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Historical Analysis of Reservoir Storage Trends and Resilience Across Contiguous US from 1980 – 2019

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Abstract. All major river systems in the Contiguous United States (CONUS) are impacted by dams. Many regional and global studies have looked at reservoir resilience to extreme events and quantified static characteristics, yet analysis of historical reservoir operations has been limited by a lack of data. Here we use the first national dataset of historical reservoir operations in CONUS, ResOpsUS, to analyze reservoir storage trends and operations over the last 40 years. We characterized seasonal operating patterns and show clear regional trends. In the eastern US which is dominated by flood control storage we see that storage peaks in the winter months with sharper decreases in operational range in the summer. While in the more arid western US where storage is predominantly for irrigation, we find that storage peaks during the spring and summer with increases in the operational range during the summer months. The Lower Colorado region is an outlier because it is arid and dominate by irrigation, but its seasonal storage dynamics more closely mirrored that of flood control basins. Consistent with previous studies we show that reservoir storage has decreased over the past 40 years, although our national fraction filled decreases are 50% less than those shown previously. We also find that declines are occurring faster in more arid regions. Operational ranges (i.e. the difference between monthly max and min storage) have been increasing over time in more arid regions and decreasing in more humid regions. We also quantified hydrologic drought using the standardized streamflow index (SSI) and compared the time it took for reservoir storage (expressed as anomalies in fraction filled) and SSI to recover. As would be expected, we see longer drought periods and more prolonged negative reservoir storage anomalies in the more arid basins. That said, nearly all regions have reservoir storage that takes longer to recover from drought that the streamflow.

1. Introduction

The Contiguous United States (CONUS) contains tens of thousands of dams that have greatly impacted all major river systems in the United States (Grill et al., 2019; Patterson & Doyle, 2019). Of the more than 52,000 storage structures total, 4% are denoted as large dams with a storage capacity greater than 10 km^3(Lehner et al., 2011). Large dam operations and resilience to climate extremes have been studied at both the regional and national level (Adusumilli, Borsa, Fish, McMillan, & Silverii, 2019; Di Baldassarre et al., 2018). However, existing reservoir studies have been greatly limited by the lack of historical data. Until recently we lacked a national repository of reservoir operations. As a result, national reservoir studies have historically relied on static datasets of reservoir properties combined with models to simulate operations, or inferred operating curves based various remote sensing and water demand data (Petra Döll, Kaspar, & Lehner, 2003; Hanasaki, Kanae, & Oki, 2006; Lehner

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et al., 2011; Voisin et al., 2013). Here we provide the first national evaluation of historical reservoir behaviors based exclusively on direct observations of reservoir storage levels and releases provided by reservoir operators. This work is made possible by the recently published ResOpsUS dataset, which contains historical reservoir operations for more than 600 large dams in the US (Steyaert, Condon, Turner, and Voisin (2022). We explore spatial and temporal trends in reservoir storage dynamics and drought vulnerabilities to better understand how reservoirs have reshaped the water networks and supply in the United States.

There are 2,000 large dams are spread out across the US (defined as dams with a maximum storage capacity greater than 0.1 cubic kilometers and dam wall greater than 15 meters according to the International Coalition of Dams standards). In general, the eastern US has a greater density of large dams, while total reservoir storage capacity is higher in the western US (Graf, 1999). This trend is due to 1) the need for numerous structures to provide flood control and navigation operations in the more humid eastern part of the country, and 2) the need for large storage capacity with carryover storage to support water demands in the more arid western United States (Benson, 2017; Haddeland, Skaugen, & Lettenmaier, 2006; Ho et al., 2017; Patterson & Doyle, 2019).

Dams have many positive impacts on water management. By regulating the flow of rivers, dams provide reliable water supplies, enable year-round navigation, protect communities against damaging floods, and support regional economic development (Benson, 2017; Boulange, Hanasaki, Yamazaki, & Pokhrel, 2021; Ho et al., 2017; Ortiz-Partida, Lane, & Sandoval-Solis, 2016; Patterson & Doyle, 2018). In fact, Finally, there is a strong reliance on reservoir systems to provide water supply, hydropower, and irrigation uses especially in more arid regions (Di Baldassarre et al., 2018).
In snowmelt dominated basins, reservoirs capture spring runoff and augment water supplies in the summer when agricultural demands are high but streamflow would naturally be low (e.g. Turner, Xu, and Voisin (2020) and Giuliani and Herman (2018)). Additionally, increasing reservoir storage capacity in the Western US has built agricultural resilience to drought (Smith & Edwards, 2021). Reservoirs can also decrease the severity of extreme weather events like floods and droughts(Brunner, 2021).

While dams promote provide stable water supplies and help protect against extreme events such as floods and droughts, they also have many harmful impacts on local and regional ecosystems. Numerous studies show that seasonal shifts in reservoir release alter river connectivity and affect ecological communities (Grill et al., 2019; Ho et al., 2017; Lehner et al., 2011). Dams also disrupt natural temperature, dissolved oxygen, and sediment regimes, all leading to loss of biodiversity in managed river systems (Chen & Olden, 2017; Collier, Webb, & Schmidt, 1997; P. Döll et al., 2012; Johnson, Olden, & Vander Zanden, 2008; Nilsson & Berggren, 2000). Increased water demands in the western United States specifically have changed runoff regimes along the Pacific coast (Haddeland et al., 2006).

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Also, in recent years studies have begun to question the conventional wisdom that dams provide more reliable systems particularly as we start to see climate extremes that fall outside what these systems were engineered for. It has been argued that large storage reservoirs in the western United States have actually increased regional sensitivity to climatic variabilities (particularly droughts) and has locked the region into potentially unsustainable water use (Adusumilli et al., 2019; Di Baldassarre et al., 2018). In part because the region is now reliant on a cumulative storage capacity that is one third of the total storage capacity in CONUS and has seen a large increase in water usage to support agriculture and population growth (Di Baldassarre et al., 2018). Similarly in the Eastern US we are seeing flashier systems can disrupt reservoir operations (Lehner, Czisch, & Vassolo, 2005; Naz et al., 2018). Hydropower reservoirs in the Western United are also threatened by projected streamflow variability increases the increase the likelihood that late summer energy demands are not met as operations shift to accommodate streamflow (Voisin et al., 2016). In fact, in all regions, reservoirs increase the duration of extreme events by increasing the spatial connectedness (Brunner, 2021). Decreasing storage trends have also been linked to decreasing reservoir resilience in the southwestern regions and the Mississippi basin where reservoir storage has struggled to recover after recent droughts(Hou, van Dijk, Beck, Renzullo, & Wada, 2021). This is contrasted by Giuliani and Herman (2018), who found that large dams in California with limited storage fluctuations are more drought resilient than smaller dams.

Numerous studies have noted declining reservoir storage across the US over time. Nationally, reservoir storage has declined by at least 10% over the past thirty years (Adusumilli et al., 2019; Hou et al., 2021; Randle et al., 2021; Zhao & Gao, 2019). However, there are regional differences and not all locations have experienced declining storage (Hou et al., 2021). In general, arid regions such as the southwestern United States and more humid regions in the south-eastern United States have seen the largest storage declines when compared to the rest of the United States (Hou et al., 2021). These arid regions, such as the Southwestern United States, have historically seen the largest storage declines (Zhao & Gao, 2019). Most recently the megadrought in the western US has caused unprecedented streamflow declines (Williams, Cook, & Smerdon, 2022) and reservoir levels in this region are at historic lows (Cayan et al., 2010; Williams et al., 2022).

Nationally, declines in storage have been linked to sedimentation (Randle et al., 2021; Wisser, Frolking, Hagen, & Bierkens, 2013), increases in streamflow variability (Naz et al., 2018) and increased evaporative losses (Zhao & Gao, 2019). In the southwestern United States, the decreasing storage trends are strongly linked to reductions in precipitation over the last thirty years and high evaporation rates (Barnett & Pierce, 2008; Prein, Holland, Rasmussen, Clark, & Tye, 2016; Zhao & Gao, 2019). In the southwestern and north-western United States (water poor regions) have decreasing water area trends that are exacerbated by increasing evaporation rates (Zhao & Gao, 2019; H. Zou et al., 2019). Comparatively the south-eastern and Great Plains regions of the United States (more water rich regions) exhibit increasing water body area trends, which are due to being less water limited (Z. Zou et al., 2018).

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Despite the critical role that reservoirs play in our natural and managed systems, the lack of national operations data has limited the approaches that we can use to study operations. Previous national work on reservoir impacts, and storage trends is based on hydrologic models which make assumptions about operations, or remote sensing which cannot directly observe storage. There are some studies based on direct operations acquired from agencies; however, these have been limited to regional study areas (Steyaert et al., 2022; Turner, Steyaert, Condon, & Voisin, 2021; Voisin et al., 2016).

Many large-scale models use inferred rules curves based on static reservoir storage capacity values (Petra Döll et al., 2003; Ehsani, Vörösmarty, Fekete, & Stakhiv, 2017; Haddeland et al., 2006; Hanasaki et al., 2006; Voisin et al., 2013; Yassin et al., 2019). These approaches generally use inferred releases based on demand, static storage capacity values and modelled inflows to derive storage relationships (Petra Döll et al., 2003; Ehsani et al., 2017; Haddeland et al., 2006; Hanasaki et al., 2006; Voisin et al., 2013; Yassin et al., 2019). These models often rely on simplifying assumptions such as lumping reservoirs into categories based on main use, or assuming dead storage is equal to 10% of total storage capacity. Unfortunately, these inferred operations are limited by a lack of real observations (Wada et al., 2017).

Remote sensing is another common approach is to use to examine storage changes over large spatial scales (Adusumilli et al., 2019; Hou et al., 2021; Zhao & Gao, 2019). These methods involve gathering data from satellite missions such as GRACE or Landsat and aggregating the pixel values (usually at 0.5 degree resolution) into gridded data that can be employed in national and regional models to model reservoir dynamics (Zhao & Gao, 2019). These aggregated pixels can also be analyzed on various timesteps (usually on daily, weekly, or yearly scales) to observe changes in water body area. While these studies have greatly contributed to the understanding of climatic impacts on reservoir storage, they are limited by their 0.5-degree spatial resolution. Additionally, many remote sensing studies are limited by the lack of temporal data before the early 2000s which makes it impossible to study trends (Adusumilli et al., 2019; Hou et al., 2021; Zhao & Gao, 2019). Finally, remote sensing studies can only directly investigate reservoir surface area and storage must be back calculated from an elevation-storage relationship on a dam-by-dam basis.

The most direct approach to evaluate reservoir patterns is to use direct observations of storage, release and inflow gathered from reservoir operators. However, direct observation studies have focused on smaller regional domains where data is more easily gathered. For example, (Turner et al., 2021) and (Patterson & Doyle, 2018) used direct observations to explore regional dynamics and extrapolate them to similar reservoirs and regions nationally.

