Response to Reviewer #1 Comments:

In this manuscript, Hou et al. estimated water storage dynamics for more than 6,000 reservoirs worldwide from 1984 to 2015 using a combination of Landsat imagery, radar satellite altimetry, and geostatistical modeling. They also analyzed the patterns of increasing and decreasing trends globally. Finally, they attributed reservoir storage changes to climate and human variables and found that precipitation and river inflows largely dominated reservoir storage changes.

I feel this is a very interesting study. Previous studies provided long-term storage changes for only dozes of reservoirs. It is really great to see a global dataset of more than 6,000 reservoirs, as compiled in this study. Their attributions on the reservoir storage changes can potentially inform local to regional water resources management. However, I have some major concerns on the quality of the global dataset and the methodology that they applied to attribute the storage changes.

We thank the reviewer for the detailed and valuable comments and suggestions, which will enable us to greatly improve the quality of our manuscript. Below please find our response to reviewer's comments in detail.

R1C1) The Landsat satellites does not provide global coverage in the 1980s and maybe in the 1990s as well (Murray et al 2019). The authors did not acknowledge this limitation while stating they quantified reservoir storage from 1984 to 2015 globally. Is the produced storage time series consistent through 1984 to 2015? Could you provide a figure documenting the number of observations in each year in the time series from 1984 to 2015?

"Murray, N. J. et al. The global distribution and trajectory of tidal flats."

We agree that Landsat-derived products have limitations on providing observations in the 1980s. But this issue predominantly occurs in Oceania, Siberia, Greenland and parts of central and eastern Asia (Pekel et al. (2016); https://www.nature.com/articles/nature20584/figures/5). Landsat-derived water observations are available from 1984 onwards for most parts of Northern America, South America, Africa, Europe, and western and eastern Asia.

Furthermore, Zhao and Gao (2018) developed an algorithm to fill gaps in time series when the contamination/occultation in a Landsat image is between 5-95%, and applied interpolation and extrapolation for the missing monthly area estimates (i.e., no images or >95% invalid data). As a result, in their reservoir area product, there are 5,917 reservoirs that have Landsat observations every month from 1984 - 2015 (Fig. 1).

Despite that, we were still cautious in using the reservoir area data for long-term storage trend analysis. First, we removed reservoirs for which over five years of data were inter- or extrapolated. Second, we filtered out reservoirs with observations for less than 360 months (30 years), e.g. in New Zealand. After these steps, we found that 4,573 reservoirs constructed before 1984 have consistent Landsat observations and these were used for long-term analysis, compared to the 6,690 reservoirs for which we produced monthly storage dynamics.

We will better explain these steps in the revised manuscript.

R1C2) While this study produces storage changes for a greater amount of reservoirs globally, I do not think the authors fully addressed the limitations that prevent previous studies from documenting reservoir storage dynamics with a better spatial coverage. The authors estimated storage changes for the 132 large reservoirs with both water areas and levels without assessing their consistency. Without a high correlation between water areas and levels, it makes no sense to me to combine these two to deduce storage changes. The authors need to refer to existing studies (e.g., Busker et al.) on quality control before simply combining satellite observations. The authors used a geostatistical method to estimate the storage changes in the vast majority of reservoirs, on which I have an even greater concern. The authors need to be aware that the mean depth, as archived in the HydroLakes dataset, is a ratio of the total volume and maximum lake area. The mean depth does not provide any meaningful information of the actual water depth. Additionally, the geostatistical model adopted by Messager et al. is a spatial model measuring the relationship between the total storages and maximum areas for a large group of water bodies. The authors tried to use the outcome (e.g., mean depth) to estimate storage changes in each individual reservoir, which differs from the purpose of the Messager et al. Unless the authors provide a comprehensive validation, I am not convinced the proposed method is feasible to estimate storage changes for the majority of studied reservoirs here.

"Busker, T. et al. A global lake and reservoir volume analysis using a surface water dataset and satellite altimetry. Hydrol. Earth Syst. Sci. 23, 669–690 (2019)."

