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Water storage variability across Brazil

Variabilidade do armazenamento de água no Brasil

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ABSTRACT

Brazil hosts a large amount of freshwater. Knowing how this stored water is partitioned in space and time between surface and subsurface components is a crucial step towards a more correct depiction of the country's water cycle, which has major implications for decision making related to water resources management. Here, we extracted monthly water storage (WS) variability, from 2003 to 2020, based on multiple state-of-the-art datasets representing different WS components – groundwater (GW), soil moisture (SM), surface waters (SW), and artificial reservoirs (RS) – in all Brazilian Hydrographic Regions (BHRs), and computed each component's contribution to the total variability. Most of the variability can be attributed to SM (40-68%), followed by GW (18-40%). SW has great influence in the north-western BHRs (humid monsoon influenced) with 18-40% and the southern BHRs (subtropical system influenced) with 5-10%. RS has important contributions in the Paraná with 12.1%, São Francisco with 3.5%, and Tocantins-Araguaia with 2.1%. In terms of long-term variability, water storages have been generally decreasing in the eastern and increasing in north-western and southern BHRs, with GW and RS being the most affected, although it can also be observed in SW peaks. Comparisons made with previous studies show that the approach and datasets used can have a considerable impact in the results. Such analysis can have broad implications in identifying the nature of amplitude and phase variability across regions in order to better characterize them and to obtain better evaluations of hydrological trends under a changing environment.

Keywords: Water storage partitioning; Brazilian hydrographic regions.

RESUMO

O Brasil abriga uma grande quantidade de água doce. Saber como essa água armazenada é repartida no espaço e no tempo entre os componentes superficiais e subsuperficiais é crucial para uma representação mais correta do ciclo hídrico do país, o que tem grandes implicações para a tomada de decisões relacionadas à gestão dos recursos hídricos. Neste estudo, extraímos a variabilidade mensal do armazenamento de água, de 2003 a 2020, com base em diferentes fontes que representam o estado da arte da informação sobre diferentes componentes de armazenamento - águas subterrâneas, umidade do solo, águas superficiais, e reservatórios artificiais – em todas as regiões hidrográficas brasileiras, e computamos a contribuição de cada componente em relação a variabilidade total. A maior parte da variabilidade pode ser atribuída a umidade do solo (40-68%), seguida por águas subterrâneas (18-40%). Águas superficiais tem grande influência nas regiões hidrográficas do noroeste (influência de sistemas de monção) com 18-40% e nas BHRs do sul (influência de sistemas subtropicais) com 5-10%. O estoque em reservatórios artificiais tem contribuições importantes nas regiões do Paraná com 12,1%, do São Francisco com 3,5% e do Tocantins-Araguaia com 2,1%. Em termos de variabilidade de longo prazo, os estoques de água têm geralmente diminuído nas regiões leste e aumentado no noroeste e no sul, sendo os estoques de águas subterrâneas e reservatórios os mais afetados, embora essa tendência também possa ser observada nos picos de água superficial. Comparações feitas com estudos anteriores mostram que a abordagem e os conjuntos de dados utilizados podem ter um impacto considerável nos resultados. Tal análise pode ter amplas implicações na identificação da natureza da variabilidade de amplitude e fase entre as regiões, a fim de melhor caracterizá-las e obter melhores avaliações das tendências hidrológicas.

Palavras-chave: Compartimentação de armazenamento de água; Regiões hidrográficas brasileiras.

INTRODUCTION

Brazil hosts the largest amount of freshwater on the planet (Food and Agriculture Organization of the United Nations, 2003). Because of its great water resources availability, it is fundamental to have an integrated framework that links water resources to the economic system. Although there are some global approaches to make this link (United Nations, 2012) with applications in Brazil (Agência Nacional de Águas e Saneamento Básico, 2018), the methodology is still very broad given the amount of data necessary to meet the frameworks, as datasets covering different aspects of the water cycle can be very difficult to obtain. A meaningful of the methodology is to obtain accurate estimates on the stored water within different components (soil, rivers, reservoirs, etc), for which the use of regional/global available datasets, especially those based on remote sensing and hydrological modelling techniques, is feasible for very large areas.

Still, knowing how water storage variability is distributed among the storage components is still a challenge, with only a few attempts being made in this regard (e.g. Getirana et al., 2017; Hu et al., 2017; Pokhrel et al., 2013). A quantitative analysis covering the entire Brazilian territory, using state-of-the-art remote sensing and model-based datasets, is still lacking in the scientific literature. Such analysis could have broad implications for water accounting frameworks and water resources management, for instance by fostering a more correct depiction of the Brazilian water cycle in land surface models and global hydrological models.

Since 2002, monthly changes of Terrestrial Water Storage (TWS) have been monitored at regional and continental scales (10^4 to 10^6 km^2) by the Gravity Recovery and Climate Experience (GRACE) and the GRACE Follow-on (GRACE-FO) missions (Landerer et al., 2020; Tapley et al., 2004). These data have been extensively used in hydrological studies of large basins, as they provide reliable information with relatively low uncertainty (Scanlon et al., 2016; Wiese et al., 2016). However, TWS integrates all continental water stored on and beneath the land surface, and for the partitioning of TWS variability into other components, additional data sources are needed. In recent years, several products based on Earth observations (both in situ and remote sensing), modelling, and/or reanalysis have been made available for water estimations in terms of both fluxes and storage variability, oftentimes covering large continental areas and even the whole globe (Rodell et al., 2004; Siqueira et al., 2018). Using storage estimations from these regional or global products, alongside with GRACE, is a good alternative for water accounting frameworks.

Therefore, TWS from GRACE can be used either to validate model storage outputs (e.g. Getirana et al., 2017; Paiva et al., 2013; Pokhrel et al., 2013; Siqueira et al., 2018) or combined with soil moisture (SM) and surface water (SW) storages to estimate groundwater storage changes as a residual from water balance equations (e.g. Hu et al., 2017; Melati et al., 2019). Although previous studies have found significant SW contributions to water storage variability in the Amazon (Getirana et al., 2017; Hu et al., 2017; Paiva et al., 2013; Pokhrel et al., 2013), other regions in the country may have been misrepresented, as there are large SW systems besides the Amazon – e.g. in Pantanal and in Bananal Island. Moreover, the contribution of large hydropower reservoirs (RS) can be significant in some regions – e.g. in the Paraná and São Francisco river basins.