The lack of national data has limited our understanding of historical reservoir storage vulnerabilities, and resilience. Previous studies looking at reservoir resilience and trends such as Adusumilli et al. (2019), Di Baldassarre et al. (2018), Hou et al. (2021) were only able to look at static reservoir values or modelled releases derived from these static values. Here we use the first national dataset of direct reservoir observations, ResOpsUS to evaluate historical trends in reservoir storage. ResOpsUS

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contains daily inflow, outflow, storage, and release data for over 600 large reservoirs (maximum storage capacity greater than 0.01 km^3) from over 40 agencies spread out throughout the CONUS domain with most of the coverage from 1980 – 2020. Using ResOpsUS, we aim to better understand historical reservoir storage dynamics both seasonally and over time. Specifically, we explore regional differences in seasonality (Section 3.1), historical reservoir trends over the past 40 years (Section 3.2) and historical sensitivity to drought (Section 3.3).

2. Methods

The bulk of our analysis on historical reservoir operations uses data provided by reservoir operators in the ResOpsUS dataset (Steyaert et al., 2022). First, we aggregated the data in ResOpsUS by hydrologic regions in CONUS. The data from ResOpsUS is combined with other existing datasets on historical reservoir operations and hydroclimatic variables to explore seasonal dynamics, storage trends, and drought sensitivity (Section 2.1). Data processing and storage calculations used for trend analysis are summarized in Sections 2.2 and 2.3 respectively. We also calculated standardized streamflow indices for all regions that were used in our drought analysis (Section 2.4). All scripts for analysis are located on GitHub and linked in Section 6: Data Availability.

2.1 Data

Historical reservoir storage, the main component of our analysis, was pulled from ResOpsUS (Steyaert et al., 2022). We also used static reservoir properties from Global Reservoirs and Dams Dataset (GRanD) (Lehner et al., 2011) and hydrologic boundaries from Watershed Boundary Dataset (WBD) dataset from NHD (Geological, 2004). For our drought sensitivity analysis, we used the United States Geological Survey reference gages from the GagesII dataset (Falcone, 2011), and stream gage timeseries data from the National Water Information Systems (NWIS) Mapper from the United States Geological Survey (Survery, 2016).

The ResOpsUS dataset is the most comprehensive dataset of historical reservoir operations in the US. It contains daily historical timeseries data for 678 large reservoirs (reservoirs with a storage capacity greater than 10 km^3) including storage, inflow, releases, elevation, and evapotranspiration. Periods of coverage vary by dam (partially due to reporting and partially due to variability in dam construction dates) as do the variables provided. Overall reservoir storage and release timeseries are the most comprehensive, especially in the period from 1980 – 2019. We focus primarily on storage data for this analysis as it is the most consistently reported in this dataset. ResOpsUS has daily storage records for over 600 dams and covers 99% of all the reservoirs in the database.

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The reservoir data in ResOpsUS was obtained directly from the reservoir operators. Steyaert et al. (2022) noted there were some point errors, but no direct clean-up of the data was done. Therefore, we preformed minor data processing to ensure consistency in our analysis. First, we processed the reservoir storage timeseries to check for outliers. To do this we linked ResOpsUS with the Global Reservoirs and Dams dataset (GRanD). GRanD contains static reservoir data such as storage capacity, construction date and reservoir main use for 6,862 dams throughout the world and 2,000 in the CONUS domain. After we linked the two datasets, we then identified outliers where the reported ResOpsUS storage exceeded the maximum storage capacity of the dam reported in GRanD. For these outliers, we adjusted the storage value to the maximum storage capacity. Secondly, we filled in missing storage values using linear interpolation. We also checked the period of record for every dam. In the rare instance that the build date in GRanD was later than the data start date in ResOpsUS, we amended the start date in GRanD to align with the data from ResOpsUS.

Historical streamflow data was obtained from the United States Geological Survey's NWIS database. This streamflow data provided the basis for our Standardized Streamflow Index (SSI) calculations to quantify hydrologic drought periods. For each region, we limited out analysis to gages that were listed as 'Reference' gages in the GagesII dataset. This ensured that our derived standardized streamflow indices had little impact from the dams in the CONUS domain and therefore droughts could be mostly attributed to streamflow regime changes. Each region has multiple reference gages with which we calculated Standardized Streamflow Indices for.

2.2 Regional Storage Calculations

The reservoir storage and storage capacity timeseries were aggregated by the two digit USGS Hydrological Units (HUC2s) and used to calculate the fraction of storage filled of each region (Geological, 2004). We opted to use the HUC2 boundaries to ensure that our sample size per region consistent of at least 10 dams. There are an average 110 dams per region. Although there is great variability from region to region, some regions have 15 dams (i.e. the Lower Colorado), while others have 200 (i.e. Missouri region).

In addition to evaluating total storage, we also calculate regional fraction filled (FF) to normalize the storage values and more directly compare across regions. Fraction filled (FF) time series were calculated using Equation 1 for daily time steps across the entire period of record that exists within the original ResOpsUS time series data.

$$\mathrm{FF}_{\mathrm{R,d}} = \frac{\sum_{\mathrm{i=1}}^{\mathrm{n}} \mathrm{storage}_{\mathrm{i,d}}}{\sum_{\mathrm{i=1}}^{\mathrm{n}} \mathrm{capacity}_{\mathrm{i}}} \quad , \tag{1}$$

Where FF is the fraction filled for region R on day d, $\mathrm{storage}_{\mathrm{i,d}}$ is the reservoir storage for a given dam *i* on day *d* and $\mathrm{capacity}_{\mathrm{i}}$ is the reservoir storage capacity for dam i. Results are summed regionally for all active dams (n) in a region on a given day

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where 'active' dams are those dams for which a storage value is available in ResOpsUS. Daily fraction filled time series were averaged monthly and over the water year periods from 1980 – 2019. Note also that we are dividing here by the reservoir storage capacity of dams that are actively reporting storage for ResOpsUS on a given day. Therefore, the Fraction Filled metric also normalizes for differences in the timing of dam construction and storage reporting.

Fraction filled analysis is only preformed for those regions where the ResOpsUS dataset has sufficient coverage to be representative of regional storage dynamics. To be included for analysis we must have storage data covering at least 40% of the total storage capacity reported in GRanD for a given region. Storage covered was calculated by summing reservoir storage capacity for all the dams in a region contained in ResOpsUS and dividing this value by the total storage capacity of all the dams in the same region in GRanD. Of the 18 regions in the United States, twelve had enough data to be kept in our analysis (Figure 1).

Seasonal aggregation was done by grouping monthly fraction filled values and then taking the maximum, minimum and median across different periods. Regional trends were calculated via Sens slopes using the fraction filled time series from 1980 – 2019. All Sens slope in this paper were calculated with a 95% confidence interval and a p value of 10% (0.1) was used as significant. Trends in the monthly range were calculated by taking the range of each month and year (i.e. January 1980, February 1980, etc.) and then plotting all the monthly ranges across time. Sens slopes were calculated for these fits using the same 95% confidence interval and p value of 0.1.

2.3 Standardized Streamflow Index Calculations

We compare reservoir storage with Standardized Streamflow Index (SSI) (Yassin et al.) to explore reservoir response and resilience to hydrologic drought periods. SSI was calculated using all the reference stream gages in each region that had over 70% of their record covered from 1980 – 2020 using the workflow created by Vicente-Serrano Sergio et al. (2012) and then equations 2 and 3.

The calculation of SSI is done by determining the cumulative distribution function of streamflow for a given gauge and calculating the probability of exceedance for each streamflow value at each time step. We calculated regional Standardized Streamflow Indices (SSI) using aggregated stream gage data. Starting from the Gages II dataset (Falcone, 2011) we calculated SSI for all reference gages with at least 70% complete observations from 1980 – 2019. Reference gages are designated as minimally impacted by anthropogenic factors. We use the workflow from Vicente-Serrano Sergio et al. (2012) to calculate the standardized streamflow index for each stream gage. We chose to fit the General Extreme Value (GEV) distribution to each month of streamflow data as Vicente-Serrano Sergio et al. (2012) determined this was the most flexible and could show solutions for negative values. After fitting the GEV distribution the SSI values van be calculated as follows:

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$$W = \sqrt{-2 * \log{(P)}} \text{ for } P \leq 0.5 \,, \tag{2}$$

$$SSI = W - \frac{C_o + C_1 * W + C_2 * W^2}{1 + d_1 * W + d_2 * W^2 + d^3 * W^3} \,, \tag{3}$$

Where P is the probability of exceedance at a determined x value. If P> 0.5, then P is replaced by 1- P and the sign of the resultant SSI value is inverted. $C_o = 2.514417$, $C_1 = 0.802853$, $C_2 = 0.010328$, $d_1 = 1.432788$, $d_2 = 0.189269$, and $d_3 = 0.001308$ (Vicente-Serrano Sergio et al., 2012).

After SSI values are calculated for each stream gage, aggregated by region and then a regional mean is calculated. These aggregated values are then analyzed in conjunction with the fraction filled to determine relationships between drought periods and reservoir fraction filled. First, we took the five-year rolling average of the regional SSI to smooth out the curve and remove the seasonal trends. From this rolling average, we calculated the median SSI value across the 1980 – 2019 period. Standardized values that drop below the median and stay below for multiple months are denoted as drought periods, while values that are greater than the median and stay above the median for multiple months are denoted as non-drought periods. Each region has three to four drought periods.

2.4 Fraction Filled Anomaly and Recovery Ratio

The fraction filled anomaly is used to normalize storage by month (equation 4) so we can compare drought impacts across regions. To start, we calculated the monthly (m) median FF value across the full time period from 1980 – 2019 for each region (R) denoted as $FF_{R,m}$ in equation 4. Then, every daily FF value was matched to the correct month so that we could calculate the difference between the daily value and the monthly median. Daily fraction filled timeseries where then further aggregated to monthly for the drought sensitivity and recovery analysis (Section 3.4).

$$Anomaly_{R,d} = FF_{R,d} - FF_{R,m} \quad , \tag{4}$$

We then quantified several metrics for each drought. First, we calculated the drought recovery time as the date at which the SSI or FF anomaly values were equal to or greater than the respective value at the start of the drought period. We then define the recovery ratio (RR) as the time it took the fraction filled anomaly to recover divided by the time it takes the SSI values to recover. Recovery ratio values less than 1 denote that the drought metric took longer to recover and RR values greater than one denote that the fraction filled anomaly took longer to recover.

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3. Results

First, we evaluate regional differences in seasonal reservoir operations (Section 3.1). We then examine the storage trends over the past 40 years (Section 3.2). Finally, we explore sensitivities to hydrologic drought periods (Section 3.3). In all cases we study the 12 bolded regions in Figure 1d that have sufficient data in ResOpsUS.

Throughout our discussion we explore relationships between reservoir settings, operational uses, and the observed behaviors. Figure 1 maps reported reservoir usages nationally along with aridity to provide additional context for discussion. As shown in Figure c, reservoirs in CONUS have a variety of primary uses ranging from flood control, irrigation, recreation, water supply, navigation, fisheries and other. There are some clear regional trends. The western US is dominated more by irrigation uses, while flood control is the domainte usage along and east of the Mississippi River (Figure 1a-b). In ResOpsUS, flood control and irrigation main uses are the most numerous, however, there are a concentration of navigation, hydroelectricity, water supply and recreation main uses across CONUS (Figure 1c). Irrigation and water supply main uses are typically west of the Mississippi, while flood control main use reservoirs exist throughout the entirety of the CONUS domain. California has the largest percentage of irrigation reservoirs with the Great Basin and Rio Grande following close behind (Figure 1a). There are no irrigation reservoirs in the dataset East of the Mississippi where the climate is more humid (Figure 1d). Comparatively, flood control reservoirs have the highest concentration along the Mississippi Bains. All regions aside from the Lower Colorado have at least 1 flood control reservoir (Figure 1b). Navigation reservoirs are concentrated in the south-eastern portions of CONUS especially in the Ohio, South Atlantic, Lower Mississippi and Texas Gulf regions. Hydroelectricity reservoirs are most common the Tennessee Basin and South Atlantic.