"Messager, M. L., Lehner, B., Grill, G., Nedeva, I. & Schmitt, O. Estimating the volume and age of water stored in global lakes using a geo-statistical approach. Nat. Commun. 7, (2016)."

We thank the review for this suggestion. Following comments R1C2 and R1C7, we will increase correlation (R) thresholds between A-L and between A-V for reservoir storage estimation. We regard R values above 0.7 as indicating strong correlation, and will use this as the correlation threshold. For group A, we will only calculate reservoir storage when the correlation between A-L is above 0.7. Storage dynamics between 1984-1993 (when altimetry data is not available) will be estimated using A if the correlation between A-V is above 0.7 between 1993-2015. We will update the subsequent long-term analysis as well. We can confirm that these stricter measures do not affect the conclusions of our study, however.

We would like to clarify that we did not directly use the mean depth archived in the HydroLAKES dataset (Messager et al., 2016). Indeed, this value is not related to the geo-statistical model and is simply the ratio of the reported volume and lake area. Rather, the geo-statistical model provides the empirical relationship of the mean depth with water surface area and the average slope within a 100 m buffer around the water body (Table S2; Supplementary Material). Messager et al. (2016) have validated the predicted lake depth and volume derived from the geo-statistical model against observed data. The symmetric mean absolute percent error (Eq. (1)) and correlation between predicted and observed lake depth are 47.4% and 0.71,

respectively (Messager et al., 2016). Furthermore, the SMAPE and correlation between predicted and reference volume are 48.8% and 0.95, respectively (Messager et al., 2016).

$$SMAPE = 100 \times \frac{1}{N} \sum \frac{|\text{observed value} - \text{predicted value}|}{(\text{observed value} + \text{predicted value})/2} \quad \textbf{(1)}$$

We used this statistical model to estimate reservoir depth and volume dynamics from 1984-2015. We will clarify how we used the geo-statistical model for storage estimation in the revised manuscript. In addition, also responding to comments R1C2 and R1C13, we will include the absolute error (SMAPE) in Fig.2 and Fig.3 (L205-210) and list the SMAPE and correlation metrics (Table 1 and 2) for individual reservoirs in supplementary material.

R1C3) The presented attribution on reservoir storage changes seems to be so simplified that I have many concerns. First, the authors simply compared the directions of the trend in reservoir storage versus that in potential drivers but the analysis only produces coincidence rather than causation. Second, the authors conclude that the evaporation did not significantly impact the reservoir storage but the calculation for the evaporation is too cheap. The authors may need to use more advanced approaches (e.g., Zhao and Gao) in order to draw a confident conclusion. Third, reservoirs, particularly large ones as documented in GranD dataset, are highly regulated by humans. The authors depend on the outputs of global models on estimating human water release from reservoirs. Are the data really reliable for producing trend in human release for each reservoir? In sum, the authors need to pay careful attention to these limitations that potentially affect their conclusions.

"Zhao, G. & Gao, H. Estimating reservoir evaporation losses for the United States: Fusing remote sensing and modeling approaches. Remote Sens. Environ. 226, 109–124 (2019)"

We thank the reviewer for this comment, but in fact we explicitly considered the difference between coincidence and causation in our study. In a first step, we indeed looked at the coincidence of trends. We identified that the spatial distribution of trends of storage and in situ river flow show very similar global patterns (Fig. 4; L225-227). We could not relate each individual reservoir to a corresponding river gauge because the limited number of gauging stations upstream of reservoirs cannot accurately represent overall reservoir inflows. In a second step, therefore, we performed trend analysis using modeled river flow (validated against in situ river flow in Fig.8b; L272-275) at the basin scale, given total basin water storage can be expected to respond to a change in overall precipitation and streamflow. We confirmed the same directions of trends between precipitation, streamflow and reservoir storage in most basins globally, though not all (Fig. 7; L269-271). Third, we focused more on attribution by calculating Pearson correlations among the different variables, which obviously can provide evidence for, but not proof of, a causative relationship. Thus, we showed that there are reasonably strong correlations among linear trends in precipitation, streamflow and reservoir storage (Fig. 8a and c; L272-275). Furthermore, positive relationships between annual time series of storage change and reservoir inflow and between reservoir inflow and precipitation were found in a majority of

basins globally (Fig. 9; L276-278). We will attempt to clarify the logic of our analysis in the revised manuscript.