In this context, the aim of this study is to quantify TWS contributions from each of the storage components (GW, SM, SW, and RS), in terms of monthly averages and time series analyses, at all Brazilian Hydrographic Regions (BHRs). To achieve that, we used data from multiple sources, which we consider the most reliable estimates available at the moment. This analysis can help future decision-makers in quantifying water storage contributions across large regions.

MATERIAL AND METHODS

Study area: Brazilian hydrographic regions

All analyses were performed considering the 12 Brazilian Hydrographic Regions (BHRs), presented in Figure 1 alongside with the official Brazilian open water dataset from ANA (Agência Nacional de Águas e Saneamento Básico, 2021b). These are official hydrological divisions from the Brazilian National Water and Sanitation Agency (ANA), with areas ranging from 1.7×10^5 to 38×10^5 km^2 (Table 1). As Brazil hosts large river networks with a wide variety of characteristics, the division of the country into these units is suited to applications involving water resources planning and management, and provides a reasonable way to characterize WS partitioning. Most regions are drained by the main rivers that cover the country's territory (Amazon, Tocantins-Araguaia, Parnaíba, São Francisco, Paraná, Uruguay, and Paraguay), while others are formed by grouping smaller and/or coastal basins (Western Northeast Atlantic, Eastern Northeast Atlantic, East Atlantic, Southeast Atlantic, and South Atlantic).

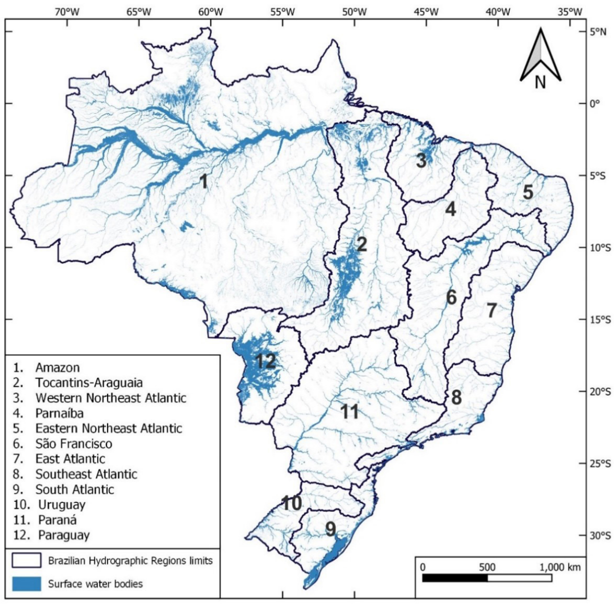

Figure 1. Brazilian Hydrographic Regions (BHRs) according to ANA, with their respective identification numbers.

Data acquisition and processing

We collected data from multiple sources, including TWS from GRACE, soil moisture from GLDAS, surface water storage from a hydrological-hydrodynamic model (MGB-SA), and reservoir storage from the ANA Reservoir Monitoring System database (SAR). These data were used to compute groundwater storage changes by using a water balance approach. Because of the coarser spatial (0.5º) and temporal (monthly) resolution of GRACE among the datasets, we resampled all data to match GRACE resolutions. In addition, GRACE only provides TWS variability, thus we normalized values from all datasets by subtracting the 2003-2020 means. Additional details about the datasets are provided in the next subsections and in Table 2.

Total water storage

The GRACE mission was launched in 2002, providing monthly spatial information on the Earth's gravitational field until 2017 (Tapley et al., 2004). Its successor, the GRACE Follow-On (GRACE-FO) mission, was launched in May 2018 and still orbits the atmosphere (Landerer et al., 2020), continuing the data collection from the first mission. The data presents some gaps in specific months, as well as in the period between the first and the second mission (from July 2017 to May 2018) – more details at Jet Propulsion Laboratory (2022a).

Temporal variations on the Earth's gravitational field can be mostly attributed to changes on terrestrial water storage (Sheffield et al., 2009), which has great potential for use in hydrological studies. To process GRACE gravitational data into water storage variability, several solutions have been developed by different research centres. They are grouped by the usage of Spherical Harmonics (SH) (Landerer & Swenson, 2012) or Mass Concentration Blocks (mascons) (Watkins et al., 2015). For hydrological analyses, the mascons solution presents several advantages in relation to the SH (Scanlon et al., 2016), and for that reason it is the one used here. Data were obtained from the JPL RL06M v.2 product, which is available at Jet Propulsion Laboratory (2022b).

In this product, raw information from the GRACE(-FO) twin satellites is processed at 3-degree mascons, which are used to filter out noise from initial observations. Later, a Coastline Resolution Improvement (CRI) filter is applied to separate land and ocean portions. Finally, a set of gain factors (obtained by a hydrological model) are used to resample the data to a 0.5-degree spatial resolution. One can choose to use data with (0.5-degree) or without (3-degrees) gain factors. Here, we decided to use gain factors as it provides finer spatial resolution, which allows a better spatial visualization and interpretation without compromising the information obtained across large regions (> 10^4 km^2). We also chose to use a baseline average comprising the whole period (2003-2020), instead of the commonly used 2004-2009, because it is better to visualise long-term means and does not affect the computations of components' contributions.

Table 1. IDs and areas of the Brazilian Hydrographic Regions (BHRs).

ID	Hydrographic Region	Area (km^2)
1	Amazon	3,800,000
2	Tocantins-Araguaia	967,000
3	Western Northeast Atlantic	254,000
4	Parnaíba	344,000
5	Eastern Northeast Atlantic	287,000
6	São Francisco	640,000
7	East Atlantic	374,000
8	Southeast Atlantic	230,000
9	South Atlantic	186,000
10	Uruguay	174,000
11	Paraná	880,000
12	Paraguay	363,000

Reservoir storage

According to official reports from the National Water Agency, around 93% of the storage capacity is destined to hydropower purposes (Agência Nacional de Águas e Saneamento Básico, 2021a), from which 98% are stored in large power plants associated to the Brazilian National Interconnected System (SIN). Although there are 3,661 reservoirs in SIN, 90% of the active (i.e. variable) storage is represented by 159 of them (Agência Nacional de Águas e Saneamento Básico, 2021a), which correspond to

Table 2. Datasets used in this study.