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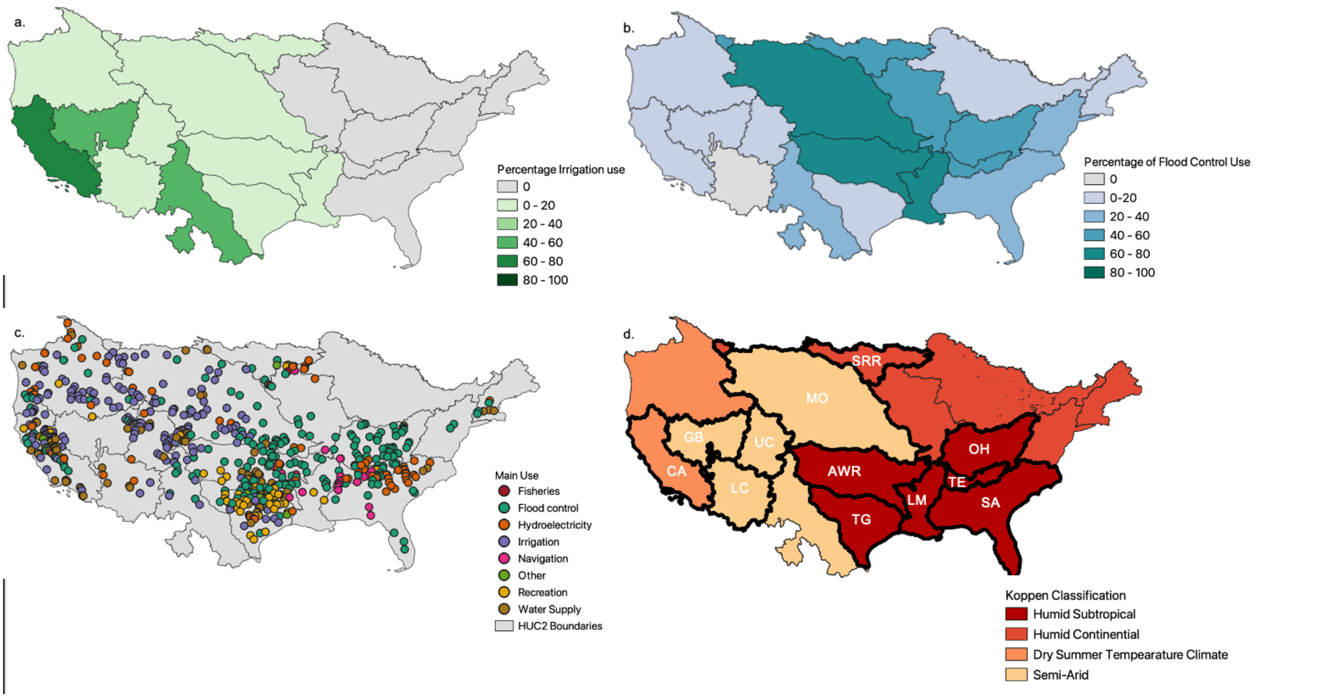

Figure 1: Maps depicting the percentage of storage capacity used for irrigation (a) and flood control (b), point locations of all dams in ResOpsUS colored by main use (c) and aridity of all regions with the 12 main regions in this study outlined (d). Panel a and b are calculated by summing up the total storage capacity of dams with irrigation (panel a) or flood control (b) as their main use and dividing that number by storage capacity in each region. Grey shading in both denotes regions that do not have any irrigation or flood control dams. Dams that did not have a main use are not mapped in panel c. Panel d depicts the mode of the Köppen-Geiger climate index pixels in the to classify the regional climates for each HUC2. Panel d also contains the abbreviations of the basin names pulled from the USGS HUC2 watershed boundaries dataset as denoted in Table 1.

Spatial patterns in reservoir purpose correlate with national climate patterns. Figure 1d shows the aridity indices according to the Köppen- Geiger index (Kottek, Grieser, Beck, Rudolf, & Rubel, 2006). The Köppen-Geiger index uses annual precipitation and temperatures to classify climates into four main groupings: tropical, dry, continental, and polar. Of these, the continental United States contains all except polar. For each HUC2 region, we used zonal statistics to calculate the number of pixels in each Köppen-Geiger climate index in order to quantify the regional climates. The north-eastern United States is humid continental meaning that seasonal precipitation variability is small, and temperatures are relatively cool (less than 22 degrees Celsius) all year. The south-eastern United States is primarily humid subtropical which has warm and moist conditions in the summer months which makes summer the wettest season. The midwestern United States is semi-arid with warm summers, snowy winters, and large diurnal temperature swings. Finally, the West Coast is dry summer temperate which is characterized by moderate temperatures and changeable, rainy weather with hot and dry summers.

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Outside of the Pacific Northwest and California regions, it gets more humid as you move from west to east across the United States. The most arid regions exist in the southwestern United States and the coasts are much more humid. While not all regions have sufficient operations data for analysis, the 12 regions that are included do span dry summer temperate regions (California), semi-arid regions (Upper Colorado, Missouri, Great Basin, Lower Colorado), humid continental regions (Souris Red Rainy), and humid subtropical regions (Texas Gulf, Arkansas White Red, Lower Mississippi, Ohio, South Atlantic, Tennessee).

USGS HUC2 Region Name	Abbreviation in Figures
CA	California
GB	Great Basin
LC	Lower Colorado
US	Upper Colorado
TG	Texas Gulf
AWR	Arkansas White River
MO	Missouri
SRR	Souris Red Rainy
LM	Lower Mississippi
SA	South Atlantic
TE	Tennessee
OH	Ohio

Table 1: USGS HUC2 names and corresponding abbreviations used in all figures. Basins are labelled from West to East coast.

3.1 Spatial Patterns in Reservoir Operations

In this section, we explore spatial patterns in regional reservoir operations using four main metrics: (1) monthly median fraction filled, (2) interannual variability in monthly fraction filled (referred to as the monthly storage range), (3) monthly operating ranges (i.e. the difference between maximum and minimum storage within a given month) and (4) storage variance within each month (referred to as operational variance).

Based on the great variability in aridity and reservoir purpose across the US, we expect to see regional differences in both reservoir levels and seasonal operating patterns. Figure 2m shows the median fraction filled values across the 40-year study period from 1980 – 2019. Overall, we see that more arid regions and irrigation dominate regions tend to have larger median fraction filled values (greater than 0.5). Most notably, the Upper Colorado region has a median fraction filled between 0.75 and 1.0. Conversely, the more humid regions with greater flood control percentages in the southeast have median fraction filled values that sit between 0.25 and 0.5. Not surprisingly these results align well with the historical analysis of Graf (1999), who investigated how storage capacity and population density changed in CONUS specifically looking at reservoir use. Although, we would like to highlight that that analysis was based on static reservoir values as opposed to operational data.

Monthly maximum and minimums fraction filled values illustrate regional differences ion seasonal operating patterns. Five of the regions have median storage peaking during June. Irrigation dominated regions (Missouri, Upper Colorado, Lower Colorado, Great Basin, Souris Red Rainy, Figure 2e, h-l) have maximum storage peaks later than June (typically in July and

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August). This could correspond to water being held in storage later in the year to support summer irrigation. Conversely, regions with more flood control reservoirs (Ohio, Tennessee, Lower Mississippi, Texas Gulf, Arkansas White River, and South Atlantic, Figure 2a-d, f-g) generally have median fraction filled peaks in May. We also see that more humid regions tend to have less month-to-month variation in the median fraction filled, while more arid regions like the Colorado and the Great Basin have stronger seasonal trends.

The interannual variability in monthly fraction filled (referred to as monthly storage range) for the 40-year period shown in Figure 2 by the shaded areas. Monthly storage ranges generally follow the same overall trends seen in the median values (i.e. monthly range peaks in the same month as median fraction filled values peak). However, monthly range peaks in the spring in the more humid basins (Figure 2a-d). Tennessee is an exception to this as the interannual range has two peaks, one in May and one in July. Souris Red Rainy has a minimum value in May right before the median fraction filled peak in June. Comparatively, the maximum range for Lower Colorado is in July and the lower bound of the median fraction filled values stays the same from season to season. In general, the biggest monthly ranges are seen in arid basins except for seasonal peaks in Ohio.

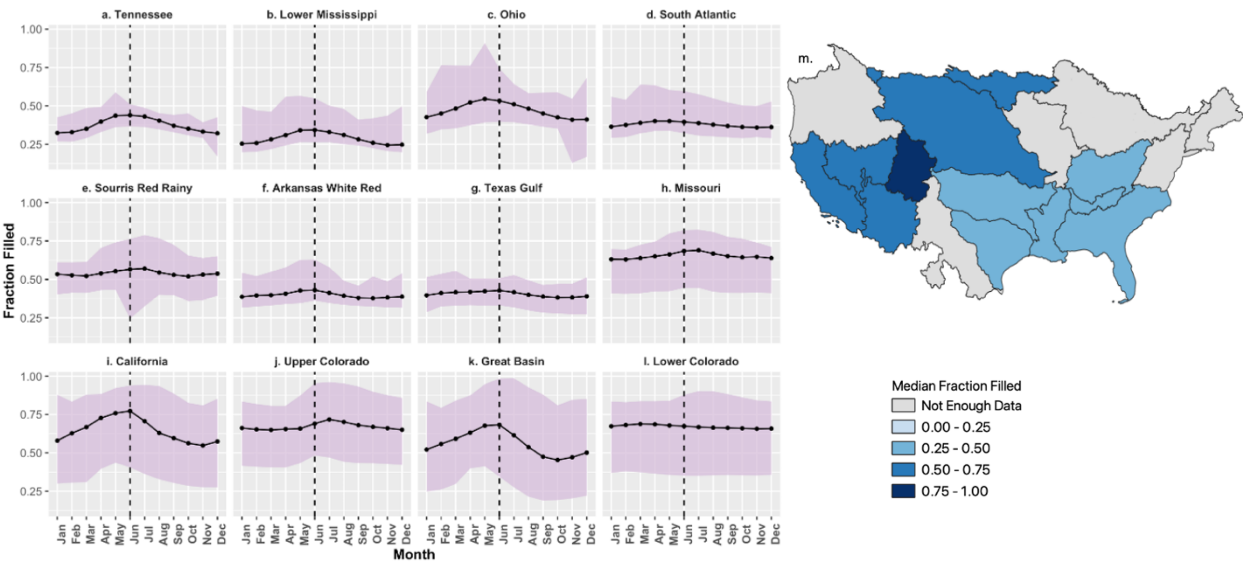

Figure 2: Median monthly reservoir fraction filled (black line) and the monthly fraction filled range in purple shading from 1980-2019 (panels a – l) and median fraction filled values (panel m). The vertical dashed line corresponds to the month of June as a reference point. Regions are organized from most humid to most arid regions.