With regards reservoir evaporation, we believe our estimates are robust. Zhao and Gao (2019) estimated evaporation losses for 721 reservoirs in the contiguous United States using three different meteorological datasets, including TerraClimate, North American Land Data Assimilation System phase 2 (NLDAS-2) forcing and Global Land Data Assimilation System Version 2 and Version 2.1 (GLDAS-2 and GLDAS-2.1). We used their monthly reservoir evaporation amount (1000 m^3/month) to analyse the trends in net evaporation and compared the trends with the ones derived from the W3 model (Van Dijk et al. 2018) for 721 reservoirs. The results show strong agreement in derived linear trends, especially with regard to the more detailed TerraCliamte dataset (Fig.2). Various hydrological variables estimated by the W3 model have been evaluated in previous studies. Therefore, we argue that the E_0 derived from the W3 model are entirely appropriate to analyze linear trends in net evaporation.

The eartH2Observe model estimates do not include the impacts of reservoirs on river flows, and there is currently no global hydrological model that is capable of estimating the impact of historical operational water management at the reservoir or basin level with any acceptable degree of accuracy. Instead, we focused on all relevant variables for the reservoir water balance and tried to infer the influence of the remaining unknown variable (i.e. reservoir releases). Specifically, we did analyse the interaction between precipitation/streamflow/evaporation and reservoir volume and inferred the influence of human activity given that the water volume dynamics in a reservoir is the net balance of inflow (streamflow, affected by precipitation), net evaporation (i.e., evaporation minus direct precipitation) and reservoir releases (L306-312). We will clarify the approach to infer the role of human activity in reservoir storage long-term changes in the revised manuscript.

Specific comments:

R1C4) Line 25: “The majority of …particularly in South America, Southeast Asia and Africa”. The authors may consider add more relevant references here.

“Wang, J. et al. GeoDAR: Georeferenced global dam and reservoir database for bridging attributes and geolocations. Earth Syst. Sci. Data 0–52 (2021)”

“Mulligan, M., van Soesbergen, A. & Sáenz, L. GOODD, a global dataset of more than 38,000 georeferenced dams. Sci. Data 7, 1–8 (2020).”

Thanks. We will include these two references.

R1C5) Line 65: Schwatke et al. 2019 is another study on estimating long-term lake area changes.

Schwatke, C., Scherer, D. & Dettmering, D. Automated Extraction of Consistent Time-Variable Water Surfaces of Lakes and Reservoirs Based on Landsat and Sentinel-2. Remote Sens. 11, 1010 (2019)

We will include this paper in the revised manuscript.

R1C6) Line 89: It is hard to understand "coefficient of determination" here. Could you define or explain it?

As we used Pearson correlation throughout this paper, we will convert coefficient of determination (R^2) to Pearson correlation (R).

R1C7) Line 120: I do not quite understand what's the purpose showing the correlation between A0 and calculated V0 (based on A0). It makes more sense to me to show the correlation between A0 and h0 as these two are independent estimates. The authors may only need to consider a pearson' R greater than 0.8 (or R2 higher than 0.6) as correlation between A-L or A-V should be pretty high, otherwise it indicates substantial uncertainty in the data sets.

Thank you for this suggestion. We will increase correlation (R) thresholds between A-L and between A-V for reservoir storage estimation. Please see our response to R1C2 for full details (the first paragraph).

R1C8) Line 135: the equation does not make sense to me. The authors need to show more details about the rationale.

We apologize for the confusion. We will clarify the rationale of this equation.

R1C9) Line 150: "Only 132 reservoirs with both area and level observations….". Do you conclude based on the 132 reservoirs or all reservoirs, majority of which do not have both observations?

We performed a long-term trend analysis for 4,573 reservoirs, including both Group A (have area and level observations) and Group B (have only area observations). We will modify these sentences to clarify this information.

