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Remotely sensed reservoir water storage dynamics (1984-2015) and the influence of climate variability and management at global scale

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Abstract. Many thousands of large dam reservoirs have been constructed worldwide during the last seventy years to increase reliable water supplies and support economic growth. Because reservoir storage measurements are generally not publicly available, so far there has been no global assessment of long-term dynamic changes in reservoir water volume. We overcame this by using optical (Landsat) and altimetry remote sensing to reconstruct monthly water storage for 6,743 reservoirs worldwide between 1984 and 2015. We relate reservoir storage to resilience and vulnerability and analyse their response to precipitation, streamflow and evaporation. We find reservoir storage has diminished substantially for 23% of reservoirs over the three decades but increased for 21%. The greatest declines were for dry basins in southeastern Australia (-29%), the USA (-10%), and eastern Brazil (-9%). The greatest gains occurred in the Nile Basin (+67%), Mediterranean basins (+31%) and southern Africa (+22%). Many of the observed reservoir changes were explained well by changes in precipitation and river inflows, emphasising the importance of multi-decadal precipitation changes for reservoir water storage, rather than changes in net evaporation or (demand-driven) dam water releases.

1. Introduction

Globally the number of large reservoirs - dams impounding more than 3 million m^3 (ICOLD 2020) - reached 58,713 in 2020 with a combined capacity of more than 10,000 km^3 (Chao et al. 2008). By 2015, reservoirs provide 30–40% of global irrigation water requirements, 17% of electricity generated, and various other services, including domestic and industrial water supply, recreation, fisheries, and flood and pollution control (Maavara et al. 2020; REN21 2016; Yoshikawa et al. 2014). With projected population increase, demand for water and electricity are also expected to increase substantially (Crist et al. 2017; Zarfl et al. 2015). More dams will likely be built to support increased irrigation for food production and to meet energy demand. For example, by 2014, there were 3,700 hydropower dams either under construction or planned worldwide. The majority of these are in developing countries, particularly in South America, Southeast Asia and Africa (Bonnema et al. 2016; Zarfl et al. 2015). However, constructing new reservoirs has become challenging due to a shortage of suitable construction sites and remaining ‘underdeveloped’ water resources, as well as increased recognition of the profound impacts

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that impoundments have on the local population and riverine ecosystem (Grill et al. 2015; Grill et al. 2019; Lehner et al. 2011; Nilsson et al. 2005).

Adding to the challenge, evidence is emerging that existing reservoirs in some regions have experienced diminished water storage. Recent water supply failures or near-failures have occurred in the US Colorado River Basin since 2000 (Udall and Overpeck 2017), southeast Australia between 2002–2009 (Van Dijk et al. 2013), Barcelona, Spain, in 2007–2008 (March et al. 2013), Sao Paolo, Brazil, in 2014–2015 (Escobar 2015) and Cape Town, South Africa, in 2015–2017 (Sousa et al. 2018). However, it is unclear if these events are part of a global climate trend or due to local supply or demand changes. The underlying causes are also not necessarily the same in each case: reservoir storage dynamics are the net result of river inflows, net evaporation (i.e., evaporation minus direct precipitation onto the reservoir) and dam water releases to water bodies and users downstream. A change in the balance between these three terms leads to a change in the storage level. There are also interactions. The physical connection between precipitation, streamflow generation and atmospheric moisture demand creates positive feedbacks in storage volume changes: e.g., assuming the entire water supply system experiences comparable dry conditions, inflows will decrease while net evaporation and downstream demand for water releases for consumptive use will increase. To mitigate this feedback, reservoir operation rules will typically aim to reduce dam releases in response to lowering storage levels. Only a detailed analysis of the water balance of an individual reservoir can conclusively separate the contributions of these three processes to a change in water storage. However, in practice, a loss of reservoir water storage in the presence of a decrease in upstream or downstream river flows within the river system indicates that reduced precipitation conditions are the most likely cause, whereas the absence of such a precipitation and streamflow decrease, or even an increase, points towards less prudent reservoir operation, possibly in response to increased demand. Therefore, knowledge of temporal trends in reservoir storage and river flow can be combined to interpret whether trends in reservoir water storage are widespread globally, and if so, whether they are likely to be due to changing climate conditions or due to other factors. For the majority of large reservoirs, operators keep records of releases and estimated storage volume, inflows and net evaporation. Unfortunately, these data are typically not publicly available, for a variety of commercial, logistical, political and security reasons. Probably mainly because of this, so far there has been no attempt at a global assessment of long-term dynamic changes and attribution of trends in water reservoir storage.

Satellite remote sensing has been widely used to measure reservoir water height, extent and storage. Mulligan et al. (2020) developed a global geo-referenced database containing more than 38,000 georeferenced dams and their associated catchments, but without any descriptive features and measurement information. Database for Hydrological Time Series over Inland Waters (DAHITI) (Schwatke et al. 2015) and the U.S. Department of Agriculture's Foreign Agricultural Service (USDA-FAS) Global Reservoirs and Lakes Monitor (G-REALM) (Birkett et al. 2010) are the two most comprehensive dataset offering global surface water body height variations derived from satellite altimetry, such as Jason-1, Jason-2, Jason-3, TOPEX/Poseidon, and ENVISAT. Several regional and global reservoir water extent dynamics datasets were also

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produced based on MODIS or Landsat imagery (Khandelwal et al. 2017; Ogilvie et al. 2018; Yao et al. 2019; Zhao and Gao 2018). Reservoir volume dynamics can be estimated at either regional or global scale using existing datasets and approaches to derive both height and extent from remote sensing, but this approach is only suitable for a limited subset number of reservoirs worldwide due to wide spacing of the satellite altimetry tracks (Busker et al. 2019; Crétaux et al. 2011; Duan and Bastiaanssen 2013; Gao et al. 2012; Medina et al. 2010; Tong et al. 2016; Zhang et al. 2014). Messager et al. (2016) estimated the volume of lakes and reservoirs with a surface area greater than 0.10 km^2 at global scale using a geo-statistical model based on surrounding topography information. However, these estimates were not dynamic time series, and so do not enhance our understanding of the influence of climate change and human activity on global reservoir storage.

In this study, we reconstructed monthly reservoir storage for 1984-2015 worldwide using satellite observations, and examined long-term trends of global reservoir water storage, and changes in reservoir resilience and vulnerability over the past three decades. We investigated interactions between precipitation, streamflow, evaporation, and reservoir water storage based on comprehensive analysis of streamflow from a multi-model ensemble and as observed at ca. 8,000 gauging stations, precipitation from a combination of station, satellite and forecast data, and open water evaporation estimates. Part of our objective was to determine the extent to which climate variability and human activity each affected global reservoir water volume over the past three decades.

2. Data and methods

2.1. Data

2.1.1 Surface water extent

The Landsat-derived Global Surface Water Dataset (GSWD) (Pekel et al. 2016) provides statistics on the extent and change of surface water at the global scale over the past three decades at a spatial resolution of 30 m. Clouds, cloud shadows and terrain shadows cause errors or missing data for individual months, but Zhao and Gao (2018) developed an automated method to reduce these issues and enhance the accuracy of reservoir surface water extent estimates. They applied this method to produce a monthly time series of surface water extent dataset for 6,817 reservoirs worldwide, based on mapping of the location and high-water mark as contained in the Global Reservoir and Dam database (GRanD) (Lehner et al. 2011). The average coefficient of determination (R) between satellite-derived extent and observed elevation or volumes was improved from 0.43 to 0.84 based on the algorithm developed by Zhao and Gao (2018). The resulting data are available from 1984 to 2015 and were used in this study.