We also consider operational storage range which is the range of storage with each month. Not that, this is different from the monthly storage range which is maximum and minimum storage seen in a given month across our 40-year study period. The operational range is the maximum minus minimum storage in a single month.   Figure 3 plots the median monthly operating range for all years, as well as the maximum and minimum by basin. Small values here indicate little variability within storage

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values for a given month, while large values can indicate significant filling or draining. Except for the South Atlantic region (Figure 3d), the variability in operating ranges goes down as aridity increases (moving from top left to bottom right in Figure 3). While the minimum operating range stays constant across all seasons, the maximum operating range typically occurs in the spring months with peaks for humid and flood control dominated regions. Irrigation regions have peak operating range values in the summer (July and August). Notably, Lower Colorado has a slight peak in April, yet the seasonal line is fairly flat.

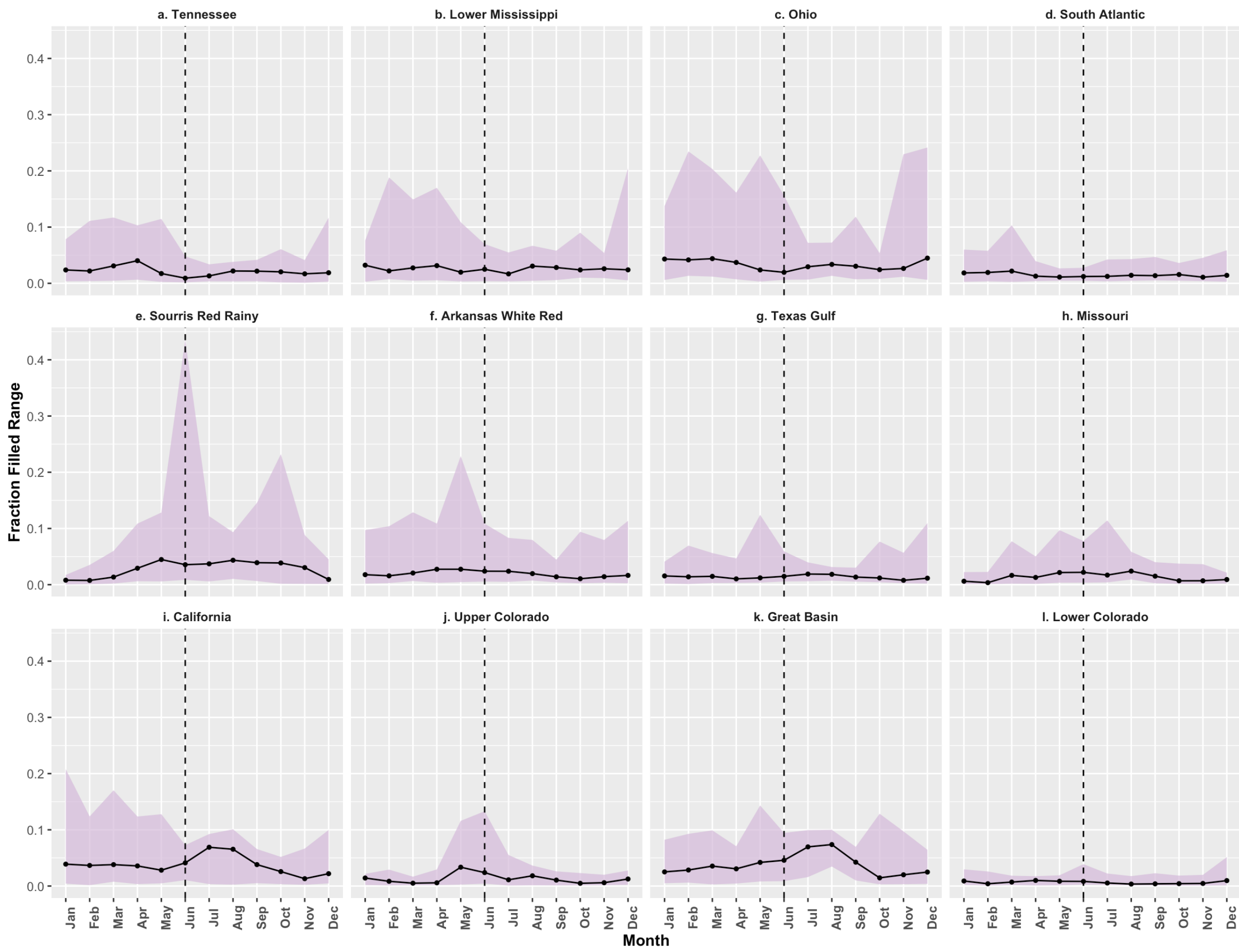

Figure 3:Median operating range of reservoir storage (black line) per month and the maximum and minimum range values for each month in purple shading. The dashed line corresponds to the month of June to provide a point of reference Median, maximum and minimum values are calculated for the monthly storage range (daily maximum – daily minimum storage) each month across the 1980 – 2019 water year period. As in figure 2, regions are organized from most humid to most arid regions (a-i).

We observe two main types of behavior for the median operating range: basins with clear seasonal variability and those without. The Tennessee, Lower Mississippi, Ohio, South Atlantic, Arkansas White Red, Texas Gulf, Missouri, and Lower Colorado (Figure 3a-d, f-h, l) all have very little monthly variability in their operating ranges. The majority of these regions are humid, and the dominant storage purpose is flood control. The Lower Colorado is an outlier as it is arid and irrigation

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dominated; however, this dynamic is to be expected as the flows in the Lower Colorado are heavily regulated and controlled by the Colorado River Compact. California, Upper Colorado, Great Basin and Souris Red Rainy (Figure 3e, i-k) all have a clear seasonal cycle in the operating ranges. All these regions exhibit a peak in median operating range during the spring or summer months and, with the exception of Souris Red Rainy, are predominately semi-arid. Peaks in the spring would be consistent with reservoir filling in snowmelt dominated basins (Souris Red Rainy, and Upper Colorado), while summer peaks may reflect drawdown for irrigation in the summer (California and Great Basin regions). Finally, the operational range variability (purple shading) peaks based on main use with non-irrigation uses (mainly in the eastern US) peaking in winter and irrigation uses (the Western US) in late spring and summer.

Lastly, we consider operational variance which is the monthly variance in the fraction filled over the 40-year period. This is a useful metric because unlike the operating range (which is calculated by taking the difference of the maximum and minimum) the variance is a more wholistic measure of variability within a month (Figure 5). Overall, the seasonal patterns in operational variance (Figure 5) align with the seasonal patterns in operational range. More humid regions depict increased operational variance during the winter and early spring, and declines in the summer and fall. The semi-arid regions (Figure 5, panels e-h) have operational variance peaks in the spring and summer with the Texas Gulf region (Figure 4g) being an outlier with seasonal variance peaks in the late summer. The semi-arid and arid regions (Figure 5i-l) have operational variance peaks in the late summer. Interestingly, we see that some regions that have small seasonal variability in their operational ranges have stronger seasonal patterns in their operational variance. For example the Missouri, Lower Colorado, Tennessee, Texas Gulf, Ohio, and Arkansas White Red (Figure 5a, c, f-h) have operational variance peaks in the winter and early spring but no equivalent peaks in operational range. Lower Colorado is unique in that the operational range does not appear to have any monthly differences, yet the operational variance has a strong peak in the spring. In addition, California and Lower Mississippi display monthly variances that do not align with the operational ranges. California has a strong operational variance peak in July and August which is delayed from the operational range peak in June (Figure 4i). Lower Mississippi (Figure 4b) has high operational variance across all months without a definitive peak, unlike the operational range which has a distinct peak in the winter (Figure 4b). On average, this aridity relationship does hold (high operational variance in more humid and flood control

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dominated regions with lower operational variance in the more arid regions).

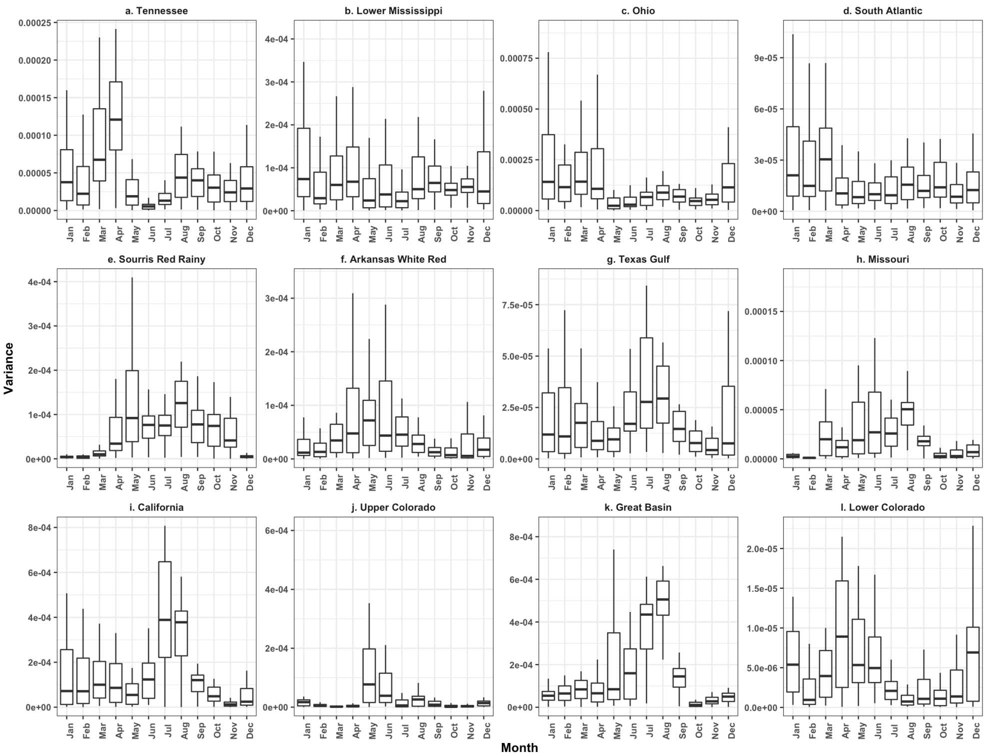

Figure 4: Boxplots of monthly fraction filled variance for each region. Each point in the boxplot is one monthly variance value calculated from daily fraction filled values. The plots have free y scales to show the variation in reservoir variance more clearly. They are grouped by region. Panels are arranged from most humid to most arid.

3.2 National Storage Trends

Over the past hundred years, reservoir storage capacity has steadily increased across the US (Figure 5a). In the 1950s total storage capacity rapidly increased with a construction boom (Benson, 2017; Di Baldassarre et al., 2018; Ho et al., 2017). Starting in 1975, dam construction began to slow down as environmental regulations increased and prime locations for large dams were increasingly taken. By the 1980s total storage capacity in CONUS levelled off and the era of large dam building came to an end.