R1C10) 164: It seems the MSWEP v1.1 may not be the latest version of the dataset.

Although there is a latest version of MSWEP now, we carried out our study using MSWEP 1.1 two years ago. We will consider using the latest MSWEP product, but among us are authors of the MSWEP product and with knowledge of the changes between successive versions we do not expect any important impact for the type of long-term analysis done here.

R1C11) 192: The authors only validated on 1% of the studied reservoirs and the validation samples are located in U.S. only, which could be a concern.

We provide validation of our calculated storage volumes for 65 reservoirs with publicly available storage data from US and Australia and cross-validation between two volume estimation methods for 33 reservoirs globally. Please see our response to R1C2 for full details (the second paragraph). We note that the availability of such ground data is limited, which was the primary reason for us to develop a remote sensing-based methodology. However, to further demonstrate the validity of our storage estimates, we compared our product with MODIS-derived water

storage dynamics from 1992 to 2018 for another 100 reservoirs from Tortini et al. (2020) in L202-204.

R1C12) 194: What do you mean by "published"? The authors use pearson's R (correlation) for doing validation, which does not give insights on the accuracy of estimated values.

We will change "published" to "observed". We think Pearson correlation is the most important validation metric for this study as we focused on trend analysis and this depends on temporal pattern rather than absolute value. However, we will include the absolute error (SMAPE) valuation and compared this validation to Messager et al. (2016). Please see our response to R1C2 for full details (the second paragraph).

R1C13) Figure 2: it would be more clear to show global-scale evaluation and move the evaluations on individual cases into the supplementary.

Thank you for this suggestion. We will show the validations for individual reservoirs in supplementary material. Please see our response to R1C2 for full details (the second paragraph).

R1C14) Line 214: "a positive trend in combined global reservoir storage of 3.1 km3 per yr". This rate seems to less than 10% of earlier estimates on global reservoir storage rates (e.g., Chao et al.). Could you provide an uncertainty estimate for this rate?

"Chao, B. F., Wu, Y. H. & Li, Y. S. Impact of artificial reservoir water impoundment on global sea level. Science (80-.). 320, 212–214 (2008)."

We explicitly performed trend analysis for the reservoirs constructed before 1984 only (L150-152), to remove the influence of new reservoir water impoundments from 1984-2015. This was done to provide a clearer understanding on the interaction between precipitation/streamflow/evaporation and reservoir volume. Our study differs from Chao et al. (2008), who focused on cumulative storage by increased water impoundment. We will clarify this in the revised manuscript.

R1C15) Line 215: "this was almost entirely explained by positive trends for the two largest reservoirs in the world, Lake Kariba (+0.8 km3 yr-1) on the Zambezi River and Lake Aswan". This statement is confusing. I know some completed projections of megadams in China and Brazil, such as the three gorges dams.

Please refer R1C14. Many mega-dams in China and Brazil were constructed after 1984 and have not been included in our long-term analysis. We will clarify this in the revised manuscript.

R1C16) Line 219: "while 948 reservoirs showed increasing trends, distributed in northern North America and southern Africa". The reported hotspots of increasing reservoir storage are inconsistent with the patterns of recent dam booms.

Please refer R1C14. We did not consider dams constructed after 1984 for long-term analysis. We will clarify this in the revised manuscript.

R1C17) Figure 4: This map is confusing to me. For example, China may be the global lead in dam constructions during the study period. Why its reservoir storage decreased? Is the data correctly shown in this map?

Please refer R1C14. The map shows trends for reservoirs constructed before 1984. We will clarify this in the caption of Fig.4.

R1C18) Line 245: "We summed storage for individual reservoirs to calculate combined storage in 134 river basins worldwide". Do reservoirs show a similar pattern of storage change in the same river basin? Is it more meaningful to analyze each of them individually?

A majority of reservoirs in each basin shows the same trends where there is a significant trend in total storage (Fig. 11; L301-305). We showed the trend analysis at both the individual (Fig.4a; L225-227) and basin scale (Fig.7c; L269-271). Due to the limited abilities of the hydrological model to simulate inflow for individual reservoir, we performed our climate analysis at the basin scale instead, given total basin water storage can be expected to respond to the change in overall precipitation and streamflow.

