

# Water Resources Research®

## RESEARCH ARTICLE

10.1029/2021WR030799

## Drought Cycle Analysis to Evaluate the Influence of a Dense Network of Small Reservoirs on Drought Evolution

G. G. Ribeiro Neto<sup>1</sup> , L. A. Melsen<sup>1</sup> , E. S. P. R. Martins<sup>2,3</sup> , D. W. Walker<sup>4</sup> , and P. R. van Oel<sup>4</sup> 

<sup>1</sup>Hydrology and Quantitative Water Management, Wageningen University, Wageningen, The Netherlands, <sup>2</sup>Research Institute of Meteorology and Water Resources (FUNCEME), Fortaleza CE, Brazil, <sup>3</sup>Federal University of Ceará (UFC), Fortaleza, Brazil, <sup>4</sup>Water Resources Management Group, Wageningen University, Wageningen, The Netherlands

### Key Points:

- We evaluated how a network of small, unmonitored, and generally informal reservoirs induce and modify drought events
- “Drought Cycle Analysis” is a novel method for studying the evolution of drought
- Hydrological drought events can last significantly longer due to the presence of many small upstream reservoirs

### Correspondence to:

G. G. Ribeiro. Neto,  
[germano.gondimiribeironeto@wur.nl](mailto:germano.gondimiribeironeto@wur.nl)

### Citation:

Ribeiro Neto, G. G., Melsen, L. A., Martins, E. S. P. R., Walker, D. W., & van Oel, P. R. (2022). Drought Cycle Analysis to evaluate the influence of a Dense Network of small reservoirs on drought evolution. *Water Resources Research*, 58, e2021WR030799. <https://doi.org/10.1029/2021WR030799>

Received 9 JUL 2021  
Accepted 23 DEC 2021

### Author Contributions:

**Conceptualization:** G. G. Ribeiro Neto  
**Formal analysis:** G. G. Ribeiro Neto  
**Investigation:** G. G. Ribeiro Neto  
**Methodology:** G. G. Ribeiro Neto  
**Supervision:** L. A. Melsen, E. S. P. R. Martins, P. R. Oel  
**Validation:** G. G. Ribeiro Neto  
**Writing – original draft:** G. G. Ribeiro Neto  
**Writing – review & editing:** L. A. Melsen, E. S. P. R. Martins, D. W. Walker, P. R. Oel

**Abstract** Drought-affected regions often contain high densities of small reservoirs, usually informally built, as drought-coping mechanism. These structures influence socio-hydrological dynamics and have the potential to alter hydrological processes relevant to drought emergence and development. This study aimed to analyze the influence of a high concentration of small reservoirs on the intensification and evolution of drought events. We present an innovative method, which we call “Drought Cycle Analysis”, that tracks the concomitance of precipitation and water storage deficit and associates this with four drought stages: Wet Period, Meteorological drought, Hydro-meteorological drought and Hydrological drought period. The methodology was tested for the Riacho do Sangue River watershed located in the semi-arid region of northeast Brazil. We used a combination of satellite imagery (Landsat 5, 7 and 8) and an empirical equation to estimate the volume stored in the dense network of small reservoirs. Using the Drought Cycle Analysis, we show that the unmonitored small reservoirs induced and modified drought events, extending the duration of hydrological drought on average by 30%. Furthermore, this extension can double for specific drought events. The Drought Cycle Analysis method proved useful for monitoring and comparing the evolution of different drought events, in addition to being applicable as an auxiliary tool in the improvement of water resources management of large reservoirs. This study demonstrates the importance of considering small reservoirs in water resource management strategy development for drought-prone regions.

**Plain Language Summary** Droughts are one of the disasters that produce the most intense socioeconomic impacts. Drought occurrence used to be attributed to long periods of lack of rain. However, it is now known that human actions can contribute to the development of this disaster. The coping and adaptation measures for droughts vary widely among societies around the world. One of the most common strategies for reducing drought-related impacts is the construction of small reservoirs, which ironically may again contribute to hydrological drought emergence and intensification at regional scale. In order to explore this effect, we estimated what the concentration of water would be in a semi-arid region of Brazil if these small reservoirs had never existed and compared it to the real situation. Through an innovative method that combines rain and water storage data in addition to satellite data, we analyzed these two scenarios and found that for this region drought events last on average 30% longer due to the high concentration of small reservoirs. For specific events, the length of the hydrological drought even doubles due to the presence of many small reservoirs. This study demonstrates the importance of considering small reservoirs in drought management strategy development for drought-prone regions.

## 1. Introduction

The construction of reservoirs without a systematic and holistic analysis of the watershed can lead to a concentration of water in certain parts of the basin, and scarcity elsewhere (Di Baldassarre et al., 2018). In this way, reservoirs can intensify or induce drought events, defined as periods of exceptional lack of water that negatively impact human activities or environmental demands (Van Loon, Stahl, et al., 2016; Van Loon, Gleeson, et al., 2016). This, in turn, can result in water availability inequality and thus societal pressure to build more reservoirs, which may further aggravate the problem. Both large publicly managed reservoirs and smaller privately owned reservoirs can play a role in this process. Especially because the latter are usually unmonitored, their influence on water distribution during drought events is unclear (Habets et al., 2018). Understanding the hydrological impact of a Dense Network of (small) Reservoirs (DNR) is highly relevant, both from a societal as well as from a water management perspective.

© 2022. The Authors.

This is an open access article under the terms of the [Creative Commons Attribution License](https://creativecommons.org/licenses/by/4.0/), which permits use, distribution and reproduction in any medium, provided the original work is properly cited.

