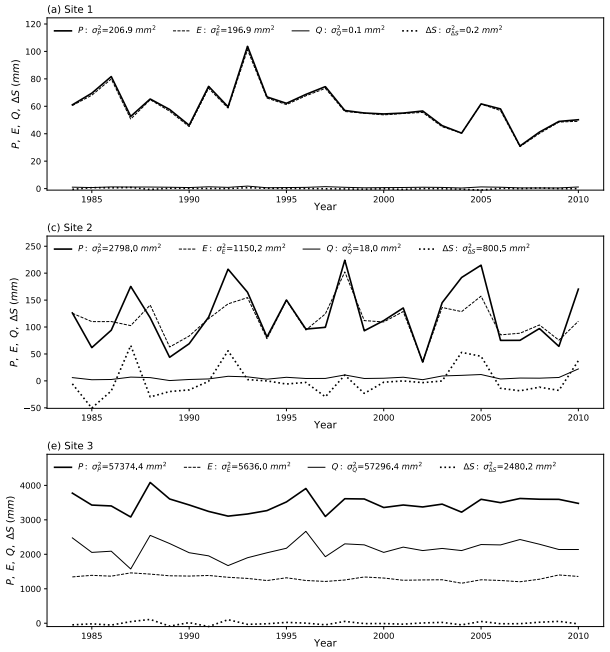


Figure ~~9~~11. Locations of three representative grid-cells used as case study sites.



(b) Variance-covariance matrix (Site 1, unit: mm^2)

	E	*Q*	*ΔS*
E	196.9	3.4	1.5
Q	3.4	0.1	0.0
ΔS	1.5	0.0	0.2
Inter-annual variance of *P* : 206.9			

*Note: The values along the diagonal of each line are variance values for *E*, *Q*, and *ΔS*, and other values are covariance values between the two crossed components.

(d) Variance-covariance matrix (Site 2, unit: mm^2)

	E	*Q*	*ΔS*
E	1150.2	71.2	269.2
Q	71.2	18.0	74.3
ΔS	269.2	74.3	800.5
Inter-annual variance of *P* : 2798.0			

(f) Variance-covariance matrix (Site 3, unit: mm^2)

	E	*Q*	*ΔS*
E	5636.0	-4548.6	651.7
Q	-4548.6	57296.4	-122.2
ΔS	651.7	-122.2	2480.2
Inter-annual variance of *P* : 57374.4			

Figure 102. Inter-annual time series (*P*, *E*, *Q* and *ΔS*) and the associated variance-covariance matrix (*E*, *Q* and *ΔS*) for case study Sites 1-3. Left column shows time series for (a) Site 1, (c) Site 2 and (e) Site 3, with right column i.e., (b), (d) and (f), the associated variance-covariance matrix for three sites. Note that the covariance values in the tables should be multiplied by two to agree with the variance-covariance balance in Eq. (2).

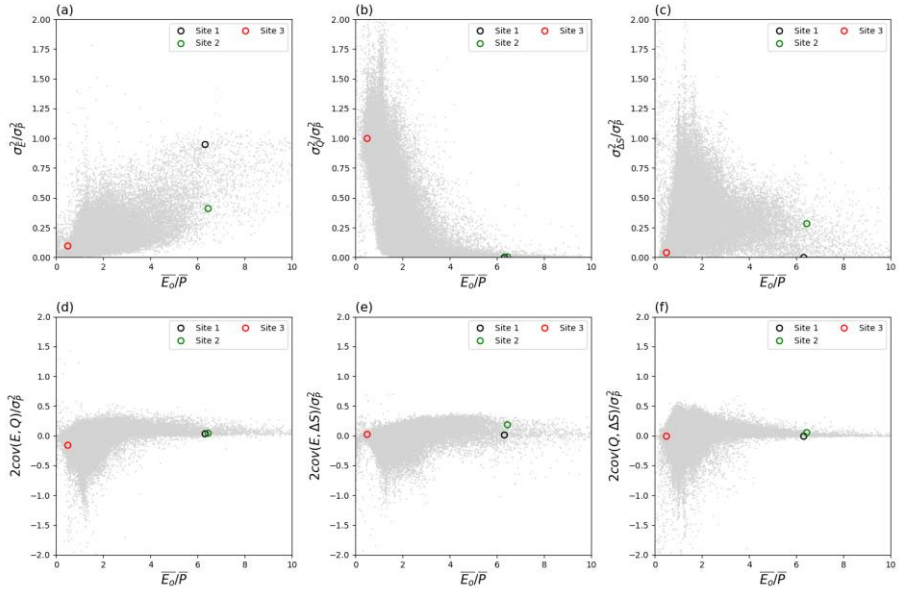


Figure 1~~1~~3. Location of three case study sites in the water cycle variability space. The grey background dots are from ~~Fig. 8~~Fig. 6.

