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A Multidecadal Analysis of Reservoir Storage Change in Developing Regions

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ABSTRACT: The limited amount of shared reservoir monitoring data around the world is insufficient to quantify the dynamic nature of reservoir operation with conventional ground-based methods. With the emergence of the Reservoir Assessment Tool (RAT) driven by a multitude of Earth-observing satellites and models, historical observation of reservoir operation spanning 35 years was made using open-source techniques. Trends in reservoir storage change were compared with trends of four critical hydrologic variables (precipitation, runoff, evaporation, and Palmer drought severity index) to understand the potential role of natural drivers in altering reservoir operating pattern. It was found that the reservoirs in Africa were losing active storage at a rate of more than 1% per year of total storage capacity. Smaller reservoirs (with a capacity of less than 0.5 km^3) in Southeast Asia were found to experience a sharp gain in storage of 0.5%–1% per year of total storage capacity. Storage change trends of large reservoirs with multiple years of residence time that are designed for strategic water supply needs and drought control were found to be less affected by precipitation trends and influenced more by drought and evaporation trends. Over Africa, most reservoir storage change trends were dictated by evaporation trends, while South Asian reservoirs appear to have their storage change influenced by drought and evaporation trends. Finally, findings suggest that operation of newer reservoirs is more sensitive to long-term hydrological trends and the regulated surface water variability that is controlled by older dams in the upstream.

KEYWORDS: Africa; Amazon region; Asia; Hydrologic models; Remote sensing; Rivers; Societal impacts

1. Introduction

Globally, reservoirs provide 30%–40% of global irrigation water requirements and 17% of the electricity demand, and fulfill other services such as domestic and industrial water supply, recreation, fisheries, and flood control (Yoshikawa et al. 2014). In recent years, dam development has increased in developing countries to meet increasing demand for water, food, and electricity for a growing population (Zarfl et al. 2014). According to Grill et al. (2015), existing dams have altered 48% of the global rivers, which is predicted to increase to 93% if all planned dams are built by 2030. Construction of new dams is likely to become more difficult in the coming years due to a dwindling number of viable sites left along the free-flowing reaches of rivers. Also, due to well-known negative impacts of older dams on the local population and ecosystem, construction of newer dams may become harder to justify in many places around the world (Grill et al. 2015; Lehner et al. 2011; Nilsson et al. 2005). Hereafter, the terms dams and reservoirs will be used interchangeably.

Besides the challenges to future dam building, several water supply shortages have already been reported in many parts of the world from existing dams. The Colorado River basin of the United States post-2000 (Udall and Overpeck 2017), São Paulo in Brazil (Escobar 2015), and Cape Town in Africa (Sousa et al. 2018) are some examples of how existing dams cannot meet water requirements for stakeholders. As rivers become more regulated, it is now timely to study the dynamic behavior of existing reservoirs over multiple decades. A multidecadal observation of reservoir operations can provide insights of the basinwide resources and help water managers cope better with the climate change impacts.

Despite the importance of analyzing multidecadal reservoir dynamics for water management planning, few studies have synthesized existing methodologies to paint a more comprehensive picture. Here, we refer to reservoir dynamics as representing the complete state of a reservoir comprising inflow, surface area, active storage (and change), evaporation, and release. Methods and analysis for a partial assessment of reservoir state have been reported though, often with the use of remote sensing. Such partial assessment typically involves estimation of either reservoir height/surface extent or changes in storage and have improved our understanding of reservoirs in many regions. For example, there is now a rich body of work using satellite remote sensing on the dynamics of lakes and wetlands (e.g., Wang et al. 2014; Birkett 1998) and reservoirs (e.g., Li et al. 2020; Khandelwal et al. 2017; Gao et al. 2012). Such collective work provides many techniques spanning various satellite sensors, such as nadir radar or laser altimeters and visible/microwave imagers. In addition to reporting a partial state of the reservoir, past studies are mostly local or regional or involve only a handful of reservoir sites. The maximum number of reservoirs studied in one investigation that we could find from published literature was 347, as reported by Li et al. (2020).

Recently, Dawson et al. (2015) studied 11 reservoirs of the southern Great Plains using measured data of inflow, precipitation, and water withdrawal. They assessed long-term spatiotemporal characteristics of water quality and quantity of reservoirs along the Brazos River and the Colorado River with a first-order trend without using any process-based models of the reservoir functions. Keys and Scott (2018) studied volumetric variations in 10 large tropical reservoirs and lakes using Moderate Resolution Imaging Spectroradiometer (MODIS) satellite imagery and satellite radar

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altimetry. However, the method is not scalable to reservoirs with surface area less than 10 km^2 due to the coarse (500 m–1 km) resolution of MODIS imagery data. Duan and Bastiaanssen (2013) have proposed a method for long-term volumetric estimation of reservoir storage using satellite altimetry with satellite imagery which is limited to reservoirs having altimeter overpasses. Declining water storage capacity was studied by Wisser et al. (2013) using an approach of sediment flux and installed reservoir capacity and assuming simplified reservoir operating patterns. Gao et al. (2012) studied 34 reservoirs and their storage variability using MODIS data. Recently, Li et al. (2020) developed a reservoir bathymetry dataset for 347 reservoirs that they claim represent 50% of world's reservoir capacity.

While past studies provide a platform for partial analysis of reservoir operating trends, some limitations remain. These are 1) lack of scalability to detect regional or global patterns of thousands of reservoirs without extensive validation; 2) use of simplistic methods based on multiple reservoir operating assumptions, rather than relying on observations, to parameterize the relationship between reservoir operation and its natural drivers; and 3) lack of rigorous spatial–temporal characterization of reservoir dynamics at basin-continental scale. Such limitations are understandable if one tracks the evolution of the state of the art of reservoir operation modeling. Until recently, a comprehensive analysis of reservoir dynamics has been absent due to lack of consistent spatiotemporal reservoir monitoring data.

The most accurate way of getting consistent information on reservoir dynamics is to get in situ or ground-based measurement of reservoir surface area, elevation, storage change, inflow, and outflow, which is nearly impossible for most reservoirs for several reasons. A vast majority of the world cannot afford ground measurement of hydrological parameters due to budgetary constraints, especially in developing regions of Africa, South and Southeast Asia, and South America (Solander et al. 2016). Institutional capacity of riparian nations for basinwide cooperation is another major issue in sharing reservoir monitoring data. Even if reservoirs are observed using ground-based methods, the measurements are generally not shared universally, to the best of our knowledge, due to the restrictions imposed by national governments (Alsdorf et al. 2007).

In the absence of necessary ground data for studying the complete reservoir dynamics, the best way forward is to use publicly available open-source physically based models and satellite Earth observations that are capable of representing actual state of reservoir operation. Such a trend has recently been observed in studies based on a plethora of satellite observations and physical modeling systems (Bonnema et al. 2016; Bonnema and Hossain 2017; Hossain et al. 2019; Biswas et al. 2020; Gao et al. 2012; Li et al. 2020). In particular, we need to highlight here the recent emergence of the Reservoir Assessment Tool (RAT) (Biswas et al. 2021). RAT has addressed, perhaps for the first time, the current limitations in reservoir operations monitoring in ungauged and developing regions using advancements made in information technology and distributed modeling. The RAT framework currently monitors 1598 reservoirs in Southeast Asia, Africa, and South America region in near–real time at water management scales (i.e., biweekly), utilizing the advancements in cloud computing, land surface modeling, and satellite remote sensing and big-data analytics. Using RAT, we now have a record of the dynamics of the complete reservoir state from 1985 onward.