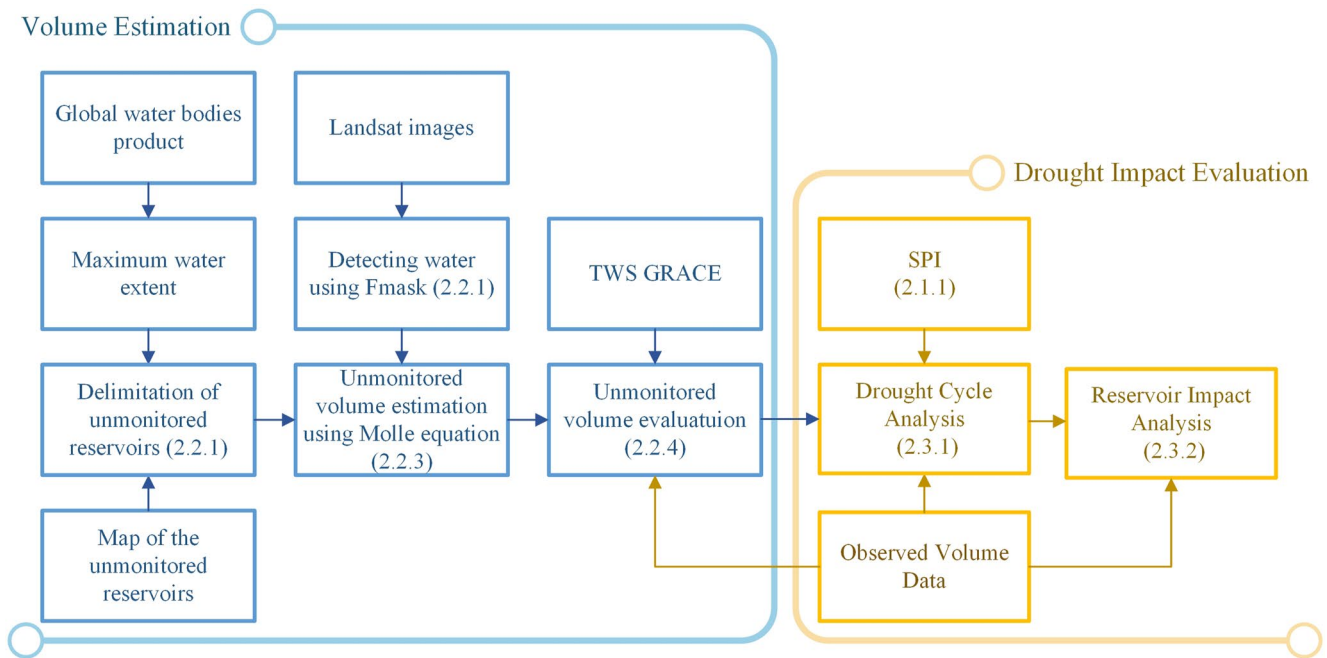
Dense networks of small reservoirs occur in many places around the world: Australia (Fowler et al., 2015), North-east Brazil (Mamede et al., 2012), Ethiopia (Lasage et al., 2015), France (Habets et al., 2014), Ghana (Annor et al., 2009), India (Mialhe et al., 2008), South Africa (Hughes & Mantel, 2010), South Brazil (Collischonn et al., 2011), Southern Brazilian Amazon (Arvor et al., 2018), Southern Syria (Avisse et al., 2017), West Africa (Liebe et al., 2005), and Zimbabwe (Sawunyama et al., 2006). It is expected that small reservoirs, when analyzed individually, would not cause major impacts to a hydrological system, since their maximum storage capacity is negligible. However, the accumulated effect of a DNR may be greater than the impact of a single large reservoir. Evaluating a DNR is, however, not a trivial task. These DNRs often occur in regions where there is a general lack of observational data, and furthermore, such analysis requires incorporating many informal, small and private reservoirs that are unmonitored and rampantly constructed.

The semi-arid region of Brazil occupies about 11% of the Brazilian territory (1,542,000 km<sup>2</sup>) and contains 30% of its population (Marengo et al., 2020). It is an example of a region with a high concentration of reservoirs with great variation in size and storage capacity. The region has a highly irregular spatio-temporal precipitation regime and a predominance of soils and geology with low water storage capacity, which creates a dependency on the superficial storage of water, and means the region is frequently affected by intense drought events (Marengo, Alves, et al., 2017; Marengo, Torres, & Alves, 2017). A recent drought event lasted almost seven years (2012–2018) with accumulated losses up to 2016 of over US \$30 billion (Marengo, Alves, et al., 2017; Marengo, Torres, & Alves, 2017). These conditions stimulated the construction of both small (capacity less than 0.2 hm<sup>3</sup>) and large/middle-sized reservoirs, and for centuries this has been the main coping strategy for drought in this region (Rebouças, 1997). Most of the small reservoirs aim to meet the demands of subsistence farmers (who mostly depend on this water source for their livelihood) only in the short term. These structures therefore play a relevant societal role on a local scale. However, it remains unclear how the DNR, in a region such as the semi-arid region of Brazil, influences the emergence, intensification and propagation of drought events at watershed level. A more detailed picture of this situation can be exemplified within Ceará (a state in semi-arid Brazil) where it is estimated that there are close to 100,000 reservoirs (FUNCEME, 2021); for some regions of this state the reservoir concentration is higher than 7 reservoirs per km<sup>2</sup>. The regulatory agencies operating in Ceará systematically monitor the volume of 155 large/middle-sized reservoirs, for the remaining more than 99,000 reservoirs, information and characterization remain unknown.

Mapping reservoir locations and estimating storage capacities of numerous small reservoirs using remote sensing products may be a suitable approach to capture the hydrological impacts of a DNR on drought events. Full calculation of storage capacities requires topographic or bathymetric surveys which can be very time consuming and require substantial specialized efforts. Several studies employed remote sensing to estimate storage capacity of reservoirs, based on a combination of optical satellite imagery and digital elevation models or topography/bathymetric surveys (Avisse et al., 2017; Getirana, 2016; Peng et al., 2006; Pereira et al., 2019; Rodrigues et al., 2012; Sawunyama et al., 2006; Van Den Hoek et al., 2019; Vanthof & Kelly, 2019; Zhang et al., 2016). Most studies also relied to some extent on in situ surveys, or presented methods that were suitable only for large reservoirs, which limits their application to a region with a large number of small reservoirs. Furthermore, these studies did not analyze the impact that these small reservoirs have on the studied hydrological system, particularly during drought events.

There are studies that evaluated the impact of reservoirs on drought development. However, most of these studies focused on large reservoirs (Biemans et al., 2011; Di Baldassarre et al., 2018; van Langen et al., 2021; van Oel et al., 2011; Van Oel et al., 2018; Wu et al., 2017). Although some studies have analyzed the effect of small reservoirs on sediment/water dynamics (Berg et al., 2016; Bronstert et al., 2014; Mamede et al., 2018; Medeiros et al., 2014; Medeiros et al., 2010), the hydrological availability (Malveira et al., 2012), evaporation losses (Craig, 2008; Gallego-Elvira et al., 2010; Tanny et al., 2008), and streamflow impact (Habets et al., 2018; Lasage et al., 2015; Lowe et al., 2005), there is a scientific gap related to the cumulative effect of a DNR on drought in a hydrological system.

In this study we analyzed the effect of a DNR on the evolution and intensification of drought events. For this, we present the “Drought Cycle Analysis” which is a new method for drought evaluation, based on the combination of a precipitation index and information directly related to impacts generated by drought events. We employed remote sensing to estimate the volume stored in the DNR, and use the Drought Cycle Analysis to estimate the effect of this storage on drought impact. The method was tested for the Riacho do Sangue watershed in Ceará state



**Figure 1.** Flowchart of the methodology. The blue and yellow colors indicate the processes related to Reservoir volume estimation (step 1) and Drought impact evaluation (step 2), respectively. The numbers refer to the sections of this manuscript.

in Brazil. Unveiling the role of small, unmonitored reservoirs on drought development is relevant information for water managers, which tend to focus mainly on monitored reservoirs, thereby ignoring the role that the DNR might have on drought onset and duration.