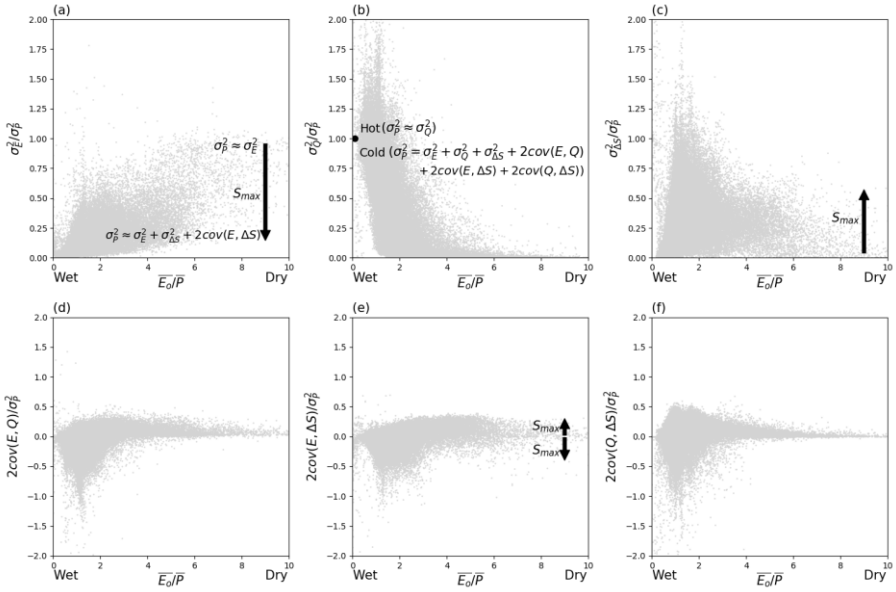


Figure 1~~2~~4. Synthesis of factors controlling variance partitioning. The arrows denote trends with increasing S_{max}. The grey background dots are from ~~Fig. 8~~Fig. 6.

Inter-annual variability of the global terrestrial water cycle

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Supplementary Material

This Supplementary Material contains Figures S1-S12~~10~~ and Table S1.

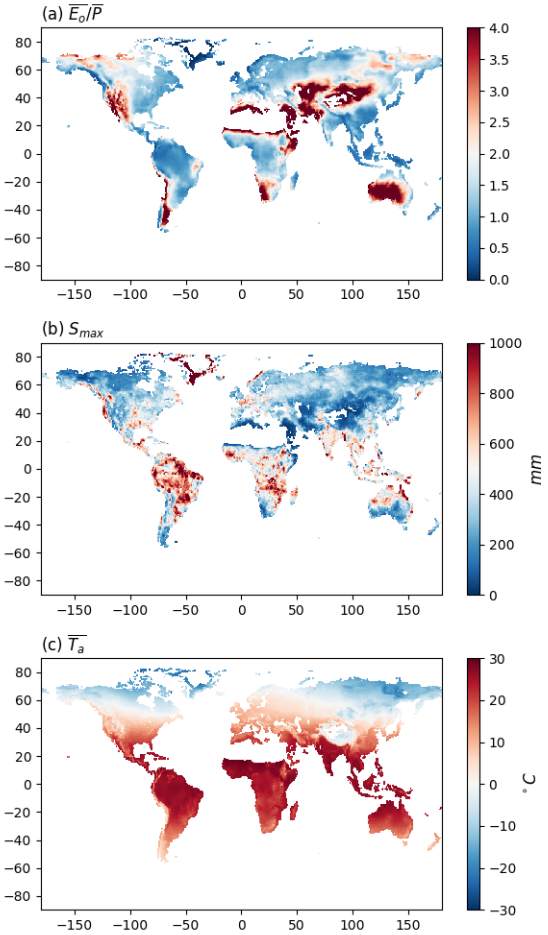


Figure S1. (a) Aridity index ($\overline{E_o}/\overline{P}$), (b) water storage capacity (S_{max}) and (c) mean annual air temperature ($\overline{T_a}$) used in the analysis.

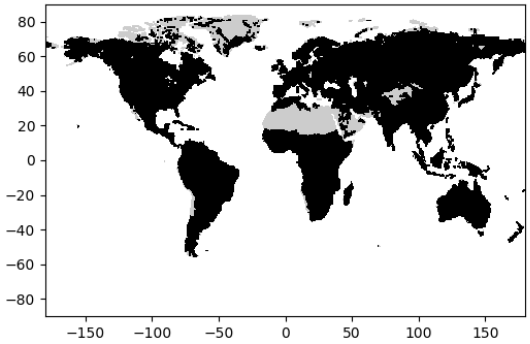


Figure S2. Spatial mask used in this study. Grey areas (e.g., Himalayan region, Sahara Desert, Greenland) have been masked out of the CDR database.