Product	Description	Spatial Resolution	Period
Total Water Storage (TWS)			
GRACE	Gravitational anomalies relative to a baseline	0.5º	2003 to 2020
Soil Moisture (SM)			
GLDAS	Land surface modelling and data assimilation of satellite and ground-based observational data	0.25º	2000 to 2020
Surface Water (SW)			
MGB-SA	Hydrological-hydrodynamic modelling of South America region	Vector-based (rivers with Δx= 15 km)	1990 to 2020
Reservoir Storage (RS)			
SAR-ANA	Brazilian National Water and Sanitation Agency Reservoir Monitoring System	-	2000 to 2020

the ones used in this work. We obtained time series of active volume, inflow and outflow for the SIN reservoirs through the SAR-ANA platform (Agência Nacional de Águas e Saneamento Básico, 2022), and the georeferenced reservoir polygons from the Brazilian open water dataset. First, monthly storage values for each reservoir were computed by considering the active volumes on the first day of each month, from 2003 to 2020. Next, the storage at reservoir locations was matched to the GRACE resolution grid (0.5º) according to the following steps:

- The SIN reservoir polygons are converted into a regular 90m resolution grid. The high-resolution pixels (90 m) within the reservoirs are defined here as "open water pixels";
- For a given reservoir *i*, the summed area of all open water pixels inside each coarse resolution cell *j* ($Aow_{i,j}$) associated to that reservoir is computed;
- Assuming that the total storage of a reservoir *i* ($VRStot_i$) is distributed proportionally to the fraction of total open water pixels, the storage in a given cell *j* linked to the reservoir *i* ($VRS_{i,j}$) is estimated as:

$$\mathrm{VRS}_{i,j} = \mathrm{VRStot}_i \times \left(\frac{\mathrm{Aow}_{i,j}}{\mathrm{A}_i} \right) \tag{1}$$

Where A_i is the area of reservoir i.

Surface water storage

Estimates of surface water storage were obtained from the continental-scale MGB model (acronym for *Modelo de Grandes Bacias,* in Portuguese), which was developed for the entire South America (MGB-SA) (Siqueira et al., 2018). MGB–SA is a semi-distributed, hydrologic-hydrodynamic model that uses conceptual and physically-based equations to simulate vertical water and energy budget, and flow propagation along river networks. The model is discretized into 33,749 unit-catchments with approximate 300 km^2 of area, and further into Hydrological Response Units based on land cover and soil classes, and each unit-catchment is associated to a single 15 km-long river segment. Water is routed through river networks using the local inertial approximation of shallow water equations proposed by Bates et al. (2010), enabling the calculation of surface water stored in river channels and floodplains. The floodplain is treated as a simple storage model, i.e., there is no floodplain flow parallel to the river direction. We chose the MGB–SA because it covers all Brazilian hydrographic regions and was extensively validated for South American basins using both in situ gauges and remote sensing datasets (Siqueira et al., 2018).

MGB–SA was formerly calibrated for 1990-2010 using the Multi-Source Weighted Ensemble Precipitation (MSWEP) v1.1 daily dataset (Beck et al., 2017) and monthly means of other climatic variables (surface air temperature, relative humidity, wind speed, sunlight hours, atmospheric pressure) as model forcing. However, as MSWEP v.1.1 data are not available from 2015 onwards (only for more recent versions of this dataset), we used data from the Global Precipitation Measurement mission (GPM) to extend the MGB–SA simulations until 2020. Daily precipitation data from the Integrated Multi-Satellite Retrievals for GPM (IMERG) final run (Skofronick-Jackson et al., 2017) were obtained at 0.1º spatial resolution and interpolated to the MGB–SA unit-catchments. In addition, IMERG data were bias corrected to MSWEP by adjusting gamma distributions for both datasets in the period 2000–2014 and applying the quantile-quantile mapping method (Teutschbein & Seibert, 2012) to IMERG precipitation from 2015 to 2020.

Monthly averages of surface water volume for a given unit-catchment, which include the volume stored in the main river and adjacent floodplain, as well as the remaining surface water that has not yet reached the channel, were divided by its corresponding unit-catchment area to obtain storage in mm. Next, surface water estimates at the unit-catchment level were spatially aggregated into 0.5º cells by using a weighted average approach:

$$\mathrm{VSW}_j = \frac{\sum_{n=1}^{N} \left(\mathrm{A}_n \times \mathrm{V}_n \right)}{\sum_{n=1}^{N} \mathrm{A}_n} \tag{2}$$

Where: VSW_j is the volume of surface water for cell j (mm), n and N are the unit-catchment index and the total number of unit-catchments with centroid located inside the cell *j*, A_n and V_n are the area (km^2) and volume of surface water (mm) related to the unit-catchment *n*, respectively.

Soil moisture storage

We used the root zone soil moisture product of the Global Land Data Assimilation System (GLDAS). It consists of an ingestion of satellite and ground-based observational data across the globe, which uses land surface modelling with data assimilation techniques (Rodell et al., 2004). The model was forced with atmospheric data from the National Oceanic and Atmospheric Administration (NOAA), precipitation data from the Climatology Project (GPCP) and solar radiation data from the Agricultural Meteorological Modelling System (AGRMET).

GLDAS soil moisture data have been largely used by regional and global analyses of water budget, presenting satisfactory estimations (e.g. Bi et al., 2016; Rzepecka & Birylo, 2020; Sazib et al., 2018; Spennemann et al., 2015). Also, it covers the longest period of data availability among the soil moisture products available on the Google Earth Engine (GEE) database. As GEE offers a free cloud-based platform that allows computations on large datasets (Gorelick et al., 2017), we used it to preprocess the GLDAS root zone soil moisture data, converting it from 3-hourly to monthly temporal resolution, and resampling from 0.25 to 0.5 degrees spatial resolution to match TWS from GRACE. It was not necessary to perform a reprojection to align the grids, as both datasets used the same datum (WGS84).