As previously noted, the ResOpsUS dataset that we are using for our analysis includes data for 678 dams, roughly 85% of the dams with a storage capacity greater than 1,000 MCM and 77% of the total storage in CONUS (Figure 5a dashed line). While all of the storage is not included in this dataset, Figure 5a shows that there is a similar temporal trend in the reservoir storage covered in ResOpsUS and the total national storage (i.e. rising most rapidly up to 1980 and then levelling off). It should also

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be noted that reservoir storage capacity decreases in ResOpsUs after 2020 are due to missing data in recent years for the ResOpsUS dataset, and not an indication of dam removal (recall that the ResOpsUS storage capacity is reporting only the capacity of those dams that have data each year).

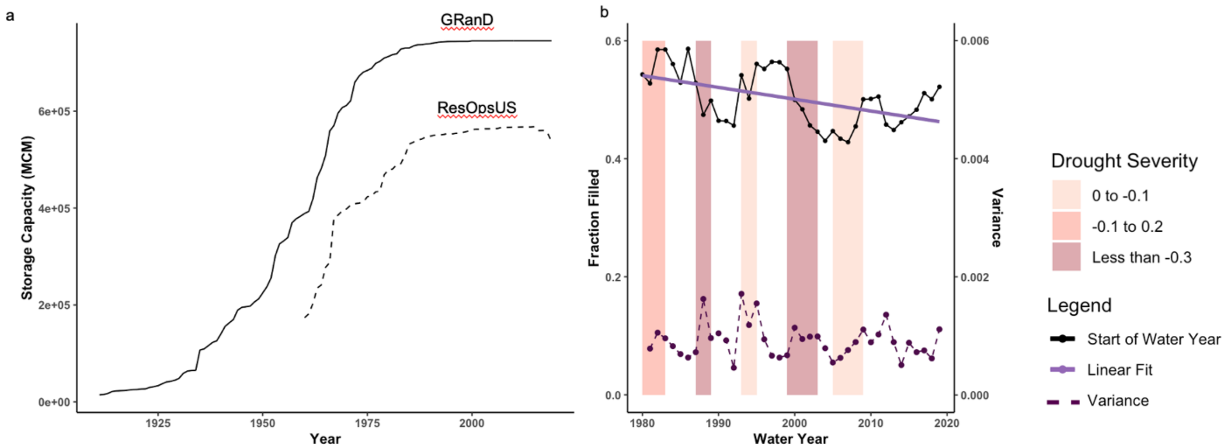

Figure 5: Total storage capacity reported by GRanD (solid line) and the storage capacity of 679 large dams in ResOpsUS (dashed). (b) The reservoir fraction filled value on October 1st from the ResOpsUS data from the forty-year period from 1980 – 2019 (interannual fraction filled). The lavender line is the linear fit through this entire period of record with a slope of -0.002 fraction filled per year and a p value of 0.01. The colored rectangles depict the drought periods with darker colors referring to more severe droughts (SPI values less than -0.3), medium dark (SPI values between -0.1 and -0.3) and lighter bars for least severe droughts (values between 0 and -0.1).

While reservoir storage capacity has held steady over the past 40 years (1980 – 2019), interannual fraction filled has steadily decreased over this time period denoted by the linear fit (lavender) of the October first fraction filled values (black line) in Figure 5. There can be many reasons for storage declines (i.e. sedimentation, increased demand, evaporative losses, decreased precipitation). However, broadly speaking, decreases in interannual fraction filled are correlated to climatic shifts as illustrated by drops after extreme drought periods (colored in maroon). Conversely, during non-drought periods and less severe droughts (pale pink) we see that reservoirs are able to recover, although not fully (as indicated by the declining trend). Overall, reservoir storage peaks at 60% fraction filled in the 1989 and drops all the way to 43% in 2007. In more recent years, there is some recovery of fraction with a final value of 53%. We also plot the reservoir fraction filled variance over time (Figure 5b, note this is the annual variance of daily fraction filled values, referred to as annual storage variance). Annual storage variance peaked in 1995 and does not demonstrate the same clear trend, as was shown with storage. Variance generally increases during drought periods and is lower during non-drought periods. This means that variance is peaking during the same periods that storage is dropping suggesting an inverse relationship between variance and storage levels.

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3.3 Regional Storage Trends

Next, we evaluated regional storage trends for the 12 regions that had 50% or more storage covered. We calculate a linear trend using the first month of the water year (October) values from 1980 - 2019 (Figure 6a- l). From this, we identified three behavior types: 1) low interannual variability and no statistically significant linear trend (Figure 6, a-d, f, and g), 2) more interannual variability but no linear trend (Figure 6e, h, k) and 3) high variability and trends (Figure 6i, j, k). Tennessee, Lower Mississippi, Ohio, South Atlantic, Arkansas White Red, and Texas Gulf display slight linear interannual fraction filled trend and have very small changes in interannual storage. These regions are dominated by flood control, navigation and hydroelectricity, main uses that require stable heads to generate use. Additionally, these regions are all humid (a-d) and semi-arid (Figure 6f, g). This is consistent with results of section 3.1 which showed that the more humid and flood control dominated parts of the country tend to have lower storage values overall and less variability in storage. Of these the Lower Mississippi, Tennessee, and Ohio regions have statistically significant linear trends. Only Tennessee has a positive trend in this grouping (Figure 6 m).

The second set of regions (Souris Red Rainy, Missouri and Great Basin, Figure 6e, h, k) all have large interannual variability with small linear trends. These regions have larger carryover storage and are mainly water supply and irrigation dominated and are all more arid (i.e. semi-arid and dry summer temperate). Conversely California and Upper Colorado (Figure 6i and j) have both high interannual variability and storage trends. These storage trends are significant and strongly negative for Upper Colorado, but not California (Figure 6m). In these regions, reservoir storage appears to be strongly influenced by dry periods as shown by the shading in Figure 6.

Finally, the Lower Colorado (figure 6l) does not fit into any of these groupings. This basin has a strong linear trend and little interannual variability. This semi-arid basin mainly consists of irrigation, water supply and hydroelectricity main uses yet we only see the interannual variability similar to non-irrigation reservoirs. This is likely because storage in the Lower Colorado is dominated by storage in Lake Mead as the Hoover dam holds a large fraction of the total storage in the basin. Additionally, the Colorado River compact dictates the releases and therefore the storage in Lake Mead which has seen historic lows due to the megadrought in the southwestern United States (Williams et al., 2022). This said, the strong negative trend in the Lower Colorado is a cause for concern and has been a topic of much discussion as the Western US is currently experiencing a megadrought (Figure 6m) (Williams et al., 2022).

We also observe the degree of storage drawdown that happens over drought periods regionally (i.e. the grey shaded periods in Figure 6). In all basins, storage decreases during the dry periods. However, in humid regions and regions where flood control is the dominant reservoir purpose these declines appear to be much smaller. This is consistent with previous results showing that these locations maintain less storage overall and have smaller operational ranges. Semi-arid basins with higher levels of

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irrigation and water supply uses have sharper drawdown patterns during drought. Again, this is consistent with previous results showing larger operational range and carry over storage in these areas. In most cases, reservoir storage goes down during drought. There are, however, notable periods in all regions where storage increases. Examples include Souris Red Rainy and Texas Gulf during the drought periods in the early 1980s and the drought in the early to mid 1990s for Upper and Lower Colorado. More detailed regional analysis is required to understand the causes of these increases.

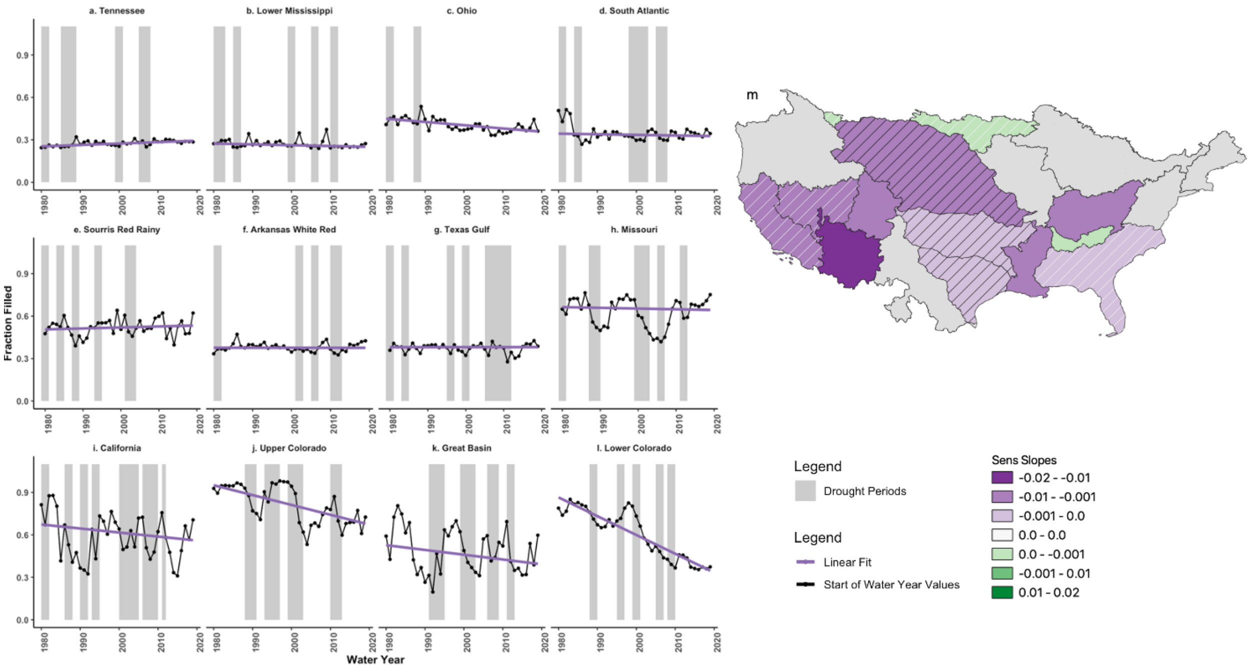

Figure 6: Regional interannual fraction filled from October 1980 – October 2019 (a-l) and associated map of Sens slope values (m). The black lines are October storage, and the lavender is the linear trend. The maroon boxes correspond to periods where SPI values were less than -0.3. Sens slopes (m) range from -0.013 (dark purple) to 0.0011 (green) based with similar trends based on aridity. P values are calculated using a 95% confidence interval. The horizontal white and black lines denote the regional p values that are above the 10% probability (10 – 50% for the white lines and > 50% for the black lines) threshold and are not considered statistically significant.

In addition to overall storage trends, we evaluate whether there have been historical trends in operational range (i.e. the difference between maximum and minimum storage in a given month) for each year. For every region, we calculate a time series of monthly operational ranges and fit linear Sens slopes to each month to evaluate whether the operational range is increasing or decreasing for that month over time. Figure 7 depicts these trends as bar plots colored by positive (blue) or negative (pink) and shaded by statistically significant (dark) or non-significant (light) p values at a significance of 5%. Positive trends mean that the interannual operational range is increasing over time and negative trends mean that this interannual operational range is decreasing over time. Regions such as Souris Red Rainy, California, Lower Mississippi, Upper Colorado, and Great Basin have more positive months than negative months indicating that overall, their interannual operational range is increasing over time. Conversely, basin such as Tennessee, Ohio, South Atlantic, Arkansas White Red, Texas Gulf, Lower

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Colorado, and Missouri have interannual operational ranges that are decreasing over the past 40 years. Missouri and Lower Mississippi are unique examples as the majority of their interannual operational range slopes are quite small except for one month: December for Lower Mississippi and May for Missouri.