The core concept of the RAT framework is a satellite data–based mass balance approach as shown in Eq. (1):

$$O = I - E - \Delta S, \tag{1}$$

where O = outflow, I = inflow, E = evaporative loss, and ΔS = storage change. The latest available visible and near-infrared (NIR) images (with cloud filtering) and area–elevation curve are used to calculate the storage change of any reservoirs. Reservoir inflow is simulated by using a hydrological model forced with the latest available satellite based meteorological variables (i.e., precipitation, maximum, minimum temperature, and average wind speed). Evaporative loss from the reservoir surface is calculated as well from the outputs of the hydrological model. Finally, reservoir outflow is calculated using reservoir inflow, storage change, and evaporation from the mass balance Eq. (1). All of the monitoring variables (i.e., reservoir inflow, storage change, evaporative loss, reservoir outflow, operating rule curve) are routinely updated based on the latest available satellite observations and continuous hydrologic modeling in the RAT framework at least once a month. The methods for estimating such a complete state of reservoir dynamics are based on techniques reported in regional validation work in South Asia (80 dams), Southeast Asia (20 dams), and North America (2 dams) (Bonnema et al. 2016; Bonnema and Hossain 2017; Hossain et al. 2019; Biswas et al. 2021). The RAT framework, which can be publicly accessed from http://www.satellitedams.net or http://depts.washington.edu/saswe/rat_beta, has application potential in transboundary basins and data-scarce regions of the world (Rougé et al. 2018).

It is important to mention at this stage that the RAT is not purported as a framework that is able to capture all the world's reservoirs. First of all, it is fundamentally impossible to model all the world's reservoirs as the total number is not only uncertain, but also likely in the millions (Lehner et al. 2011). Second, to model or estimate even hundreds of thousands of reservoirs, the Earth observation data processing requirement in the cloud would be in the petabyte scale, requiring massive institutional infrastructure. The current version of RAT that models 1598 reservoirs processes 2 TB day^{-1} of data in the cloud afforded by Google which provides Google Earth Engine cloud functionality freely to the scientific community. To keep the computational burden manageable for multidecadal analysis over a global domain, a macroscale hydrologic model with large grid cell size (>5 km) such as the Variable Infiltration Capacity (VIC) model needs to be used to estimate inflow. Such a choice keeps the total number of grid cells to process for each time step in the millions rather than billions for the RAT tool.

Current flow direction datasets for identifying river network for hydrologic models are also of a resolution that requires most, if not all, dams to be manually checked for accuracy against independently derived cloud-free visible

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imagery on rivers. In our study, approximately 21% of the initial dam sites had to be discarded during initial check of flow direction compatibility with reservoirs. From a shortlisted set of 1735 reservoirs over South America, Africa, and Asia, a further 137 had to be discarded using a widely used flow direction map derived from HydroSHEDS (at 6-km resolution). Such a quality control procedure is critical because of the coarser spatial resolution of the river flow direction that is often unable to geo-connect with the reservoirs either because the reservoir is small or because the river had gradually changed course.

It is worth mentioning that while a more comprehensive dam database such as Global Georeferenced Database of Dams (GOODD) Database on about 38 000 dams by Mulligan et al. (2020) could be used in RAT, such a database provides only location of the dam inferred purely from satellite imagery. Thus, unlike current and most widely used dam databases such as the GranD v1.3 (Lehner et al. 2011; updated in 2019), the GOODD database does not yet provide comprehensive metadata on each dam's physical characteristics, year of construction, and nominal surface area. Without such data, it is impossible to carry out any multidecadal analysis of reservoir behavior as a function of age and capacity.

In this study, the available spatially and temporally consistent record of dynamics of reservoir state from RAT was used to efficiently quantify reservoirs' multidecadal operating behavior according to underlying parameters (such as age, capacity, residence time, and hydroclimatologic trends). The core objective of this study is the quantification of the long-term variability of active storage change of reservoirs and identification of the potential natural drivers of this change (hereafter "parameters" will also be used for "drivers"). The storage change variability, which represents the interplay between human decision-making and nature, was quantified based on the reservoir size, age, residence time, and region (South America, Africa, and Southeast Asia). The research question that this study tries to ask is, *How have the world's large reservoirs in developing regions been operated over the last three decades and what are the potential drivers of reservoir storage change trends?* Hereafter, the term storage will refer to active storage of the reservoir.

2. Data and methods

a. Datasets

The GranD Dam Database version 1.3 (Lehner et al. 2011) was used in this study, which is a georeferenced reservoir database and is now available publicly for global-domain studies. It contains 7320 reservoirs with a cumulative storage capacity of about 6800 km^3. From the HydroSHEDS database (Lehner and Grill 2013), 21 river basins were selected from Southeast Asia, Africa, and South America regions with a minimum of 20 dams in a basin. We used RAT simulated outputs (i.e., reservoir surface water extent area time series, area–elevation relationship curve, and simulated storage change of the reservoirs) for the GranD reservoirs in South America, Africa, and Southeast Asia. *Landsat 5* and Global Surface Water Dataset (GSWD; Pekel et al. 2016) used to extend the reservoir surface water extent time series to 1985.

The hydrologic drivers used in this study were extracted from ERA5-Land, which is a reanalysis product. ERA5-Land is a reanalysis dataset (available in Google Earth Engine Data Asset ID: ECMWF/ERA5_LAND/MONTHLY) that provides a consistent view of the evolution of land and atmospheric variables over several decades at an enhanced spatial resolution of 0.1°. ERA5-Land has been produced by replaying the land component of the ECMWF ERA5 climate reanalysis. This reanalysis combines model data with observations from across the world and is available at a monthly scale from 1981 to 2020. Precipitation, evaporation, and runoff were extracted from ERA5-Land data for analysis of reservoir storage change. Also, the Palmer drought severity index (PDSI), a commonly used indicator for drought, was extracted from the TerraClimate data (available in Google Earth Engine Data Asset ID: IDAHO_EPSCOR/TERRACLIMATE; Abatzoglou et al. 2018) for the purpose of comparing drought severity with reservoir storage variability.

b. Methodology

The methodology performed in this study can be classified in four steps: 1) preparation of long-term reservoir surface water extent area time series and storage change from RAT framework; 2) classification of dams based on size, age, and residence time; 3) extraction of variables over the selected basins from the ERA5-Land reanalysis data in Google Earth Engine; and 4) long-term trend and correlation analysis. A step-by-step discussion of these steps is presented in the following subsections.

1) PREPARATION OF LONG-TERM STORAGE CHANGE DATA ~~FROM THE RAT FRAMEWORK~~

During the development of the RAT framework, performance of the water extent area extraction methods was analyzed using the ground based storage data of 77 reservoirs. The extraction methods have been elaborated in Table 4 of Biswas et al. (2021). The framework was extensively validated for *Landsat 8*, and it was found that the normalized difference water index (NDWI; McFeeters 1996) performed best among various methods for reservoir surface area estimation (Biswas et al. 2021). For this study, it was necessary to prepare a longer (multidecadal) record, and thus we also incorporated *Landsat 5* data to yield more than 30 years of operating pattern from 1985. To derive the water extent area from *Landsat 5*, several index-based methods were also tested, and it was found that the dynamic surface water extent (DSWE; Jones 2019) performed the best. The list of index-based methods used this study was discussed in Table 4 of Biswas et al. (2021). In Fig. 1, a flowchart is shown on how the DSWE algorithm was applied to generate reservoir surface water extent time series from *Landsat 5* data and how it was then merged with the time series from *Landsat 8* based surface water extent area. F1 F2

First, the monthly average surface water extent area was created for each of the reservoirs from the GSWD dataset. Then, a monthly mosaic image of the available *Landsat 5* (or *Landsat 8*) scenes over the reservoir was made by filtering cloudy pixels. Then, the image with more than 90% cloud contamination was discarded from the analysis. If the image