Groundwater storage

With all previous data processed at monthly time step, 0.5º grid resolution, and normalised by the mean value of 2003-

2020 period, GW was computed as a residual of the water balance by subtracting the other storages from TWS at every pixel i and time step t, following Equation 3:

$$GW_{i,t} = TWS_{i,t} - SM_{i,t} - SW_{i,t} - RS_{i,t} \quad (3)$$

Where GW is groundwater storage variability, TWS is total water storage variability, SM is soil moisture storage variability, SW is surface water storage variability, and RS is reservoir storage variability.

Computing the contributions of each WS component

To estimate the contribution of each component on TWS variability, we used the impact index (I) proposed by Getirana et al. (2017). The impact index measures the contribution of a given hydrological compartment as the ratio between its mean annual amplitude – expressed by the sum of the absolute monthly climatological anomaly values – and the sum of mean annual amplitudes from all hydrological compartments. The greater the monthly anomaly relative to the other components, the closer I is to 1, and the sum of I of all components equals 1. The index is preferable to the ratio of amplitudes (i.e. the difference between monthly climatological maximum and minimum) due to occasional lags between the different WS components, which may result in unrealistic values. The index is calculated following Equations 4-5:

$$I_j = \frac{C_j}{\sum_{j=1}^{nc} C_j} \quad (4)$$

$$C_j = \sum_{m=1}^{12} \left| S_{j,m} - \bar{S}_j \right| \quad (5)$$

Where j represents each WS component, m represents the climatological month, S is the mean climatological storage for month m, in mm, $\bar{S}_j$ is the long-term mean storage, in mm, nc is the number of components (in this case, 4), and C is the sum of all absolute monthly climatological anomalies of the storage component (S).

RESULTS

Contribution of each WS component

The spatial distribution of contributions among the water storage components (GW, SM, SW and RS) is presented in Figure 2. It is possible to observe some sudden breaks in GW

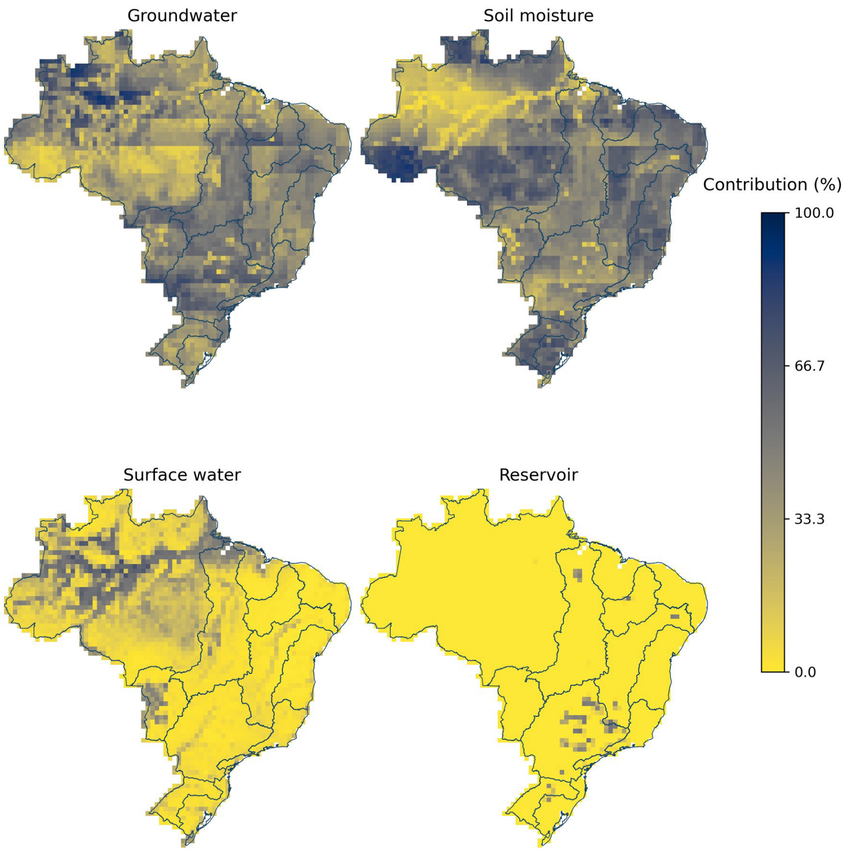

Figure 2. Spatially distributed contributions I (at 0.5° spatial resolution) of each WS component on TWS variability, based on the Impact Index.

and SM, which occur due to the use of gain factors in GRACE data for downscaling from the 3-degrees mascons to 0.5-degree pixels. These breaks are not observed in SW and RS because their contributions are more localised and usually smaller. Overall, the subsurface components (GW + SM) have the greatest contribution across the country. Exceptions are observed along extensive floodplain systems, where SW play an important role, such as in the Amazon, Tocantins-Araguaia, São Francisco, Paraná and Paraguay basins, and along some isolated spots where RS has important contribution on TWS, like in the Paraná, Uruguay, lower São Francisco, and Tocantins-Araguaia basins.

Figure 3 shows the contribution of these components on TWS variability after pixels are spatially aggregated for each BHR. The contribution in terms of percentages is presented in Table 3 and in terms of monthly means in Figure 4. SW contribution is the highest in the Amazon region (~40%) and particularly high in the Northern and Western BHRs (Tocantins-Araguaia, WNA, and Paraguay with ~18-20%), where more humid conditions occur and floodplain systems are highly present. The contribution of SW to TWS changes is moderate (5-10%) in the southern portion of the country (Southwest Atlantic, South Atlantic, and Uruguay). Reservoir storage has mild contributions on TWS variability (1-4%) along most BHRs (Tocantins-Araguaia, Parnaíba, São Francisco, Southeast Atlantic, South Atlantic, and Uruguay), and a substantial contribution (~12%) can be observed in the Paraná basin. Subsurface water has the highest contribution (GW + SM) on TWS variability in all BHRs, with values ranging from 60-80% in the Northwestern regions (Amazon, Tocantins-Araguaia, WNA, and Paraguay) to >80% in the remaining regions. From these, SM dominates the contribution in all BHRs (from 40% to 68%) with exception of the Paraná basin, where the contribution of GW is slightly higher than that of SM (43.6% against 40.9%). The contribution of GW ranges from less than 20% in the Amazon to up ~40% in São Francisco, Southeast Atlantic and Paraná regions.