We have grouped behavior into four categories. First, the Tennessee, South Atlantic, Ohio and Lower Colorado regions (Figure 7a, c-d, l) have three or more negative monthly trends that are statistically significant. All these regions have statistically significant negative trends in July and August with Tennessee, Ohio and South Atlantic having statistically significant trends in the summer months (June – August). Apart for the Lower Colorado, these regions are primarily humid with low carryover storage. The second set are regions that have predominately positive trends and greater than or equal to three statistically significant trends (Souris Red Rainy, California and Upper Colorado (Figure 7e, i, j). Of these regions, Souris Red Rainy and Upper Colorado have statistically significant positive trends in the spring and summer, while California has statistically significant trends in the fall. The positive and statistically significant values indicate that these regions have seen increase in interannual operational range during these seasons compared to their counterparts with negative trends. The last group are regions without statistically significant trends (Lower Mississippi, Texas Gulf, Great Basin, Arkansas White Red, and Missouri (Figure 7b, f-h, k).

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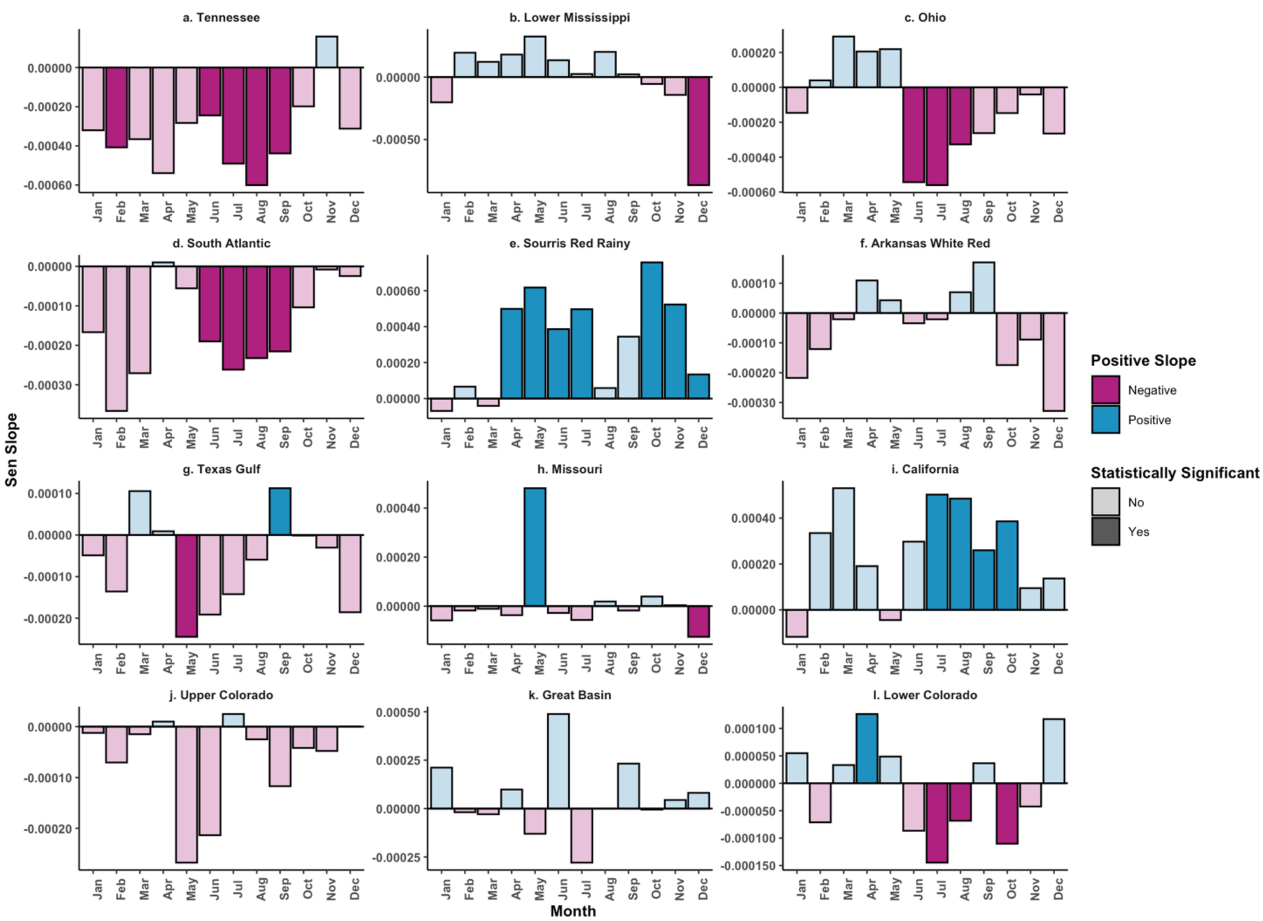

Figure 7: Trends in the monthly fraction filled range from 1980-2019. Bars are colored by not statistically significant (light) and statistically significant (dark). The p value is calculated with a 95% confidence interval and significant values are less than 0.1. Each panel pertains to a specific region within the United States where most of the storage capacity is covered (greater than 50%). Panels are organized from wettest to driest region.

3.4 Hydrologic Drought Sensitivities and Resilience

Building upon the qualitative analysis of storage trends with respect to drought periods in Figure 6, we also conduct a quantitative analysis of storage response to drought on both a regional and individual reservoir scale. Here we evaluate fraction filled sensitivity to hydrologic drought using and Standardized Streamflow Index. We do this analysis regionally for hydrologic droughts from 1980 to 2019.

First, we look at the regional recovery in response to hydrologic drought (Figure 8). As described in Section 2.5, the recovery ratio is the ratio between fraction filled anomaly recovery time and drought index recovery time. We calculated the average

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recovery ratio for the three to four droughts periods that fall below the median SSI value in each region (Figure 8a) across the 40-year study period. In some regions that experienced significant long term storage trends, specifically the Lower Mississippi, Upper Colorado and Ohio regions, reservoir fraction filled never recovered from the drought and we removed these from the average recovery ratio. Figure 8b depicts the recovery periods for fraction filled anomalies and SSI colored by region. We capped the fraction filled anomaly recovery time at 50 months (eight years) as there were only 5 regions that experienced longer fraction filled anomaly recovery longer than this period.

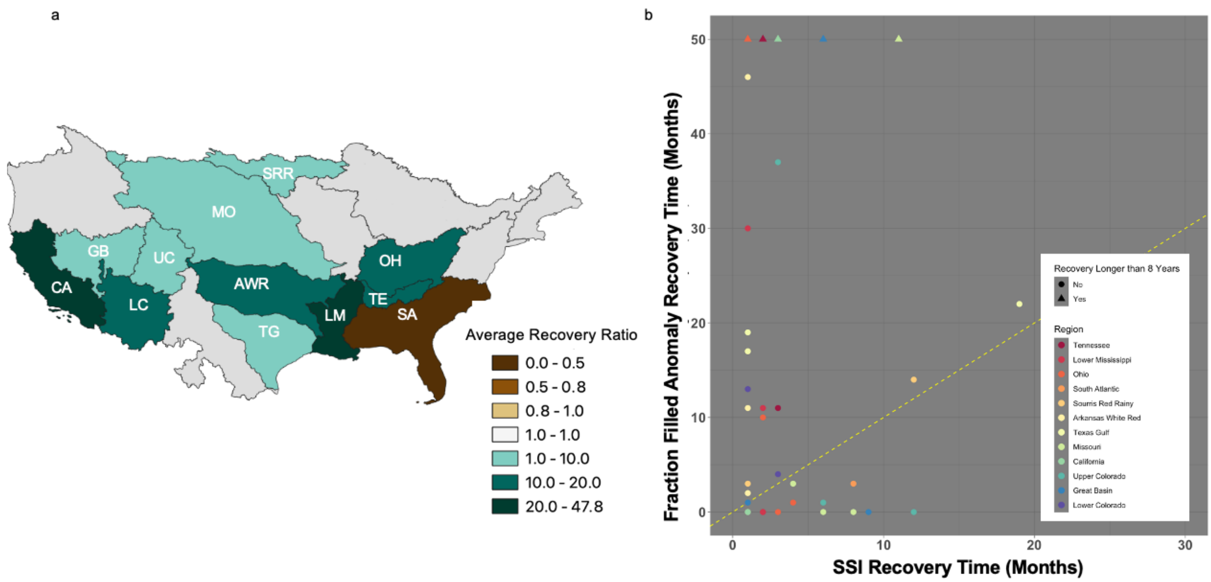

Figure 8: Map (a) of regional recovery ratio and scatter plot (b) of storage recovery time versus hydrologic drought recovery time. Values in the map (a) that are less than one (brown) on the map correspond to regions where SSI recovers slower, while regions where the recovery ratio is greater than one (blue) denote that storage takes longer to recover. Panel a also contains the regional abbreviations to allow for a clearer comparison with the scatter plot in panel b. The points in panel b are colored by region and values are capped at 50 months (8 years) for storage recovery. For both plots, we removed any instances where SSI or storage did not recover so our averages and scatters were not skewed.

The South Atlantic region is the only location with recovery ratio less than one (indicating that the reservoir storage recovers faster than the drought index) (Figure 8a). This is potentially due to the higher amount of hydropower dams, lower interannual storage and high humidity in this basin. All the other basins exhibit average fraction filled recovery times that are longer than hydrologic drought periods. Of these basins, 45% show average storage ratios that are between one and 10 (Souris Red Rainy, Upper Colorado, Great Basin, Missouri, and Texas Gulf (Figure 8a). The increase in the average recovery ratio is potentially due to these basins having more interannual storage and irrigation uses than the South Atlantic region. 33% of the regions present fraction filled anomaly recovery values between 10 and 20 (Lower Colorado, Arkansas White Red, Ohio, and

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Tennessee). Finally, the largest average recovery ratio and therefore slowest fraction filled anomaly recovery relative to hydrologic drought occurs in the California and Lower Mississippi regions.

While these averages yield insights into the general recovery dynamics, the scatter plot shows the individual drought dynamics better. Regions with points that plot above the one-to-one line denote drought periods where storage took longer to recover than SSI. Similar to the map, the scatter plot (Figure 8b) demonstrates that fraction filled anomalies take longer to recovery than SSI. Texas Gulf and Lower Colorado are the only basins that have all drought periods above the one-to-one line. Every other region, aside from the South Atlantic region, contain drought periods that sit both above and below the one-to-one line. While some regions Ohio and Texas Gulf) exhibit linear relationships between the points below the one-to-one line, others (Missouri, Ohio, Upper Colorado, Great Basin, Lower Mississippi, Tennessee, and South Atlantic) have periods with longer SSI recovery times when compared to fraction filled anomaly recovery times. In fact Missouri, Ohio, Tennessee, Great Basin, and Texas Gulf all have drought periods that take over 50 months (8 years) for fraction filled anomaly to recovery and therefore their average recovery ratios are skewed by this point.