2.1.2 Surface water height

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The US Department of Agriculture's Foreign Agricultural Service (USDA-FAS) provides near-real-time surface water height anomaly estimates every ten days for 301 lakes and reservoirs worldwide. The water surface height product (G-REALM) was produced by a semi-automated process using data from a series of altimetry missions including Topex/Poseidon (1992-2002), Jason-1 (2002-2008), Jason-2 (2008-2016) and Jason-3 (2016-present) (Birkett et al. 2010). The root-mean-square error (RMSE) of G-REALM altimetry data is expected better than 10 cm for the largest water bodies (e.g., Lake Victoria; 67,166 km^2) and better than 20 cm for smaller ones (e.g., Lake Chad; 18,751 km^2) (Birkett et al. 2010). The advantage of using satellite radar altimeter to measure surface water height is that it is not affected by weather, time of day, and vegetation or canopy cover. The G-REALM data is currently only available for lakes and reservoirs with an extent greater than 100 km^2 although observations for water bodies between 50–100 km^2 are expected in future.

Table 1 List of the spatial data used in the analyses with source, resolution and temporal coverage of data

Name and Abbreviation	Temporal Range	Spatial Resolution	Temporal Resolution	Data Source	Notes
Global Reservoir Surface Area Dataset (GRSAD)	1984-2015	30 m	Monthly	Zhao and Gao (2018)	Surface water extent for 6,817 reservoirs worldwide
Global Reservoirs and Lakes Monitor (G-REALM)	1992-present	N/A	10-Day	US Department of Agriculture's Foreign Agricultural Service (USDA-FAS) (Birkett et al. 2010)	Near-real-time surface water height anomaly for 301 lakes and reservoirs worldwide
eartH2Observe water resources reanalysis	1980-2014	0.25°	Daily/Monthly	Schellekens et al. (2017)	Global surface runoff ensemble mean of eight state-of-the-art global models
Multi-Source Weighted-Ensemble Precipitation (MSWEP)	1979-2015	0.25°	3-Hour	Beck et al. (2017)	Global precipitation by merging gauge, satellite, and reanalysis data
The Worldwide Water (W3) model	1980-2014	0.25°	Daily/Monthly	Van Dijk et al. (2018)	Global open water evaporation (Priestley-Taylor potential evaporation)
Global Reservoir and Dam Database (GRanD)	N/A	N/A	N/A	Lehner et al. (2011)	Global 6,862 reservoir attributes
HydroBASINS	N/A	N/A	N/A	Lehner and Grill (2013)	Global watershed boundaries and sub-basin delineations

2.1.3 Auxiliary Data

Daily and monthly *in situ* river discharge observations were collated as part of previous research (Beck et al. 2020) from different national and international sources (Table S1). In total, we archived 22,710 river gauging records. Global monthly surface runoff estimates for 1984–2014 were derived from the earthH$_2$Observe water resources reanalysis version 2 (Schellekens et al. 2017), calculated as the mean of an ensemble of eight state-of-the-art global models, including HTESSEL, SURFEX-TRIP, ORCHIDEE, WaterGAP3, JULES, W3RA, and LISFLOOD (for model details refer to

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Schellekens et al. (2017)). Precipitation estimates were derived from a combination of station, satellite, and reanalysis data (MSWEP v1.1) (Beck et al. 2017). The representative maximum storage capacity reported in the GRanD v1.1 database (Lehner et al. 2011) was used as a reference value to calculate absolute storage changes. The HydroBASINS (Lehner and Grill 2013) dataset was used to define basin boundaries.

2.2 Global reservoir storage estimation

In total, 132 large reservoirs (Group A; Fig. 1) had records of both surface water extent and height for the overlapping period 1993–2015. We estimated the height and area at capacity as the maximum observed surface water height and extent, respectively, and calculated reservoir storage volume (V_o in GL or 10^6 m^3) as:

$$V_o = V_c - (h_{\max} - h_o)(A_{\max} + A_o) / 2 \qquad (1)$$

where A_o (km^2) is the satellite-observed water extent, A_{max} the maximum value of A_o, h_o (m) the satellite-observed water height, h_{max} the maximum value of h_o, and V_c (GL) the storage volume at capacity. There were 78 reservoirs with a relationship between A_o and V_o for this overlapping period with a Pearson's $R \geqslant 0.4$ (19% between 0.4-0.6, 32% between 0.6-0.8 and 49% between 0.8-1). For these reservoirs, V_0 was estimated going back to 1984 using a cumulative distribution function (CDF) matching method based on A_0.

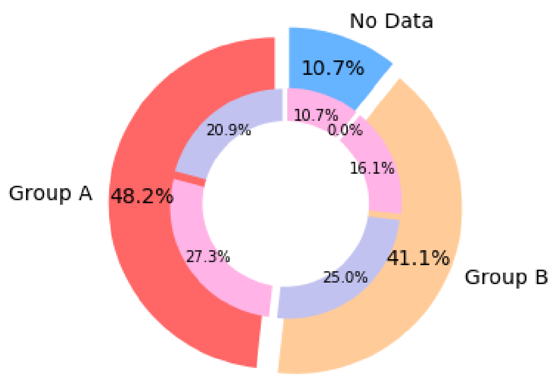

Figure 1 The total storage capacity in Group A (red) and B (brown) and left unaccounted (blue) and the combined capacity of reservoirs for which the data were suitable (teal) or unsuitable (pink) for long-term analysis.

For 6,611 reservoirs with water extent observations only (Group B; Fig. 1), we used the HydroLAKES method (Messager et al. 2016) to estimate storage. The mean lake or reservoir depth can be estimated using the empirical equation based on water surface area and the average slope within a 100 m buffer around the water body (Messager et al. 2016). Four empirical equations were developed by Messager et al. (2016) for different lake size classes (i.e., 0.1–1, 1–10, 10–100 and 100–500 km^2) (Table S2). For each reservoir, water depth dynamics (D in m) from 1984-2015 were calculated using the surrounding average slope from HydroLAKES and surface water extents (Zhao and Gao 2018) based on the empirical equation

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appropriate for the reservoir size. Assuming maximum observed surface water extent (A_{max}) as the area at capacity (V_c), a bias-corrected water depth (D^* in m) was calculated by solving D based on the ratio of water depth (V_c/A_{max} in m) at capacity and maximum observed depth (D_{max} in m):

$$D^* = \frac{D}{D_{\max}} \times \frac{V_c}{A_{\max}} \qquad (2)$$

Storage volume (V_o in MCM) for 1984–2015 was subsequently estimated based on surface water extent (A_0 in m) and bias-corrected water depth:

$$V_o = D^* A_o \qquad (3)$$

Time series of *in situ* reservoir storage volume measurements are publicly available for a small subset of reservoirs. They can be used to evaluate the uncertainty in the satellite-based storage estimates. Furthermore, data records for some storages can be found in the published literature, derived from grey literature or proprietary data sources. Given the emphasis in trend analysis was on relative changes between the pre- and post-2000 periods, the evaluation of satellite-derived reservoir storage focuses on Pearson's correlation (R) values as a measure of correspondence. In this study, we regard R values ranging from 0.4-0.7 as robust, and 0.7-1 as strong.