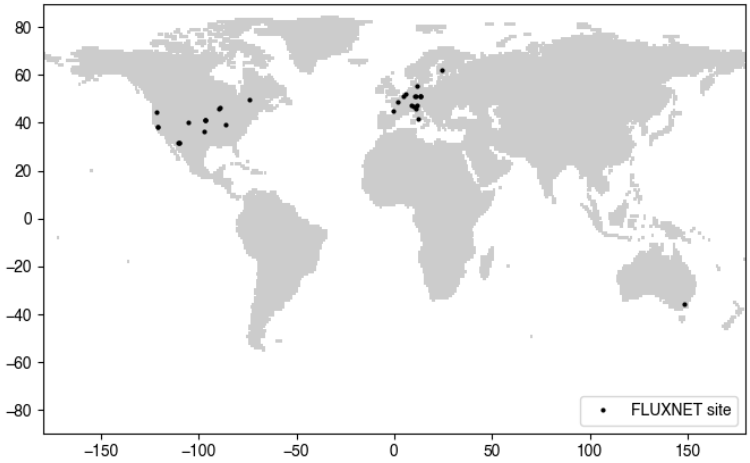


Figure S32. Location of the 32 FLUXNET sites used to evaluate the ~~compared with the~~ Climate Data Record (CDR).

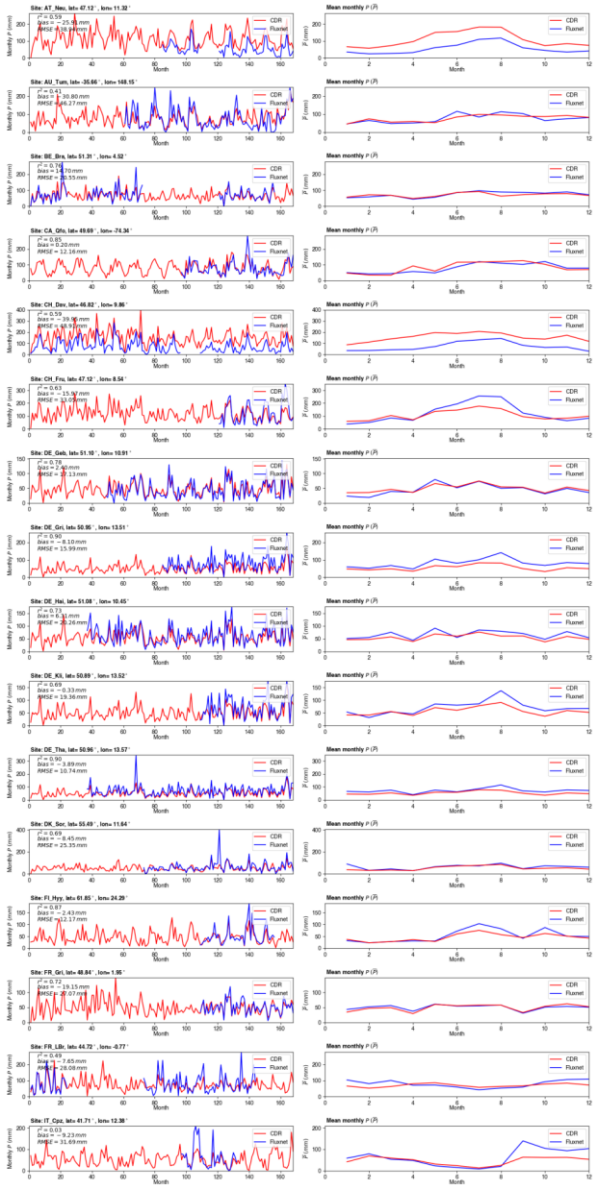


Figure S43. Comparison of monthly precipitation *P* time series (left panels) and mean monthly *P* (right panels) between FLUXNET ~~site~~ observations at 32 sites (Table S1) and the Climate Data Record (CDR).