4. Discussion

In general, we find that more humid regions have lower storage capacity and lower median fraction filled, while more arid regions have higher median fraction filled. This difference, noted by Graf (1999); Ho et al. (2017), is due to regional reservoir uses as large water storage uses (irrigation and water supply) are mainly seen in the Western more arid United States, while the eastern more humid United States contains more flood control and hydropower uses. Additionally, the more humid regions also have lower monthly storage ranges without strong seasonal cycles. This is due in part to the lower storage capacity dams without strong intra-annual storage changes (Benson, 2017; Patterson & Doyle, 2018). This is complimented by seasonal increases in fraction filled variance in the winter and spring for humid and flood control dominated regions to support flood control and navigation operations and ensure reservoir stable reservoir storage. Conversely, more arid regions with higher concentrations of irrigation main uses have spring and summer peaks to support runoff in snowmelt dominated basins (Upper Colorado and upper California) and irrigation uses.

Median fraction filled peaks in May for flood control uses which could be due to reservoir operators maintaining low storage in the spring to prevent downstream flooding. Additionally, there are decreased monthly variations in flood control reservoirs as operators are attempting to keep their storage levels consistent with the maximum storage range peaking in the spring. Flood control and hydropower reservoirs have a much lower spread with peaks in the spring and winter as operators bring storage back to normal operating values. This dynamic is complimented by the overall operational variance, where more humid and flood control dominated regions have a much higher variance as operators work to keep reservoir storage more steady and lower for irrigation dominated regions as operators are focused on storing water to be used at non-peak periods.

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While flood control reservoirs have peaks in May, irrigation and many arid reservoirs have fraction filled peaks in June which suggests longer storage times. Irrigation reservoirs are also dominated by strong filling cycles have strong seasonal trends in their monthly storage ranges. Irrigation and water supply uses have monthly storage range peaks in the summer to support water supply for humans and plants during periods where precipitation and runoff is limited. This strong seasonality shows up in the operating range spread which is quite large in irrigation dominated basins with a wider spread during late spring and early summer (the main irrigation period in the United States). Arid regions have delayed peaks in their operations due in part to irrigation being separate from filling as operators strive to hold water later in the summer when supply is not as consistent. These regions also have a larger interannual variability when looking between water years (Figure 3). The interannual variability is consistent with what we would expect for irrigation reservoirs where operators strive to provide stable releases in the summer irrigation season and to support usage in times of drought.

Across CONUS, we find a strong negative trend in reservoir storage which is consistent with previous studies (Adusumilli et al., 2019; Hou et al., 2021; Randle et al., 2021; Zhao & Gao, 2019). Only the Tennessee basin has a slightly positive trend in storage over the past 40 years. This is due in part to the abundance of flood control and navigation reservoirs and increases in streamflow which potentially combine to increase the total storage held in this region (Naz et al., 2018). Declining storage trends are concerning in regions such as the Lower Colorado and Upper Colorado where the impact of a megadrought is threatening water supplies (Williams et al., 2022). Similarly, in the Lower Mississippi, low storage levels can threaten the operation of navigation reservoirs that support the transport of goods longitudinally in the United States. While these findings are all consistent with previous studies (Adusumilli et al., 2019; Hou et al., 2021; Randle et al., 2021; Zhao & Gao, 2019)our analysis specifically uses historical records that allow us to look at monthly trends, seasonalities in the declines, and direct relationships with hydrologic droughts.

While storage has been declining over time with few exceptions nationally, we see more variability in the trends of operational ranges. In more arid basins such as the Upper Colorado, Souris Red Rainy, and California the operational range has been increasing. While in more humid basins, such as the Tennessee, Ohio, and South Atlantic regions operational ranges have been decreasing.

In addition to looking at storage trends, we also are able to determine reservoir resilience to hydrologic drought. Perrings (1998) defined resilience as the "measure of the ability of a system to withstand stresses and shocks – it's ability to persist in an uncertain world." Resilience is not necessarily a good thing as previous studies have shown that reservoirs historical resilience has led to overconfidence in reservoir operations that have actually increased unsustainable usage in arid regions and increased the number of people prone to flood risk (Adusumilli et al., 2019; Collenteur, de Moel, Jongman, & Di Baldassarre, 2015; Di Baldassarre et al., 2018). From the storage trends in the previous section, we observe direct adaptation

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to decreased storage in the Western United States. To accommodate decreasing storage, the operational range is increasing over time which suggests that reservoir operators are increasing the available water supply and potentially increasing unsustainable usage (Di Baldassarre et al., 2018). While regional storage declines after a drought (figure 6) in all basins, only the more humid basins are able to build backup effectively and are therefore more resilient to droughts. This said, the long-term storage declines in the Western United States demonstrate that large systems are susceptible to droughts and are not resilient. Tennessee, with its positive storage trend, is more resilient to droughts. However, as most of this basin is comprised of flood control and navigation reservoirs, there could be increased vulnerabilities to respond to floods if storage has increased into the flood pool.

Building on the storage trend analysis we consider recovery ratios to hydrologic droughts using SSI as our drought metric. More humid basins have lower recovery ratios while more arid regions have higher recovery ratios for hydrologic drought. This means that it takes much longer for storage to build back up in the arid regions relative to the length of the drought than it does in humid regions. It should be noted however that some of our recovery ratio values may be lengthened by the negative trends in storage which can be cause by long term supply and demand imbalances that occur regardless of drought. This said, Upper Colorado, Texas Gulf, and Great Basin have individual droughts where SSI takes almost ten years to recover while the fraction filled anomaly recovers quickly due potentially to higher intra-annual storage. The South Atlantic is an outlier as it is the only basin that has recovery ratios less than one. This flood control dominated region is more resilient to droughts, however (as we have seen in recent years) this does not make it less vulnerable to flood risk.

Throughout our study we find the Lower Colorado to be unique in many regards. The Lower Colorado has very low seasonal variations in median fraction filled values and operating range. With seasonal peaks during the summer (consistent with irrigation uses) and operational range peaks in April (consistent with flood control uses). Additionally, the spread of the operational range is quite similar to flood control reservoirs as it is kept quite steady with little to no monthly variations. Finally, the fraction filled variance peaks in the winter and early spring with no monthly changes. These dynamics are most likely the result of the fact that most of the water supply comes from reservoir releases from the Upper Colorado basin. The negative storage trend is concerning as this basin is water limited and extractions are routinely out pacing the inputs from the Upper Colorado. Combined with the current mega drought (Williams et al., 2022) facing the western United States, there is an large increase in vulnerability to drought in this region.

Further research into the specific dynamics observed in meteorological and streamflow drought would increase the understanding of how regional uses and dam size contribute to reservoir resilience. Additionally, this analysis focused on the recovery ratios (fraction filled anomaly recovery time divided by drought index recovery time) and did not look at how drought length and severity affect the recovery value. In our preliminary analysis of this, we did not see large differences due to drought length, but further analysis regarding drought severity could be done to enhance the impact droughts, such as the megadrought

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in the southwestern United States, may have on reservoir storage levels. Finally, expanding the ResOpsUS dataset to include more dams in the size data scarce regions would allow for a deeper regional comparison to investigate seasonal reservoir dynamics and storage trends across the entirety of CONUS as our analysis is skewed by data in the Western United States.

5. Conclusion

Here we use the first national dataset of direct reservoir observations, ResOpsUS to explore historical trends in reservoir storage. ResOpsUS contains daily inflow, outflow, storage, and release data for over 600 large reservoirs (maximum storage capacity greater than 0.01km^3) from over 40 agencies spread out throughout the CONUS domain. We present the first national analysis of historical reservoir operations across the contiguous US based entirely on direct reservoir operations. We show that median storage peaks in winter and spring for the eastern US and summer for the Western US (Figure 2). The Lower Colorado is a unique outlier as the majority of its seasonal dynamics appear quite similar to more humid and flood control dominated basins of the eastern US. This is because flow in the Lower Colorado's inflow is primarily a function from releases from upper basin dams which are heavily regulated by the Colorado River Compact.

Over our 40-year study period (1980-2019), 83% regions we evaluated had decreasing storage trends with five of these trends being statistically significant. Of these five trends, the Lower Colorado is the most negative due to storage declines caused by the ongoing mega drought in the past 20 years (Williams et al., 2022). The Tennessee region is the only basin with a has a positive storage trend, potentially due to increased streamflow across the eastern US and decreasing operational ranges (Naz et al., 2018). Operational ranges have been increasing over time in more arid regions and decreasing in more humid regions.

In general, we find that reservoirs fraction filled anomalies recovers more slowly than streamflow to droughts. Of all the twelve regions in this study, the South Atlantic has the most resilience to drought with an SSI recovery ratio between 0.5 and 0.8. Of the other regions, California and the Lower Mississippi have the largest recovery ratio which depicts decreased resilience to drought. When looking at individual drought periods (something not easily done without direct observations of storage) we see that the Lower Colorado and Texas Gulf are the most concerning basins as fraction filled does not recover from any of the drought periods analyzed (Figure 8b).

6. Code Availability

All codes for this analysis are hosted on GitHub at this link: https://github.com/jsteyaert/ResOpsUS_Analysis

7. Data Availability

All the raw data in this analysis was obtained via Zenodo using the DOI in Steyaert et al. (2022). All regional fraction filled values can be found in the data/HUC_FF folder at the GitHub link in Section 6. Code Availability.

8. Author Contribution

Jennie C. Steyaert and Laura E. Condon designed the experiments and discussed the research trajectory. All analysis and preliminary draft writing was done by Jennie C. Steyaert. Laura E. Condon provided review and feedback regarding analysis results and the draft.

9. Competing Interests

The authors declare that they have no competing interests

10. Acknowledgements

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References

Adusumilli, S., Borsa, A. A., Fish, M. A., McMillan, H. K., & Silverii, F. (2019). A Decade of Water Storage Changes Across the Contiguous United States From GPS and Satellite Gravity. *Geophysical Research Letters, 46*(22), 13006-13015. doi:https://doi.org/10.1029/2019GL085370

Barnett, T. P., & Pierce, D. W. (2008). When will Lake Mead go dry? *Water Resources Research, 44*(3).

Benson, R. (2017). Reviewing Reservoir Operations: Can Federal Water Projects Adapt to Change? *Columbia Journal of Environmental Law, 42*(2), 75. doi:https://digitalrepository.unm.edu/law_facultyscholarship/415

Boulange, J., Hanasaki, N., Yamazaki, D., & Pokhrel, Y. (2021). Role of dams in reducing global flood exposure under climate change. *Nature Communications, 12*(1), 417. doi:10.1038/s41467-020-20704-0

Brunner, M. I. (2021). Reservoir regulation affects droughts and floods at local and regional scales. *Environmental Research Letters, 16*(12), 124016. doi:10.1088/1748-9326/ac36f6

Cayan, D. R., Das, T., Pierce, D. W., Barnett, T. P., Tyree, M., & Gershunov, A. (2010). Future dryness in the southwest US and the hydrology of the early 21st century drought. *Proceedings of the National Academy of Sciences of the United States of America, 107*(50), 21271-21276. doi:10.1073/pnas.0912391107

Chen, W., & Olden, J. D. (2017). Designing flows to resolve human and environmental water needs in a dam-regulated river. *Nat Commun, 8*(1), 2158. doi:10.1038/s41467-017-02226-4

Collenteur, R. A., de Moel, H., Jongman, B., & Di Baldassarre, G. (2015). The failed-levee effect: Do societies learn from flood disasters? *Natural Hazards, 76*(1), 373-388. doi:10.1007/s11069-014-1496-6

Collier, M., Webb, R. H., & Schmidt, J. C. (1997). *Dams and Rivers: A Primer on the Downstream Effects of Dams* (Circular 1126). Retrieved from

Di Baldassarre, G., Wanders, N., AghaKouchak, A., Kuil, L., Rangecroft, S., Veldkamp, T. I. E., . . . Van Loon, A. F. (2018). Water shortages worsened by reservoir effects. *Nature Sustainability, 1*(11), 617-622. doi:10.1038/s41893-018-0159-0

Döll, P., Hoffmann-Dobrev, H., Portmann, F. T., Siebert, S., Eicker, A., Rodell, M., . . . Scanlon, B. R. (2012). Impact of water withdrawals from groundwater and surface water on continental water storage variations. *Journal of Geodynamics, 59-60*, 143-156. doi:10.1016/j.jog.2011.05.001

Döll, P., Kaspar, F., & Lehner, B. (2003). A global hydrological model for deriving water availability indicators: model tuning and validation. *Journal of Hydrology, 270*(1-2), 105-134.