2.3 Trend analysis and attribution

We were able to estimate monthly storage dynamics for 6,743 out of the 6,862 reservoirs reported in the GRanD database (Lehner et al. 2011), accounting for 89.3% of the total 6,197 km^3 reported cumulative capacity (Fig. 1). There were only 132 reservoirs for which both extent and height observations were available (Group A), but this relatively small number already accounted for almost half of global combined capacity (Fig. 1). To analyse long-term changes in reservoir storage between 1984–2015, we removed all reservoirs that were destroyed, modified, planned, replaced, removed, subsumed or constructed after 1984 or for which more than five years of water extent observations needed to be interpolated because of lacking data (Zhao and Gao 2018). This left 4,589 of the initial 6,743 reservoirs available for analysis, *i.e.*, 68% of reservoirs, together accounting for 45.9% of combined global capacity (Fig. 1).

We calculated linear trends between 1984–2015 in annual reservoir storage, observed streamflow, modelled streamflow, and precipitation for each basin (HydroBASINS Level 3). Trend significance was tested using the Mann-Kendall trend test ($p<0.05$). The linear trends in modelled streamflow were validated by observed data. We also analysed the correlations between precipitation/streamflow and storage in terms of both time series and linear trend. Net evaporation was calculated for each reservoir as follows:

$$E_n = A(E_o - P) \qquad (4)$$

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where E_n (mm) is cumulative monthly net evaporation loss (or gain, if negative), A is reservoir surface area (km^2) from Zhao and Gao (2018), E_0 (mm) is open water evaporation (Priestley-Taylor potential evaporation from the W3 model (Van Dijk et al. 2018)), and P is precipitation (mm) from MSWEP v1.1 (Beck et al. 2017). The reservoir net evaporation summed for each basin and the ratio of the respective trends in net evaporation and storage were calculated to determine whether the former could explain the latter. Trends in storage and observed streamflow for individual reservoir and river were also analysed to provide additional information about spatial distribution of trends. Unlike the analysis at basin scale above, we do not relate the trend of each individual reservoir to a corresponding river gauge. This is becaucse there is typically a limited number of gauging station upstream a reservoir, and as such these river flow gauging data cannot accurately represent overall reservoir inflows.

Changes in reservoir resilience, and vulnerability between 1984–1999 and 2000–2015 were analysed at the scale of river basins. The reliability, resilience and vulnerability (RRV) criteria can be used to evaluate the performance of a water supply reservoir system (Hashimoto et al. 1982; Kjeldsen and Rosbjerg 2004). The calculation requires that an unsatisfactory state can be defined in which the reservoir cannot meet all water demands, leading to a failure event. *Reliability* indicates the probability that the system is in a satisfactory state:

$$Reliability = 1 - \frac{\sum_{j=1}^{M} d(j)}{T} \qquad (5)$$

where *d(j)* is the time length of the j^{th} failure event, *T* is the total time length, and *M* is the number of failure events. Unfortunately, a single threshold for failure events is not readily determined: firstly, because we did not have access to water demand and release data for each reservoir, and, secondly, because reservoirs are typically operated in response to more than a single threshold. Instead, we assumed that the reliability of each reservoir is designed to be 90%, leaving it in an unsatisfactory state for the remaining 10% of the time. This assumption made it possible to calculate resilience and vulnerability for each reservoir for the assumed 90% threshold. *Resilience* is a measure of how fast a system can return to a satisfactory state after entering a failure state:

$$Resilience = \left\{ \frac{1}{M} \sum_{j=1}^{M} d(j) \right\}^{-1} \qquad (6)$$

Vulnerability describes the likely damage of failure events:

$$Vulnerability = \frac{1}{M} \sum_{j=1}^{M} v(j) \qquad (7)$$

where *v(j)* is the deficit volume of the j^{th} failure events. The change in vulnerability was expressed relative to the maximum deficit volume observed.

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3. Results

3.1 Validation of global reservoir storage estimates

Monthly storage data with at least 20-year time series of 67 reservoirs via the US Army Corps of Engineers and Australian Bureau of Meteorology were collected. The *R* between published and estimated volumes was above 0.9 for 67% of the 67 reservoirs (31 reservoirs with capacity between 10-100 MCM, 25 ones between 100-1,000 MCM, 7 ones between 1,000-10,000 MCM, 4 ones with capacity above 10,000 MCM), and above 0.7 for 90% of them. Some validation examples, including robust, typical, and poor agreement are shown in Fig. 2. Annual average water levels for Lake Aswan, the largest reservoir in the world, were published as a graph (El Gammal et al. 2010); a comparison shows good agreement between the satellite-derived storage and *in situ* measurements with R=0.97 (Fig. S1). Assuming the estimation method for Group A is more accurate than that for Group B, the latter can be evaluated against the former. The results show that 25 of the total 39 overlapping estimated reservoirs (3 reservoirs with capacity between 100-1,000 MCM, 27 ones between 1,000-10,000 MCM and 9 ones with capacity above 10,000 MCM) show strong agreement ($R \geq 0.9$) between the two methods. Some validation examples representing good, typical, and poor agreement are shown in Fig. 3. The average Pearson correlation between our Landsat-derived water volumes and published MODIS-derived estimates (Tortini et al. 2020) from 1992 to 2015 for 100 reservoirs achieved 0.87, and the *R* values does not differ remarkably from different sizes of reservoirs.

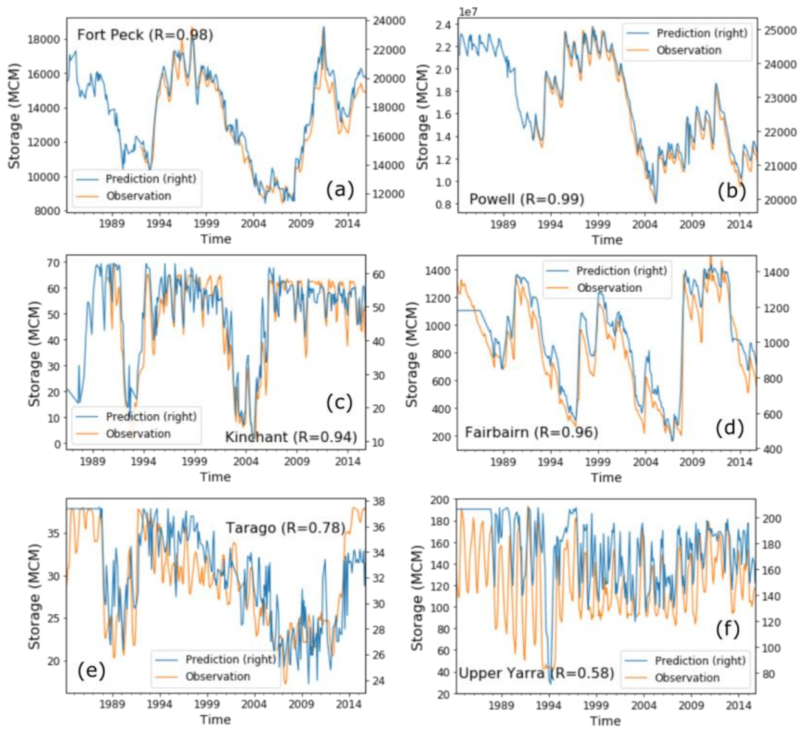

Figure 2 Validation of monthly reservoir storage time series reconstruction against *in situ* storage data, showing (a, b) robust, (c, d) typical and (e, f) poor results.