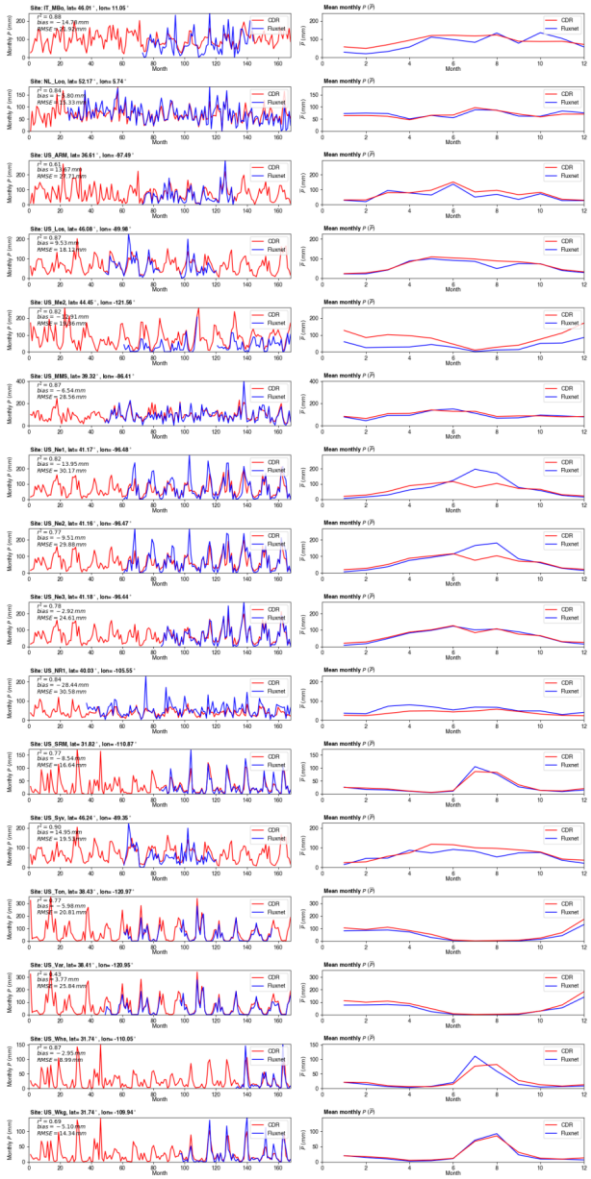


Figure S43 continued.

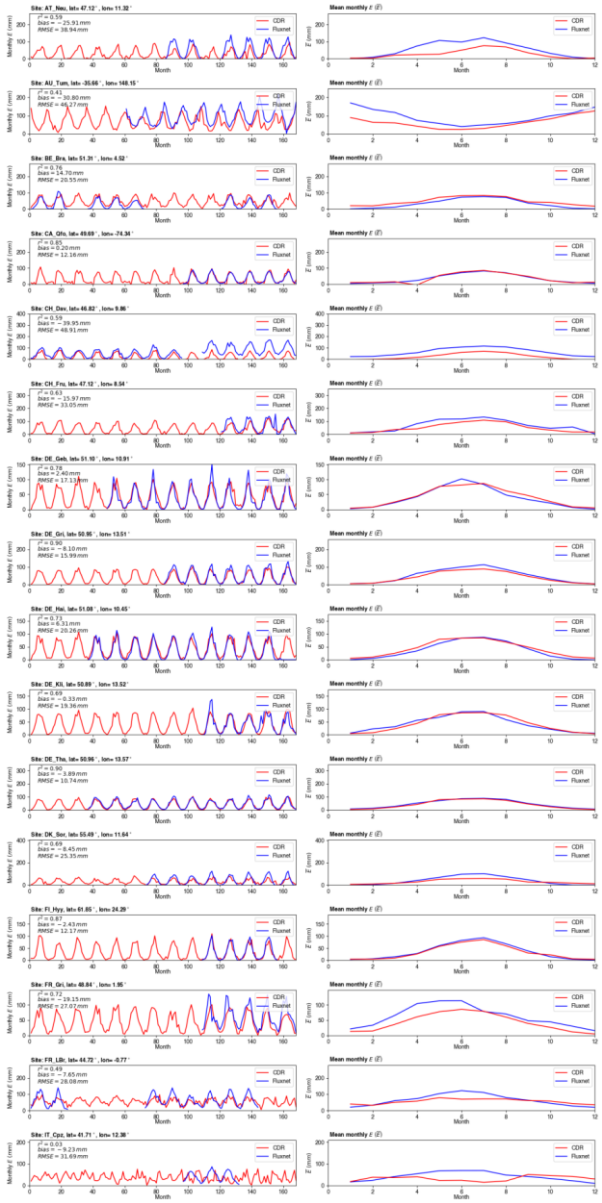


Figure S54. Comparison of monthly evapotranspiration *E* time series (left panels) and mean monthly *E* (right panels) between FLUXNET site observations and the Climate Data Record (CDR).

