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Reservoir storage and hydrologic responses to droughts in the Paraná River basin, south-eastern Brazil

Davi de C. D. Melo[1,2], **Bridget R. Scanlon**[2], **Zizhan Zhang**[2], **Edson Wendland**[1], **and Lei Yin**[3]

[1]Department of Hydraulic and Sanitary Engineering, University of São Paulo, Avenida Trabalhador São-carlense, 400, Parque Arnold Schimidt, São Carlos, SP, 13566-590, Brazil
[2]Bureau of Economic Geology, University of Texas at Austin, 10100 Burnet Rd, Austin, TX 78758, USA
[3]Department of Geological Sciences, Jackson School of Geosciences, University of Texas at Austin, 23 San Jacinto Blvd & E 23rd St, Austin, TX 78712, USA

Correspondence to: Davi de C. D. Melo (melo.dcd@gmail.com)

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Abstract. Droughts are particularly critical for Brazil because of impacts on water supply and because most (70 %) of its electricity is derived from hydroelectric generation. The Paraná basin (PB), a major hydroelectric producing region with 32 % (60 million people) of Brazil's population, recently experienced the most severe drought since the 1960s, compromising the water supply for 11 million people in São Paulo. The objective of this study is to quantify linkages between meteorological and hydrological droughts based on remote sensing, modelling, and monitoring data using the Paraná River basin in south-eastern Brazil as a case study. Two major meteorological droughts were identified in the early 2000s and 2014, with precipitation 20–50 % below the long-term mean. Total water storage change estimated from the Gravity Recovery and Climate Experiment (GRACE) satellites declined by 150 km^3 between April 2011 and April 2015. Simulated soil moisture storage declined during the droughts, resulting in decreased runoff into reservoirs. As a result, reservoir storage decreased by 30 % relative to the system's maximum capacity, with negative trends ranging from 17 (May 1997–April 2001) to 25 $km^3\,yr^{-1}$ (May 2011–April 2015). Storage in upstream reservoirs is mostly controlled by natural climate forcing, whereas storage in downstream reservoirs also reflects dam operations. This study emphasizes the importance of integrating remote sensing, modelling, and monitoring data to evaluate droughts and to establish a preliminary understanding of the linkages between a meteorological and hydrological drought for future management.

1 Introduction

Droughts have large-scale socio-economic impacts, responsible for 35 % of disaster-related deaths and 200 billion US dollars (USD, adjusted to 2012 by WMO) in losses globally between 1970 and 2012 (WMO, 2014). In South America, 48 droughts were responsible for 23 % (USD 16.5 billion) of losses caused by disasters (1970–2012), including the 1978 Brazilian drought, responsible for a loss of USD 8 billion (WMO, 2014).

There are a variety of different types of droughts, including meteorological, agricultural, hydrological, and socio-economic (Wilhite and Glantz, 1985). Investigating individual types of drought limits understanding of how they are connected, i.e. how meteorological drought (precipitation deficit) propagates through the hydrological system, resulting in socio-economic drought, for example. Socio-economic drought is characterized by the failure to supply economic goods (water, hydroelectric power, etc.) as a result of water deficits (Wilhite and Glantz, 1985). Because these drought types are usually related to one another, societal impacts of droughts are often conveyed through linkages between them (Fiorillo and Guadagno, 2009).

Establishing linkages between meteorological and hydrologic droughts is challenging due to the large spatio-temporal variability in water distribution. Increasing availability of remotely sensed terrestrial total water storage anomalies (TWSA) data from the Gravity Recovery and Climate Experiment (GRACE) satellites, precipitation estimates from the Tropical Rainfall Measuring Mission (TRMM), and evap-

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otranspiration (ET) estimates from the Moderate Resolution Imaging Spectroradiometer (MODIS) greatly enhances our ability to assess linkages between the different types of droughts (Tapley et al., 2004; Huffman et al., 2007; Mu et al., 2007). In addition to remote sensing data, Global Land Data Assimilation Systems (GLDAS) land surface models (LSMs) provide valuable data on water budgets related to droughts (Rodell et al., 2004).

Meteorological drought indicators, such as the Standardized Precipitation Index (SPI), have been used to forecast hydrologic droughts based on a Streamflow Drought Index (Tigkas et al., 2012; Fiorillo and Guadagno, 2009). Major hydrological regimes have been characterized using satellite data (GRACE, TRMM) and GLDAS LSMs (Awange et al., 2014). GRACE satellite data have been used to assess impacts of droughts on TWSA in large basins globally (Long et al., 2013; Leblanc et al., 2009).

In Brazil, drought-related studies have focused mostly on the Amazon basin (Frappart et al., 2012; Nepstad et al., 2004; Yin et al., 2014) or semi-arid north-eastern Brazil (Marengo et al., 2013). However, south-eastern Brazil (80 million people), accounting for 55 % of national GDP in 2012 (IBGE, 2010, 2014), has been subjected to two major droughts since 2000. The early 2000s drought was responsible for a major energy crisis in Brazil, leading to energy-rationing programmes and even blackouts, attributed in part to limited transmission and interconnection (Rosa and Lomardo, 2004). The more recent drought (2014) compromised the water supply for 11 million people in Brazil's largest metropolis: São Paulo.

Reservoir levels in São Paulo's main water supply system (Cantareira system) dropped below 15 % capacity. The 2014 drought jeopardized potable water supplies of 130 cities (28 million people) in the south-eastern region (Lobel et al., 2014), where there are ≈ 50 reservoirs with individual areas exceeding 1000 ha, mostly in the Paraná basin. The 2014 water year (September 2013–August 2014) was the driest on record in the São Paulo city area since 1962 (Coelho et al., 2015a), with simulated reservoir dynamics changing in response to drought (Coutinho et al., 2015). Analysis of GRACE TWSA data indicates that between February 2012 and January 2015, total water storage declined by 6 $cm\,yr^{-1}$ (56 $km^3\,yr^{-1}$, totalling 160 km^3) in south-eastern Brazil as a result of reduced rainfall (Getirana, 2015).

In this context, it is reasonable to ask whether the meteorological forcing is primarily responsible for the socioeconomic droughts in the region. Would an improved electric distribution system avoid the blackouts that occurred in the early 2000s? Is the water crisis in São Paulo solely linked to meteorological factors? Was 2014 also the driest water year in the entire south-eastern region in decades? Were these two droughts similar and, if so, did they result in similar impacts? Finding the linkages between different types of droughts is important to answer these questions. Hence, the objective of this study is to address the following questions related to linking meteorological and hydrological droughts in the Paraná River basin in south-eastern Brazil.

- What are the intensity, extent, and duration of the recent droughts?
- What are the drought impacts on terrestrial total water storage and reservoir storages?
- How do the droughts propagate through the hydrologic system?
- How are different reservoirs operated under drought conditions?

The Paraná basin (PB) was selected as a case study because of the severity of recent droughts and widespread impacts on water supply and hydroelectricity generation. To answer these questions, we used remotely sensed total water storage anomalies from GRACE (Sects. 2.1 and S3.4 in the Supplement), remotely sensed and ground-based gridded rainfall data sets (Sects. 2.1 and S3.3), remotely sensed ET (Sects. 2.1 and S3.3), simulated soil moisture storage and runoff from four LSMs (Sects. 2.1 and S3.2), and monitoring data from 37 reservoirs (Sects. 2.1 and S3.1). We used (i) statistical indices to characterize meteorological and hydrologic droughts (Sects. 2.2 and S4.3) and (ii) tests statistics to evaluate the impacts on reservoir storage (Sects. 2.2, 4.1 and 4.2), and (iii) studied differences and similarities between individual reservoirs (Sects. 2.2 and S4.4).

Unique aspects of this study include the preliminary assessment of droughts using a variety of remote sensing, modelling, and monitoring approaches and indicators, comparison of multiple droughts and related hydrologic impacts, and a variety of scales of analyses from regional evaluation using GRACE satellites to local reservoir responses. This study builds on previous studies, such as the evaluation of drought in south-eastern Brazil based on GRACE satellite data by Getirana (2015) by expanding remote sensing, modelling, and monitoring data.