R1C19) Line 268: "In summary, we did not find evidence for widespread reductions in reservoir water storage due to increased releases". Reservoir storage increase could be a result of increased impoundments. Did you consider that?

Please refer R1C14. We have removed the effect of the increased reservoir water impoundments from 1984-2015. Therefore, reservoir storage increase cannot be a result of increased impoundments.

R1C20) Line 339: As Zhao and Gao used contaminated Landsat imagery to increase the monthly coverage of reservoir areas by 80%, do the estimates from poor-quality images affect your storage analysis? I know some studies (e.g., Busker et al) only adopted good-quality images due to this issue.

"Busker, T. et al. A global lake and reservoir volume analysis using a surface water dataset and satellite altimetry. Hydrol. Earth Syst. Sci. 23, 669–690 (2019)."

We think the consistency of observations from 1984-2015 is more important for long-term analysis. This is the reason why we used the reservoir area product developed by Zhao and Gao (2018). In addition, Zhao and Gao (2018) demonstrated that the correlations between observed and estimated reservoir areas were improved from 0.66 to 0.92 by 'repairing' contaminated Landsat images.

Table 1 The SMAPE and Pearson correlations between predicted and reference volumes for 65 reservoirs.

Grand ID	Dam Name	Latitude	Longitude	Capacity (MCM)	R	SMAPE (%)
307	Fort Peck Dam	48.00	-106.41	23560	0.98	28.58
597	Glen Canyon	36.94	-111.49	25070	0.99	39.12
753	Garrison Dam	47.51	-101.43	30220	0.97	30.98
870	Oahe Dam	44.46	-100.40	29110	0.97	30.48
6199	Darwin River Dam	-12.83	130.97	265	0.90	8.20
6579	Tinaroo Falls	-17.16	145.55	407	0.91	11.05
6581	Paluma	-18.95	146.15	12.3	0.77	18.28
6582	Copperfield River Gorge	-19.04	144.12	20.6	0.79	14.54
6583	Ross River	-19.41	146.74	417	0.95	59.49
6586	Peter Faust	-20.37	148.38	500	0.94	28.74
6588	Burdekin Falls	-20.65	147.14	1860	0.89	14.70
6592	Eungella	-21.14	148.39	131	0.94	27.14
6593	Kinchant	-21.21	148.90	62.8	0.94	22.11
6594	Fairbairn	-23.65	148.07	1440	0.96	29.56
6595	E.J. Beardmore	-27.91	148.65	101	0.84	30.51
6600	Windamere Dam	-32.73	149.77	368	0.96	26.89
6603	Carcoar Dam	-33.62	149.18	35.8	0.96	12.45
6605	Wyangala	-33.97	148.95	1220	0.97	22.22
6613	Burrinjuck	-35.00	148.60	1026	0.92	39.02
6618	Blowering	-35.40	148.24	1628	0.92	42.00
6619	Googong	-35.42	149.26	124.5	0.97	7.52
6620	Bendora	-35.45	148.83	11.1	0.37	12.17
6621	Corin	-35.54	148.84	75	0.72	19.99
6629	Eucumbene	-36.13	148.61	4800	0.99	34.55
6652	Malmsbury	-37.21	144.37	18	0.92	43.73
6655	Lauriston	-37.27	144.39	20	0.80	13.98
6656	Upper Coliban	-37.29	144.39	37.5	0.80	57.93
6657	Rosslynne	-37.47	144.57	24.5	0.93	75.76
6658	White Swan	-37.52	143.92	14.1	0.91	23.12
6659	Yan Yean	-37.55	145.13	32.7	0.93	43.44
6662	Greenvale	-37.63	144.90	27.5	0.83	11.88
6663	Maroondah	-37.64	145.56	28.4	0.65	46.40
6664	Upper Yarra	-37.67	145.90	207.2	0.58	38.91
6667	Silvan	-37.84	145.42	40.2	0.27	8.21
6668	Glenmaggie	-37.91	146.80	190	0.84	39.69
6669	Cardinia	-37.97	145.39	288.9	0.90	19.06
6670	Tarago	-38.02	145.94	37.5	0.78	13.47
6673	Devilbend	-38.29	145.11	14.5	0.93	9.82
6676	West Barwon	-38.53	143.72	21.7	0.74	61.63
6701	Awoonga High	-24.07	151.31	300	0.96	40.04
6702	Callide	-24.37	150.62	127	0.96	49.09
6703	Cania	-24.65	150.98	89	0.93	60.31
6704	Fred Haigh	-24.87	151.85	586	0.97	15.20
6706	Glebe Weir	-25.46	150.03	17.3	0.69	35.41
6707	Boondooma	-26.10	151.43	212	0.93	11.58