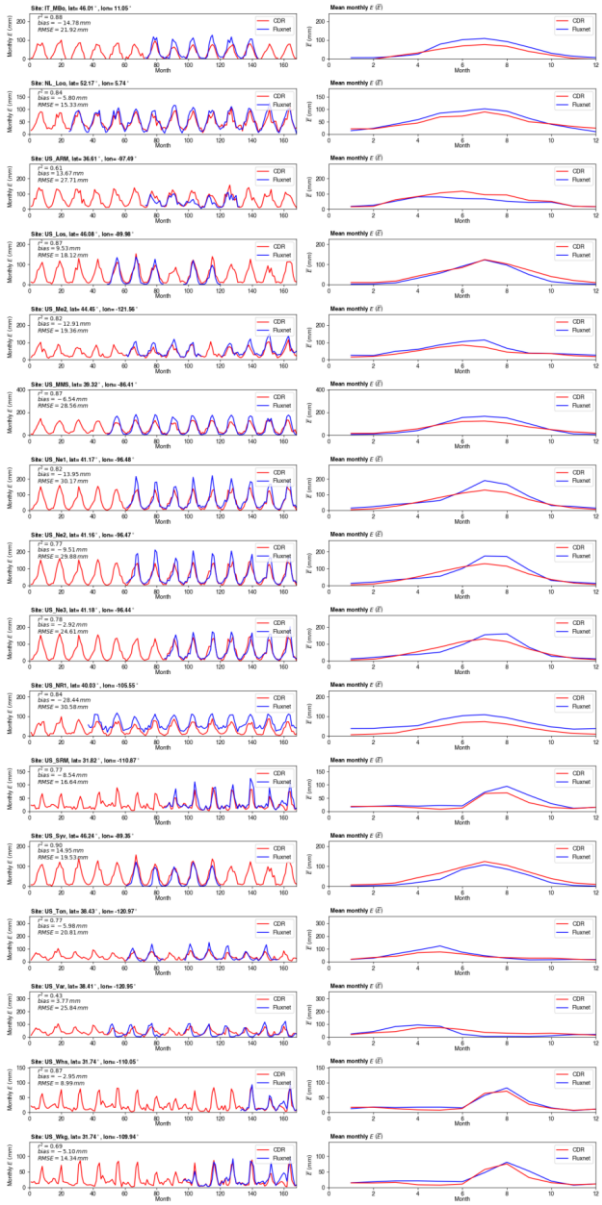
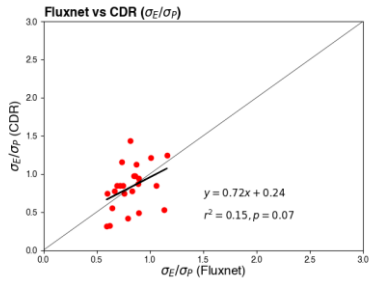


Figure S54 continued.



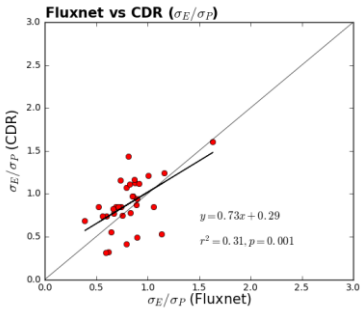


Figure S65. Comparison of ratio of standard deviation of monthly evapotranspiration *E* to precipitation *P* (σ_E/σ_P) between FLUXNET site observations and the Climate Data Record (CDR).

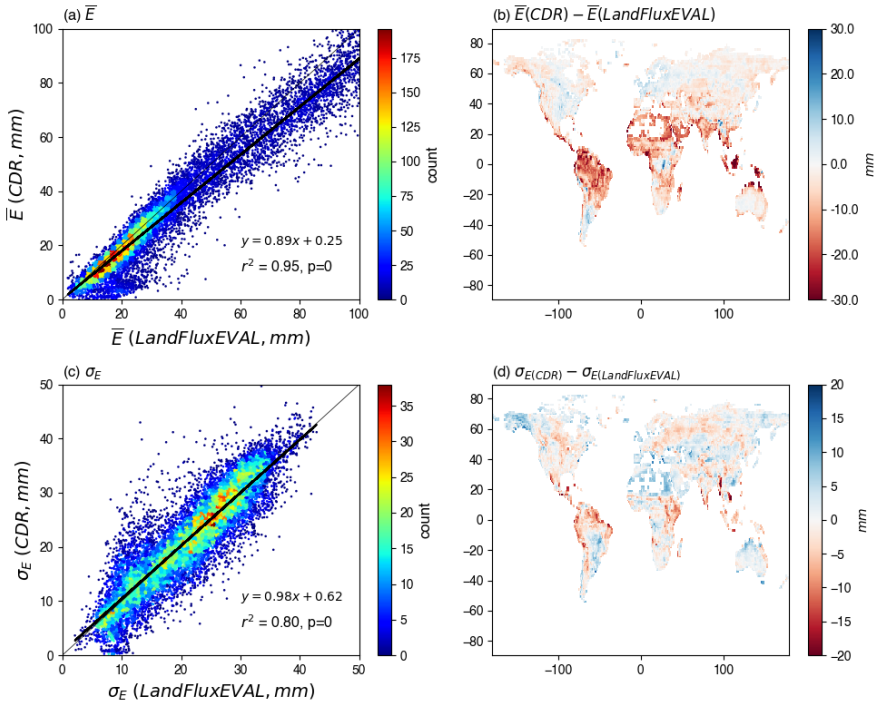


Figure S76. Comparison of monthly evapotranspiration *E* between LandFluxEVAL and Climate Data Record (CDR) databases. Top panels (a) (b) show comparison of the mean monthly ($\overline{E}$) while bottom panels (c) (d) show comparison of the standard deviation (σ_E) of monthly *E*.