The Paraná basin is one of the most studied areas in Brazil, given its relevance in the national context. Previous hydrologic studies in this area include assessment of climate change impacts on water resources (Adam et al., 2015; Nóbrega et al., 2011), energy and hydrologic modelling (Camilloni et al., 2013; Ruhoff et al., 2013; Getirana et al., 2010), assessment of remotely sensed evapotranspiration (Ruhoff et al., 2013), and energy-based estimation of evapotranspiration (Ruhoff et al., 2012). In terms of drought-related studies, the area of the Paraná River basin is much larger than evaluated in some previous analyses that were restricted to São Paulo (Coelho et al., 2015b, a; Coutinho et al., 2015). Another recent study brought some insights regarding drought propagation by quantifying the time lag responses of the hydrological system to meteorological shifts; they found a lag of ≈ 6 months between significant change in SPI and reservoir storage, and ≈ 1 month between SPI and

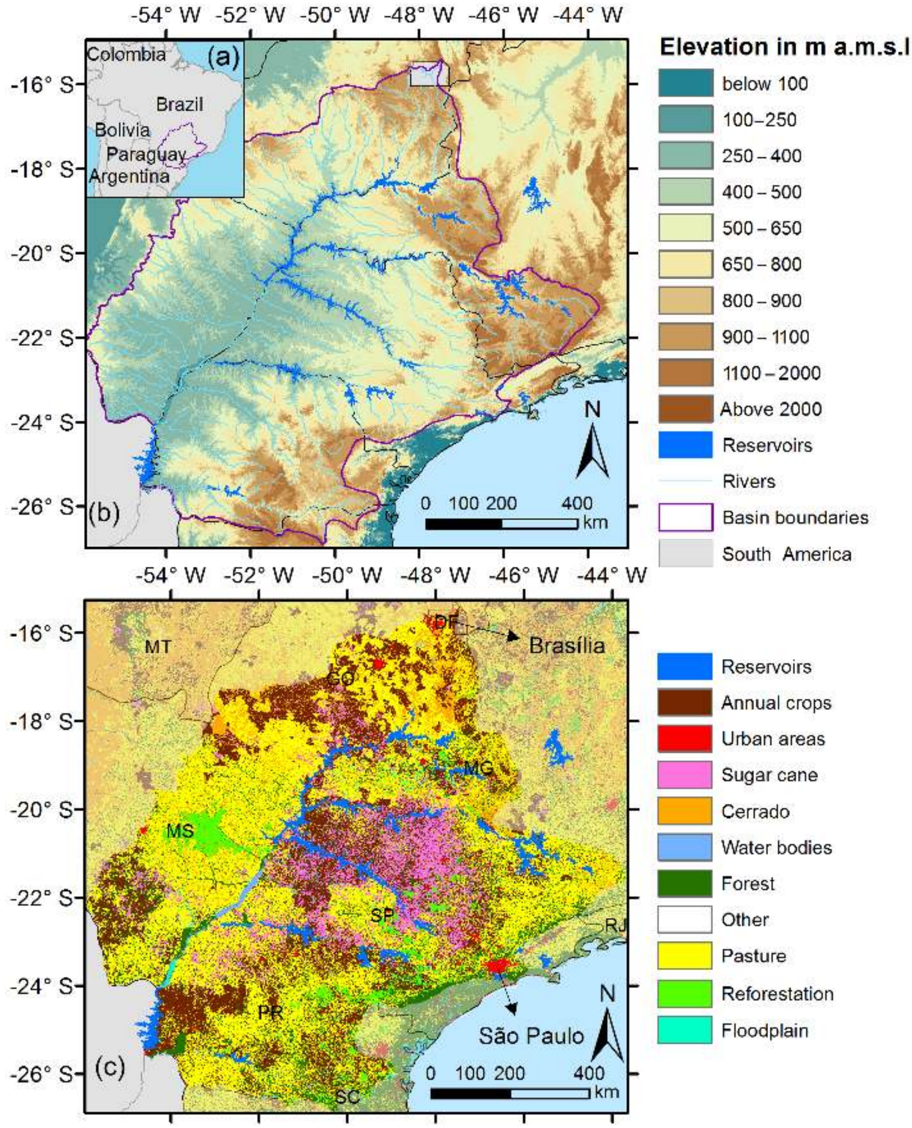

Figure 1. (a) The Paraná River basin in the national context. **(b)** The analysed reservoirs are highlighted in the digital elevation map (1" horizontal resolution; Valeriano and Rossetti, 2012) and in **(c)** the 2012 land use map (FEALQ, 2014). States include Distrito Federal (DF), Goiás (GO), Minas Gerais (MG), São Paulo (SP), Paraná (PR), Santa Catarina (SC), and Mato Grosso do Sul (MS).

river discharge (Melo and Wendland, 2016). The large areal extent allows surface reservoir impacts to be assessed at local to system scales, considering upstream–downstream drought impacts based on observed reservoir storage (RESS) data. The results of this study should enhance our understanding of linkages between meteorological and hydrologic droughts to better manage water resources in this region and other similar regions.

2 Study area, data, and methods

The study area (830 000 km^2) comprises the contributing basins to 37 reservoirs: 35 within the Paraná basin (PB) and two other nearby reservoirs (Três Marias and Paraibuna) selected because they are in areas affected by the 2014 drought (Fig. 1 and Table S2 in the Supplement). The Paraná basin was originally covered by Cerrado and Mata Atlantica biomes which have been replaced by pasture (44 %), annual crops (24 %), sugarcane (9 %) with original Cerrado, and forests only occupying 7–9 % each of the land area (FEALQ, 2014). Most of the reservoirs are located near the centre of the basin, where the land use consists, basically, of annual crops and sugar cane. Centre pivots in the region are mainly located in the northern and south-eastern parts of the PB (Fig. S2f in the Supplement). Mean rainfall is 1500 mm yr^{-1} and temperature is 23 °C (1980–2014; Xavier et al., 2015).

The topography in the PB consists, basically, of high plains with maximum altitudes higher than 2000 m a.m.s.l. (Fig. 1). Most of the PB is under temperate highland tropical climate with dry winters (Cwb) and humid subtropical climate with hot summer (Cfa) or with dry winter (Cwa; Fig. S3b). This basin covers parts of seven Brazilian states (SP, MG, DF, GO, MS, PR, and SC; Fig. 1). The population in the basin (60 million in 2010) represents 32 % of the Brazilian population (Sect. S2.2), including the most populated city in Brazil (São Paulo), with 11 million people in 2015 (ANA, 2010).

The Cantareira system, São Paulo's main water supply system, has an overall storage capacity of $1.45\,km^3$, including the following reservoirs and respective storage capacities: Jaguari ($0.14\,km^3$), Jacareí ($0.89\,km^3$), Cachoeira ($0.11\,km^3$), and Atibainha ($0.3\,km^3$). Extended dry periods can be critical for the Cantareira and other surface systems. Since the 1960s, seven droughts (1977, 1984, 1990, 1992, 2001, 2012, and 2014) reduced reservoir storage supplies for São Paulo (Coelho et al., 2015a). The Cantareira system contribute 47 % ($33\,m^3\,s^{-1}$) of the total water supply to São Paulo's metropolitan region that encompasses 39 municipalities (19.6 million people in 2007; Whately and Diniz, 2009). Before the water crises caused by the 2014 drought, 8.8 million people were supplied by the Cantareira system, with ≈ 164 L per inhabitant per day (SABESP, 2014).

2.1 Data sources and processing

This section provides a general overview of the data sets used in this study. Additional details are provided in Sect. S3.0. Ground-based rainfall data (P_{obs}) from ≈ 1270 gauges (Fig. S3) for the period 1995–2013 were interpolated to a $0.25° \times 0.25°$ grid by Xavier et al. (2015). Because P_{obs} is not available throughout the whole analysed period, remotely sensed rainfall estimates (P_{Sat}) were derived from the Tropical Rainfall Measuring Mission (TRMM) Multisatellite Precipitation Analysis (TMPA) 3B43 version 7 product, for the period 2013–2015.

The GRACE-based monthly gravity solutions in spherical harmonic format from April 2002 through to April 2015 were obtained from the University of Texas Center of Space Research (CSR; Bettadpur, 2012). To reduce noise while minimizing signal loss, we applied standard post-processing, including truncation to degree and order 60, de-striping (Swenson and Wahr, 2006), and application of a 250 km fan filter (Zhang et al., 2015). Then the filtered monthly gravity fields, after removing the mean, were converted to total water storage anomalies (TWSAs) in gridded $1° \times 1°$ degree solutions to match outputs from land surface models spatially.

The analysis of soil moisture storage (SMS) and runoff (R_{off}) is based on outputs from four land surface models (LSMs) from GLDAS 1.0: NOAH, Mosaic, VIC, and CLM (Rodell et al., 2004). The number of vertical layers (VL) and respective depths (D) varies among LSMs: CLM (10 VL, $0 \leq D \leq 3.43$ m), Mosaic (3 VL, $0 \leq D \leq 3.5$ m), NOAH (4 VL, $0 \leq D \leq 2.0$ m), and VIC (3 VL, $0 \leq D \leq 2.0$ m). SMS is the average layer soil moisture (ALSM) from individual LSMs. ALSM was obtained by depth-averaging the water amounts in specific soil layers. Descriptions of the LSMs and GLDAS are provided in Sect. S3.2. The ET data sets used were derived from the global ET algorithm (ETGlob) developed by Zhang et al. (2010) and from the MOD16 global evapotranspiration product (Mu et al., 2011; Sect. S3.3).