## 2. Materials and Methods

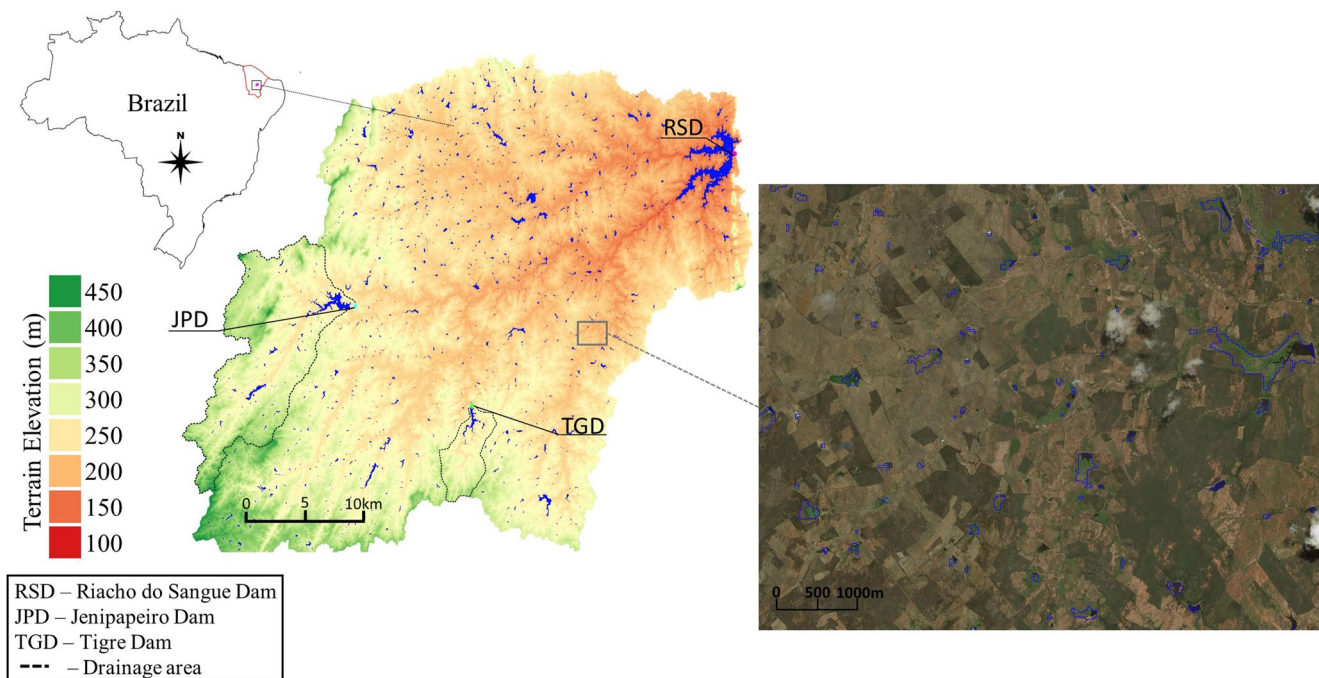
The goal of this study is to understand how small reservoirs can influence the intensification and evolution of drought events. The methodology consists of two main steps:

1. Reservoir Volume Estimation: Estimating the volume stored in the DNR based on remote sensing products and an empirical equation. We used the Surface Water Extension (SWE) time series of each reservoir as an input to the Molle equation (Molle, 1989, 1994) which relates this information to the volume stored in these structures. The location of each reservoir was obtained using the map of unmonitored reservoirs (FUNCEME, 2021) created by Research Institute of Meteorology and Water Resources of Ceará (FUNCEME). The SWE time series were extracted from 331 images (from 1986 to 2020) of Landsat (5, 7 and 8) scene 217/064 reclassified with the Fmask algorithm (Zhu et al., 2015; Zhu & Woodcock, 2012). We selected Landsat images that had less than 40% of cloud. The volume estimation procedure is described in Section 2.2.
2. Drought Impact Evaluation: Evaluating the role of a DNR in the evolution of a drought event. We developed a new methodology, which we call “Drought Cycle Analysis”, based on a combination of the Standardized Precipitation Index (SPI) and the hydrological Volume Deviation (VD), which is described in Section 2.3.

The graphical summary of the methodology is presented in Figure 1.

### 2.1. Study Area

We applied our analysis to the Riacho do Sangue watershed (1368 km<sup>2</sup>) which is part of the Jaguaribe river basin (75,000 km<sup>2</sup>) and is located in Ceará State in Brazil (Figure 2). This watershed was selected because of its high density of reservoirs and due to the frequent experience of drought impacts. The average annual precipitation and potential evapotranspiration in the Riacho do Sangue watershed is respectively 740 mm and 2300 mm (1981–2019). A crystalline complex associated with shallows soils limits the occurrence of aquifers in this regions.



**Figure 2.** Location and topography of the Riacho do Sangue watershed with the three large monitored reservoirs indicated. The small and unmonitored reservoirs are indicated by the dark blue color (1138 reservoirs). The gray rectangle is a detailed example of the high concentration of small reservoirs in the Riacho do Sangue watershed.

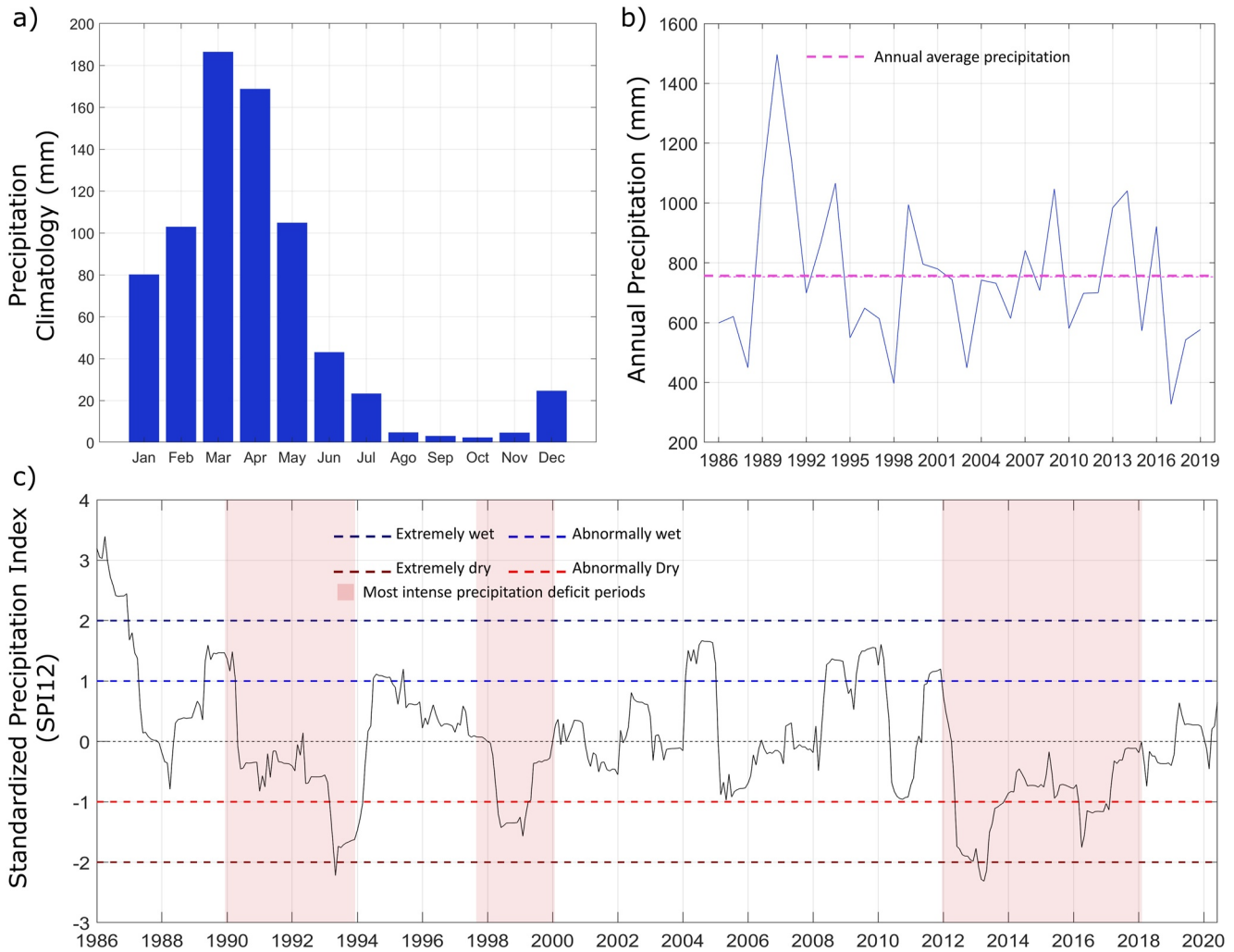
Consequently, in combination with the meteorological characteristics, all rivers in the region are intermittent (de Araújo & Bronstert, 2016; Fontenele et al., 2014). The study area has three reservoirs that are managed and operated by governmental agencies: Riacho do Sangue Dam (RSD), Tigre Dam (TGD) and Jenipapeiro Dam (JPD; Figure 2). Their maximum storage capacities are respectively 58.43 hm<sup>3</sup>, 3.51 hm<sup>3</sup> and 14.59 hm<sup>3</sup>.