Ehsani, N., Vörösmarty, C. J., Fekete, B. M., & Stakhiv, E. Z. (2017). Reservoir operations under climate change: Storage capacity options to mitigate risk. *Journal of Hydrology, 555*, 435-446. doi:10.1016/j.jhydrol.2017.09.008

Falcone, J. A. (2011). *GAGES-II: Geospatial Attributes of Gages for Evaluating Streamflow*. Retrieved from Reston, VA: http://pubs.er.usgs.gov/publication/70046617

Geological, S. (Cartographer). (2004). National Hydrography Dataset. Retrieved from https://search.library.wisc.edu/catalog/9910061259502121

Giuliani, M., & Herman, J. D. (2018). Modeling the behavior of water reservoir operators via eigenbehavior analysis. *Advances in Water Resources, 122*, 228-237. doi:10.1016/j.advwatres.2018.10.021

Graf, W. L. (1999). Dam nation: A geographic census of American dams and their large-scale hydrologic impacts. *Water Resources Research, 35*(4), 1305-1311. doi:10.1029/1999wr900016

Grill, G., Lehner, B., Thieme, M., Geenen, B., Tickner, D., Antonelli, F., . . . Zarfl, C. (2019). Mapping the world's free-flowing rivers. *Nature, 569*(7755), 215-221. doi:10.1038/s41586-019-1111-9

Haddeland, I., Skaugen, T., & Lettenmaier, D. P. (2006). Anthropogenic impacts on continental surface water fluxes. *Geophysical Research Letters, 33*(8). doi:10.1029/2006gl026047

Hanasaki, N., Kanae, S., & Oki, T. (2006). A reservoir operation scheme for global river routing models. *Journal of Hydrology, 327*(1), 22-41. doi:https://doi.org/10.1016/j.jhydrol.2005.11.011

Ho, M., Lall, U., Allaire, M., Devineni, N., Kwon, H. H., Pal, I., . . . Wegner, D. (2017). The future role of dams in the United States of America. *Water Resources Research, 53*(2), 982-998. doi:10.1002/2016wr019905

Hou, J., van Dijk, A., Beck, H., Renzullo, L., & Wada, Y. (2021). Remotely sensed reservoir water storage dynamics (1984–2015) and the influence of climate variability and management at global scale. *Hydrol. Earth Syst. Sci. Discuss., 2021*, 1-23. doi:10.5194/hess-2021-350

Johnson, P. T. J., Olden, J. D., & Vander Zanden, M. J. (2008). Dam invaders: impoundments facilitate biological invasions into freshwaters. *Frontiers in Ecology and the Environment, 6*(7), 357-363. doi:10.1890/070156

Kottek, M., Grieser, J., Beck, C., Rudolf, B., & Rubel, F. (2006). World Map of the Köppen-Geiger climate classification updated. *Meteorologische Zeitschrift, 15*(3), 259-263. doi:10.1127/0941-2948/2006/0130

Lehner, B., Czisch, G., & Vassolo, S. (2005). The impact of global change on the hydropower potential of Europe: a model-based analysis. *Energy Policy, 33*(7), 839-855. doi:https://doi.org/10.1016/j.enpol.2003.10.018

Lehner, B., Liermann, C. R., Revenga, C., Vörösmarty, C., Fekete, B., Crouzet, P., . . . Wisser, D. (2011). High-resolution mapping of the world's reservoirs and dams for sustainable river-flow management. *Frontiers in Ecology and the Environment, 9*(9), 494-502. doi:10.1890/100125

Naz, B. S., Kao, S.-C., Ashfaq, M., Gao, H., Rastogi, D., & Gangrade, S. (2018). Effects of climate change on streamflow extremes and implications for reservoir inflow in the United States. *Journal of Hydrology, 556*, 359-370. doi:10.1016/j.jhydrol.2017.11.027

Nilsson, C., & Berggren, K. (2000). Alteration of Riparian Ecosystems Caused by River Regulation. *BioScience, 50*(9), 783 - 792. doi:10.1641/0006-3568(2000)050[0783:AORECB]2.0.CO;2

Ortiz-Partida, J. P., Lane, B. A., & Sandoval-Solis, S. (2016). Economic effects of a reservoir re-operation policy in the Rio Grande/Bravo for integrated human and environmental water management. *Journal of Hydrology: Regional Studies, 8*, 130-144. doi:10.1016/j.ejrh.2016.08.004

Patterson, L. A., & Doyle, M. W. (2018). A Nationwide Analysis of U.S. Army Corps of Engineers Reservoir Performance in Meeting Operational Targets. *JAWRA Journal of the American Water Resources Association, 54*(2), 543-564. doi:10.1111/1752-1688.12622

Patterson, L. A., & Doyle, M. W. (2019). Managing rivers under changing environmental and societal boundary conditions, Part 1: National trends and U.S. Army Corps of Engineers reservoirs. *River Research and Applications, 35*(4), 327-340. doi:10.1002/rra.3418

Perrings, C. (1998). Resilience in the Dynamics of Economy-Environment Systems. *Environmental and Resource Economics, 11*(3), 503-520. doi:10.1023/A:1008255614276

Prein, A. F., Holland, G. J., Rasmussen, R. M., Clark, M. P., & Tye, M. R. (2016). Running dry: The US Southwest's drift into a drier climate state. *Geophysical Research Letters, 43*(3), 1272-1279.

Randle, T. J., Morris, G. L., Tullos, D. D., Weirich, F. H., Kondolf, G. M., Moriasi, D. N., . . . Wegner, D. L. (2021). Sustaining United States reservoir storage capacity: Need for a new paradigm. *Journal of Hydrology, 602*, 126686. doi:https://doi.org/10.1016/j.jhydrol.2021.126686

Smith, S. M., & Edwards, E. C. (2021). Water storage and agricultural resilience to drought: historical evidence of the capacity and institutional limits in the United States. *Environmental Research Letters, 16*(12), 124020. doi:10.1088/1748-9326/ac358a

Steyaert, J. C., Condon, L. E., Turner, S. W. D., & Voisin, N. (2022). ResOpsUS, a dataset of historical reservoir operations in the contiguous United States. *Sci Data, 9*(1), 34. doi:10.1038/s41597-022-01134-7

Survery, U. S. G. (2016). National Water Information System. In. USGS Water Data for the Nation data available on the World Wide Web.

Turner, S. W. D., Steyaert, J. C., Condon, L., & Voisin, N. (2021). Water storage and release policies for all large reservoirs of conterminous United States. *Journal of Hydrology, 603*, 126843. doi:https://doi.org/10.1016/j.jhydrol.2021.126843

Turner, S. W. D., Xu, W., & Voisin, N. (2020). Inferred inflow forecast horizons guiding reservoir release decisions across the United States. *Hydrology and Earth System Sciences, 24*(3), 1275-1291. doi:10.5194/hess-24-1275-2020

Vicente-Serrano Sergio, M., López-Moreno Juan, I., Beguería, S., Lorenzo-Lacruz, J., Azorin-Molina, C., & Morán-Tejeda, E. (2012). Accurate Computation of a Streamflow Drought Index. *Journal of Hydrologic Engineering, 17*(2), 318-332. doi:10.1061/(ASCE)HE.1943-5584.0000433

Voisin, N., Kintner-Meyer, M., Skaggs, R., Nguyen, T., Wu, D., Dirks, J., . . . Hejazi, M. (2016). Vulnerability of the US western electric grid to hydro-climatological conditions: How bad can it get? *Energy, 115*, 1-12. doi:https://doi.org/10.1016/j.energy.2016.08.059

Voisin, N., Li, H., Ward, D., Huang, M., Wigmosta, M., & Leung, L. R. (2013). On an improved sub-regional water resources management representation for integration into earth system models. *Hydrology and Earth System Sciences, 17*(9), 3605-3622. doi:10.5194/hess-17-3605-2013

Wada, Y., Bierkens, M. F. P., de Roo, A., Dirmeyer, P. A., Famiglietti, J. S., Hanasaki, N., . . . Wheater, H. (2017). Human–water interface in hydrological modelling: current status and future directions. *Hydrol. Earth Syst. Sci., 21*(8), 4169-4193. doi:10.5194/hess-21-4169-2017

Williams, A. P., Cook, B. I., & Smerdon, J. E. (2022). Rapid intensification of the emerging southwestern North American megadrought in 2020–2021. *Nature Climate Change, 12*(3), 232-234. doi:10.1038/s41558-022-01290-z

Wisser, D., Frolking, S., Hagen, S., & Bierkens, M. F. P. (2013). Beyond peak reservoir storage? A global estimate of declining water storage capacity in large reservoirs. *Water Resources Research, 49*(9), 5732-5739. doi:https://doi.org/10.1002/wrcr.20452

Yassin, F., Razavi, S., Elshamy, M., Davison, B., Sapriza-Azuri, G., & Wheater, H. (2019). Representation and improved parameterization of reservoir operation in hydrological and land-surface models. *Hydrology and Earth System Sciences, 23*(9), 3735-3764. doi:10.5194/hess-23-3735-2019

Zhao, G., & Gao, H. (2019). Estimating reservoir evaporation losses for the United States: Fusing remote sensing and modeling approaches. *Remote Sensing of Environment, 226*, 109-124. doi:10.1016/j.rse.2019.03.015

Zou, H., Liu, D., Guo, S., Xiong, L., Liu, P., Yin, J., . . . Shen, Y. (2019). Quantitative assessment of adaptive measures on optimal water resources allocation by using reliability, resilience, vulnerability indicators. *Stochastic Environmental Research and Risk Assessment, 34*(1), 103-119. doi:10.1007/s00477-019-01753-4

https://doi.org/10.5194/egusphere-2022-1051
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Zou, Z., Xiao, X., Dong, J., Qin, Y., Doughty Russell, B., Menarguez Michael, A., . . . Wang, J. (2018). Divergent trends of open-surface water body area in the contiguous United States from 1984 to 2016. *Proceedings of the National Academy of Sciences, 115*(15), 3810-3815. doi:10.1073/pnas.1719275115