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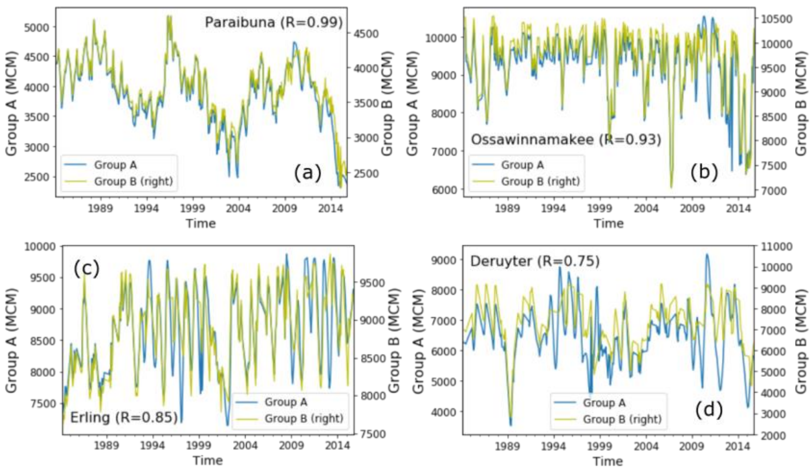

Figure 3 Validation of monthly reservoir storage time series reconstruction for Group B against results obtained using the method for Group A, showing (a) robust, (b and c) typical and (d) poor agreement.

3.2 Changes in global reservoir storage, resilience and vulnerability

The trends ($p<0.05$) of water volume dynamics for 4,589 reservoirs and river discharge time series from around 8,000 gauging stations between 1984 and 2015 were analysis here (Fig. 4). We found no systematic global decline in reservoir water availability. Overall, there was a positive trend in combined global reservoir storage of +3.1 $km^3 yr^{-1}$, but this was almost entirely explained by positive trends for the two largest reservoirs in the world, Lake Kariba (+0.8 $km^3 yr^{-1}$) on the Zambezi River and Lake Aswan (+1.9 $km^3 yr^{-1}$) on the Nile River (Fig. S2). Reservoir with increasing storage trends are nearly as common as declines. 1,034 reservoirs showed decreasing trends, mainly concentrated in southwest America, eastern South America, southeast Australia and parts of Eurasia, while 948 reservoirs showed increasing trends, distributed in northern North America and southern Africa (Fig. 4a). The global reservoir storage trending pattern is similar with global river discharge tendency. In particular, a majority of rivers in southwest America, eastern South America, and southeast Australia have reduced river flows (Fig. 4b). There was no apparent relationship between primary reservoir purpose (i.e., irrigation, hydroelectric power generation, domestic water supply) and overall trend, arguably a first tentative indication that climatological influences dominate changes in release management.

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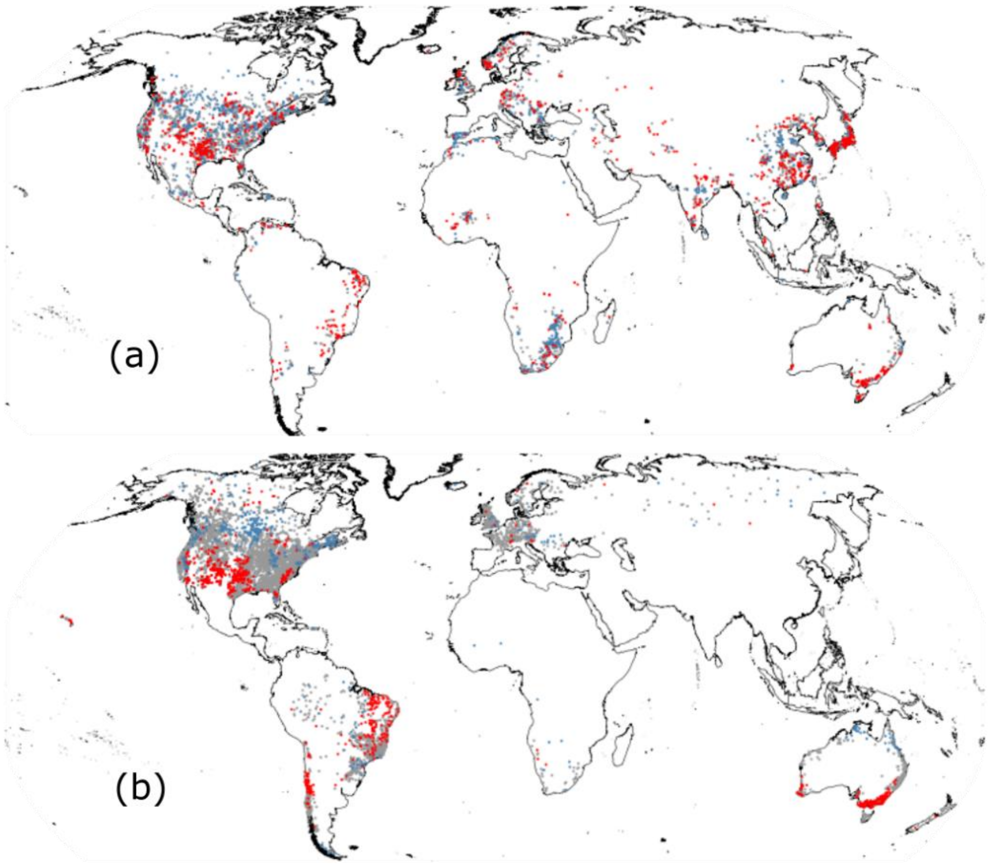

Figure 4 The trends of storage (a) and observed streamflow (b) for individual reservoir and river globally (p<0.05; increasing: blue; no change: grey; decreasing: red).

The resilience of reservoirs in southwest America (including Mississippi Basin), central Chile, eastern South America, southeastern Australia, the coast of southeastern Africa and central Eurasia have reduced sharply between 1984 and 2015, and the vulnerability of these reservoirs have increased by more than 30% (Fig. 5). In contrast, reservoirs in western Mediterranean basins, the Nile Basin and southern Africa have stronger resilience and less vulnerability than before (Fig. 5). All these changes are attributed to changes in reservoir storage, as we found there are a robust positive relationship (R = 0.64) between changes from the pre-2000 to the post-2000 period in storage and resilience, and a strong negative relationship (R = -0.79) between resilience and vulnerability (Fig. 6). This means that if a reservoir has a decreasing storage, there would be a risk of falling to low capacity more often and enduring larger deficits than before. Increasing storage has the potential to create other issues, such as overtopping, dam collapse, downstream flooding caused by untimely releases during the wet season, etc. (Simonovic and Arunkumar 2016).