### 2.1.1. Precipitation Regime Characterization

To characterize the precipitation regime of the study region, we evaluated three variables: climatology (Figure 3a), interannual variability (Figure 3b) and the time series of the Standardized Precipitation Index application (SPI, McKee et al., 1993) at the 12-month time scale (Figure 3c). The SPI is calculated through two steps. First, the accumulated precipitation data (e.g., a moving window of 12 months) was fitted to a gamma distribution and then transformed into a normal distribution, in line with the guidelines of the World Meteorological Organization (World Meteorological Organization, 2012). The values of this index can be interpreted as the number of standard deviations by which the precipitation deviates from the long-term mean. This information is relevant for understanding the emergence and propagation of drought events in the study area. As can be seen in Figure 3a, the precipitation in the study area has an intense seasonality, the first 5 months of the year usually receive close to 85% of the annual precipitation. We chose to use the 12-month time scale (SPI12) because in this way, each SPI time step considers the entire rain season, which is most relevant to the study area. A shorter time scale (e.g., 3 or 6 months) could capture a reduction in precipitation during the dry season, and indicate a meteorological drought related to this situation. However, reductions in rainfall during the dry season are less relevant for the study area as it hardly rains during this period and the vast majority of socio-economic activities in this region depend directly on precipitation from the rainy season. Due to the characteristics of the precipitation regime in the study area, the use of SPI with a time scale below 12 months can lead to the identification of drought events not directly linked to the dynamics that we seek to explore in this study. Details on the SPI calculation methodology can be found in Guttman (1999) and McKee et al. (1993). We used the average precipitation over the study area to calculate the SPI, since this variable does not show strong spatial variability over the study region.

The second version of the Climate Hazards Group InfraRed Precipitation with Stations product (CHIRPS, Funk et al., 2015) was utilized to represent the precipitation of the study area. This product runs from 1981 to near-present and integrates satellite imagery with rain gauge data to create gridded precipitation time series with





**Figure 3.** Discretization of the temporal variation of precipitation in the study area. (a) Climatology of precipitation over the study period, (b) Time series of annual precipitation, (c) SPI12 time series.

quasi-global coverage (50°S–50°N, 180°E–180°W) at 0.05° resolution. This product was selected due to its high accuracy for the semi-arid region of Brazil (Paredes-Trejo et al., 2017) and its high spatio-temporal resolution.

We found through an analysis of SPI12 and scientific literature review (Cunha et al., 2015; Jose A. Marengo et al., 2020; E. Martins et al., 2015; E. S. P. R. Martins et al., 2018) that the most relevant periods related to the occurrence of precipitation deficits in the study area were 1990–1994, 1997–2000, and 2012–2018. Drought events were identified and further investigated using the Drought Cycle Analysis method (see Section 2.3.1).

## 2.2. Reservoir Volume Estimation

### 2.2.1. Delimitation of Unmonitored Reservoirs

The estimation of the water volume stored in a Dense Network of (small) Reservoirs (DRN) starts with defining the Maximum Surface Water Extent (MSWE). This information is used to delimitate the area to estimate the temporal variation of the surface water extent, which is the input for the estimation of the volume stored in each reservoir (see Section 2.2.3) of the DRN. We used the Maximum water extension product that was developed by Pekel et al. (2016) which is available in the Global Surface Water Explorer platform (<https://global-surface-water.appspot.com/>). This product has global coverage, a 30m spatial resolution, and was developed based on 37 years of satellite imagery data from the Landsat missions (5, 7, and 8). This product considers all water bodies; there

was no differentiation between those that have natural or anthropogenic origin. Therefore, we used the recently released map of unmonitored reservoirs, established by FUNCEME (FUNCEME, 2021), which is currently the most accurate product regarding the location of these structures in the study area. The FUNCEME map was developed based on high-resolution satellite imagery from the CBERS 4A satellite (spatial resolution ranging from 2 to 8 m) and only reservoirs with a dam structure of at least 20 m long were counted (FUNCEME, 2021). According to this product, the study area features a DNR with 3,432 reservoirs, of which 1138 have also been identified in the Maximum water extension product developed by Pekel et al. (2016). This means that 2294 reservoirs possibly present a MSWE smaller than the pixel area of Landsat derived products (900 m<sup>2</sup>). Since it was not possible to extract the Surface Water Extension (SWE) time series of these structures, these reservoirs were not included in the estimated volume stored in the DNR. We note that the median size of the 1138 identified reservoirs is 3,600 m<sup>2</sup>.