There are a large number of reservoirs in the PB, several of which with negligible volumes in the context of this study. Considering the effort to compile and process the data from individual reservoirs, only reservoirs with individual areas exceeding 1000 ha were selected for analysis (criterion I). The volume of a reservoir with an area less than 1000 ha ranges around $0.25\,km^2$, accounting for less than 0.1 % of the average storage capacity analysed in this study. Approximately 50 reservoirs remained after the application of criterion I. Most of those reservoirs have the primary purpose of generating hydroelectricity. A second criterion was applied, removing cases whose time series contained gaps accounting for more than 50 % of their records. Due to data limitations, only 37 of the 50 reservoirs were considered in this study. The maximum storage capacity of the 37 reservoirs is $\approx 250\,km^3$. Daily data on inflow, outflow, water level and storage for 37 reservoirs were downloaded from the Brazilian Water Agency (ANA, Agência Nacional de Águas) website for the period January 1995–June 2015.

2.2 Data analyses

The Standardized Precipitation Index (SPI) was selected as the meteorological drought index because it is probabilistic, its implementation is relatively simple, and its interpretation is spatially invariant (Guttman, 1998). SPI uses historical rainfall data to determine, at different timescales, the periods of positive and negative anomalies in rainfall based on the cumulative probability of rainfall occurrence over an area or point (McKee et al., 1993). We used the 12-month SPI based on historical monthly rainfall data relative to a 35-year time span (1980–2015; Sect. 4.3).

The Streamflow Drought Index (SDI; Nalbantis and Tsakiris, 2008) was selected as the hydrologic drought index because it is analogous to SPI in that it is computationally inexpensive, easy to implement, and reduces the drought characterization to a simple severity vs. frequency relationship (Nalbantis and Tsakiris, 2008). For each water year, SDI is obtained for overlapping periods of 3, 6, 9, and 12 months based on cumulative streamflow data. In addition, it is not data demanding as it requires only streamflow data (Sect. S4.3). For practical purposes, drought onsets were classified when SPI or SDI were < -1 for at least 6 months. Further details related to calculating SDI are provided in Sect. 4.3.

The statistical significance of reservoir depletion and trends in monthly reservoir storage were investigated by applying the non-parametric Mann–Whitney U test (MW U) and a modified version of the rank-based non-parametric Mann–Kendall test (MK), respectively (Mann and Whitney, 1947; Kendall, 1975). The MW U test is a common alternative to the parametric Student's t test for testing whether two samples come from the same population (Sect. 4.1). The MK method is used to avoid making assumptions regarding the distribution of the data and reducing sensitivity to outliers (Hamed, 2008). To overcome possible issues due to positive correlation in the analysed time series (Sect. S4.2), we adopted a modified MK trend test for seasonal data with serial correlation (Hirsch and Slack, 1984).

Hierarchical clustering (HC) was used to group the reservoirs and is a commonly adopted approach to identify similar groups among hydrological time series (Brito Neto et al., 2015). The similarities among elements and groups of elements are measured by a distance function (Bailey, 1994) which, along with the maximum cluster distance, compose the main parameters to be defined in a HC method. In this study, we used the Euclidean distance (see Sect. S4.4 for equations) as a distance function because it has been shown to produce good results in past studies (Ramoni et al., 2002) and is available in the Matlab toolbox used here. The maximum cluster distance (MCD) defines the distance below which the objects are considered as part of a single group (Fig. S12). In this study, we adopted an interactive process to define MCD in which various values were tested, the resulting clusters were observed, and a final option was chosen based on its capability to represent the variability existing in the sample. The elements used to generate the clusters are time series of normalized monthly reservoir storage (Sect. S4.4); that is, we seek to group the reservoirs with similar responses at a monthly scale. Hence, the clustering analysis performed here does not consider other reservoir characteristics such as storage capacity, location, and shape.

3 Results

3.1 Meteorological droughts

Two distinct droughts were identified in the Paraná basin between 1995 and 2015 based on SPI (Fig. 2). The first drought began in October 1999 and extended through to August 2000, during which SPI was ≤ -1.25, characterizing a moderate to severe drought ($-2 \leq \text{SPI} \leq -1$). This drought was followed by a moderately dry year as the average SPI was ≈ -0.6 during the rainy season of 2001 (December–February). The second driest period occurred between February 2014 and November 2014, with SPI ≤ -1.20 (Fig. 2). The first drought is hereafter referred to as the early 2000s drought and the second drought as the 2014 drought. The 2014 rainfall deficit was previously identified as part of a prolonged drought (2012–2015) by Getirana (2015), who applied break tests to TWSA time series and found a change occurring in February 2012. Although our analysis of GRACE-based TWSA also indicates an abrupt change between 2011 and 2012, this change in TWSA reflects a hydrological drought.

The intensity and duration of the drought are spatially variable. Rainfall anomalies in water year (WY) 2001 (September 2000–August 2001) were more negative over the eastern and northern parts of the Paraná basin, whereas the spatial extent of the 2014 drought was greater as most of the PB experienced a reduction of 20–40 % in annual rainfall (Fig. 3). Most of the reservoirs are in areas where rainfall deficits ranged from 20 to 50 % of the long-term average (1982–2015). The negative rainfall anomalies decreased towards the south-western portion of the basin, which experienced a positive anomaly of up to 20 %. Between 2002 and 2009, two periods of average rainfall with different inter-annual ranges were found, followed by an extremely wet year (WY 2010), mainly over the south-eastern part of the PB (Fig. 3), after which rainfall systematically decreased.

3.2 GRACE total water storage anomaly and component storages

The GRACE satellite data provide valuable information on the regional extent of drought impacts on total water storage anomaly (TWSA), despite its coarse spatial resolution (≈ 100–$200\,\text{km}^2$; Fig. 4). TWSA data from GRACE do not include the 2001 drought as its monitoring period is from 2002 to the present. Analysis of GRACE data indicates greater depletion in TWSA (≈ -60 to $\approx -90\,\text{mm yr}^{-1}$ between April 2011 and April 2015) in south-eastern Brazil, which corresponds to the north-eastern part of the PB. This range encompasses the results reported for the period between February 2012 and January 2015 by Getirana (2015), whose findings indicate a water depletion rate of $-61\,\text{mm yr}^{-1}$ in south-eastern Brazil ($\approx 920\,\text{km}^2$), corresponding to $\approx 160\,\text{km}^3$ over 3 years. The spatial extent of the negative TWSA (Fig. 4) is generally consistent with the spatial distribution in the negative rainfall anomaly in WY 2014 (Fig. 3).

GRACE TWSA shows large seasonal variability as a result of seasonal fluctuations in soil moisture storage (SMS) from LSMs and monitored reservoir storage RESS (Fig. 5). Interannual variability in GRACE TWSA shows anomalously wet years in 2007 and 2010, related to elevated rainfall. SMS and RESS were also above average in those years. The peak TWSA in January 2007 shows the rapid response of the system to the peak in SPI during the same period (Fig. 2). Note that SPI was low or close to 1 between 1999 and 2006; therefore, the peak TWSA was not preceded by high rainfall in 2006. There is a long-term decline in TWSA from April 2011 to April 2015 ($37\,\text{km}^3\,\text{yr}^{-1}$, $42\,\text{mm yr}^{-1}$), totalling $148\,\text{km}^3$. Depletion in TWS ($42\,\text{mm yr}^{-1}$) is greater than that in SMS and RESS combined ($24\,\text{mm yr}^{-1}$) by $\approx 40\,\%$. The discrep-