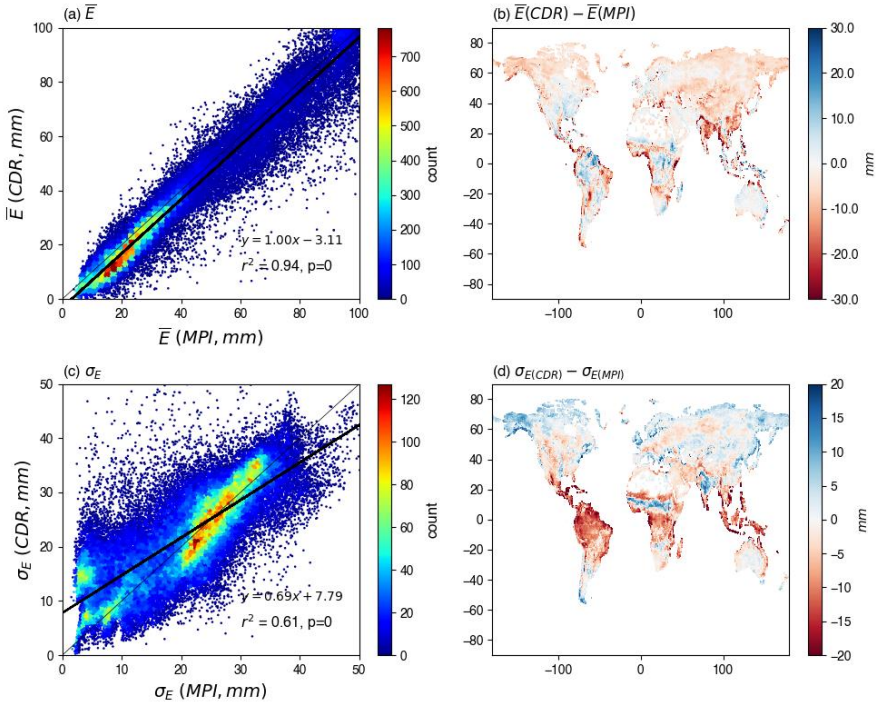


Figure S8. Comparison of monthly evapotranspiration *E* between Max Planck Institute (MPI) and Climate Data Record (CDR) databases. Top panels (a) (b) show comparison of the mean monthly ($\overline{E}$) while bottom panels (c) (d) show comparison of the standard deviation (σ_E) of monthly *E*.

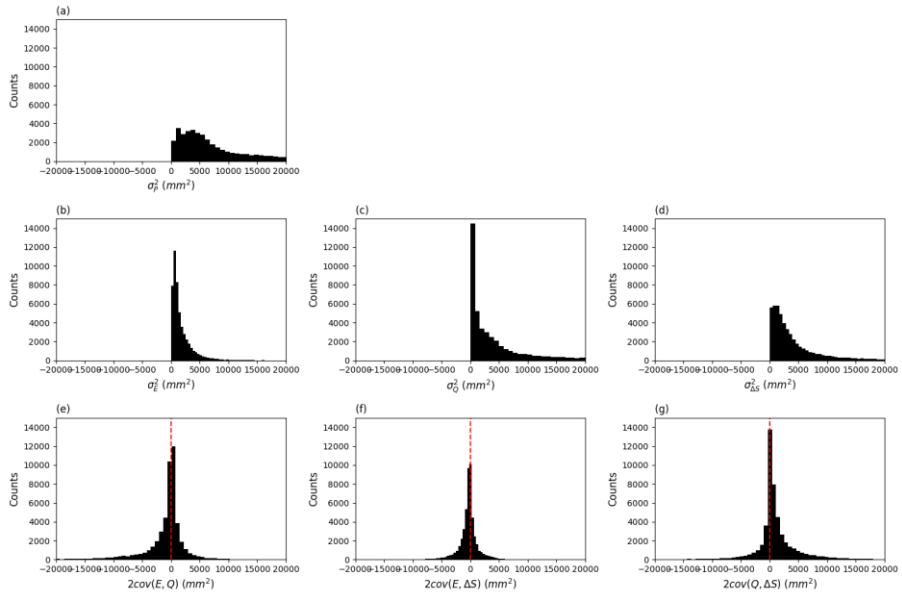


Figure S9. Distribution for each of the ~~of~~ water cycle variances (σ_P^2, σ_E^2, σ_Q^2, $\sigma_{\Delta S}^2$) and covariances ($cov(E, Q)$, $cov(E, \Delta S)$, $cov(Q, \Delta S)$) shown in Fig. 3. Note that we have multiplied the covariances by two (see Eq. 2).

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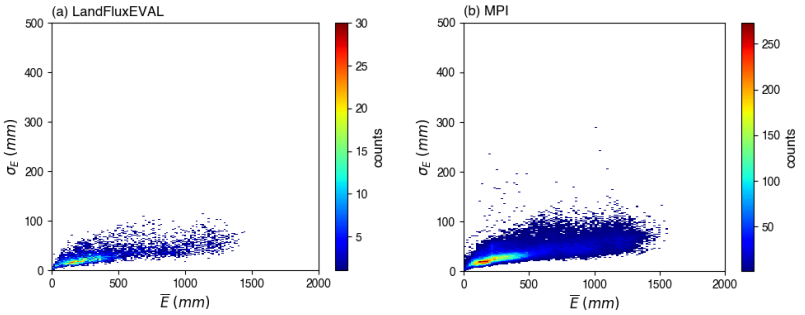

Figure S108. The same as Fig. 46b in main text but using evapotranspiration *E* data from the (a) LandFluxEVAL and (b) MPI databases.