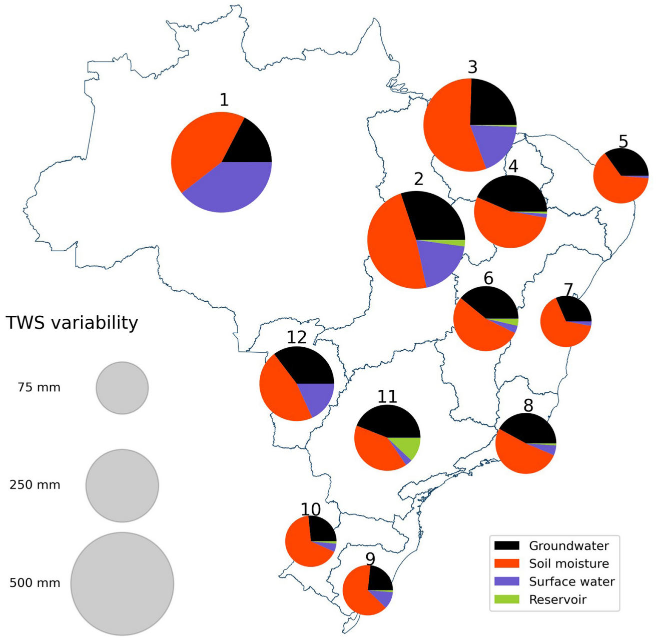

Figure 3. Pie charts representing the contributions of each water storage component on the Brazilian Hydrographic Regions (BHRs), indicated by their respective identification numbers (referred in Figure 1). Pie size proportional to total water storage variability.

Temporal variability

Figure 5 and Figure 6 present time series of monthly water storage variability in subsurface (GW + SM) and surface (SW + RS) components, respectively. In recent years (2013 to 2020), GW shows an increase in the Amazon, South Atlantic, Uruguay, and Paraguay regions, whereas a decrease is observed in the Tocantins-Araguaia basin and in the east portion of the country (Parnaíba, Eastern Northeast Atlantic, São Francisco, East Atlantic, and Southeast Atlantic regions). In the Paraná basin, GW presents wetter conditions in the periods of 2010-2013 and 2016-2017, and a drier condition in the 2014-2015 period. Temporal variability of SM does not show clear positive or negative trends in most BHRs, even though it is the main contributor on TWS variability. Regarding SW, low values conditions are nearly constant, with exceptions at Uruguay and Paraguay regions, and peak values are highly variable, with 2009 presenting the highest peaks in most BHRs. As for RS, only in São Francisco and Paraná this component has notable contribution on TWS variability. In these regions, a

Table 3. Contributions (in %) of each water storage component on each Brazilian Hydrographic Region.

ID	Hydrographic Region	GW	SM	SW	RS
1	Amazon	17.4	43.2	39.5	0.0
2	Tocantins-Araguaia	30.1	48.3	19.5	2.1
3	Western Northeast Atlantic	24.5	56.2	18.7	0.7
4	Parnaíba	43.5	53.8	1.7	1.0
5	Eastern Northeast Atlantic	34.9	63.6	1.4	0.0
6	São Francisco	39.1	53.6	3.8	3.5
7	East Atlantic	31.5	65.7	2.8	0.0
8	Southeast Atlantic	42.0	51.6	5.3	1.0
9	South Atlantic	23.3	64.4	11.1	1.2
10	Uruguay	26.6	66.7	5.2	1.5
11	Paraná	44.0	40.6	3.4	12.0
12	Paraguay	35.4	46.5	18.2	0.0