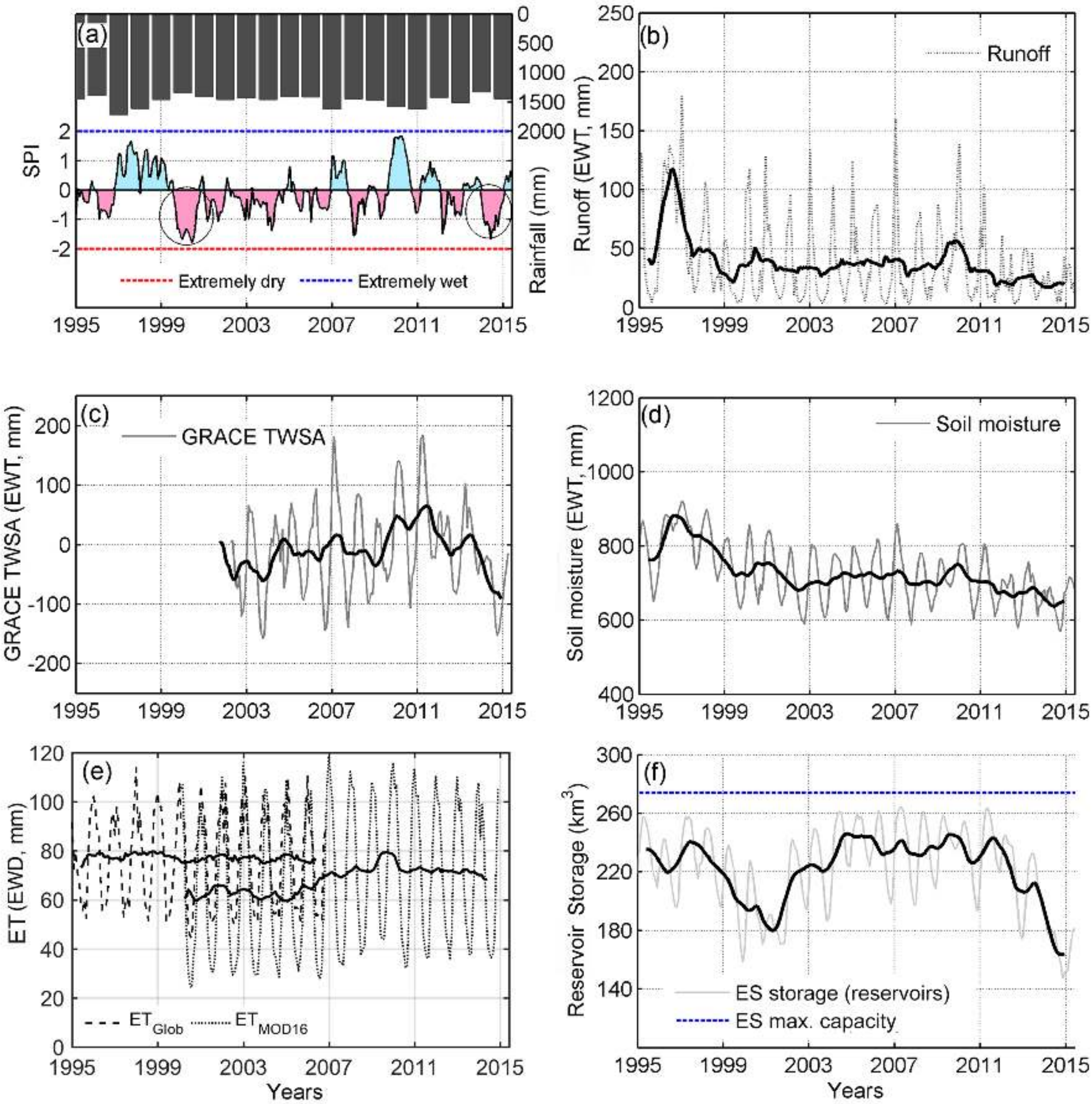

Figure 2. Time series of **(a)** rainfall and SPI, **(b)** runoff, **(c)** GRACE total water storage anomaly (TWSA), **(d)** soil moisture, **(e)** evapotranspiration, and **(f)** reservoir storage in the equivalent system (ES). **(a)** Standardized Precipitation Index (SPI) categories include extremely wet ($SPI > 2$), severely wet ($1.5 \leq SPI < 2$), moderately wet ($1 \leq SPI < 1.5$), wet ($0.5 \leq SPI < 1$), normal ($-0.5 \leq SPI < 0.5$), moderately dry ($-1 < SPI \leq -0.5$), dry ($-1.5 < SPI \leq -1$), severely dry ($-2 < SPI \leq -1.5$), and extremely dry ($SPI < -2$). **(b)** Runoff, **(c)** GRACE total water storage anomaly (TWSA), and **(d)** soil moisture are expressed in equivalent water thickness (EWT).

ancy is most likely related to depletion in deep SMS or groundwater storage (GWS; Fig. S11). Simulated SMS from LSMs is restricted to the upper 2 m of the soil profile.

3.3 Analysis of combined reservoirs as an equivalent system

This section presents the results relative to the analysis of the total monthly storage of all 37 reservoirs considered as one equivalent system. According to the MW U test, there is strong evidence (probability $\geq 95\,\%$) that the early 2000s (p value $= 0.027$) and 2014 (p value $= 0.01$) droughts resulted in significant depletion of the total reservoir storage. This depletion corresponds to a reduction of $40\,km^3$ (17 %) in WY 2001 and $34\,km^3$ (15 %) in WY 2014 of the average storage volume and of $90\,km^3$ (−33 %) and $86\,km^3$ (−31 %) below the equivalent system maximum capacity.

Comparing the negative trends in RESS, the recent drought was more intense than the earlier drought: between 1997 and 2001, the equivalent RESS decreased by 17.1 relative to $25.3\,km^3\,yr^{-1}$ between 2011 and 2015 (Fig. S10). The reservoir system responded rapidly to the meteorolog-

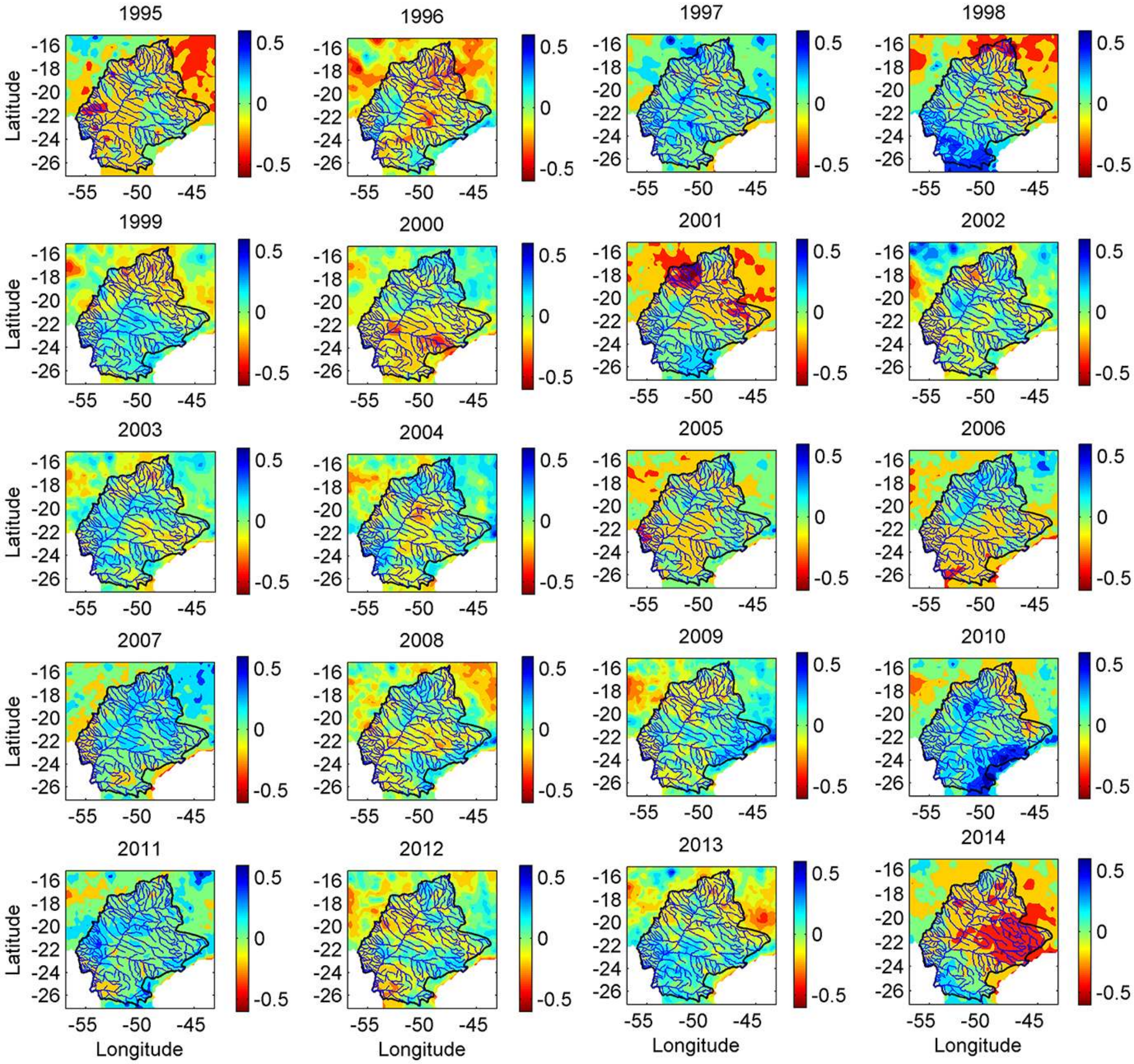

Figure 3. Rainfall anomaly relative to the 1982–2015 mean for 20 analysed water years (September–August).

ical shifts. RESS was lowest at the beginning of the water year 2001; SPI values indicate the meteorological drought began in October 1999, when the SPI was at −1.3. During the wet period of 2002, the reservoir systems began to recover and by early 2003 the reservoirs were operating at normal capacity, even though the SPI indicated a normal to moderately dry condition. Additional information about the recovery/depletion of reservoirs in a spatial context is presented in Sect. S5.7.