### 2.2.2. Detecting Water in Landsat Using Fmask

After the delimitation of the Maximum Surface Water Extent (MSWE) of each reservoir, the temporal variation of the Surface Water Extension (SWE) needed to be estimated. This is the main input to estimate the volume of water stored in the DNR (see Section 2.2.3). The SWE time series were extracted from 331 images (from 1986 to 2020) of Landsat (5, 7 and 8). We applied the Fmask algorithm (Zhu et al., 2015; Zhu & Woodcock, 2012) to systematically discriminate cloud and shadow coverage from water bodies and therefore the SWE. This algorithm allows automatic processing and analysis of Level 1 Landsat images with a cloud detection accuracy close to 96% (Zhu & Woodcock, 2012). Fmask is integrated in the Landsat Level 2 development (Frantz et al., 2018) and was well used in other studies (Abileah et al., 2011; Avisse et al., 2017; Frantz et al., 2018; Qiu et al., 2019; Schwatke et al., 2019). The input data of the Fmask are digital number values of Landsat L1T band 1,2,3,4,5,7 and band 6 Brightness Temperature (BT). The digital number values are converted to Top of Atmospheric reflectance (TOA) and brightness temperature (Celsius degree) with the LEDAPS atmospheric correction tool (Masek et al., 2006). Then routines are applied to extract potential cloud and cloud shadow layers which results in the generation of the final cloud and cloud shadowed mask (Zhu & Woodcock, 2012). The detailed methodology of this algorithm can be accessed at Zhu et al. (2015) and Zhu and Woodcock (2012).

We observed that several reservoirs present on the FUNCEME map which were also present in the MSWE product developed by Pekel et al. (2016) did not appear in the water maps generated by the original version of Fmask. Thus, we tested a modification of this algorithm to improve the water pixel identification. In the original algorithm this step is based on a logical test that uses the Normalized Difference Vegetation Index (NDVI) and Near Infrared band (NIR; Equation 1).

$$\text{Water} = (\text{NDVI} < 0.01 \ \& \ \text{NIR} < 0.11) \ \text{or} \ (\text{NDVI} < 0.1 \ \& \ \text{NIR} < 0.05) \quad (1)$$

Although the NDVI is a simple method for water identification, there are other indices that can be used for this purpose with a higher accuracy. The Normalized Difference Water Index (NDWI, McFeeters, 1996), and its modified version (MNDWI, Xu, 2006) were developed specifically for water identification with the same concept and simplicity as the NDVI. These two indices use the green band, which is more sensitive to water features compared to the red band used in the NDVI. The difference between NDWI and MNDWI is that the modified version uses the Short Wave Infrared band (SWIR) instead of NIR, since it has better cloud penetration and water has lower reflectance in this band (Xu, 2006). Consequently, MNDWI is more accurate than the original version and has been used in several studies related to water identification through remote sensing (Deng et al., 2020; Du et al., 2016; Ji et al., 2009; Wang et al., 2011; Zhang & Chen, 2017). Therefore, we proposed the following modification for the Fmask water logical test:

$$\text{Water} = (\text{MNDWI} > 0 \ \& \ \text{SWIR} < 0.07) \ \text{or} \ (\text{MNDWI} > -0.25 \ \& \ \text{SWIR} < 0.05) \quad (2)$$

Positive values for the MNDWI usually indicate water. However, the combined effect of a thin cloud layer, presence of sediment, and chlorophyll-a in water can result in negative values of MNDWI, which demands the water threshold to be manually adjusted to the situation of the study area (Ji et al., 2009; Zhang et al., 2014). Most of the water pixels are identified by an MNDWI higher than 0 and SWIR lower than 0.07. Some of the water pixels may have relatively large SWIR reflectance because of influence of thin clouds or high sediment concentration which is common in small reservoirs of the study area, and they will be captured by using MNDWI higher than -0.25 and SWIR less than 0.05.

It is expected that these modifications in Fmask will increase the sensitivity of the water pixel identification, and consequently, the estimation of the spatio-temporal variation of SWE of the unmonitored reservoirs should be more accurate. To evaluate this, we calculated the MSWE through the original version of the Fmask, and by applying the proposed changes (Equation 2) using as input Landsat images from 2009 to 2011. We chose these years as they represent a recent period in which there was above average annual accumulated precipitation (see Figure 3). We created for both Fmask versions a data set of water mask maps considering each Landsat image from the 2009–2010 period. The MSWE was then defined as being the overlay of all maps of each data set. Finally, we checked for each of the two MSWE maps how many reservoirs identified by the FUNCEME map (FUNCEME, 2021) that were also present in the MSWE Global Water Bodies product (Pekel et al., 2016) could also be identified in these maps. The proposed algorithm modification substantially improved the detection of water pixels: 40% more unmonitored reservoirs were detected using Equation 2, compared to the original version of this algorithm based on Equation 1. Therefore, we continued the analysis with the modified Fmask version.

### 2.2.3. Estimation of the Volume of Unmonitored Reservoirs

The estimation of the volume stored in the DNR was conducted using the Molle equation (Molle, 1989, 1994) that relates the SWE with the volume stored in the reservoirs ( $Vr$ ). This equation was developed using empirical data from 416 reservoirs located in the semi-arid region of Brazil (Mamede et al., 2018; Molle, 1989, 1994). The Molle equation has been validated in several studies related to the analysis of small reservoirs in this region and is also used in the deterministic, process-based, semi-distributed hydrological model WASA-SED, that was developed specifically for the hydrological simulation of semi-arid watersheds (Bronstert et al., 2014; Guntner, 2002; Krol & Bronstert, 2007; Lima Neto et al., 2011; Malveira et al., 2012; Mamede et al., 2012; Mamede et al., 2018; Medeiros et al., 2010; Medeiros et al., 2014; Pilz et al., 2019). The Molle equation looks as follows:

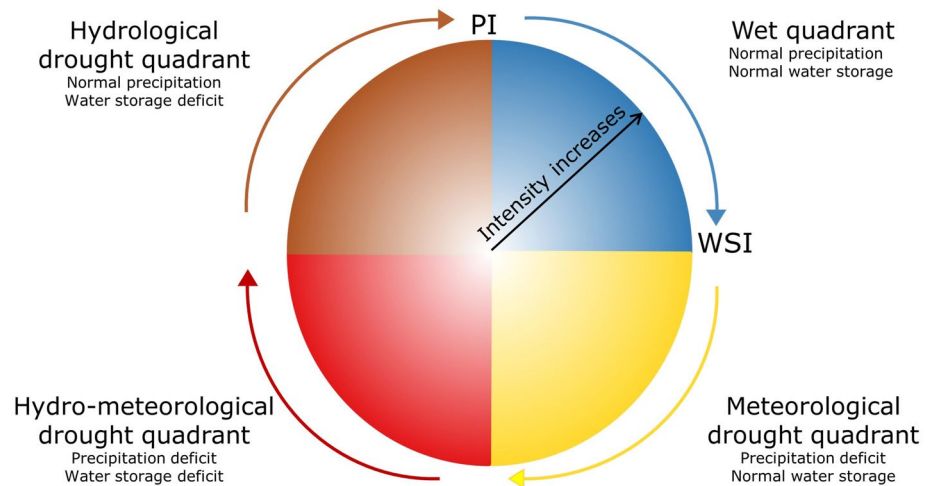
$$Vr = \frac{\sqrt[\frac{c-1}{c-d}]{\frac{SWE}{c-d}}}{d} \quad (3)$$

where “ $Vr$ ” and “SWE” are the volume stored ( $m^3$ ) and the surface water extent ( $m^2$ ) of the reservoir, respectively. “ $c$ ” and “ $d$ ” are empirical parameters, that were obtained through the analysis of 416 reservoirs conducted by Molle (1989), with values of 2.7 and 1500 respectively. We derived the SWE from Landsat (5, 7, and 8) images that were reclassified using the Fmask algorithm (see Sections 2.2.1 and 2.2.2). There were some temporal gaps in the time series of the volume stored in the unmonitored reservoirs, related to the absence of useful Landsat Images. In order to conduct scenario analysis (see Section 2.3.2) these gaps were filled with a linear regression for up to four consecutive months of lack of data, since over this timescale drastic changes in the variation trend of the storage do not occur.