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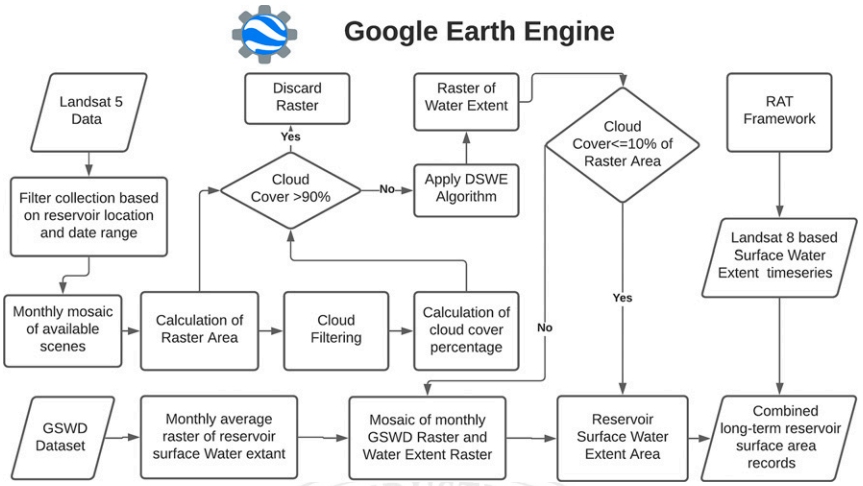
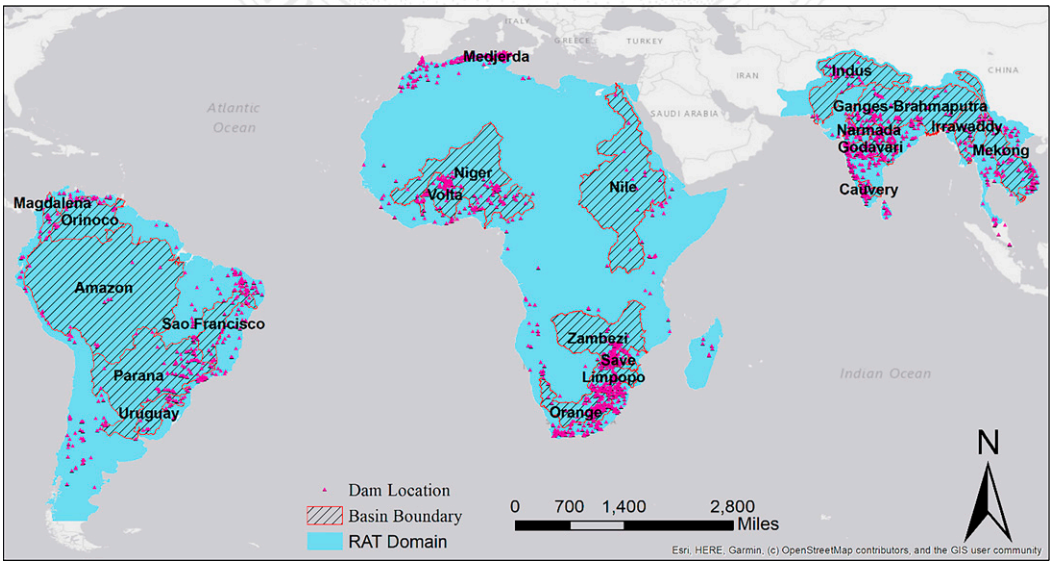


FIG. 1. Methodology to extract monthly reservoir surface water extent time series by combining *Landsat 5* and outputs from the RAT framework.

consisted of less than 10% cloud cover, no correction method was applied to that image, and the water surface area was extracted by ~~the applied~~ DSWE algorithm for *Landsat 5* and NDWI algorithm for *Landsat 8*. If the cloud cover was between 10% and 90%, the filtered out pixels were replaced with the monthly average GSWD raster data. This procedure was applied to generate long-term time series water extent data for each reservoir.

These time series data were then converted into storage change time series using the area–elevation relationship described in Biswas et al. (2021). Literature reports many area–elevation curve estimation methods such as pairing satellite-estimated reservoir surface extent (from visible imagery or microwave SAR) with reservoir height (from altimeters) (see, e.g., Li et al. 2020; Gao et al. 2012). However, we believe such techniques are limited in spatial coverage of dams due to limited spatial sampling of satellite nadir altimeters that can sample only a small fraction of the world's reservoir. Thus, we have resorted to a more global and comprehensive area–elevation curve estimation method that can be used for a current or planned dam anywhere. This method is based on the use of Shuttle Radar Topography Mission (SRTM) topographic data. As SRTM flew in February 2000, this method can only generate the reservoir's bathymetry above the water level that existed at that time. For building the area–elevation curve below that level, we therefore used a combination of extrapolation and paired Landsat and altimeter data (if available for those locations). Our procedure for estimating area–elevation curve, reverse-engineered rule curve and outflow have been thoroughly tested over multiple reservoirs of Asia (Bonnema and Hossain



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2017; Biswas et al. 2021), Africa (Eldardiry and Hossain 2019; AU4 Eldardiry and Hossain 2021), and America (Bonnema et al. 2016).

It is worth mentioning that the sedimentation behind the dam was not considered during the development of area–elevation relationship. Our derived area–elevation relationships reflect the reservoir bathymetry at one specific point in time which is the time when the SRTM mission flew (February 2000). On the other hand, reservoirs always accumulate sediment and unless they are flushed completely, the area–elevation relationship is expected to change over time. The tracking of this ~~variable area–elevation~~ is not possible in the current set up of RAT as the suspended sediment concentration and the net sediment loading at inflow and outflow are not modeled or monitored globally. Thus, all our findings that we report here are subject to some uncertainty due to the assumption of a static area–elevation curve. For the interested readers, we have provided several hands-on video tutorials on the use of SRTM data in Google Earth Engine to derive area–elevation curve step (http://depts.washington.edu/saswe/swot, under "Education and Training"). Furthermore, RAT has a publicly available GitHub page reported in Biswas et al. (2021) and on the RAT web interface with an operation manual for any user interested in replicating a tailored version a smaller region or different application.

2) Classification of dams

The GranD dams were first classified according to their size (capacity in units of million cubic meter, or 0.001 km^3, mentioned in the database). Hereafter, the term for million cubic meters will be MCM. The dams were classified into three categories as follows: small (0–400 MCM), medium (400–1000 MCM), and large (more than 1000 MCM or 1 km^3). The distribution of the different-sized dams in river basins is shown in F3 Fig. 3a. Dams were also classified based on the age (construction year of the dam mentioned in the GranD Database). They are old (more than 60 years old), medium-aged (40–60 years old), and recent (20–40 years old). In Fig. 3b, the distribution of the dams based on the dam age is ~~also~~ shown. We also classified the dams based on the residence time and defined as single-year reservoir and multiyear reservoir. Capacity of the dams mentioned in the GranD database was divided by the mean annual inflow (derived from the RAT framework generated reservoir inflow) to calculate the residence time. Distribution of the dams based on the residence time is shown in Fig. 3c.

3) Extraction of hydrologic variables from ERA5 reanalysis data

Four key hydrologic variables (precipitation, runoff, evaporation, and PDSI) were extracted from ERA5 Land reanalysis data to compare the trends of reservoir storage change time series with potential natural drivers. For each of the river basins, these hydrologic variables were extracted using Google Earth Engine. The boundary polygons of all the 23 basins were prepared and uploaded to Google Earth Engine to define the spatial processing extent of the reservoirs. Monthly precipitation, runoff, evaporation, and PDSI were then analyzed to check the correlation between the average storage change of the reservoirs within a river basin and the extracted parameters.

4) Long-term trend and correlation analysis

All extracted hydrologic variables and reservoir storage change were averaged on a moving 3-yr window to remove interannual seasonality and minimize noise in the estimates. The derived hydrologic variables were recalculated as the anomaly from the long-term mean in order to compare with storage change estimates. The analysis was performed for the period of 1984–2020 on a monthly scale. For comparison between hydrologic parameters, Spearman's rank correlation coefficient was used. Spearman's rank correlation analysis is a nonparametric measure of rank correlation (statistical dependence between the rankings of two variables). It assesses how well the relationship between two variables can be described using a monotonic function. Usually, the Spearman rank correlation will be high when the individual data point has the similar rank between the two variables and low when the observations have dissimilar rank between the two variables. Spearman's coefficient is appropriate for both continuous and discrete ordinal variables and has been used extensively in trend detection of hydrological variables (Yue et al. 2002; Chhipi-Shrestha et al. 2017; Diamantini et al. 2018).