3.4 Drought propagation through the system

Variations in precipitation translate to changes in soil moisture storage (SMS) that affect runoff (R_{off}) and ultimately impact RESS. SMS and R_{off} were similarly affected by the early 2000s drought (Fig. 2). After 2001, the almost 1 decade of relatively normal rainfall was insufficient for SMS and R_{off} to recover from the drought. Not even the extreme wet period in 2010/2011 resulted in SMS and R_{off} recovery. Given that rainfall continued to decrease in the following years, the negative trend in SMS and R_{off} persisted.

The average temperature in the Paraná basin decreased by $0.04\,^{\circ}\mathrm{C\,yr^{-1}}$ within the past 20 years (Fig. S9). However, the analysis of both temperature and ET were inconclusive regarding their impacts on reservoir storage change. Comparisons between ET estimates from the global algorithm ($\mathrm{ET_{Glob}}$) by Zhang et al. (2010) and from the MOD16 algorithm ($\mathrm{ET_{MOD}}$) by Mu et al. (2011) indicate a larger inter-annual variation of the latter relative to the former (Fig. 2). Given the large uncertainty in remotely sensed ET (Long et al., 2014), no attempt was made to identify whether

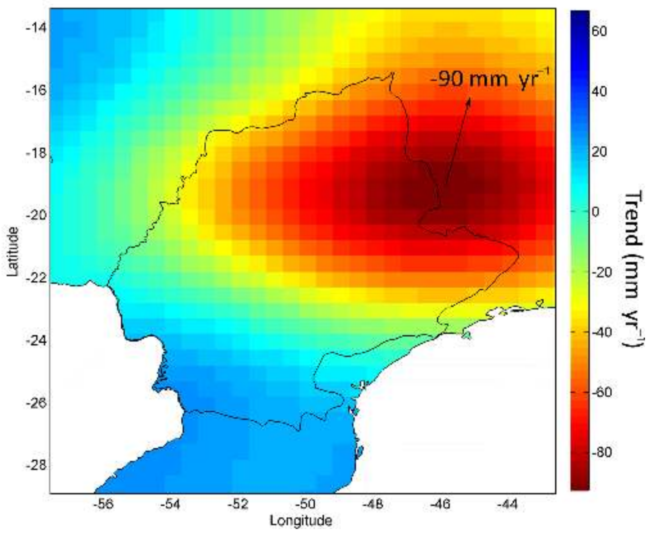

Figure 4. Spatial trends of TWSA between April 2011 and April 2015.

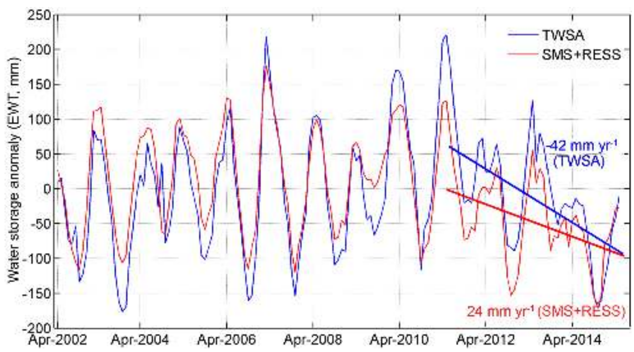

Figure 5. Water storage anomalies from GRACE TWSA, soil moisture storage (SMS), and reservoir storage (RESS), all expressed as equivalent water thickness.

the minimums are overestimated by ET_{Glob} or underestimated by ET_{MOD}; rather, we analyse the changes in ET signal. Although no significant trend of ET in response to the analysed droughts was observed with a confidence level $\geq 95\,\%$ ($\alpha = 0.05$), ET decreased by $-2.8\,\mathrm{cm\,yr^{-1}}$ between January 1998 and January 2001, and by $-0.3\,\mathrm{cm\,yr^{-1}}$ between February 2010 and February 2014 (Fig. 6). From January 2003 to January 2010, a positive trend, significant at $\alpha = 0.05$, show that ET increased by $3\,\mathrm{cm\,yr^{-1}}$. Such an increase reflects the recovery of the hydrologic system as the moisture, absent due to the drought, becomes available again to be consumed by the vegetation.

In terms of annual ET, the ET_{MOD} signal is practically invariant from 2000 through to 2006, but a discrete increase in the moving average suggests that ET rates were higher in the following years (2007–2014; Fig. 6). An increase in ET (70 to 200 mm) was observed in most of the Paraná basin, especially over the contributing areas of most of the analysed reservoirs (Fig. 6). Loarie et al. (2011) showed that replacing pasture by sugar cane in the Cerrado bioma increases ET, and São Paulo state (30 % of the PB) has been reported as the largest producer of sugar cane (Rudorff et al., 2010). However, the comparison between Figs. 1 and 6 shows a higher increase in ET ($\geq$ 120 mm) in the PB occurring mostly in areas with annual crops and pasture, whereas the increase in ET in areas preponderantly occupied by sugar cane ranged from 0 to 200 mm. Further investigation would be necessary to, precisely, identify the causes of that increase.

The analysis of R_{off}, SMS, and TWSA provides insights into the mechanisms that may explain the reservoir responses to droughts. According to the SPI, the rainfall regimes during both droughts are similar; however, the greater impacts on reservoir storage in 2014 are likely explained by different antecedent soil moisture conditions. The fact that SMS did not recover after the early 2000s drought implies that higher rainfall amounts would be required for recovery to overcome the cumulative SMS deficit. The extremely wet conditions in 2010/2011 were only sufficient to partially replenish the reduced SMS. Complementary graphs are presented in Sect. S4.2. Runoff can be classified as infiltration excess (when rainfall exceeds the infiltration rate of the soils) or saturation excess (when soils are close to saturation) and differs from river discharge. Therefore, R_{off} is highly sensitive to SMS conditions. If rainfall is insufficient to recover SMS, then R_{off} cannot recover either. After 2010/2011, SMS, R_{off}, and TWSA continued to decline; hence, the main inflow to the reservoirs (river discharge), which depends on runoff and baseflow (groundwater discharge to streams), also decreased. The years preceding the early 2000s drought were wetter than those preceding the 2014 drought: SPI exceeded 1.5 (severely wet) throughout most of the 1997 through 1999 period, and SMS and Roff were more than 20 % higher than the following years. Therefore, SMS links meteorological drought to R_{off}, which affects the primary input to RESS: streamflow.

Streamflow data were used to calculate the Streamflow Drought Index and provide insights into linkages between meteorological and hydrologic droughts (Fig. 7) for the water years of 2001 (WY 2001) and 2014 (WY 2014). In general, meteorological droughts resulted in hydrologic droughts, as indicated by the extremely low values of the SDI, where the SPI was negative (Fig. 7). However, some upstream reservoirs (highlighted with arrows) seem to have buffered the effects of the 2014 drought in the downstream reservoirs. Although the SPI indicates a severe to extremely dry situation (SPI < -2) over those reservoirs, the SDI increased from upstream (SDI < -2.50) to downstream ($-2.5 <$ SDI < -2.0). This means that the river discharge deficit (hydrologic drought) caused by the meteorological drought was (modestly) attenuated by the upstream reservoirs.