### 2.2.4. Evaluation of the Volume of Unmonitored Reservoirs

As previously explained, there are no observational data regarding the water volume stored in the Dense Network of (small) Reservoirs (DNR) of the study region. It is therefore not possible to quantitatively validate the estimation of the stored water volume in these structures, but we can assess the plausibility. The Riacho do Sangue watershed presents characteristics that can be used to assess the plausibility of the estimated storage in the unmonitored reservoirs. Firstly, a relatively strong correlation between the small unmonitored reservoirs and the large monitored reservoirs is expected, because there is a strong cause-and-effect relationship: a full DNR leads to an increase in the recharge of the large reservoirs. Another relevant aspect related to the physical characteristics of the study area is that the temporal variation of the Terrestrial Water Storage (TWS) is strongly influenced by the Surface Water Storage (SWS) which in the Riacho do Sangue watershed corresponds mainly to the volume of water stored in all the reservoirs. Therefore, it is expected that a coherent estimate of the volume stored in the unmonitored reservoirs displays a high correlation with the total volume stored in the monitored reservoirs and that the combination of these variables (SWS) presents an even higher correlation with the TWS.

We assessed the plausibility of the DNR volume storage estimates for the study area through two different statistical analyses. In the first analysis, we calculated the correlation between the estimated volume stored in the DNR with the volume stored in the monitored reservoirs during three periods (see Figure 3): Wet years (1986–1989, 1995–1997, 2001–2011 and 2019–2020); Dry years (1990–1994, 1998–2000, and 2012–2018) and the whole study period (1986–2020). This division was made because the correlation between these variables is expected to change due to the occurrence of drought events. In the second analysis, we evaluated three different correlations:



**Figure 4.** Graphical representation of the Drought Cycle Analysis. The y-axis related to a precipitation-based index, and the x-axis to a water storage index. A series of events during the evolution of a drought, or simply “drought cycle”, can be projected on the four quadrants of the “Drought Wheel”.

TWS × Monitored volume (the three large reservoirs); TWS × DNR volume (only the unmonitored and small reservoirs) and TWS × SWS (large reservoirs and DNR combined). It is expected that this last set will provide the highest correlation, since the sum is conceptually closer to the TWS.

We used the Jet Propulsion Laboratory (JPL) Mascon solution to represent the TWS derived from the spatial missions Gravity Recovery and Climate Experiment (GRACE) and Follow On (GRACE-FO). This solution has a higher spatial resolution ( $0.5^\circ$ ) and accuracy than the regular GRACE TWS products (Watkins et al., 2015). The TWS data from the GRACE and GRACE-FO missions are widely used in the scientific literature (e.g., Getirana, 2016; Li et al., 2019; Melati et al., 2019). For this analysis, we consider the period 2002–2020 which corresponds to the complete time series of this GRACE/GRACE-FO mascon product.

### 2.3. Drought Impact Evaluation

#### 2.3.1. Drought Cycle Analysis

Once the water storage of reservoirs in the Dense Network of (small) Reservoirs (DNR) was estimated, their role in drought intensification and evolution was evaluated. We present a novel method called “Drought Cycle Analysis” which is based on a combination of precipitation and hydrological indices. It classifies drought events into four possible stages regarding the simultaneous occurrence of precipitation deficit and water storage deficit. Each pair of observations is positioned on a coordinate axis divided into four quadrants, in which each is associated to a stage related to the evolution of a drought event (Figure 4). We use a hue and tone variation scheme to represent the intensity of the drought event as well as its classification. The set of these four quadrants, as well the hue and tone variation, shown in Figure 4 will be referred to as the “Drought Wheel” to simplify the presentation and discussions of the results.

The first quadrant is the “Wet quadrant”, the non-occurrence of drought. This stage is defined by positive values of the Precipitation Index (PI, vertical axis) and the Water Storage Index (WSI, horizontal axis). The next quadrant indicates the occurrence of meteorological drought, when there is a precipitation deficit ( $PI < 0$ ) but it has not yet affected water storage ( $WSI > 0$ ). The third quadrant is related to the occurrence of hydrological-meteorological drought, when the persistence and/or intensification of the precipitation deficit starts to affect water storage. This is indicated when both indices show negative values. The fourth and final quadrant is related to what we call the “Hydrological drought quadrant” and is characterized by the absence of a precipitation deficit ( $PI > 0$ ) and the persistence of hydrological impacts ( $WSI < 0$ ).

We used standardized indices since this allows a better division of the four quadrants proposed. We used the SPI12 from CHIRPS data as input to represent the precipitation index (vertical axes). The variation of the Riacho



do Sangue Dam volume was used as a proxy to analyze the water storage of the study area, since this reservoir is the largest and most important in the study area besides being located at the Riacho do Sangue watershed outlet. The volume stored in the Riacho do Sangue reservoir depends not only on climatic conditions but also on the water released by the monitored reservoirs and the overflow from small reservoirs upstream. Furthermore, as it is located in the most downstream part of the study area, the accumulated effect of the presence of small reservoirs will be most evident. As a result, this is a key variable to understand the role of the small and unmonitored reservoirs in the intensification and evolution of drought events. To use the variation of Riacho do Sangue Dam volume as a Water Storage Index (horizontal axis in the drought wheel), we standardized this variable considering a deviation from half of the maximum capacity of this reservoir and we called this Volume Deviation (VD). Thus, the VD varies from  $-1$  to  $1$ , where a positive value indicates that the reservoir is more than half full while negative values indicate the opposite. Half full is a relevant threshold to capture the emergence and propagation of hydrological drought events in the study region, because water availability is considered critical when the reservoirs has a level less than half of the maximum capacity.

The Drought Cycle Analysis was used to identify the drought events that occurred in the study area over the past 34 years. We consider that a drought event is a disaster related to the exceptional lack of water that is prejudicial for human activities or environmental demands. This method considers not only a meteorological index for monitoring droughts (the vertical axis of the drought wheel), but also information directly related to the impact that this can cause (the horizontal axis of the drought wheel), as such allowing to identify drought events. We consider that a drought event starts when the pair of observations (SPI and VD) leaves the wet quadrant and remains at least 3 months in the hydro-meteorological or hydrological drought quadrant while the cessation of a drought event occurs when these indices return to the wet quadrant.