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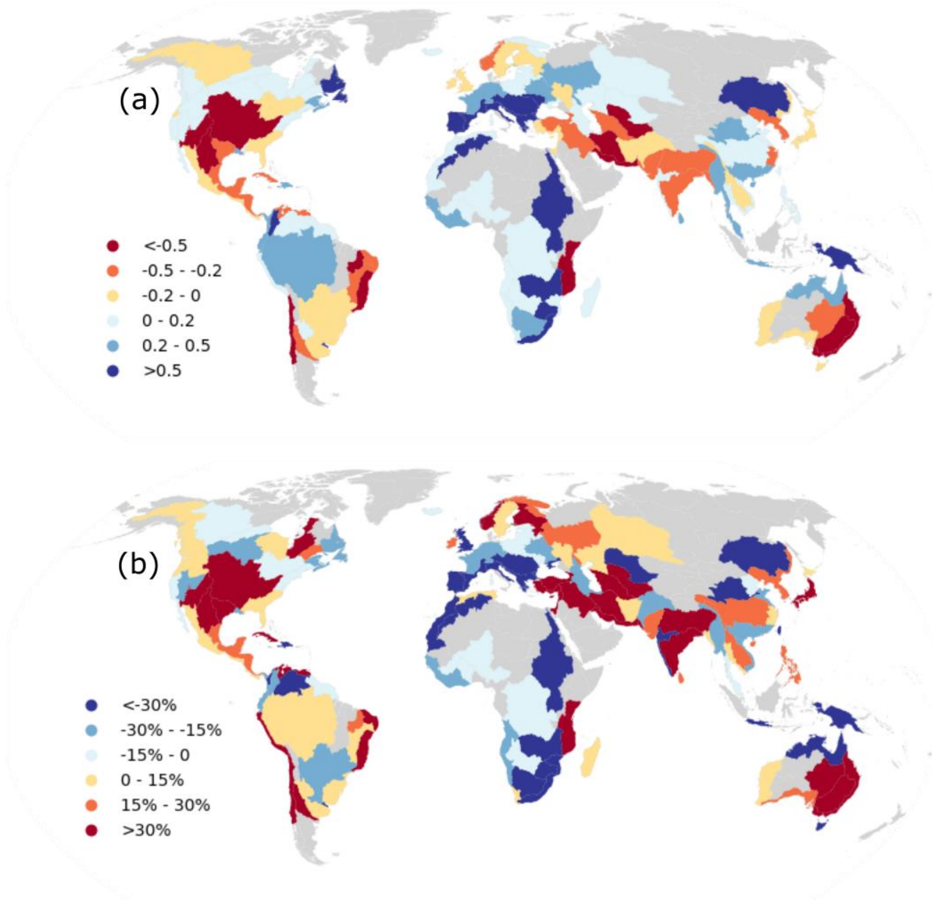

Figure 5 The change in resilience (a), and vulnerability (b) between pre-2000 and post-2000 (grey shade: no reservoir data).

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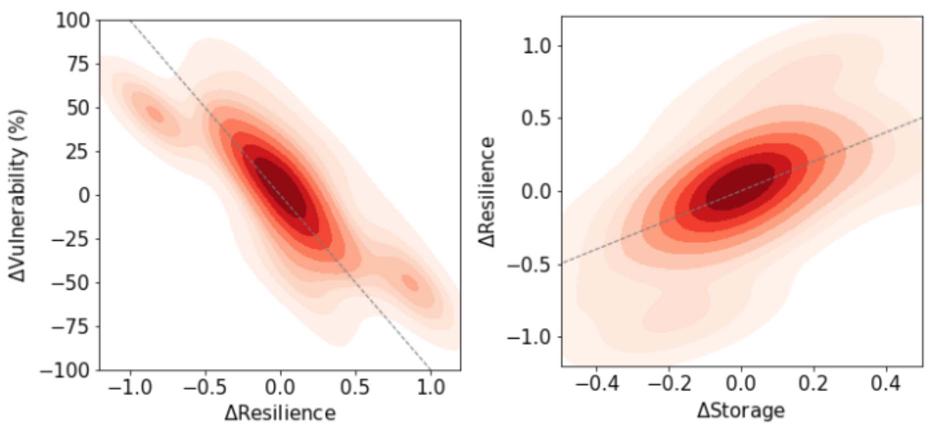

Figure 6 The relationship (dash grey line: 1: 1 line) between changes from the pre-2000 to the post-2000 period in (a) vulnerability (*ΔVulnerability*) and resilience (*ΔResilience*) and (b) mean storage (*ΔStorage*) and resilience (*ΔResilience*).

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3.3 Influences of precipitation and river flow on global reservoir storage

We summed storage for individual reservoirs to calculate combined storage in 134 river basins worldwide. Basins losing or gaining more than 5% of their combined storage over the three decades could be found on every continent (Fig. 7c). Among these, 26 (19%) showed a significant decreasing and 39 (29%) a significant increasing trend in reservoir storage (Fig. 7c). For the majority of these 65 basins, trends were of the same sign for storage, runoff and precipitation, suggesting that precipitation changes are ultimately the most likely explanation for observed trends (Fig. 7a and b). Opposite trends in precipitation (or runoff) and storage were found for 12 out of 134 basins, with six decreasing and six increasing storage trends. Most of these could be explained by spatial variation within the respective basins (Fig. S3). The linear changes in modelled streamflow were validated against changes in observed streamflow, and the Pearson's correlation between them is 0.77, which indicated modelled streamflow can reliably represent trends in river flow globally (Fig. 8b). There is a robust positive relationship (R = 0.77) between linear changes from 1984-2015 in precipitation and streamflow (basin characteristics are assumed largely unchanged in the models) (Fig. 8a). A correlation above 0.6 between them can be found in all these 134 basin except the Niger Basin in Africa and the Parana Basin in South America (Fig. 9b). Linear changes in reservoir storage also have a meaningfully positive relationship (R = 0.38, p < 0.01, ρ = 0.51) with streamflow (Fig. 8c), given the heterogeneous nature of human activities. It means a decreasing trend in streamflow (typically due to precipitation changes) generally leads to a decreasing trend in storage, and vice versa, but not necessarily proportionally. Figure 9a also shows that there are 59 basins that have a robust relationship between annual storage and inflow with R ranging from 0.4-0.8. They are mainly located in North America, southern South America, Mediterranean, southeastern Australia, and parts of Eurasia. These regions coincide with a large number of measured reservoirs (Fig. 4a) and a large total number of Landsat images over three decades (Pekel et al. 2016; Wulder et al. 2016), and vice versa. The overall relationship between reservoir storage and inflow might therefore be expected to be stronger if more reservoirs were measured and more useable Landsat imagery was available for those basins lacking them in our present analysis.. We also found that changes in net evaporation accounted for well below 10% of the overall trends in storage for each of those 65 basins, reflecting that net evaporation rarely explains more than a few per cent in observed storage changes (Fig. 10). In summary, we did not find evidence for widespread reductions in reservoir water storage due to increased releases.