Comparison between WY 2001 and 2014 shows a larger extent of the most recent drought within the Paraná basin,

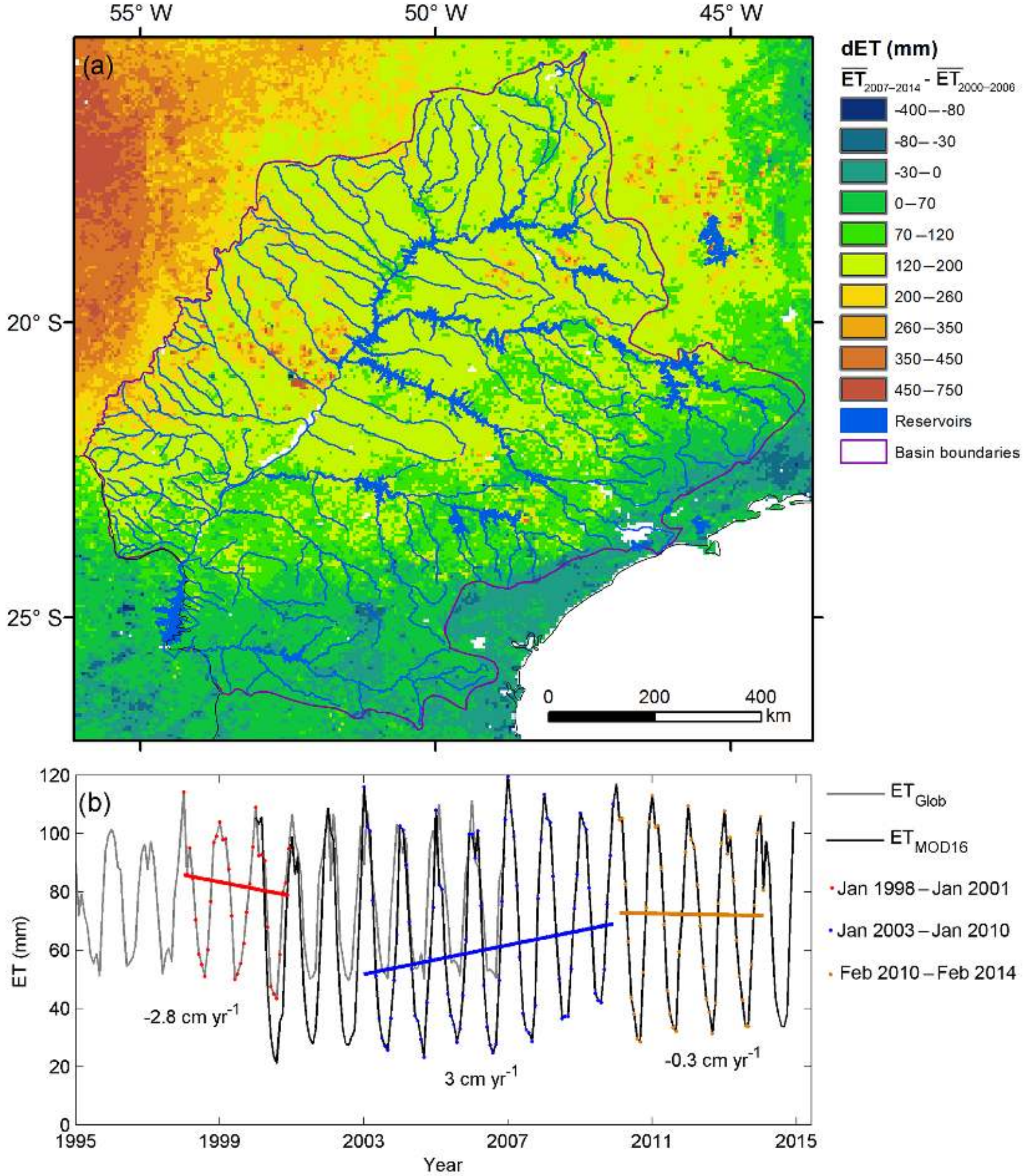

Figure 6. (a) Changes between the mean annual ET from 2007 to 2014 and 2000 to 2006; **(b)** short-term trends of ET in the Paraná basin.

which agrees with the rainfall anomaly in Fig. 3. Except for the south and central south of the PB, the extent of the hydrologic drought was more critical in WY 2014 than that observed for WY 2001. For instance, the same sub-basin in the centre of the PB had, in WY 2001, $-1 < \text{SDI} \leq 0$, whereas, in WY 2014, $-2.7 < \text{SDI} \leq -2.00$.

3.5 Cluster analysis applied to reservoir storage

Changes in RESS reflect the impacts of climate extremes through SMS and R_{off} and also reservoir management for hydroelectricity and water supply. Cluster analysis suggested that the reservoirs could be subdivided into six groups (G1, G2, ..., G6) based on the time-series signal of monthly storage (Figs. 8 and 9). The main features intended to be highlighted by creating those clusters in Fig. 9 are seasonality and changes in time, which will be discussed below. The hierarchical tree of the groups and linkages between them shown in a dendrogram were obtained by setting the maximum cluster distance (MCD) = 0.6 (Fig. 8). Although the dendrogram in Fig. 8 may suggest higher link consistency for MCD ≈ 0.5, similar characteristics of the seasonal signal would be present in the new groups formed from G1 (Sect. 5.6). Hence, the configuration in Fig. 8 was kept. Further details and discussion about such a choice are provided in Sect. S5.4. Dam operations are constrained by non-human-controlled variables

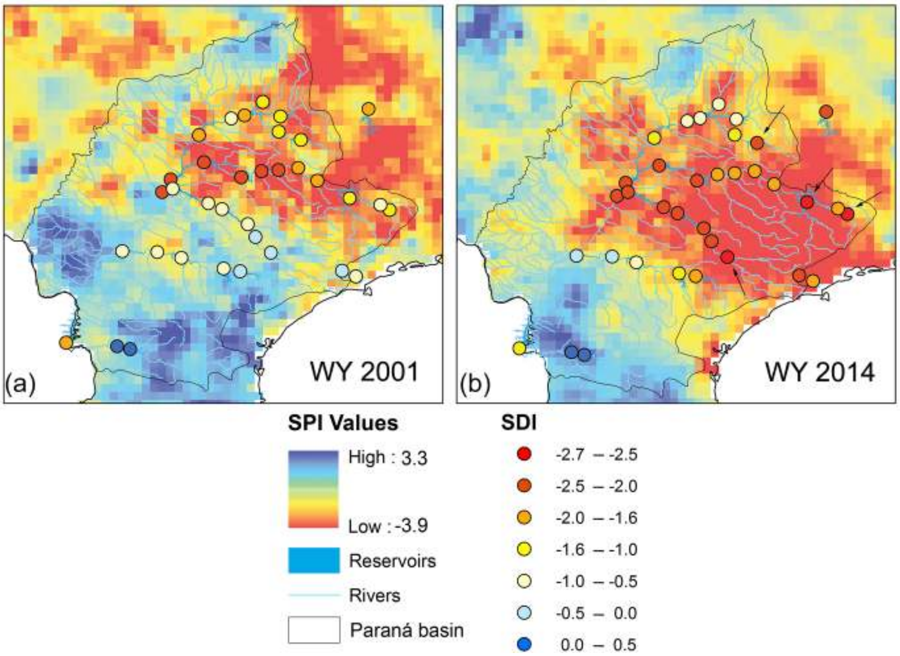

Figure 7. Spatial variation of the Standardized Precipitation Index (SPI) and Streamflow Drought Index (SDI) in the period of two droughts. SPI and SDI are shown for the water years of 2000 (September 2000 to August 2001) and 2014 (September 2013 to August 2014).

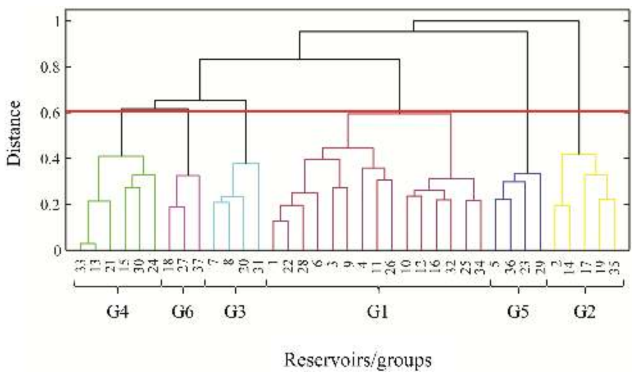

Figure 8. Dendrogram plot showing the hierarchical cluster tree. The distance between individual clusters is given by the height of the links. The red horizontal line indicates the maximum cluster distance (MCD) adopted to determine the clusters.