3. Results

a. *Distribution of dams among the river basins*

From Fig. 3, it can be seen that the highest number of reservoirs were in the Africa region, most of which are smaller reservoirs. Although the number of reservoirs is lowest in the case of the South America region, it comprises a higher number of medium and large reservoirs when compared to other two continents. When dams were compared based on their age, the South America region has the lowest number of old dams. Almost all three regions have a fair number of medium aged and recent dams which indicates the dam construction boom in those regions was a late twentieth-century phenomenon. From the classification of dams based on residence time, it can be seen the vast majority of the reservoirs in out 1598 reservoirs remain single-year reservoirs that essentially store less than a year of runoff and therefore are dictated more by the seasonal hydrology. If we focus on the distribution of dams among the continents, the Africa region has mostly single-year reservoirs whereas Southeast Asia has the largest share of multiyear reservoirs (more specifically the reservoirs located in river basins in India). A considerable number of multiyear reservoirs were also found in the South America region.

b. *Long-term trend of reservoir storage variability at different scales*

The long-term trend of storage change of individual reservoirs is shown in Fig. 4. The size of the dots represents dam size classification, and the color shows long-term trend of storage change in F4 percentage of total reservoir storage capacity per year. The

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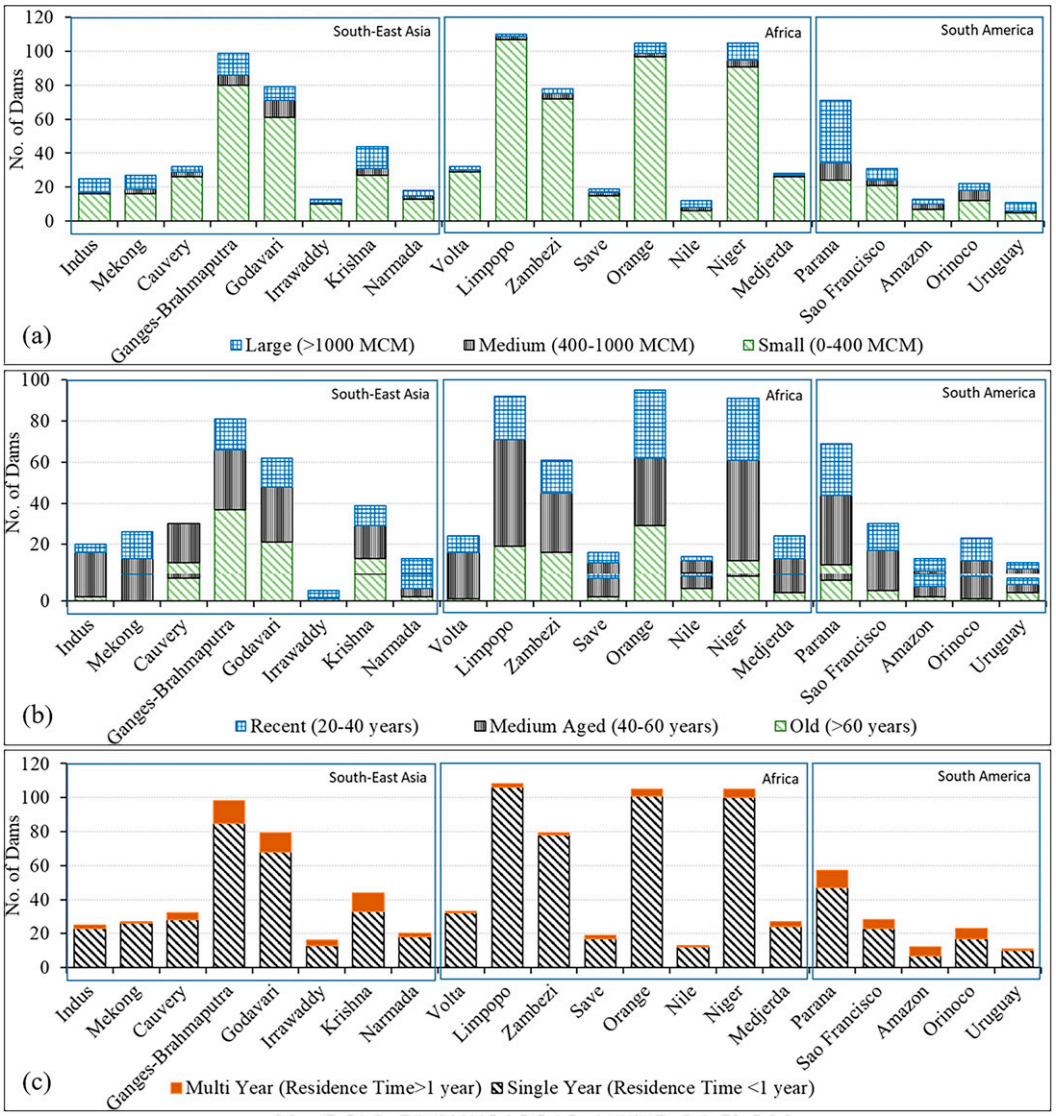

FIG. 3. Dam (reservoir) distribution among the selected river basins based on the (a) dam (reservoir) size, (b) dam age, and (c) reservoir residence time.

T1 quantification of trends is also summarized in Table 1. From Fig. 4, it can be seen that a number of reservoirs in South America have been experiencing a positive trend in storage change (more than 0.1% per year of total reservoir capacity). More reservoirs experienced a positive trend in the Southeast Asian region compared to reservoirs showing a negative trend in storage change, which indicates that the reservoirs in South America and Southeast Asia have been storing more water in recent years compared to the past. Another possible reason of the positive trend can be potentially due to the presence of comparatively higher number of medium aged and recent reservoirs in these two continents. African reservoirs show contrasting behavior. The eastern African reservoirs have seemed to experience negative to highly negative trend in storage change whereas the southern African reservoirs have experienced negative to no trend. This was possibly due to the presence of mixed-aged reservoirs where the older reservoirs have declined in storage change while newer ones are contributing to the increase in cumulative storage capacity.

The cumulative active storage change of different types of reservoirs in various river basins of the RAT domain is further illustrated in Fig. 5 for a more visual and spatial comparison. From F5 Fig. 5, it can be seen that almost all types of reservoirs have experienced a net gain in storage in the South Asia region. In other words, these reservoirs have increased in their tendency to hedge or store strategically more rather than release the water. More specifically, smaller reservoirs have experienced a highly positive trend in storage in the Ganges–Brahmaputra basin. Most of these dams have been constructed between 40 and 60 years (medium-aged reservoirs). This may be attributed to the boom in agricultural activities to meet the gap between demand

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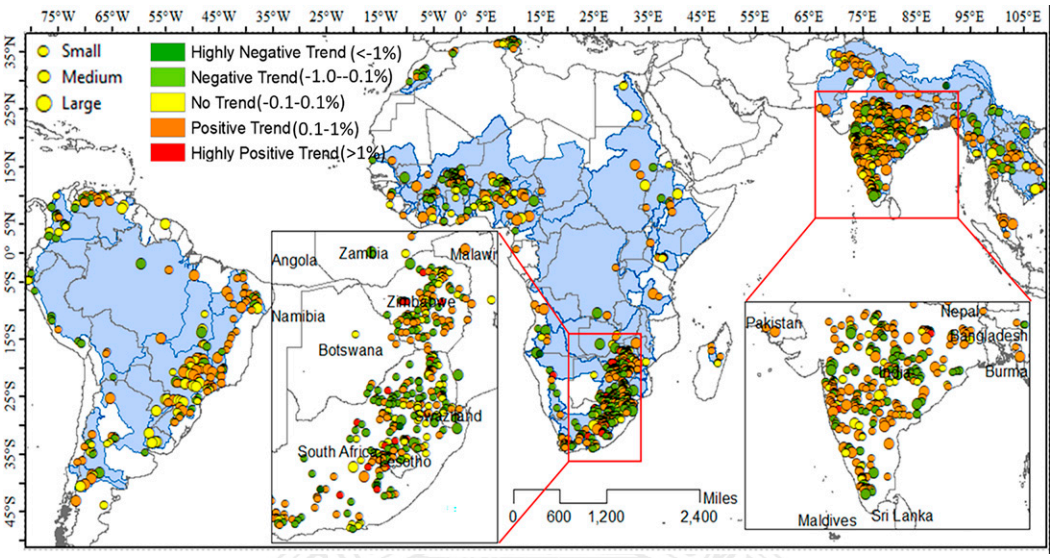

FIG. 4. Trend of active reservoir storage change included in the RAT framework. The left inset map shows South African reservoirs, and the right inset map shows the South Asia region.

and supply of irrigation water needed during the dry season (Gulati and Ganguly 2010; Patel 2013). Industrial development during the 1980s in that region might also be a possible reason for more water abstraction via storage. Any intensification in agricultural and industrial development would likely represent the lion's share of consumption of surface water and thus a greater need to regulate and store.