### 2.3.2. Reservoir Impact Analysis

The analysis of the effect of a DNR on the intensification and evolution of drought events was based on the combination of the Drought Cycle Analysis method with an event attribution analysis. For this, we compared the occurrence of drought events in two scenarios: the All Reservoirs Scenario (ARS) and the Large Reservoirs Scenario (LRS). In both scenarios, we consider the volume deviation (VD) of the Riacho do Sangue reservoir in the Drought Cycle Analysis as a proxy for the hydrological impacts due to the occurrence of drought events (see Section 2.3.1). In the ARS, all reservoirs are considered, thereby representing the actual situation. The application of the Drought Cycle Analysis for this scenario only considers as input the information related to precipitation (SPI) and and the volume deviation is calculated using the observed volume of the Riacho do Sangue reservoir.

In the LR Scenario, we assume that the small unmonitored reservoirs do not exist, and all water that would be stored in these reservoirs directly flows into the large, monitored reservoirs downstream. For this scenario, we use the estimated volume stored in the DNR, and the volume stored in the other two large monitored reservoirs (Tigre and Jenipapeiro) in the study area (see Figure 2). The assumed absence of the DNR in the drainage basin of the large monitored reservoirs could lead to an maximum capacity overflow and this extra volume would flow and reach the Riacho do Sangue reservoir. The principles considered for simulating the LR Scenario are summarized in Equations 4–7.

$$\begin{cases} \text{VLRS}_{(t,r)} = \text{VLRS}_{(t-1,r)} + \Delta\text{VARS}_{(t,r)} + \Delta\text{VDNR}_{(t,r)} + \text{ov}_{(t,r)}, & \Delta\text{VARS}_{(t,r)} \geq 0 \\ \text{VLRS}_{(t,r)} = \text{VLRS}_{(t-1,r)} \times \delta\text{VARS}_{(t,r)} + \Delta\text{VDNR}_{(t,r)} + \text{ov}_{(t,r)}, & \Delta\text{VARS}_{(t,r)} < 0 \end{cases} \quad (4)$$

$$\Delta\text{VARS}_{(t,r)} = \text{VARS}_{(t,r)} - \text{VARS}_{(t-1,r)} \quad (5)$$

$$\Delta\text{VDNR}_{(t,r)} = \begin{cases} \text{VDNR}_{(t,r)} - \text{VDNR}_{(t-1,r)}, & \text{VDNR}_{(t,r)} > \text{VDNR}_{(t-1,r)} \\ 0, & \text{VDNR}_{(t,r)} \leq \text{VDNR}_{(t-1,r)} \end{cases} \quad (6)$$

$$\delta\text{VARS}_{(t,r)} = \frac{\text{VARS}_{(t,r)}}{\text{VARS}_{(t-1,r)}} \quad (7)$$

where  $V_{LRS}(t,r)$  and  $V_{ARS}(t,r)$  are the stored volume in the large monitored reservoir “ $r$ ” for the Large Reservoir Scenario and All Reservoir Scenario, respectively, at time “ $t$ ” which is the timestep in months.  $VDNR(t,r)$  is the volume stored in the DNR located in the watershed of the analyzed large monitored reservoir “ $r$ ”.  $ov(t,r)$  is the maximum capacity overflow volume of the upstream large monitored reservoirs that the reservoir “ $r$ ” may receive.

The volume stored in large monitored reservoirs is a socio-hydrological variable, that is, its variation depends both on human actions (e.g., reservoir operation rules, water withdrawals) and natural conditions (e.g., recharge due to surface runoff and evaporation). We made some simplifying assumptions regarding the recharge and emptying patterns of large monitored reservoirs in the LRS. First, we consider that the possible volume increase in the large monitored reservoirs due to the absence of the DNR would not be enough to change the local meteorological conditions. Therefore, we consider that these conditions are the same in both scenarios. The consequence is that when there is an increase in the volume stored in the ARS, this will also occur in the LRS (Equation 4 upper part). Furthermore, we assumed no change in behavior in the LRS compared to the ARS, which could occur in response to changed storage. In periods of greater water availability it is common to have more authorization for water withdrawals and greater water release to downstream, while the opposite occurs in periods of drought. Accurately simulating this dynamic would involve a specific model based on local information. Since this is beyond the scope of this work, we decided to apply a simplified approach to capture these process. We assumed that the reduction in the volume stored in the LRS scenario would follow the same reduction rate presented in the ARS for the same month “ $t$ ” (Equations 4 and 7). For example, if in the ARS there is a 5% reduction in volume storage compared to the previous month, the same relative reduction is applied to the LRS scenario. Subject to the assumptions, the LRS captures the storage dynamics in the large monitored reservoir, given that no water is stored in upstream small reservoirs.