(e.g. natural inflows) and legal obligations to maintain outflows exceeding a minimum value ($Q_{\text{min\_out}}$) at all times. The compliance with $Q_{\text{min\_out}}$ aims to guarantee multiple uses of water resources and is defined by the Electric System National Operator (ONS – Operador Nacional do Sistema Elétrico) for each hydroelectric power plant (HEP). Hence, even though the released outflow from a given reservoir may be reduced to control the decline in storage during a drought, the reservoir will, eventually, experience some depletion given the need to observe $Q_{\text{min\_out}}$. To manage hydroelectric generation, ONS uses rainfall–runoff models forced with rainfall forecast from the ETA model (Mesinger et al., 2012); then discharge forecasts are used in stochastic models to generate scenarios of projected natural discharges at different timescales. Here, we sought to identify how human control and natural forcing dictate the responses in each reservoir.

3.5.1 Natural controls

The reservoirs in group 1 (G1, 15 out of 37) are characterized by well-defined seasonal variations, with good correspondence between storage change and natural input to the contributing basins (Figs. 9 and 10). In general, their storage through time is similar to that described by the equivalent system of reservoirs in terms of depletion during the early 2000s and 2014 droughts. Within G1 reservoirs, the inflows compare well with SPI, indicating a major role of natural forcing in reservoir responses.

Similarly, comparison between SPI, SDI, and RESS in G3 reservoirs also suggests their responses are strongly affected by natural variability (Figs. A1–A15 in the Supplement). Different responses between G1 and G3 reservoirs can be explained by climatological variations (Fig. 10). The main climatic difference between G1 and G3 reservoirs is the pronounced dry season that occurs in the climate sub-types Cwa (humid subtropical with dry winter), Cwb (temperate highland tropical), and Aw (tropical wet and dry) in G1 reservoirs, whereas rainfall is more evenly distributed throughout the year in sub-type Cfa (humid subtropical) in G3 reservoirs. The occurrence or absence of dry winters affects the

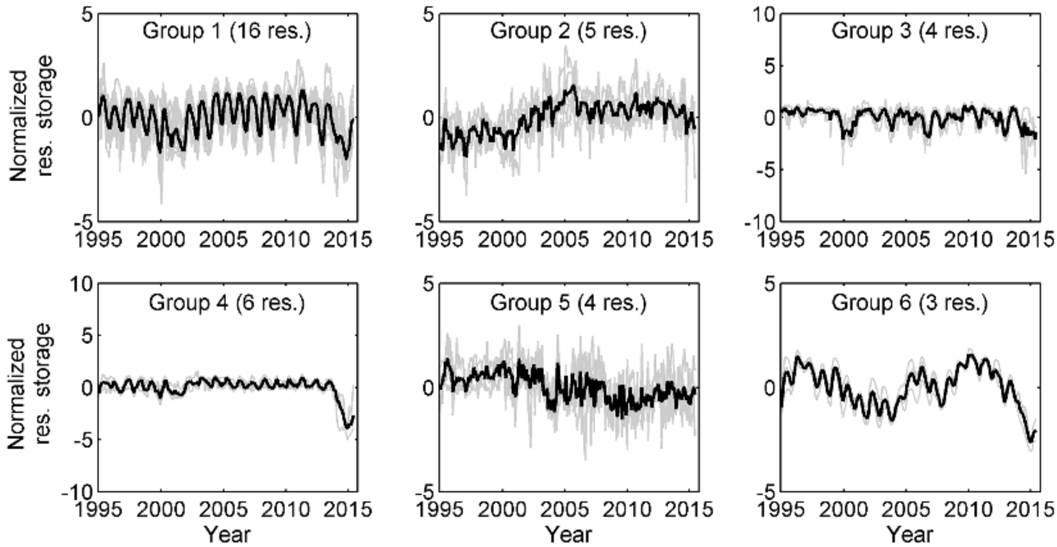

Figure 9. Time series of monthly reservoir storage of the six reservoir groups. Individual reservoirs are in light grey. Black lines show the group average.

seasonal distribution of inflows to reservoirs, hence impacting the seasonal signal in reservoir storage. Good correspondence between reservoir response and precipitation regime is not restricted to reservoirs in the upper part of the basin, i.e. reservoirs with no upstream reservoir affecting their inflow. What happens in the other cases is that the natural inflow (from undisturbed basins) contributes to the total inflow that explains the reservoir storage change as much as the regulated discharge delivered by the reservoir(s) upstream or that the outflow from upstream mimics natural discharge variations (Sect. S5.7).

Although G6 reservoirs are similar to G1 reservoirs in terms of having well-defined seasonal variations with good correspondence between precipitation variability and reservoir storage change, G6 reservoirs seem to deplete/recover more slowly than those in G1. The reservoirs of the Cantareira system are included within G6 reservoirs (Fig. S53). This system experienced major depletion as a result of natural water stress imposed by the recent drought (2014) combined with high demand from the São Paulo metropolitan area. The total rainfall in the 2014 water year was 1150 mm, 25 % lower than the average since 1995, resulting in SPI ≤ -2 (extremely dry). The lowest reservoir levels registered in the storage of the system (early 2015) reached 10 % of the total capacity, making the impacts of the 2014 drought unique.

3.5.2 Anthropogenic controls

Reservoirs in G2 and G5 do not show distinct seasonal variations, indicating that their responses are mainly governed by how they are operated and how the upstream dam is operated, given that all reservoirs in these groups are downstream of other hydroelectric power plants. In addition, the natural component of the total inflow is minimal because the upper undisturbed basin accounts for a small fraction of the total contributing area (Figs. A16–A20 and A31–S34). As a result, SPI fluctuations are not always reflected in reservoir storage. In such cases, analysis of SDI is inconclusive as it cannot provide information on natural discharge variability unless the human-controlled component of Q is removed.

For example, storage doubled in the Jaguará reservoir (G2) between 2001 and 2005 (0.04 to 0.08 km^3) even though SPI and SDI indicate the onset of a meteorological and hydrological drought (Fig. S34). That period was followed by an extremely wet year (2007/2008), but the rainfall increase was not reflected in the inflow (SDI ≈ 0) or in increased reservoir storage. Finally, no significant depletion was found during the extremely dry period in 2014. The main difference between G2 and G5 reservoirs is the change in average reservoir level (mainly after 2002), positive for G2 and negative for G5, displayed by most of those reservoirs (Fig. 9).

3.5.3 Natural and anthropogenic controls

Responses in G4 indicate that these reservoirs are equally controlled by natural and operational forcing. The natural component is reflected in the seasonality of storage variation. Their location in the PB, downstream to large reservoirs (Figs. A25–A30), makes them vulnerable to anthropogenic controls. Similar to G2 and G5 reservoirs, storage changes in G4 reservoirs are highly affected by dam operations, which implies that a precipitation deficit can be compensated by reducing outflow and benefiting from regulated discharge from upstream. However, persistence of low inflow may require operation that drastically reduces reservoir storage to main-