Table 1 The SMAPE and Pearson correlations between predicted and reference volumes for 65 reservoirs (continued).

Grand ID	Dam Name	Latitude	Longitude	Capacity (MCM)	R	SMAPE (%)
6708	Bjelke-Petersen	-26.30	151.98	125	0.98	13.87
6709	Borumba	-26.51	152.58	42.6	0.91	13.56
6715	Cressbrook	-27.26	152.20	83	0.98	29.38
6717	Perseverance Creek	-27.30	152.12	30.9	0.95	27.42
6723	Moogerah	-28.04	152.54	92.5	0.92	45.60
6725	Maroon	-28.19	152.65	38.4	0.95	21.53
6726	Leslie	-28.22	151.92	108	0.98	26.93
6728	Coolmunda	-28.44	151.22	75.2	0.93	18.06
6731	Glenlyon	-28.98	151.46	254	0.91	23.18
6731	Glenlyon	-28.97	151.45	254	0.92	20.47
6733	Copeton	-29.90	150.92	1364	0.81	42.56
6735	Split Rock Dam	-30.58	150.70	372	0.95	39.52
6736	Keepit Dam	-30.88	150.49	423	0.93	23.43
6737	Chaffey	-31.35	151.14	61.8	0.98	12.27
6738	Glenbawn	-32.10	150.99	750	0.99	9.33
6739	Chichester	-32.24	151.69	17.7	0.47	15.85
6740	Lostock	-32.33	151.46	20	0.63	9.90
6741	Glennies Creek	-32.36	151.25	283	0.97	18.70
6742	Grahamstown	-32.77	151.79	152.6	0.84	18.31
6743	Mangrove Creek	-33.22	151.13	170	0.93	49.24

Table 2 The SMAPE and Pearson correlations of predicted volumes between Group A and B for 33 reservoirs.

Grand ID	Dam Name	Latitude	Longitude	Capacity (MCM)	R	SMAPE (%)
250	Mica	52.08	-118.57	25000	0.90	15.22
253	Gardiner	51.27	-106.86	9870	0.84	3.41
297	Libby	48.41	-115.32	7434.2	0.89	15.97
310	Grand Coulee	47.95	-118.98	6395.6	0.92	13.19
370	Cascade	44.52	-116.05	805.5	0.98	15.44
597	Glen Canyon	36.94	-111.49	25070	0.99	22.43
1275	Sam Rayburn Dam And Reservoir	31.07	-94.11	7815.6	0.94	5.40
1320	International Falcon Lake Dam	26.56	-99.17	3920	0.96	13.66
1863	Buford	34.16	-84.07	3150.3	0.93	9.09
2376	Itumbiara	-18.41	-49.10	17000	0.96	7.81
2377	Emborcacao	-18.45	-47.99	17590	0.97	6.37
2388	Mascarenhas de Moraes	-20.28	-47.06	4040	0.91	3.32
2405	Capivara	-22.66	-51.36	10540	0.93	5.23
2416	Paraibuna	-23.36	-45.66	4732	0.99	5.29
2447	Passo Fundo	-27.55	-52.74	1570	0.97	6.51
2467	Araras	-4.21	-40.45	1000	0.98	12.13
2490	Boa Esperanca	-6.75	-43.57	5060	0.94	9.72
3014	Bagre	11.47	-0.55	1700	0.95	5.83
3670	Mape	6.04	11.30	3300	0.94	8.34
4212	Sterkfontein	-28.39	29.02	2620	0.99	27.54
4431	Karakaya	38.23	39.14	9580	0.87	7.70
4500	Nyumba ya Mungu	-3.82	37.47	1135	0.89	12.36
4501	Mtera	-7.14	35.98	3200	0.98	13.74
4686	Kayrakkum	40.28	69.82	4160	0.98	4.58
4702	Tarbela	34.09	72.69	13940	0.74	29.99
4715	Kajakai	32.32	65.12	2680	0.86	12.17
4739	Ukai	21.26	73.60	8510	0.80	16.18
4943	Upper Indrawati	19.28	82.83	2300	0.99	41.12
5150	Lam Pao	16.60	103.45	1430	0.97	9.93
5796	Sirindhorn	15.21	105.43	1966	0.97	8.38
5902	Shuifeng	40.46	124.97	14700	0.86	13.83
6606	Lake Victoria	-34.04	141.28	680	0.98	33.63
6653	Eildon	-37.22	145.93	3390	0.98	16.10