From Fig. 5, it can also be seen that older reservoirs in the South America region have experienced a positive trend in storage change, all of which are either small or large types of reservoirs. From the same figure, African basins are found to have mostly experienced a net loss in active storage. Smaller reservoirs (old and medium-aged) have experienced a greater rate of storage loss, which could imply that the reservoirs in those regions are either suffering from inflow reduction or increase in downstream stakeholder release or a combination of both. Another potential reason for declining storage change in Africa might be due to the decrease in precipitation amount and evaporation increase from the reservoir surface over the last few decades. The above findings were further reinforced when the reservoirs were compared based on residence time (Figs. 5g,h). It was found that both single-year and multiyear reservoirs experienced positive to highly positive trend in almost every of the river basins in the Southeast Asia region. African reservoirs experienced highly negative trend in the case of single-year reservoirs. South American single and multiyear reservoirs experienced slightly negative trend except for multiyear reservoirs of Parana River basin.

c. *Comparison of storage change trends with hydrologic trends*

The second aspect of this study compared the storage change trend with four key hydrologic parameters (i.e., precipitation, runoff, evaporation, and PDSI). All river basins and the variation in the Spearman rank correlation coefficient are shown in Fig. 6. It can be seen that different sized dams have unique correlation with each hydrologic parameter. For example, recent reservoirs in the Ganges–Brahmaputra basin have experienced a trend in storage change that follows the PDSI trend, while the correlation is negative for the old and medium-aged reservoirs. One potential reason for this could be that older reservoirs, by virtue of ~~having lost~~ more active storage through sedimentation, may have a higher tendency to store or hedge water more during droughts rather than release downstream. In the case of the Southeast Asian reservoirs, the correlation of hydrologic parameters was not as pronounced like the other two regions (South America and Africa region). In general, the Mekong, Orinocco, Zambezi, Orange, and Medjerda river basins have experienced storage change trends that are negatively correlated to PDSI. In most cases, recent reservoirs have experienced stronger correlation

TABLE 1. Quantification of the trend of reservoirs.

Trend type	Threshold values (% of total storage capacity per year)	Region showing the strongest trend
Highly negative—depletion	<-1.0	Eastern Africa
Negative—storage loss	-1 to -0.1	Southern Africa
None—steady storage	-0.1 to 0.1	–
Positive—storage gain	0.1–1.0	South America
Highly positive—hedging	>1.0	South Asia

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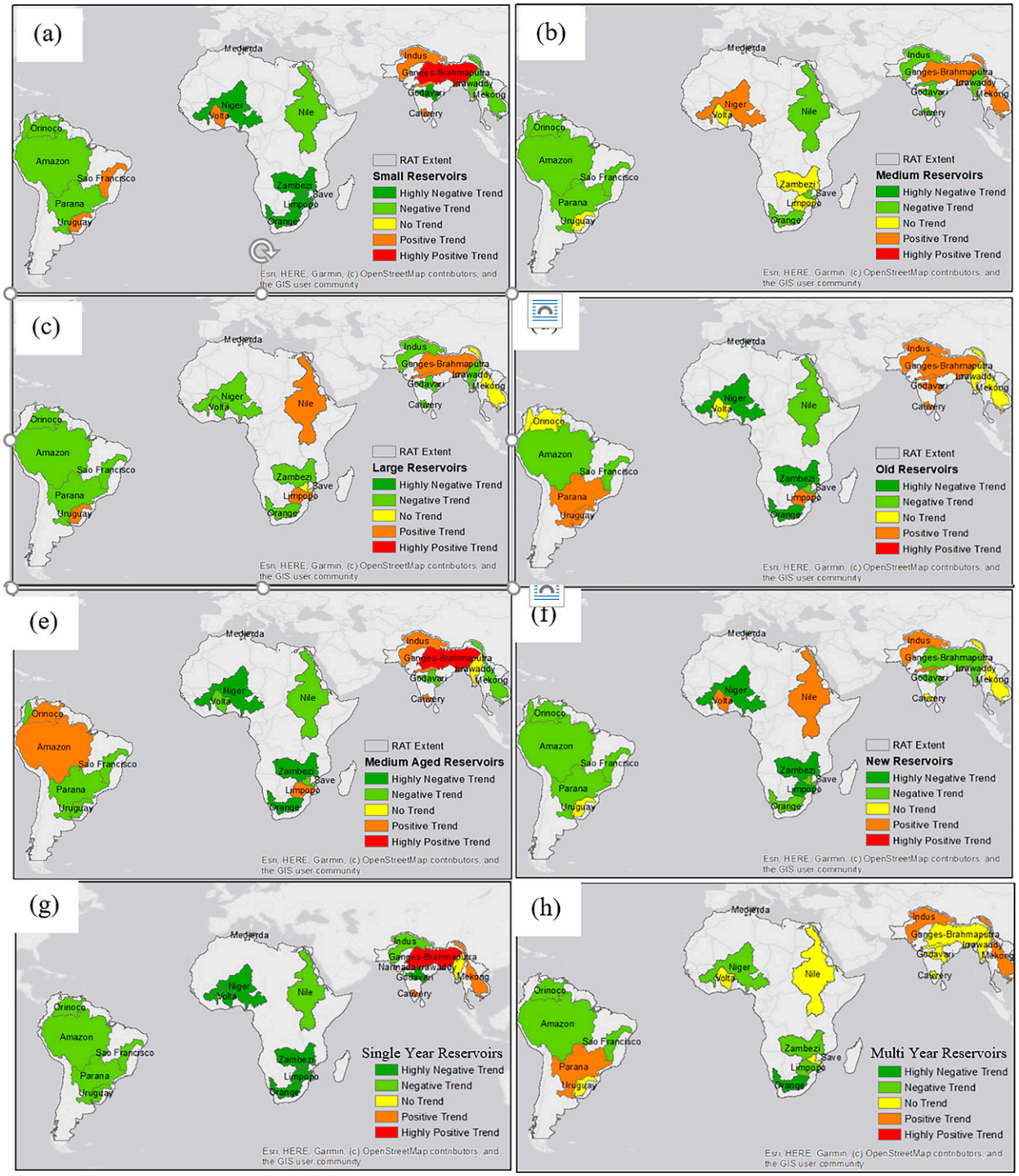

FIG. 5. Storage change trends for reservoirs in various river basins: (a) small reservoirs, (b) medium reservoirs, (c) large reservoirs, (d) old reservoirs, (e) medium-aged reservoirs, (f) recent reservoirs, (g) single-year reservoirs, and (h) multiyear reservoirs. Here single and multiyear refer to residence time of reservoirs calculated by dividing capacity by mean annual inflow.

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compared to medium aged and old reservoirs. In the case of the Zambezi River basin, negative correlations for PDSI, runoff, and precipitation and positive correlation with evaporation vary consistently with the age of the dams. This probably indicates that recent reservoirs are probably being operated more precisely by keeping in mind the limited availability of water from upstream within the basin for other stakeholders. A similar pattern can be observed in other basins as well.