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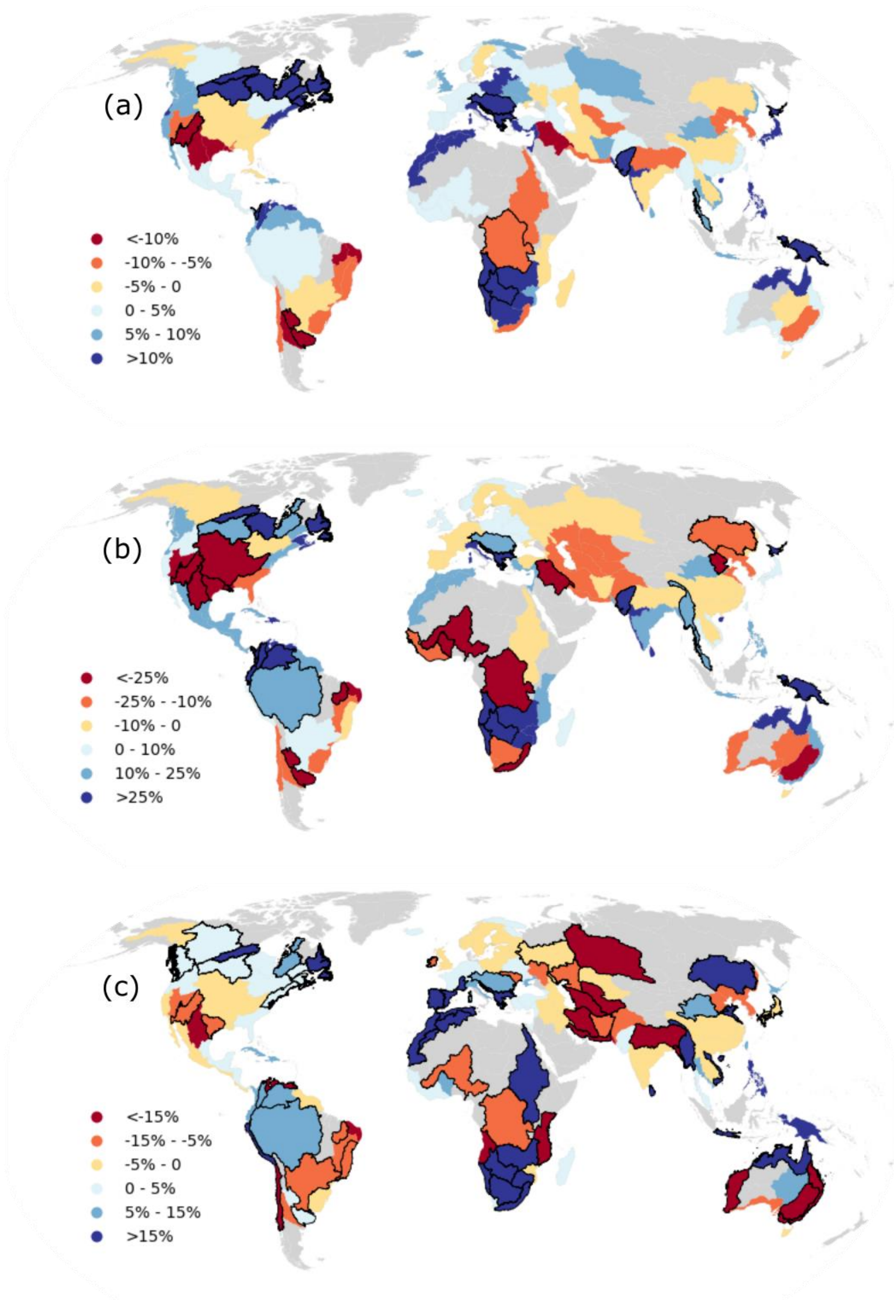

270 **Figure 7** Linear trends in annual, basin-average (a) precipitation, (b) simulated streamflow and (c) reservoir storage between 1984–2015 (grey shade: no reservoir data; black outlines: trend significant at $p<0.05$).

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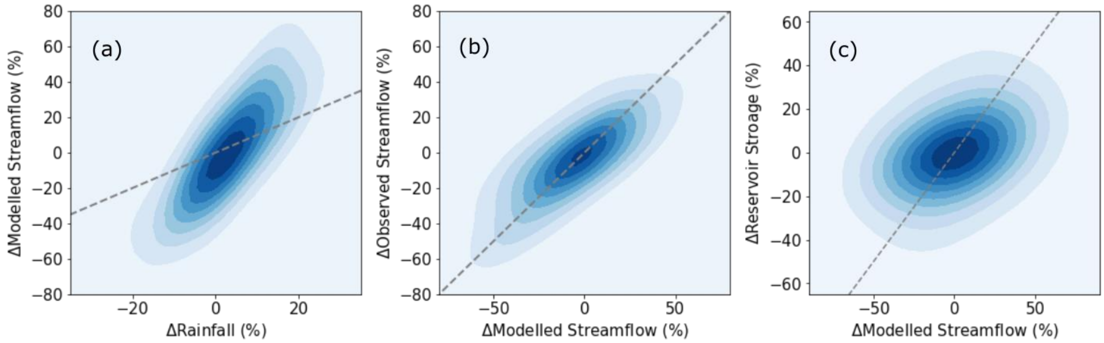

Figure 8 The relationship (dash grey line: 1: 1 line) between linear change from 1984-2015 in (a) annual precipitation (*ΔRainfall*) and modelled streamflow (*ΔModelled Streamflow*), (b) observed streamflow (*ΔObserved Streamflow*) and modelled streamflow (*ΔModelled Streamflow*) and (c) reservoir storage (*ΔReservoir Storage*) and modelled streamflow (*ΔModelled Streamflow*).

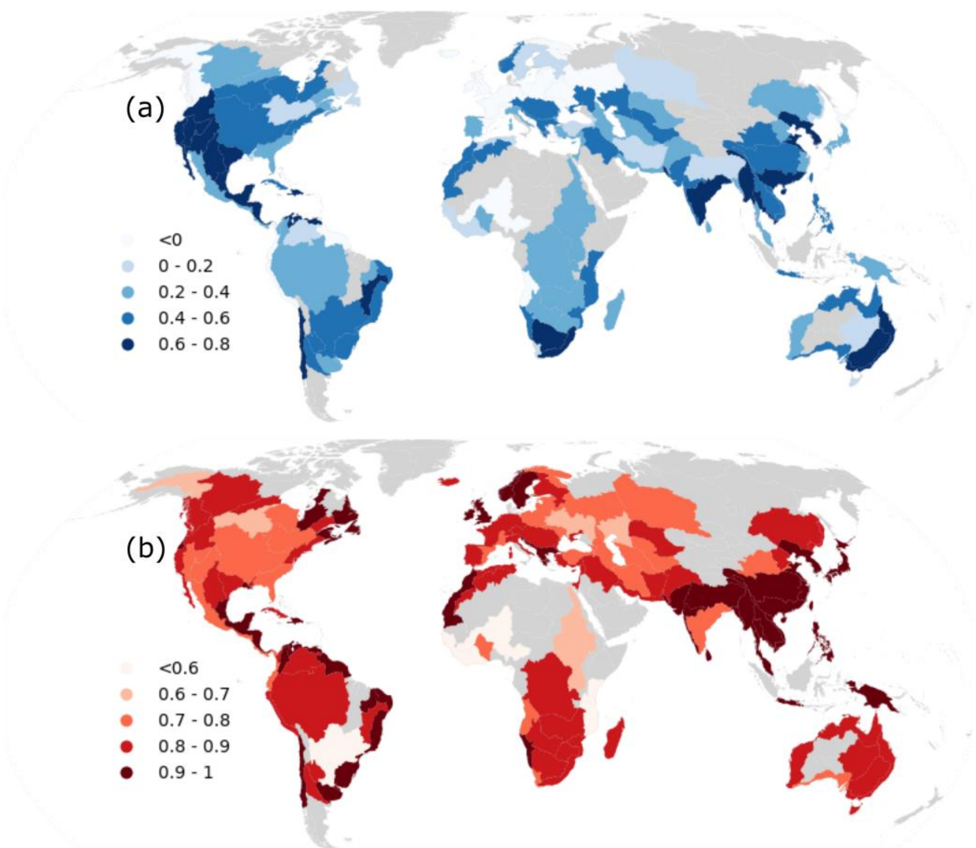

Figure 9 The correlations of annual storage change and reservoir inflow (as approximated by basin modelled streamflow) (a), and reservoir inflow and precipitation (b) in each basin.