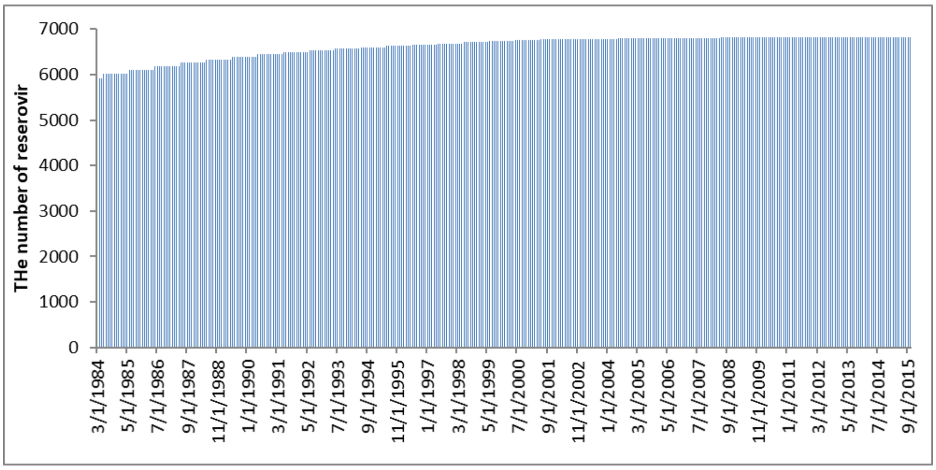

Figure 1 The number of reservoirs with Landsat observations for each month from 1984 - 2015 in the reservoir area product developed by Zhao and Gao (2018).

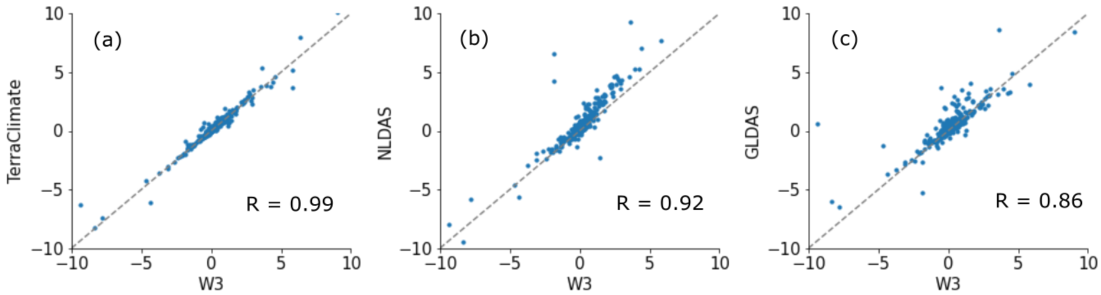

Figure 2 The comparison (dash grey line: 1: 1 line) of the linear trends in net evaporation using evaporation losses derived from the W3 model, TerraClimate, NLDA and GLDAS for 721 reservoirs.