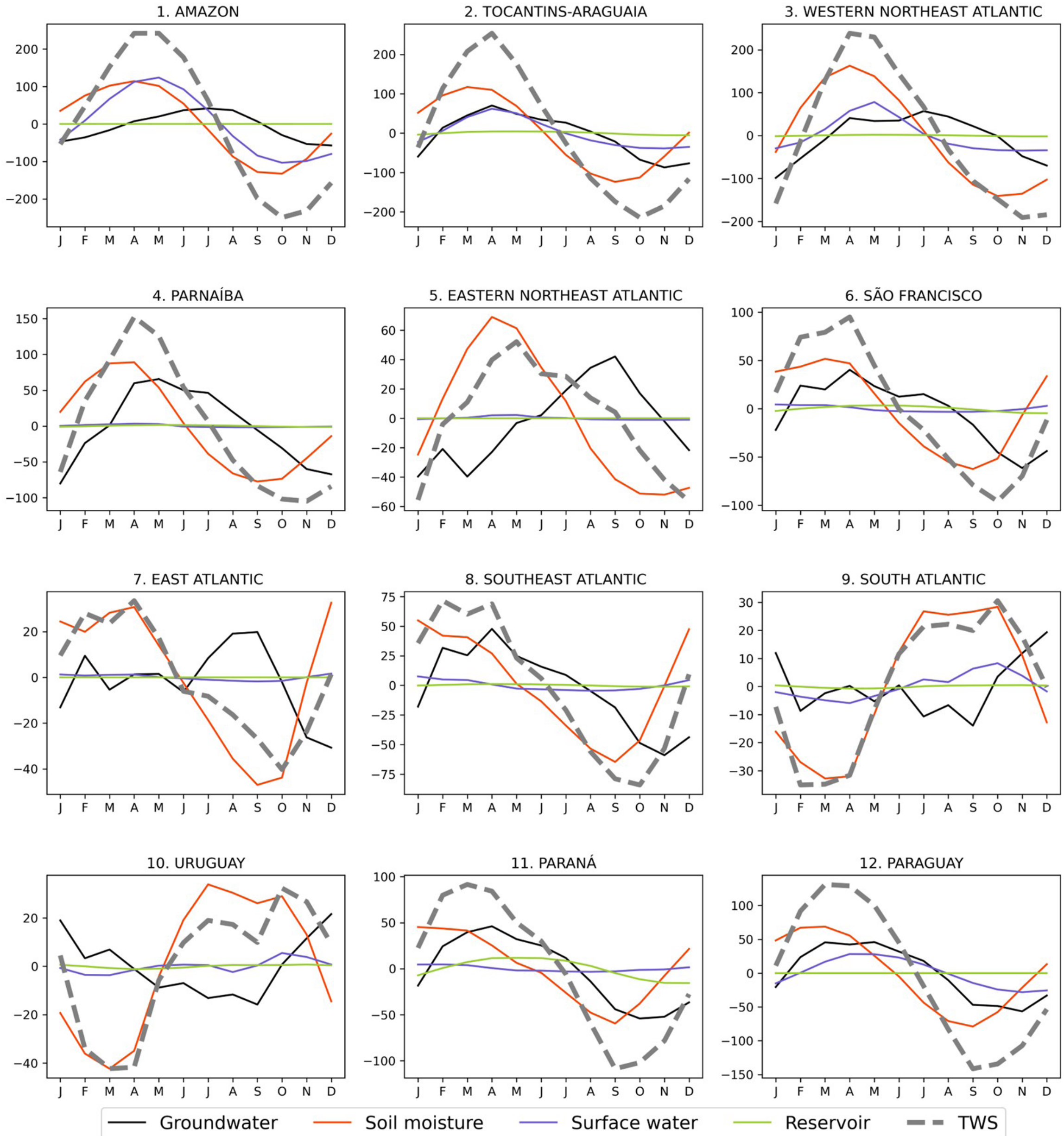

Figure 4. Monthly climatological anomalies of WS components (in mm) over BHRs.

sudden overall reduction in RS volume can be seen, indicating the recent low precipitation averages that have taken place over central and east Brazil (Getirana, 2016).

DISCUSSION

Nature of the observed variability in WS components

Overall, the magnitudes of storage variability are greater in north-western BHRs (Amazon, Tocantins-Araguaia, Western Northeast Atlantic), which are subject to strong seasonal variability due to the influence of the South American monsoon system (Marengo et al., 2012), and are smaller in south-eastern BHRs (East Atlantic, South Atlantic, and Uruguay) due to a less pronounced rainfall seasonality. GW usually peaks after SM, which can be attributed to a delayed response of the GW systems, related to SM water infiltrating into deeper soil layers. In the Amazon and Paraguay regions SW has a clear slower response than SM, possibly due to the large floodplain systems that attenuate flooding peaks in these regions (Paiva et al., 2013). Other BHRs with high SW contribution on TWS, such as Tocantins-Araguaia and Western Northeast Atlantic, seem to be less affected by these phenomena, as SM and SW are in phase with each other. In the eastern and southern BHRs (Eastern Northeast Atlantic, East Atlantic, South Atlantic, and Uruguay) GW and SM are opposite in phase. That may be partially explained by the water interchange between these compartments, as well as cycles of drought and surface temperature changes. The southern region is more influenced by the changes

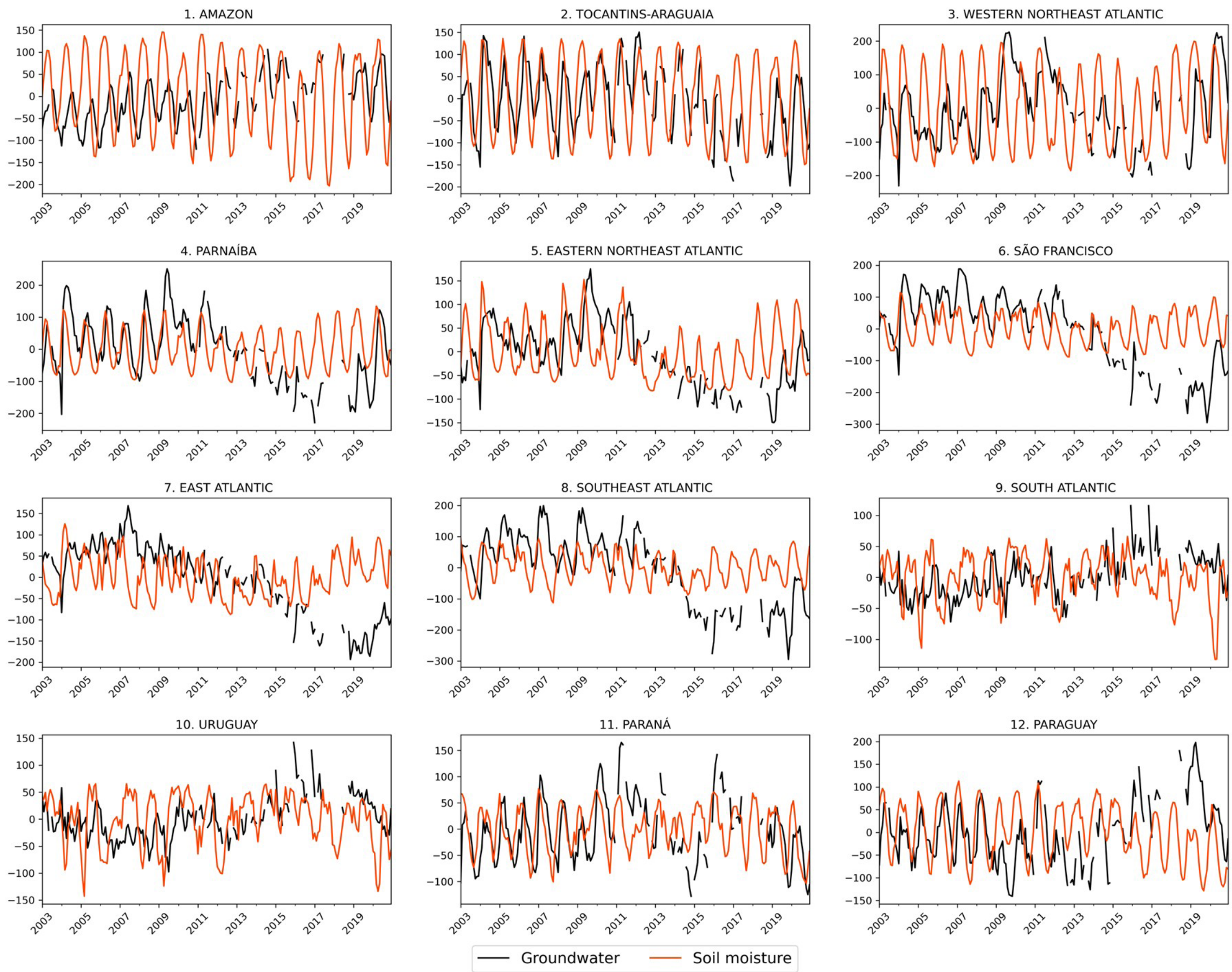

Figure 5. Time series of monthly groundwater and soil moisture storage variability (in mm) at the BHRs.