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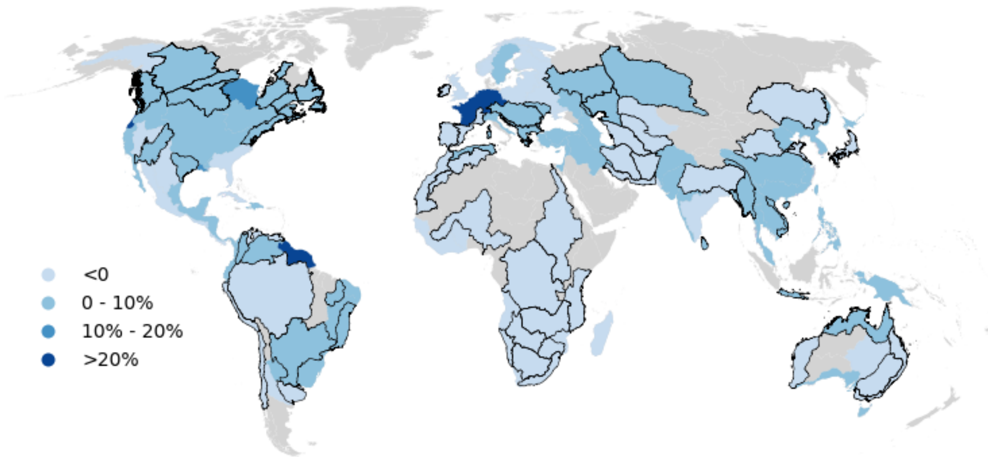

Figure 10 The ratio of the linear trends in net evaporation and in storage in each basin.

The greatest storage gains occurred in the Nile Basin (+67%), western Mediterranean (+31%) and southern Africa (+22%), and were attributed to very high inflows during 1996-2008, 2008-2010 and 1996-2000, respectively (Fig. S4). Substantial decreases were found for arid to sub-humid basins in southeastern Australia (-29%), southwestern USA (-10%) and Brazil (-9%) (Fig. 11). Both simulated and observed river discharge data show similar trends and explain the observed storage declines (Fig. 4 and Fig. 7). During Australia's Millennium Drought (2001-2009) (Van Dijk et al. 2013), river flows in the Murray-Darling Basin fell to about half that for 1984–1999 (Fig. 11a), causing a halving of combined storage, before recovering due to high inflows during 2009-2011. In the southwestern USA, three distinct dry periods occurred (Fig. 11b). Sharp decreases in river flow after 2011 in eastern Brazil led to the lowest reservoir storage levels, with combined losses of almost 18% in 2015 (Fig. 11c). Reservoirs in these basins with reduced storage also predominantly showed reduced resilience and increased vulnerability (Fig. 5).

4 Discussion

This study reconstructed monthly reservoir water storage dynamics from 1984-2015 at global scale based on satellite-derived water extent (Zhao and Gao 2018) and altimetry measurements (Birkett et al. 2010). Where no altimetry data were available, geo-statistical models (Messager et al. 2016) were applied to satellite-derived water extent for reservoir water volume estimation. About half (48.2%, including most large reservoirs) of total reported cumulative reservoir capacity (Lehner et al. 2011) around the world was measured by combining satellite-derived extent and height, while 41.1% was estimated based on geo-statistical models using remotely sensed surface area. There does not appear to be any systematic global decline in global reservoir water availability, but we found significantly decreasing trends in reservoir water volumes in southeastern Australia, southwestern USA and eastern Brazil, creating the risk that storages fall to low capacity more often (i.e., weakened resilience) and endure larger deficits (i.e., higher vulnerability).

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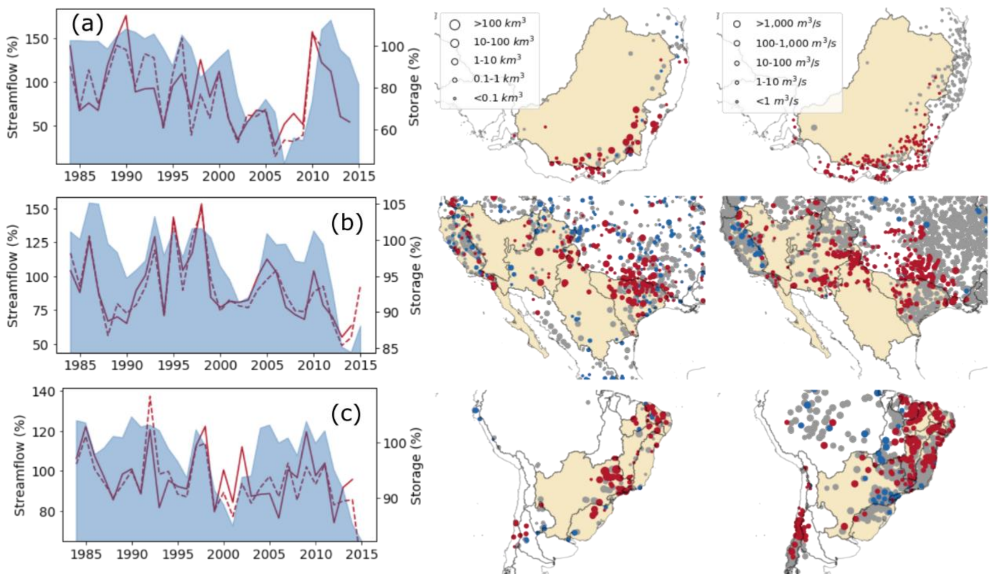

Figure 11 Time series (left column) of annual combined storage (blue shaded) along with simulated (solid) and observed (dashed line) streamflow, indexed to the reference period 1984–1999, and trends in storage (middle column) and observed streamflow (right column) during 1984–2015 ($p<0.05$; increasing: blue; no change: grey; declining: red). Shown are (top row) southeastern Australia, (second row) southwestern USA, and (third row) Brazil.

Trends in reservoir storage and river flow showed spatial consistency at both individual and basin scales globally. There was reasonably strong temporal correlation between precipitation, streamflow and storage. Changes in net evaporation only accounted for a small fraction of reservoir volume changes. Reservoir storage dynamics (ΔV) are the net result of river inflows (Q_{in}), net evaporation (E_n) and dam (demand-related) water releases (Q_{out}) as:

$$\Delta V = Q_{in} - E_n - Q_{out} \quad (8)$$

We found that ΔV responds primarily to Q_{in} and that E_n does not seem to have affected ΔV. This indicates dam (demand-related) water releases (Q_{out}) are less likely to be the main driver of storage changes (ΔV).

Accurate temporal pattern estimates were the main purpose in this study because relative water storage and long-term change are more relevant information for water resources management. Our validation results show that 90% of the reservoirs evaluated show strong correlation ($R\geq 0.7$) with water volume measured in situ. In terms of absolute value, water volume estimates were bias-corrected by representative maximum storage capacity from GRanD (Lehner et al. 2011) by assuming that the maximum observed surface water extent coincides with the area at full capacity. Biases remain in some reservoirs due to uncertainties in this maximum storage capacity. Representative maximum storage capacity values reported in GRanD were collected from different sources in the following order of priority: reported maximum or gross capacity, reported normal capacity and reported live or minimum capacity. These uncertainties in reported maximum capacity may have influenced our results for individual reservoirs. This could be solved easily if more accurate reservoir storage or capacity data were available.