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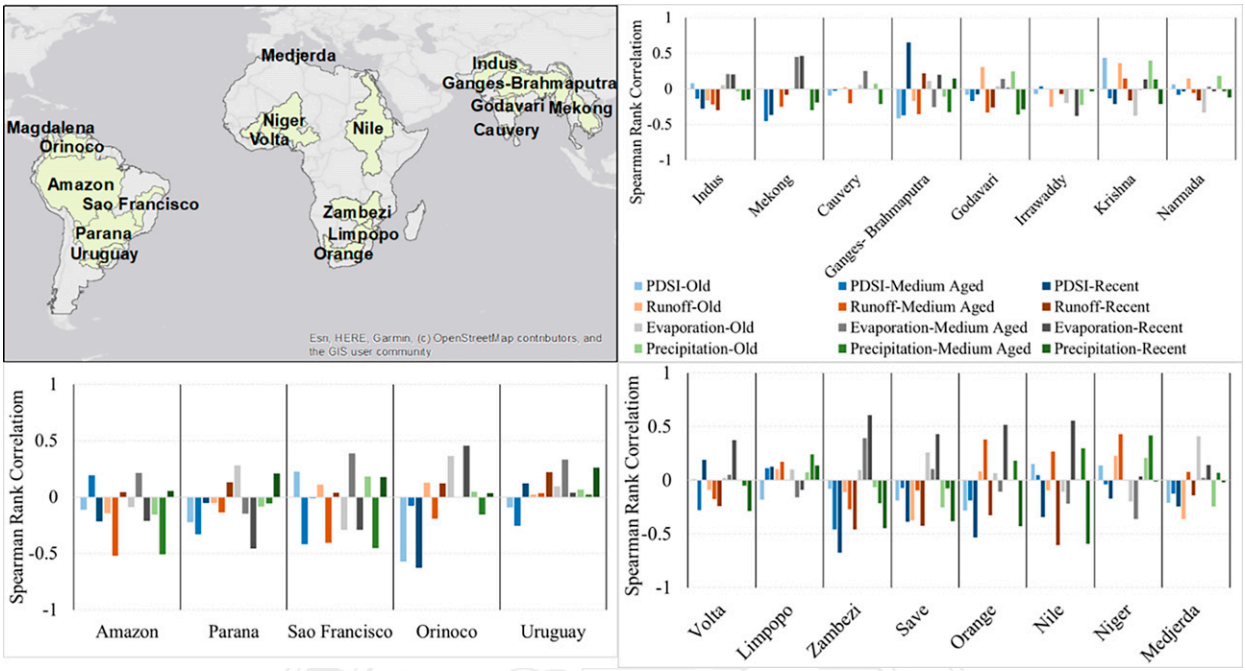

FIG. 6. Spearman rank correlation coefficient (between reservoir storage change and hydrologic parameters) comparison plot of the basins based on reservoir age. (top left) Selected river basins, (top right) basins of Southeast Asia, (bottom left) South American basins, and (bottom right) African river basins.

F7 River basins were also compared based on the size classes of reservoirs (Fig. 7). Different classes of reservoirs showed a more consistent pattern of storage change trends compared to classes based on dam age. Almost all river basins yielded a negative correlation with the PDSI except for a few reservoirs. The Parana and Orinocco river basins have experienced increase in active storage change increased during drought years by yielding highest negative correlation with the PDSI.

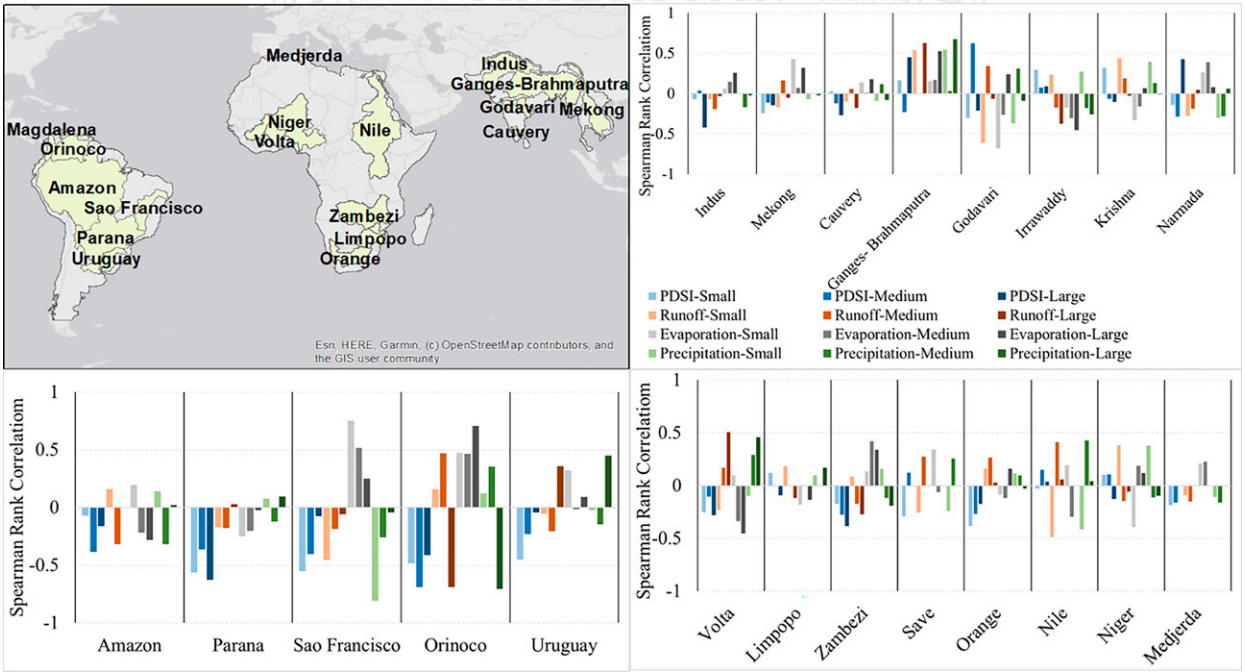

FIG. 7. As in Fig. 6, but based on the reservoir size.

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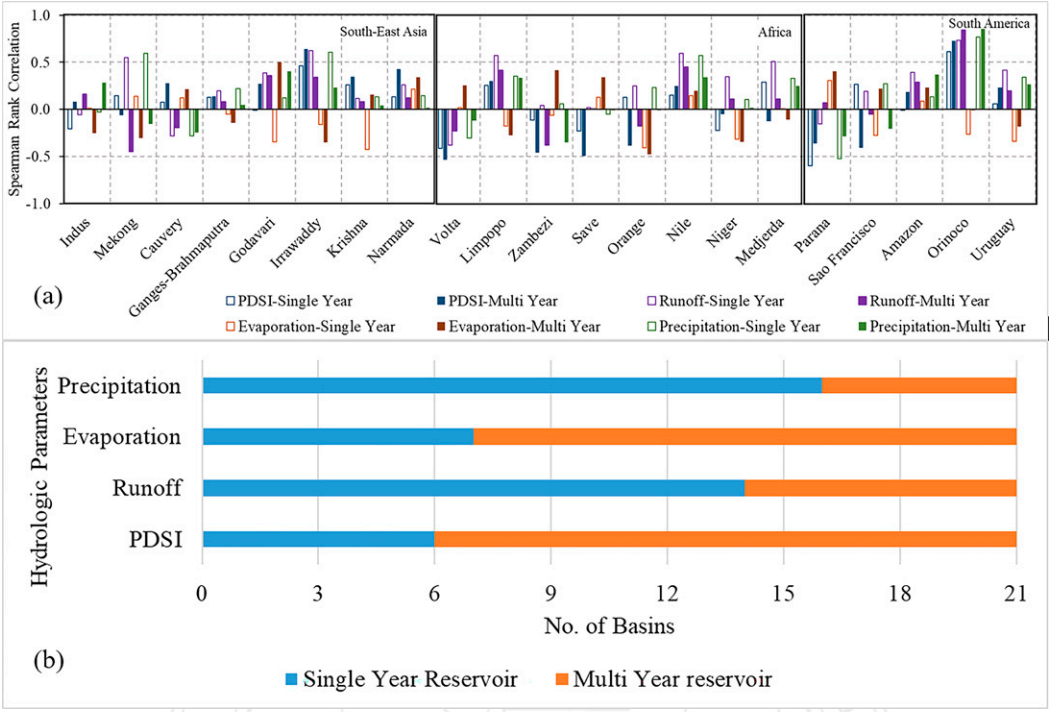

FIG. 8. (a) Spearman rank correlation coefficient (between reservoir storage change and hydrologic parameters) comparison plot for basins classified according to reservoir residence time. (b) Number of basins with higher correlation between reservoir storage change and hydrologic drivers as a function of single and multiyear residence times.