in temperature (SM peaks in the winter and sudden drop at the end of spring), whereas the eastern and central regions are more influenced by drought cycles (SM peaks at the end of the wet season and slowly reduces until the beginning of the wet season).

Regarding inter-annual changes, storage variability can be observed only by looking at GW and RS (decreases in storage variability in central and eastern Brazil). SM does not present long-term differences over the years likely due to a less sensitive response to changes in precipitation. One reason could be that the root-zone layer has upper and lower limit capacities of storing water; therefore, an increase in precipitation would result in more overland flow and not in more water in SM, and when precipitation decreases, water from GW would be brought to the root-zone layer (SM) via capillary rise or flow to the adjacent river systems (SW) via baseflow. Moreover, during consecutive years of lower precipitation, water coming to the root zone (SM) would be first available to vegetation, decreasing GW recharge. In SW, long-term differences are observed mostly for peak values, even in regions that experienced several shortages in TWS in recent years, such as all eastern BHRs (Parnaíba, São Francisco, Eastern Northeast Atlantic, East Atlantic, Southeast Atlantic) and the Paraná (Getirana, 2016; Melo et al., 2016).

Comparison with previous analyses regarding decomposition of TWS

The scientific literature already recognises the contribution of surface waters (SW + RS) on storage variability in Brazil. Similar to this study, Hu et al. (2017) used TWS from GRACE subtracting other storages, but with the objective of estimating groundwater recharge across geological sub-regions in Brazil. They used a global hydrological model for SM and SW and satellite altimetry data for the largest lakes and reservoirs. Contrary to our findings, they found surface waters being only significant in the Amazon; lakes and reservoirs were negligible in terms of water storage variability. Here, we identified a substantial contribution of SW on TWS, not just in the Amazon, but in the whole north-western portion of the country (Tocantins-Araguaia, Western Northeast Atlantic, and Paraguay), as well as in the South Atlantic region; and a significant contribution of RS in the Paraná basin, which is a clear example of considerable human intervention in hydrological functioning throughout a vast spatial domain. The notable difference of our findings can be explained by the data sources we used here to compute SW – instead of using a global hydrological model, we

Figure 6. Time series of monthly surface water and reservoir storage variability (in mm) at the BHRs.

used a hydrological model coupled to a hydrodynamic routing scheme (MGB) built to deal with the complex floodplain systems encountered in the South America region – and RS – instead of using satellite altimetry data, we used *in situ* observations from the main reservoirs that comprise the hydropower system of Brazil.

Regarding TWS partitioning, Getirana et al. (2017), Pokhrel et al. (2013) and Paiva et al. (2013) did similar analyses to the one performed here (i.e. separation of the storage components and evaluation of their contributions). The first was performed globally, and the other two were conducted over the Amazon basin. However, such studies used a different approach, by first comparing GRACE and modelled TWS as a validation step, and then using only the storages simulated by the model to assess their contributions on TWS.

In the Amazon region, Pokhrel et al. (2013) proposed that SM and GW are opposites in phase, which would be explained by the interactions between the floodplain systems, the vadose zone and the deep soil layers. In the other two studies, differently, GW and SM were in phase in the Amazon. Our results indicated that SM and GW in the Amazon are not in phase, yet they are not opposites either, with GW having a delay of about three months, as discussed in the previous subsection. An important distinction is that the findings of the mentioned studies were attributed to the whole Amazon basin, while we analysed only the portion limited by the Brazilian borders (52% of the basin area).

As for WS variability partitioning, Paiva et al. (2013) suggested that 63% of Amazon's TWS amplitude comes from SW, Pokhrel et al. (2013) accounted for 29%, and Getirana et al. (2017) for 27%. Here, we found that SW is responsible for 39% of TWS variability in the Brazilian part of the Amazon. An important distinction is that Paiva et al. (2013) and Pokhrel et al. (2013) computed contributions using the ratio of amplitudes considering the whole time series, whereas Getirana et al. (2017) and the study presented herein used the impact index, which considers only seasonal variability. Differences between these two approaches can rise as one region's sensibility to dry-wet extremes can be more prominent than seasonal variability.

In the Paraná-Paraguay region, Getirana et al. (2017) found slightly more contribution of SW (20%) than what we obtained (3% in Paraná and 18% in Paraguay). Both in the Amazon and Paraná-Paraguay, TWS estimated by their model had lower amplitude than GRACE TWS. Other regions in Brazil were not analysed in detail by the authors, giving no means for comparison.

Limitations and recommendations

It is important to note that our analysis is limited both spatially and temporally, as we provided insights only in large domains at monthly time-step. The spatial variability of environmental factors – such as climate, geology and soils – within a determined BHR can be quite significantly, which can attenuate or compensate some variability effects, misrepresenting local behaviours that cannot be seen when several distinct basins are aggregated. Moreover, a monthly time step can hide the detection of smaller changes within a month, which could have affected the compartments' response timings, such as the GW delay in relation to SM.

As discussed in the comparisons with other studies, the chosen approach can produce very different results in computing water storage contributions. While using results from a single model offers some practical advantages, as each WS component interact with the others, using TWS data from GRACE directly (e.g. for estimating GW variability) can improve the quality of the analysis, once it helps to capture hydrological processes and anthropogenic effects that models may not have the ability to simulate properly. Ideally, all variables used in large-scale studies evaluating water storage variability would come from Earth observations (both remote sensing and in situ measurements). However, we were able to obtain observed estimates only for TWS and the main human-made reservoirs in Brazil (RS).