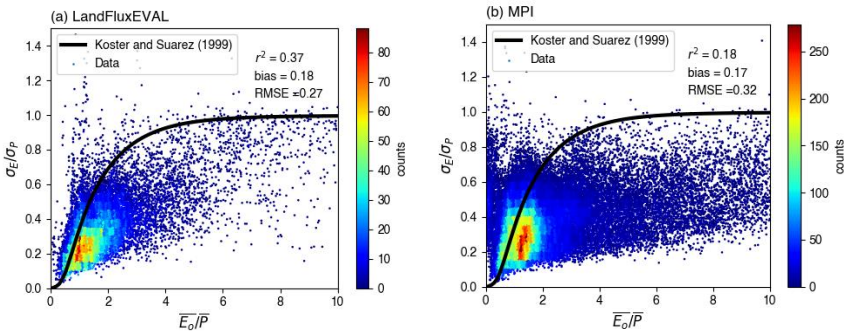

Figure S119. The same as Fig. 57a in main text but using evapotranspiration *E* data from the (a) LandFluxEVAL and (b) MPI databases.

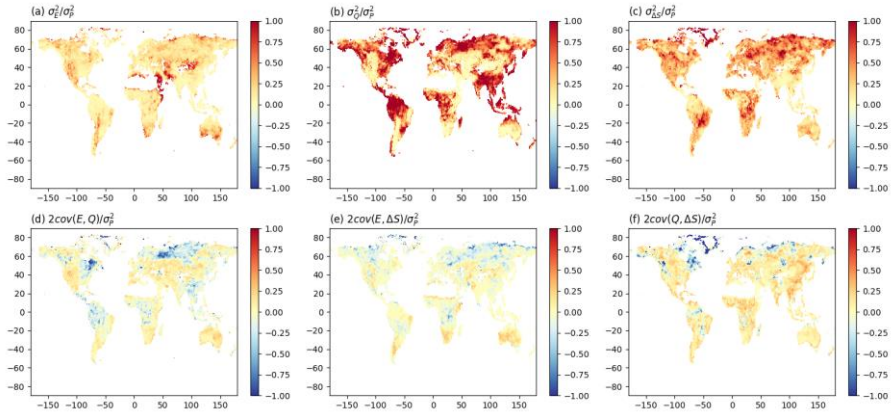

Figure S120. Inter-annual water cycle variances (σ_E^2, σ_Q^2, $\sigma_{\Delta S}^2$) and covariances ($cov(E,Q)$, $cov(E,\Delta S)$, $cov(Q,\Delta S)$) expressed as a fraction of the variance of *P* (σ_P^2). Note that we have multiplied the covariances by two (see Eq. 2).

Table S1. Summary of comparisons of monthly precipitation *P* and evapotranspiration *E* between observations at 32 FLUXNET sites and the CDR database.

Site ID	Site Name	Lat	Lon	Ref	Data period	r^2 (*P*)	bias (*P*, mm)	RMSE (*P*, mm)	r^2 (*E*)	bias (*E*, mm)	RMSE (*E*, mm)
AT_Neu	Neustift	47.1167	11.3175	Wohlfahrt et al., 2008	2004 - 2005, 2007 - 2010	**0.64**	53.54	61.53	**0.59**	-25.91	38.94
AU_Tum	Tumbarumba	-35.6566	148.1517	Leuning et al., 2005	2002 - 2010	**0.56**	1.08	39.34	**0.41**	-30.80	46.27
BE_Bra	Brasschaat	51.3076	4.5198	Carrara et al., 2004	1997 - 1998, 2000 -2002, 2007 - 2009	**0.64**	-3.05	26.66	**0.76**	14.70	20.55
CA_Qfo	Quebec - Eastern Boreal, Mature Black Spruce	49.6925	-74.3421	Bergeron et al., 2006	2005 - 2010	**0.57**	4.43	31.77	**0.85**	0.20	12.16
CH_Dav	Davos	46.8153	9.8559	Zielis et al., 2014	1997 - 2004, 2006 - 2010	**0.64**	82.53	91.39	**0.59**	-39.95	48.91
CH_Fru	Früebüel	47.1158	8.5378	Imer et al., 2013	2007 - 2010	**0.65**	-15.42	55.86	**0.63**	-15.97	33.05
DE_Geb	Gebesee	51.1001	10.9143	Anthoni et al., 2004	2001 - 2010	**0.69**	3.78	17.69	**0.78**	2.40	17.13
DE_Gri	Grillenburg	50.9500	13.5126	Prescher et al., 2010	2004 - 2010	**0.70**	-26.32	37.67	**0.90**	-8.10	15.99
DE_Hai	Hainich	51.0792	10.4530	Knohl et al., 2003	2000 - 2012	**0.70**	-10.35	23.17	**0.73**	6.31	20.26
DE_Kli	Klingenberg	50.8931	13.5224	Prescher et al., 2010	2006 - 2010	**0.68**	-13.61	28.05	**0.69**	-0.33	19.36
DE_Tha	Tharandt	50.9624	13.5652	Grünwald and Bernhofer, 2007	2000 - 2010	**0.66**	-18.71	32.35	**0.90**	-3.89	10.74
DK_Sor	Soroe	55.4859	11.6446	Pilegaard et al., 2011	2003 - 2010	**0.45**	-11.07	39.31	**0.69**	-8.45	25.35
FI_Hyy	Hyytiala	61.8474	24.2948	Suni et al., 2003	2006 - 2009	**0.78**	-7.07	20.43	**0.87**	-2.43	12.17
FR_Gri	Grignon	48.8442	1.9519	Loubet et al., 2011	2006 - 2010	**0.69**	-0.81	12.35	**0.72**	-19.15	27.07
FR_LBr	Le Bray	44.7171	-0.7693	Berbigier et al., 2001	1997 -1998, 2003 - 2008	**0.56**	-9.19	39.93	**0.49**	-7.65	28.08
IT_Cpz	Castelporziano	41.7053	12.3761	Garbulsky et al., 2008	2005 - 2007	**0.76**	-15.90	40.42	0.03	-9.23	31.69