The Narmada, Sao Francisco, Orinocco, and Zambezi basins showed positive correlation with evaporation. A wide range of relationships were found in the case of Southeast Asian reservoirs. For example, the Ganges–Brahmaputra basin shows positive correlation with most hydrologic parameters. On the other hand, the Mekong and Cauvery basins showed insignificant relationship with the hydrologic variables. From Figs. 5–7, it is clear that the reservoirs in Africa region have experienced a decreasing trend in active storage, with most of them showing a negative relationship with evaporation. This indicates that recent increase in global temperature or hydroclimatic change may have directly affected reservoir storage via increasing evaporation from the reservoir surface.

F8 In Fig. 8, rank correlations for each hydrologic driver and storage change trend were calculated for all the reservoirs per basin and shown in Fig. 8a. For generating Fig. 8b, for each hydrologic driver category shown as a horizontal bar, the number of basins was identified where the correlation for single-year reservoir was higher than multiyear reservoir. For example in Fig. 8b, for the horizontal bar on PDSI, there are six single-year reservoirs where PDSI is correlated higher with storage change trend than multiyear reservoirs. Similarly, there are 14 multiyear reservoirs where PDSI is correlated higher than single-year reservoir. Because of significantly more multiyear reservoirs having larger correlation than single-year reservoirs for PDSI, we can infer from Fig. 8b that multiyear reservoirs' storage trends are influenced more by PDSI followed next by evaporation, than single-year reservoirs.

Overall, in Fig. 8, a more nuanced and clearer picture emerges on the role of hydrologic variables. First of all, there appears in general stronger correlation between storage change trend and hydrologic variables of precipitation and runoff for reservoirs with lower (single-year) residence time than higher (multiyear) residence time. The converse is true for evaporation and PDSI. The correlations are considerably weaker for multiyear residence reservoirs for precipitation and runoff but stronger for evaporation and PDSI. This corroborates the point that storage change trends of multiyear large reservoirs, which are designed for strategic water supply needs and drought control, are less affected by precipitation trends and influenced more by drought and evaporation trends. South American reservoirs appear to have the highest correlations among the three continents which perhaps speak to the relatively lesser degree human regulation and diversion of surface water at multiyear time scales. Correlations for runoff and evaporation are also in opposite directions as would be expected. Africa remains the continent where most reservoir storage change trends are dictated by evaporation trends, while South Asian reservoirs appear to have their storage influenced by drought indicators and evaporation trends. An example case on how uniquely the storage change in the individual basins are correlated with the hydrologic drivers is presented in Figs. 9a and 9b. Two basins from two different F9 continents were selected because of their contrasting hydroclimate with Parana being humid subtropical, while Godavari is a tropical savanna basin according to the Köppen climate classification. We hypothesized that contrasting hydroclimate

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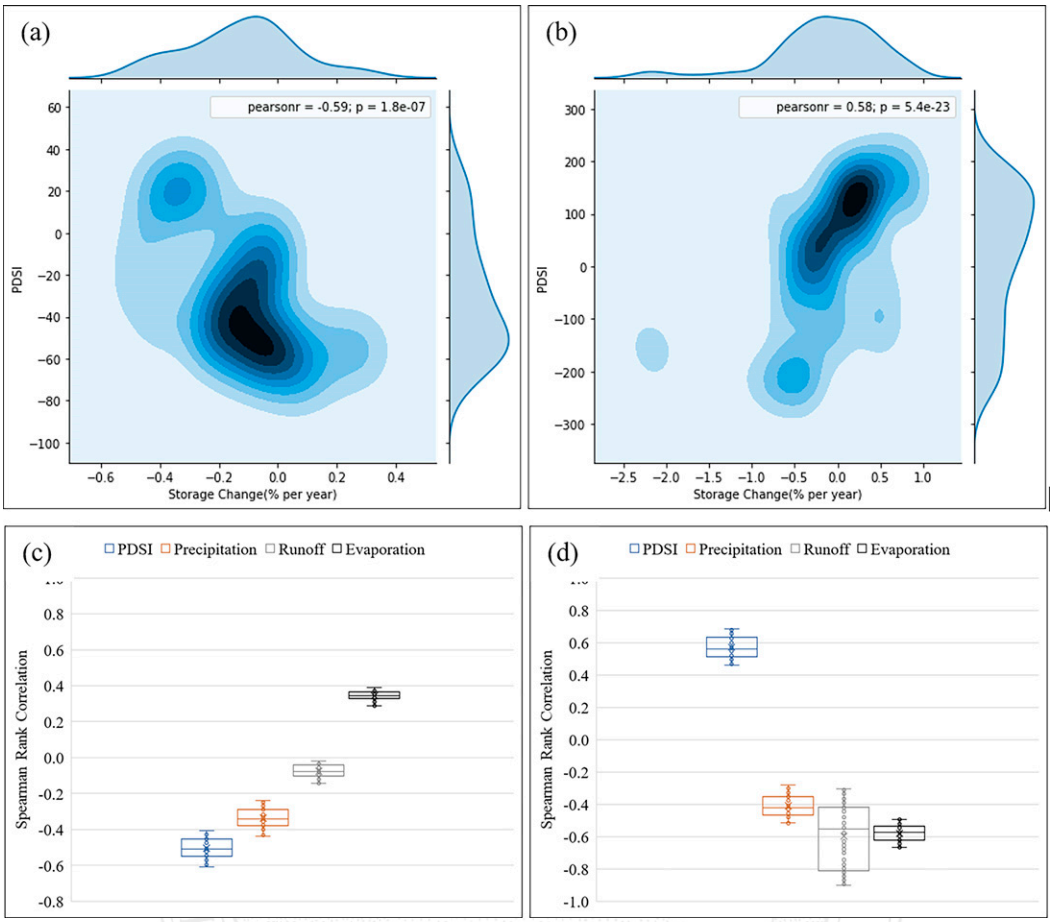

FIG. 9. (a) Kernel density estimation (KDE) plot for PDSI and storage change for Parana River basin. (b) KDE plot for PDSI and storage change for Godavari basin. (c) Variability (boxplot) of the Spearman rank correlation coefficients for individual upstream drainage area of the reservoirs and total basin area (basin average) for Parana River basin. (d) As in (c), but for the Godavari River basin.

should yield contrasting relationship between storage change and hydrologic drivers. As an example, the relationship of storage change and PDSI is presented in Figs. 9a and 9b. Completely opposite pattern of relationship with storage change is observed for the Parana River basin of South America and Godavari River basin in South Asia.

The variation of the Spearman rank correlation coefficient is shown in Fig. 10 using a boxplot comparison for the different sized and aged reservoirs. From the boxplot, the variation of relationship with different hydrologic parameters for different reservoir classes is apparent. From the left side of Fig. 10, it can be seen that the range of correlation decreases with the size of reservoirs. However, some of the basins showed a very high correlation (both negative and positive) for large reservoirs, as shown by the presence of the outliers of the boxplot. In the case of comparison among the basins based on dam age (shown on the right side of the Fig. 10), it can be seen that the correlations are more pronounced in recent reservoirs compared to old reservoirs. This may indicate that the variability in hydrologic parameters is probably being considered nowadays in the operation of recently constructed dams. In other words, the operating rule curves of newer dams may be more aligned to recent changes and climatic trends in hydrologic variables.

It is worth mentioning here that we used basin averaged values for hydrologic variables in Figs. 7, 8, 9a, and 9b. One may argue that the spatial variability of these hydrologic drivers within a river basin demand that the values be averaged over upstream drainage area for each reservoir before performing the correlation analysis. However, one major limitation of performing upstream drainage area-based analysis is preparing the upstream drainage polygons for each reservoir included in the analysis (from the total set of 1598). For instance, to generate the upstream drainage polygon for a single reservoir, the key steps are 1) manually correct the geolocation of the reservoirs, 2) fill the upstream DEM, 3) generate flow direction, 4) generate flow accumulation, and finally, 5) perform watershed analysis. For 1598 reservoirs, this would be a very complex computational endeavor.