Regarding TWS from GRACE, analyses like the one provided here are limited to large extents because of scale issues. As a general recommendation, regions larger than 100,000 km^2 (as the ones adopted in our study) will have more accurate measures of TWS variability, and regions smaller than that should be analysed carefully (Scanlon et al., 2016). In this way, modelling results that use GRACE for validation could have an advantage if used for downscaling purposes.

For RS estimation, we only accounted for the hydropower reservoirs that are part of the Brazilian National Interconnected System (SIN). A possible way to increase the accuracy of the analysis would be to include other reservoirs besides the ones existing in the SIN database. Particularly in the Brazilian semi-arid region, where lots of small dams are present (Mamede et al., 2012; Ribeiro Neto et al., 2022), the contribution of those volumes combined may be significant.

As for SW, using continental-scale hydrologic-hydrodynamic models such as MGB-SA is likely the best alternative available for the Brazilian domain. Even so, we have to consider that there is substantial uncertainty in the estimated surface water volumes and their variability. For instance, in addition to the shortcomings in representation of hydrological processes, the model has been calibrated with a limited number of gauge stations by using global precipitation data that is associated with large errors (Beck et al., 2017) and global river geometries that largely affect channel-floodplain water exchanges. Regarding uncertainties in the hydrodynamic modelling processes (e.g., associated with model parameterization or insufficient hydraulic processes representation of flood processes), there are several studies that have addressed this topic in the literature, even for the MGB model (Fan et al., 2021; Fleischmann et al., 2019, 2018, 2020; Paiva et al., 2013)

Furthermore, A cross-validation between MGB-SA flood extents and several other remote sensing-based datasets has been conducted for the Amazon basin (Fleischmann et al., 2022), albeit a more in-depth validation of simulated flooded areas over other important South American wetlands has not been performed so far. Representing inundation dynamics in the large Pantanal wetland (Paraguay basin) may require more complex flood routing methods than those used in MGB-SA (Bravo et al., 2012; Paz et al., 2011), and therefore we recognize that the contribution of SW on TWS may be underestimated in these areas. Ways to improve SW estimations lie on the better depiction of hydrological processes within the model, better parameterization, and the use of data assimilation techniques (e.g. Wongchuig et al., 2019). In the forthcoming years, we may even have access to data on water level variability with the SWOT mission (Biancamaria et al., 2016) that could be used to estimate water volumes directly or coupled with hydrological models.

The biggest challenge remains in estimating SM, as locally measured data are hard to be spatially extrapolated, and remote sensing data still require a lot of post-processing efforts, especially for deeper soil layers. Furthermore, SM data from remote sensing does not currently provide a clear advantage over GLDAS (Hu et al., 2022; Kędzior & Zawadzki, 2016; Zawadzki & Kędzior, 2016). Our best alternative to assess SM data and its relying uncertainty is to keep improving land surface models by better representations of water fluxes in the vadose zone, as well as modern data assimilation techniques.

CONCLUSION

The present study proposed to quantify the contributions of each water storage (WS) component on the total water storage variability across the Brazilian Hydrological Regions (BHRs). We achieved that goal by using combined information from multiple data sources that, to our best knowledge, reflect the best estimates available at large to continental scales. We resampled all data to the same spatial and temporal resolutions (0.5-degree and monthly, respectively), and computed the contribution of each WS component using the impact index. We also analysed data from time series, further discussing the nature of the variabilities observed and providing comparisons with previous studies.

From our results, we identified that subsurface components – soil moisture (SM) and groundwater (GW) – drive most of the water storage variability in all BHRs, with contributions varying from 40 to 68% and 17 to 40%, respectively. Still, a substantial contribution of surface water (SW) was found in north-western BHRs (humid monsoon influenced), varying from 18 to 40%, whereas mild contributions were identified in southern BHRs (subtropical system influenced), with values reaching 5 to 10%. Reservoir storage (RS) is an important contributor in the Paraná (12.1%), the São Francisco (3.5%), and the Tocantins-Araguaia (2.1%) basins. SM seems to have faster responses than GW in most BHRs, as well as SW in regions with large floodplain systems. In regions with extended dry seasons or with seasonal land surface temperatures, SM and GW seem to be opposites in phase during the annual cycle.

In terms of long-term variability, water storages have been generally decreasing in the eastern and increasing in north-western and southern BHRs. GW and RS seem to be the most affected by these trends, yet it can also be observed in SW peaks. The fact that SM is not decreasing nor increasing can be attributed to the lower and upper limit capacities of the root-zone, although it can also be due to uncertainties in the data, as it is very difficult to obtain accurate spatially distributed estimations of this variable. Future investigations are required to obtain definitive conclusions on this matter.

Moreover, this analysis has some limitations. First, aggregating data to large hydrographic regions at monthly time steps can hide smaller spatial and temporal variabilities. Second, the approach used to obtain the estimations and to compute the contributions can induce to different results, as there is no consolidated methodology for such analysis so far. Lastly, the uncertainties related to each dataset can have major implications in the results, as there is still a need for more accurate estimations of WS variables.

Finally, we stress that investigating water partitioning is fundamental to foster water resources management in Brazil. The inclusion of this type of analysis, and the incorporation of state-of-the-art modelling and remote sensing, large-scale datasets, in water-accounting frameworks is highly beneficial to guide decision-makers. It could help to identify the nature of amplitude and phase variability across regions in order to better characterize them. Also, by looking at inter-annual variability, it could assist the identification of long-term hydrological trends.

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Anderson Ruhoff: Conceptualization (equal), formal analysis (supporting), funding acquisition (lead), investigation (supporting), methodology (supporting), project administration (equal), resources (equal), supervision (equal), writing – review & editing (equal).

Rodrigo Cauduro Dias de Paiva: Conceptualization (equal), formal analysis (supporting), funding acquisition (equal), investigation (supporting), methodology (supporting), project administration (equal), resources (equal), supervision (lead), writing – review & editing (equal).

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