IT_MBo	Monte Bondone	46.0147	11.0458	Marcolla et al., 2011	2003 - 2008	**0.36**	12.43	48.14	**0.88**	-14.78	21.92
NL_Loo	Loobos	52.1666	5.7436	Moors 2012	1999 - 2010	**0.56**	-2.16	24.78	**0.84**	-5.80	15.33
US_ARM	ARM Southern Great Plains site-Lamont	36.6058	-97.4888	Baldocchi and Sturtevant 2015	2003 - 2007	**0.71**	13.53	31.78	**0.61**	13.67	27.71
US_Los	Lost Creek	46.0827	-89.9792	Baker et al., 2003	2001 - 2003, 2005 - 2006	**0.52**	7.76	32.82	**0.87**	9.53	18.12
US_Me2	Metolius mature ponderosa pine	44.4523	-121.5574	Law (2002-2014)	2002 - 2005, 2007 - 2010	**0.54**	45.31	56.84	**0.82**	-12.91	19.36
US_MMS	Morgan Monroe State Forest	39.3232	-86.4131	Novick and Phillips (1999-2014)	2001 - 2010	**0.72**	6.60	31.44	**0.87**	-6.54	28.56
US_Ne1	Mead - irrigated continuous maize site	41.1651	-96.4766	Suyker (2001-2013a)	2002 - 2010	**0.45**	-6.64	51.86	**0.82**	-13.95	30.17
US_Ne2	Mead - irrigated maize-soybean rotation site	41.1649	-96.4701	Suyker (2001-2013b)	2002 - 2010	**0.56**	-8.77	46.45	**0.77**	-9.51	29.88
US_Ne3	Mead - rainfed maize-soybean rotation site	41.1797	-96.4397	Suyker (2001-2013c)	2004 - 2010	**0.88**	2.28	21.43	**0.78**	-2.92	24.61
US_NR1	Niwot Ridge Forest (LTER NWT1)	40.0329	-105.5464	Blanken (1998-2014)	2000 - 2010	**0.51**	-16.06	29.57	**0.84**	-28.44	30.58
US_SRM	Santa Rita Mesquite	31.8214	-110.8661	Barron-Gafford et al., 2011	2004 - 2010	**0.81**	1.34	15.40	**0.77**	-8.54	16.64
US_Syv	Sylvania Wilderness Area	46.2420	-89.3477	Desai et al., 2008	2002 - 2006	**0.33**	13.17	40.68	**0.90**	14.95	19.53
US_Ton	Tonzi Ranch	38.4316	-120.9660	Baldocchi et al., 2010	2002 - 2003, 2005 - 2009	**0.89**	14.68	27.44	**0.77**	-5.98	20.81

US_Var	Vaira Ranch- Ione	38.4133	-120.9507	Baldocchi et al., 2004	2001 - 2003, 2005 - 2010	**0.86**	16.91	30.92	**0.43**	3.77	25.84
US_Whs	Walnut Gulch Lucky Hills Shrub	31.7438	-110.0522	Biederman et al., 2016	2008 - 2010	**0.65**	1.89	21.26	**0.87**	-2.95	8.99
US_Wkg	Walnut Gulch Kendall Grasslands	31.7365	-109.9419	Biederman et al., 2016	2005 - 2010	**0.78**	1.59	15.66	**0.69**	-5.10	14.34

* Significant r^2 values (linear regression $p < 0.05$) are shown in bold.

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