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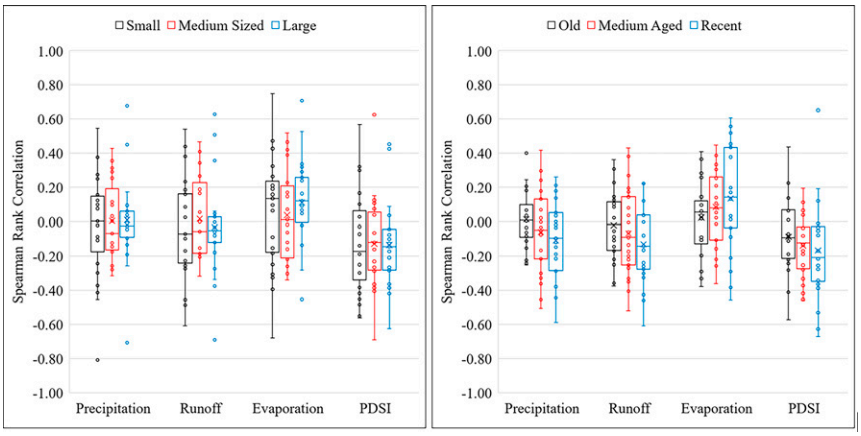

FIG. 10. Boxplot comparison of the Spearman rank correlation coefficients of reservoir based on their (left) sizes and (right) ages.

Because our study is focused more on analyzing the change of pattern (or direction) of the hydrologic drivers (rather than the actual value of the drivers) with reservoir storage change, we assumed that the inclusion of upstream drainage area only for a reservoir in calculating the correlations would have made little difference. To put our assumption to test, the upstream drainage area of 58 reservoirs of Godavari River basin and 65 reservoirs of Parana River basin were delineated. Using the delineated drainage areas of 123 reservoirs, the time series of precipitation, evaporation, PDSI, and runoff were generated and then the Spearman rank correlation coefficient for each of the reservoirs was calculated. We found that the change in correlation was modest (less than 20%) for hydrologic parameters calculated over upstream drainage area of reservoirs when compared to the same correlation calculated over the entire basin area (Figs. 9c,d). One possible reason for the modest impact of upstream drainage area of reservoirs compared to total basin area is that we are essentially focusing on the change in trends (direction) which is a much larger-scale phenomenon that extends beyond a reservoir's upstream drainage area. Another underlying reason could be due to our choice of spatial resolution (20 km × 20 km) and monthly temporal resolution of the hydrologic parameters from ERA5 data. Nevertheless, Fig. 9 demonstrate that our study is able to provide robust assessments of hydrologic drivers for reservoir storage change despite the interbasin spatial variability.

Beyond hydrologic drivers, there are likely socioeconomic and demographic drivers, such as population growth trends, agricultural water demand, and energy demand, that may have played a role in the observed storage change trends. In Fig. 11, we show the population for each basin in 1975 with F11

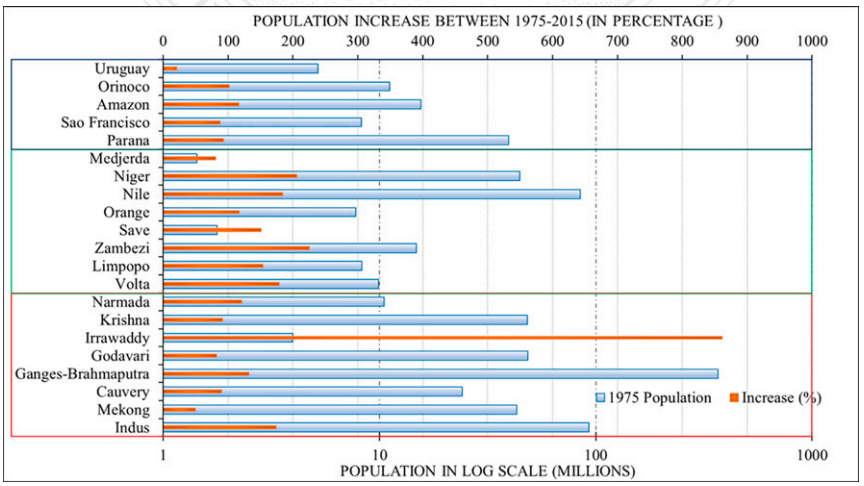

FIG. 11. Population of the selected basins for the year of 1975 and increase in population in percentage between 1975 and 2015 (population data source: Freire et al. 2016). The lower red box is over the Southeast Asia region, the middle green box is over the Africa region, and the upper blue box is over the South America region.

the percentage increase in 2015 to identify basins experiencing rapid population growth. We see that the individual population trends for each basin is not able to explain consistently the negative or positive storage change trends shown earlier in Fig. 5 for reservoirs of varying capacity or age. For example, the Uruguay basin has experienced the smallest percent increase in population among the basins considered. On Fig. 5d, for medium-sized reservoirs, we can therefore observe Uruguay to have experienced no change in storage trends (i.e., steady state). However, we also observe that the criterion of low population growth trend is not a reliable indicator for steady state of reservoir storage change for Volta, Zambezi, and Limpopo (Fig. 5d). These basins have also experienced steady state storage trends for medium-sized reservoirs, but the population growth rates are anything but low (Fig. 11). At this stage, we can only infer the following about potential socioeconomic drivers of reservoir storage change:

1) Population growth rate alone is not sufficient to improve the understanding of drivers of storage change trends. Other socioeconomic factors such as agricultural water demand and energy production water demand need to be explored.
2) A greater level of granularity for each individual reservoir (rather than a basin or even the upstream drainage area) is needed, which is beyond the scope of this paper.
3) Socioeconomic and demographic drivers do not necessarily experience uniform growth within the command area of a reservoir and hence, it may be fundamentally intractable to trace the key socioeconomic drivers of reservoir storage change only using the vantage of space.

4. Conclusions

This study quantified the impact of multidecadal reservoir operation on water availability in the ungauged regions of South and Southeast Asia, Africa, and South America. The data used in this study were prepared using a reservoir modeling framework, called the Reservoir Assessment Tool (RAT). Multidecadal observations of reservoir operations generated from the RAT framework was used to study the reservoir storage variability and identify the potential drivers of storage trend. The storage variability of the reservoirs was further quantified based on the dam size and age. The key findings of this study are as follows:

- Smaller reservoirs showed high variation in storage change trends compared to the medium and large reservoirs.
- South Asian reservoirs have experienced a net gain in active storage, indicating greater hedging possibly due to increased agricultural and hydropower demand.
- African reservoirs of all ages showed a highly negative trend in active storage change, possibly due to a decrease in inflow and an increase in evaporation from the reservoir surface.
- Storage change trends of large reservoirs with multiple years of residence time, which are designed for strategic water supply needs and drought control, are found to be less affected by precipitation trends and influenced more by drought and evaporation trends.
- The newer dams have stronger correlation with hydrologic parameters compared to the older reservoirs. This implies that newer reservoirs are likely being operated in a more realistic way by following the recent alterations in variability of hydrologic parameters.

Based on a 35-yr-long analysis, this study demonstrated one of the many potential applications of the RAT tool. The findings from this study can facilitate better planning and management of existing dams, and also help decision makers in planning and construction of newer dams. Dam operators can make a more informed decision on adaptive reservoir management with revised reservoir operation based on the findings of this study or integrate RAT framework in their tools. The long-term observations of reservoir monitoring data have been made publicly accessible through http://www.satellitedams.net/ so that users, dam operators, decision-makers, and the scientific community can benefit from this study as well as from the publicly available RAT framework. Currently, we are developing several basin and agency-specific RAT with water quality parameters for six stakeholder cases to improve water management for twenty-first-century needs. Readers can access these six new versions of RAT at http://depts.washington.edu/saswe. We hope to report on the value and impact of RAT and multidecadal analysis at a higher level of granularity in a future study.

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Data availability statement. Datasets for this research are available in Biswas et al. (2021), Abatzoglou et al. (2018), Grill et al. (2015), Zarfl et al. (2014), and Lehner et al. (2011). Data on reservoir state and codes for data processing are open-source and available on the GitHub page as follows: https://github.com/nbiswasuw/rat-reservoir_assessment_tool. Readers should also refer to http://depts.washington.edu/saswe/rat_beta to access software documentation for the reservoir assessment tool described in Biswas et al. (2021).

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