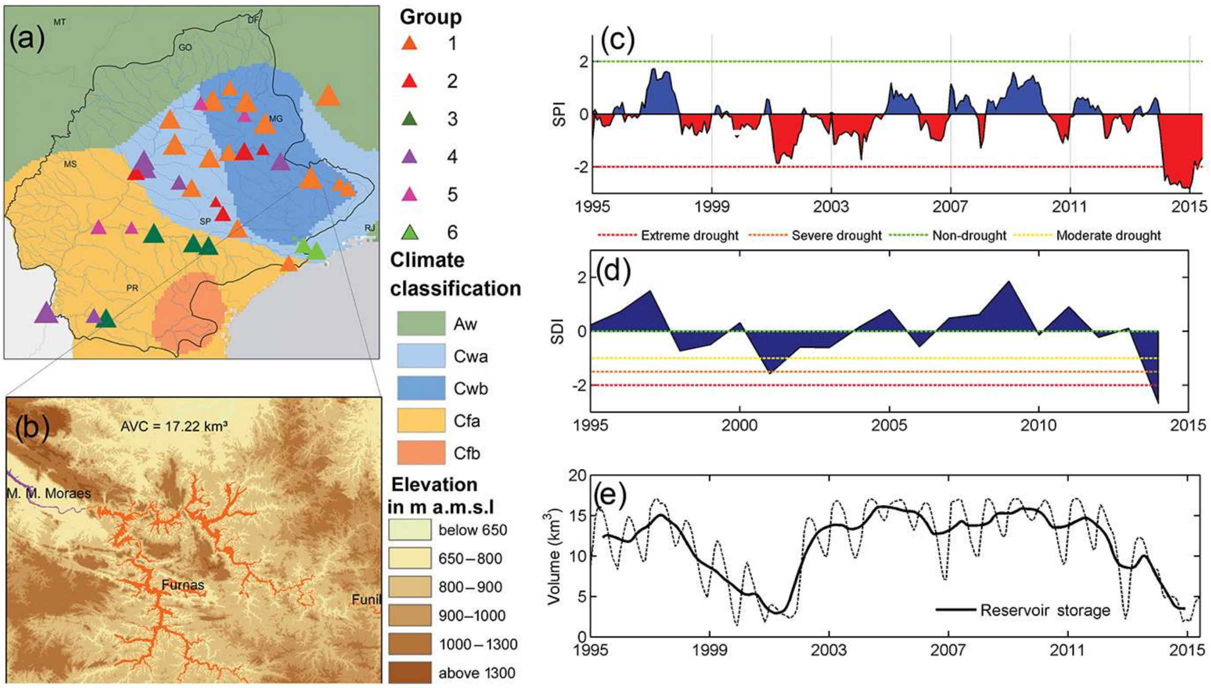

Figure 10. **(a)** The 37 analysed reservoirs in the context of the Paraná basin clustered in six groups and the number of elements per group. **(b)** Example of a typical reservoir from group 1 (16 reservoirs): Furnas hydroelectric power plant (HEP). Time series of monthly rainfall relative to the contributing area of Furnas HEP and inflow to Furnas reservoir were used to derive the Standardized Precipitation Index (SPI; **c**) and Streamflow Drought Index (SDI; **d**). Furnas monthly storage is shown in km^3 **(e)**. Hydrologic dry conditions are defined by the following states: SDI ≥ 0: non-drought; $-1 \leq$ SDI < 0: mild drought; $-1.5 \leq$ SDI < -1: moderate drought; $-2 \leq$ SDI < -1.5: severe drought; and SDI < -2: extreme drought.

tain $Q_{\text{min\_out}}$. That is precisely what happened at the M. M. Moraes Hydroelectric Power Plant (Fig. S43) in 2014 as the Electric System National Operator (ONS – Operador do Sistema Elétrico) decided to reduce the reservoir level by 8 m.

3.6 Future research

The findings presented here and in previous studies related to drought impacts in the Paraná basin are the baseline for future analysis. There are a number of gaps that need to be addressed; here we name some. A first prospect to be considered in the future is to quantify drought impacts on the regional water budget. Because remote sensing data sets, especially ET estimates, are not sufficiently reliable to close the budget (Sheffield et al., 2009; Long et al., 2014), future studies should incorporate more ground-based data, such as groundwater level data.

Further analysis of drought propagation features is necessary to better characterize such extreme events in the PB. Van Loon et al. (2012) compiled a number of studies on that topic and identified the following features: pooling (combined meteorological droughts causes a prolonged hydrologic drought); attenuation (terrestrial stores attenuate meteorological drought); lag (between meteorological drought, soil moisture, and hydrological drought); and lengthening (longer droughts moving through soil moisture to hydrological droughts). The lag feature was partially addressed by Melo and Wendland (2016) as lag times between changes in SPI, reservoir storage, and river discharge were estimated. Future researches can profit from more detailed information regarding the decision processes considered for dam operations. Such information is not usually publicly available in Brazil. Hence, this can create a good opportunity to promote more bilateral collaboration, especially between hydrology researchers and engineers.

4 Summary

Regional intense droughts in south-eastern Brazil have caused major depletion of water resources. We analysed remote sensing, monitoring, and modelling data to identify linkages between meteorological and hydrological droughts. Based on SPI, two major meteorological droughts occurred in the Paraná basin between 1995 and 2015. A moderate to severe drought ($-2 \leq$ SPI ≤ -1) occurred in the early 2000s, with SPI ≤ -1.25 between October 1999 and August 2000. The second driest period occurred between February and November 2014, with SPI ≤ -1.20. Drought intensity and duration are spatially variable. The 2014 drought was more critical over the north-eastern part of the study area, with rainfall anomalies ranging between −20 and −60 %, resulting in SPI values ≤ -2.0 for 6–12 months in some cases (e.g. Furnas reservoir, Fig. 10).

The recent drought monitored by GRACE satellites shows depletion of TWSA of $37\,km^3\,yr^{-1}$ ($42\,mm\,yr^{-1}$) over 4 years from 2011 to 2015 in the Paraná basin, totalling $150\,km^3$. Simulated SMS and monitored RESS together decreased by $24\,mm\,yr^{-1}$, accounting for 60 % of TWSA depletion. This recent drought was preceded by an earlier drought (early 2000s) that occurred prior to GRACE monitoring. Reduced rainfall and negative SPI during this drought translated to low SMS and reduced runoff (SDI anomalies), decreasing RESS by $30\,km^3$ in 2001 relative to the average storage volume. Depletion of reservoir storage caused by the early 2000s and 2014 droughts corresponds to a 31 % reduction relative to the reservoir equivalent system maximum capacity. Two negative short-term trends in RESS were found during the studied period: −17.1 (1997–2001) and $25.3\,km^3\,yr^{-1}$ (2011–2015), totalling 68 and $101.2\,km^3$, respectively.

The period between these two droughts is characterized by slightly below average to near normal rainfall; however, rainfall levels were insufficient to overcome the cumulative water deficit that built up during the early drought. Low SMS compromised recovery even after the severely wet year in 2010. As a result, the system storage reserves were low going into the recent drought and were rapidly depleted during 2014.

While GRACE satellites provide data on regional water storage depletion and recovery related to drought, SMS and R_{off} from LSMs link meteorological drought to hydrologic drought, as shown by streamflow anomalies (SDI) that are reflected in inflow anomalies to the reservoirs. However, detailed assessment of drought impacts on reservoir storage requires more thorough analysis of reservoirs at the local scale. Clustering analyses in this study revealed three groups of reservoirs (23 reservoirs) with storage controlled mainly by natural climatic forcing, two groups (9 reservoirs) controlled mainly by reservoir operations, and one group (6 reservoirs) controlled by a combination of natural and anthropogenic forcing (dam operations). The analysis highlights the importance of reservoir location within the system (upstream vs. downstream) in determining the dominant controls on drought impacts on reservoir storage. For most reservoirs, including the Cantareira system, meteorological droughts were reflected in the hydrologic system through reduced inflow to the reservoirs. The vulnerability to recent droughts in São Paulo not only underscores the need for reservoir storage expansion, but also reinforces the urgency for diversifying the water sources to enhance drought resilience. In other cases, the upstream reservoirs performed an important role in regulating river discharge and, hence, reducing meteorological drought impacts on inflow to downstream reservoirs.

A preliminary understanding of drought propagation, i.e. how the meteorological drought culminate in hydrological drought, was presented here. Our analysis indicate that socio-economic droughts (failure to supply water, electricity, etc.) in the PB are subject to a natural cascade effect (rainfall deficits > soils moisture reduction > run-off reduction > reservoir depletion) that is related to antecedent soil moisture conditions and dam operation.

An important practical measure is to continuously monitor meteorological indices such as SPI. Based on such indices, it may be possible to anticipate and reduce drought impacts by means of public campaigns to alert the population about the potential drought and to encourage reduction in water and electricity consumption. The lag time between meteorological droughts and hydrologic responses results in time for some actions to be taken to reduce drought impacts, such as modifying dam operations. Given the spatial variability of droughts and the interconnected electric grid in Brazil, another possible measure is to reduce hydroelectric generation in a region potentially affected by an imminent drought and, temporarily, increase electricity generation in other regions.

Given the uncertainties in the modelling process adopted by ONS to manage hydroelectric generation, dam operators can profit from radar-based real-time rainfall measurements or remotely sensed near-real-time rainfall estimates. The difficulty in gathering station data for short timescales emphasizes the importance of remote sensing rainfall for reservoir operations. Finally, land surface models can be used in addition to the rainfall–runoff models currently used by ONS, to project hydrologic responses by inputting weather forecast data.

This study emphasizes the importance of integrating remote sensing, modelling, and monitoring data to quantify the duration, extent, and severity of regional droughts and their impacts on water resources, specifically reservoir storage, system evaluation and detailed analysis of individual reservoirs to determine controls on reservoir response to drought (e.g. natural climate forcing vs. dam operations), and the importance of this comprehensive understanding of the linkages between the meteorological and hydrologic droughts for future management.

5 Data availability

All the data used in this study are hosted by the Laboratory of Computational Hydraulics of the University of São Paulo and are available at http://www.lhc.shs.eesc.usp.br/dados_de_pesquisa/Drought-impacts/dataset_hess-2016-258.zip.

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Author contributions. The first author collected and processed the data from GLDAS, ANA, and ONS. Zizhan Zhang processed and

analysed the data from GRACE. Lei Yin processed the rainfall data. Edson Wendland and Bridget R. Scanlon analysed the data and commented on the paper, which was written by Davi C. D. Melo and Bridget R. Scanlon.

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