The uncertainties and limitations of reservoir storage estimates are mainly from the errors in satellite altimetry data, satellite-derived water extent data, and the method used to estimate bathymetry. The quality and accuracy of these altimetry measurements depend on the size and shape of water body, surrounding topography, surface waves, major wind events, heavy precipitation, tidal effects, the presence of ice and the position of the altimeter track (Birkett et al. 2010; Busker et al. 2019). The RMSE of water level estimations of a narrow reservoir in steep terrain will be many tens of centimetres (Birkett et al. 2010; Schwatke et al. 2015). DAHITI altimetry data, with RMSE between 4-36 cm for lakes (Schwatke et al. 2015), should have similar accuracy as G-REALM, although its water level observations have so far received less evaluation. The classifier used to produce GSWD surface water data performed quite well, with less than 1% commission error and less than 5% of omission error (Pekel et al. 2016). But no-data classifications in GSWD data caused by cloud, ice, snow, and sensor-related issues could lead to large data-gaps in time series and underestimation of actual reservoir extents (Busker et al. 2019). In general, a no-data threshold is applied to monthly GSWD data for removing imagery with large percentage of contamination before deriving lake and reservoir water extent. It helps reduce the issue to some extent, but contaminated imagery would still remain in the rest of GSWD data. Zhao and Gao (2018) developed an automatic algorithm to repair contaminated Landsat imagery, based on which a continuous reservoir surface area datasets were produced. This has increased the number of effective images by 81% on average, and improved the coefficient of determination between satellite-derived extents and observed elevation or volumes from 0.735 to 0.998 for all reservoirs, from 0.598 to 0.997 for large reservoirs with extent above 10 km^2.

There are typically two ways to estimate bathymetry based on digital elevation model (DEM) for reservoirs which have no satellite altimetry measurements from space. The first approach is to develop area-elevation curve based on a DEM (Avisse et al. 2017; Bonnema and Hossain 2017). The second method is to extrapolate surrounding topography from the DEM into the reservoir to estimate bathymetry (Messager et al. 2016). Although the accuracy of these methods depend on errors inherent in DEM data, the latter one has been proven to a reliable and effective way to estimate bathymetry of global lakes and reservoirs. A coefficient of determination between predicted and reference depths of R=0.5 (N=7049) has been reported for global lakes and reservoirs (Messager et al. 2016). Therefore, this geostatistical approach was considered appropriate to estimate reservoir volumes for reservoirs that had only satellite-derived water extent observations.

The total number of Landsat images over North America, southern South America, southern Africa, central Eurasia, and Australia over the past three decades is much larger than in the rest of the world, and particularly in tropical regions (Pekel et al. 2016; Wulder et al. 2016). Regions with sparse Landsat observations can have additional uncertainties in their long-term trend analyses, although this issue has been mitigated to some extent by the approach from Zhao and Gao (2018). In

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principle, the inflow of sediments into reservoirs could contribute to decreasing storage. However, Wisser et al. (2013) showed that sedimentation caused a total decrease of global reservoir water storage of only 5% over a century (1901 to 2010), and hence we expect the effect of sedimentation on our 32-year analysis to be small.

Regional storage trends in the dam reservoirs found here are consistent with trends reported in a previous study for 200 lakes (including a few reservoirs) across North America, Europe, Asia and Africa during 1992–2019 (Kraemer et al. 2020). Both lakes and reservoirs are influenced by changing inflow and net evaporation in response to climate variability. Although human regulation has more influences on reservoirs than on natural lakes, our results suggests that overall human impacts on storage are less than natural influences. In line with the study carried out by Kraemer et al. (2020), we also found that the distribution of global lake and reservoir storage or level long-term trends does not fully reflect the "wet gets wetter and dry gets dryer" paradigm that some have predicted to occur due to anthropogenic climate change (Wang et al. 2012). Reservoirs in dry regions, such as southwest America, southeastern Australia and central Eurasia, have indeed seen derceasing combined storage, while these in wet regions, such northern North America, have increasing storage. However, at the same time we found increasing storage in dry southern Africa and decreasing storages in wet southeastern South America. Additionally, total terrestrial water storage (i.e., the sum of groundwater, soil water and surface water) derived from GRACE satellite gravimetry for the shorter period 2002-2016 showed decreases in endorheic basins in Central Eurasia and the southwestern USA and increases in Southern Africa consistent with our storage changes (Wang et al. 2018).

Given that reservoir storage dynamics are the net result of river inflows, net evaporation and dam (demand-related) water releases, we found a reasonable relationship between changes in river flow and reservoir storage, while changes in net evaporation do not seem to have affected storage trends significantly. We also infer that human activity (i.e. increased dam water releases) do not generally need to be invoked to explain changes in reservoir storage. However, there are no water demand and supply or dam operation data available globally that could serve as direct evidence, although there have been local studies. For example, reservoir operating rules (i.e. reservoir outflow) were inferred from a combination hydrologic modeling and satellite measurements for the Nile Basin, the Mekong Basin, northwest America, and forested region of Bangladesh (Bonnema and Hossain 2017; Bonnema et al. 2016; Eldardiry and Hossain 2019). It was not possible to apply the techniques used in these studies at global scale because of the resulting uncertainties in inferred reservoir inflows. To distinguish the respective influences of human activity and climate variability on reservoir dynamics, greater collaboration and public sharing of *in situ* data on reservoir storage, water release and downstream water use would be requireed. In some basins, satellite-derived upstream and downstream river discharge dynamics (Hou et al. 2020; Hou et al. 2018) and changes in irrigation area or evaporation (Van Dijk et al. 2018) may be able to provide additional information to better understand the drivers of reservoir water security. The algorithm from Zhao and Gao (2018) could in principle be used to calculate reservoir surface water extent time series beyond 2015, but is reliant on the availability of Landsat-derived GSWD (Pekel et al. 2016). Such data could also be derived from MODIS or Sentinel 2, and help understand how reservoir water storage change from

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2015 onwards. The new NASA Surface Water and Ocean Topography (SWOT) satellite mission should also provide new opportunities to cover a larger number of reservoir (> 250 m^2) with both surface water extent and height observations for storage estimations (Solander et al. 2016).

5. Conclusions

We reconstructed monthly storage dynamics between 1984-2015 for 6,743 reservoirs using satellite-derived water height and extent. For reservoirs with water extent data only, storage was estimated from surrounding topography. Over 90% of the estimated reservoir storages dynamics show robust correlations of ≥ 0.7 (67% ≥ 0.9) against publicly available observed storage volume estimates for several reservoirs in the US, Australia and Egypt. Based on the developed global dataset, we found that reservoir storage changed significantly in nearly half of all basins worldwide between 1984–2015, with increases and decreases similarly common and mostly explained by corresponding precipitation and runoff changes. Increases appeared slightly more common in cooler regions and decreases more common in drier regions. We did not find evidence that changes in water releases or net evaporation contributed meaningfully to global trends. Changes in reservoir water storage appear to be predominantly determined by periods of low inflow in response to low precipitation. Future changes in precipitation variability are among the most uncertain predictions by climate models (Trenberth et al. 2014). Therefore, a prudent approach to reservoir water management appears the only available means to avoid water supply failure for individual river systems.

Data availability: Global reservoir surface area dataset (GRSAD) is available from the Gao Research Group, Texas A&M University (https://ceprofs.civil.tamu.edu/hgao/pages/models_data.html). Surface water level lake products are courtesy of the NASA/USDA G-REALM program and can be found at https://ipad.fas.usda.gov/cropexplorer/global_reservoir/. GRanD (http://globaldamwatch.org/grand/), HydroBASINS (https://hydrosheds.org/page/hydrobasins) and HydroLAKES (https://www.hydrosheds.org/page/hydrolakes) products were developed by Global HydroLAB, McGill University. *In situ* reservoir storage data were collected from Australian Bureau of Meteorology (http://www.bom.gov.au/waterdata/) and the US Army Corps of Engineers (http://www.nwd-mr.usace.army.mil/rcc/projdata/projdata.html).

Author contribution: JH and AIJMVD conceived the idea. AIJMVD, HEB, LJR and YW guided the study. JH carried out the analysis and wrote the manuscript with contributions from all the co-authors.

Competing interests. The authors declare that they have no conflict of interest.

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