### 3. Results

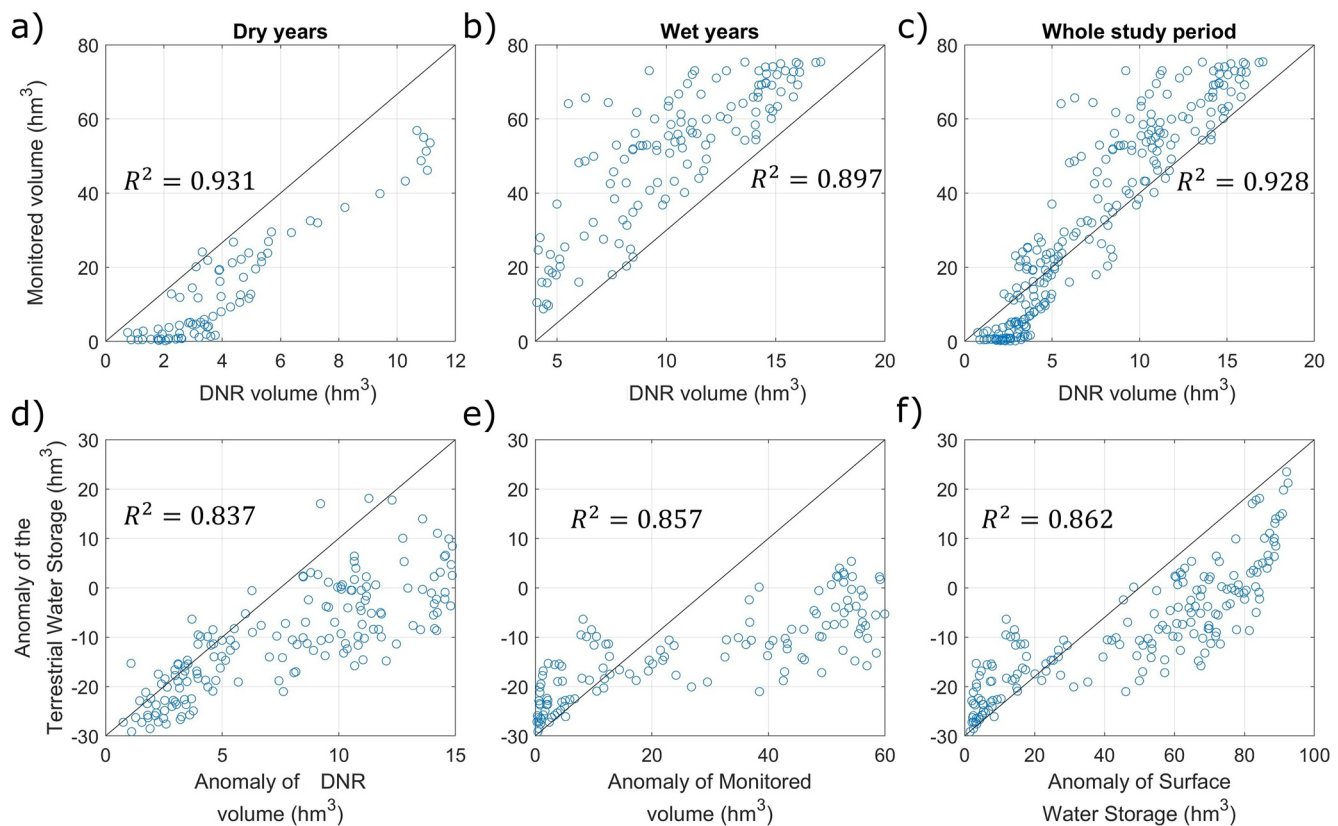
#### 3.1. Volume Estimation Comparison

The first result of this study is an evaluation of the estimated volume stored in the DNR. This was done based on the correlation between this variable and the volume stored in the monitored reservoirs, the correlation between estimated storage in the DNR and terrestrial water storage (TWS), and the combination of storage in monitored and unmonitored reservoirs compared to TWS (Figure 5). The first row of this figure shows the correlation analysis between the volume stored in the DNR (horizontal axes) and the monitored reservoirs (vertical axes) considering the dry years identified in Figure 3c (1990–1990–1994, 1998–2000, and 2012–2018), wet years (years excluding dry years) and the entire study period (1986–2020). There is clearly a high correlation between both variables, especially in the driest years, when there are more periods in which the monitored volume is closer to the total volume stored in the DNR. The second row of Figure 5 shows the results related to the TWS GRACE. The unmonitored volume estimation had the lowest correlation with the TWS GRACE, however, when this was combined with the monitored volume, the correlation increases compared to when the unmonitored volume estimation was not considered in the correlation. Even though this is an indirect assessment, the results agree with the expected pattern previously discussed (See Section 2.2.4). This indicates that we obtained plausible values of the volume stored in the DNR, which allows us to proceed with the subsequent analyses.

#### 3.2. Drought Impact Evaluation

To get a first idea of the role of small reservoirs in the evolution of drought, we compare the SPI value of each observation (represented through the color variation in Figure 6) with the volume deviation (VD) in both the All Reservoirs Scenario (ARS, representing the actual situation) and the Large Reservoirs Scenario (LRS, assuming that the small reservoirs do not exist and all water flows directly toward the large reservoirs).

In Figure 6, three distinct patterns of VD can be observed when both scenarios are compared. First, in the upper right part of the graph, a high proximity between the scenarios is observed (green rectangle), meaning that the small reservoirs have limited impact on the volume stored in the main reservoir. This is because the storage in the area was close to the maximum capacity in the All Reservoirs Scenario (see also the high SPI values). Consequently, even if the small reservoirs did not exist, an overflow would occur to the downstream part of the Riacho do Sangue watershed. In the central part of Figure 6, there is a zone in which the greatest divergence

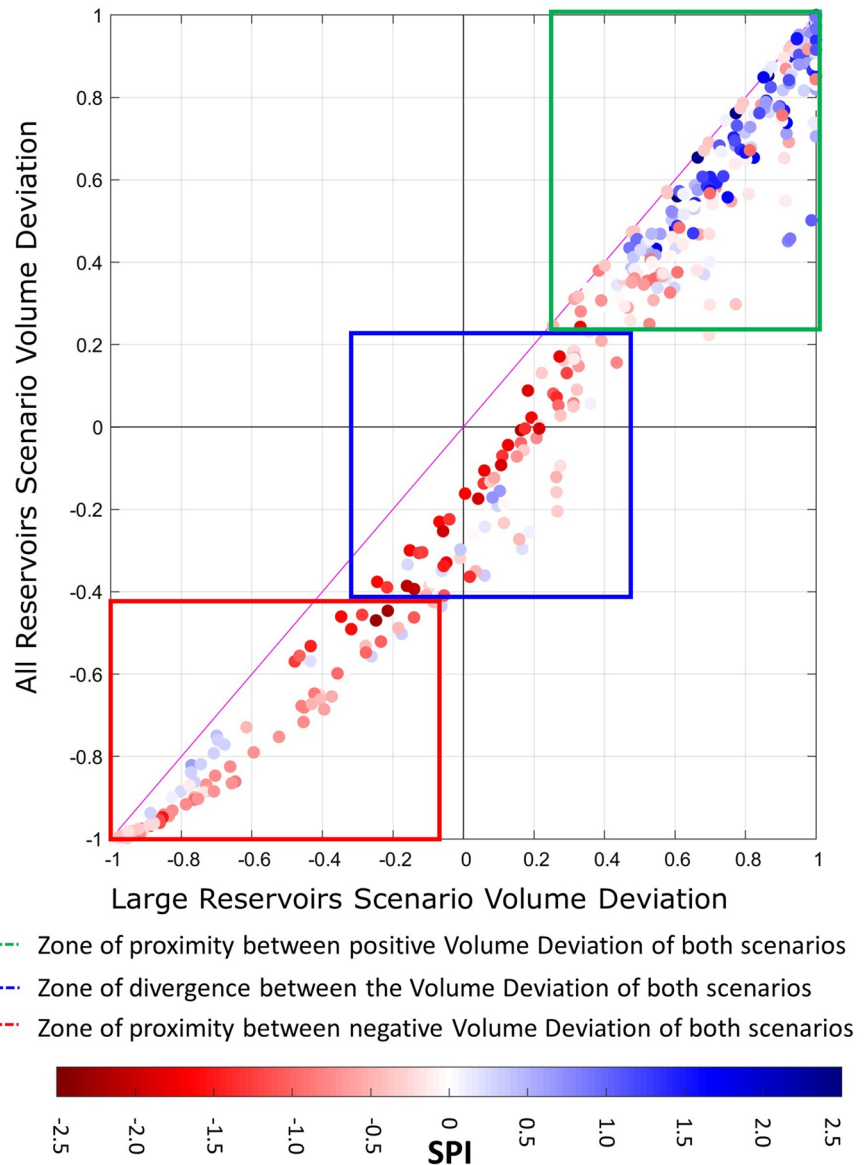


**Figure 5.** Correlation between the estimated volume stored in the DNR with the volume stored in the monitored reservoirs, and Terrestrial Water Storage obtained from GRACE/GRACE-FO mascon product. Panels(a–c) compare the estimated volume in the unmonitored reservoirs with the volume stored in the monitored reservoirs for the dry years (1990–1994, 1998–2000, and 2012–2018), wet years (1986–1989, 1995–1997, 2001–2011, and 2019–2020) and complete study period, respectively. The Anomaly of the Terrestrial Water Storage from GRACE/GRACE-FO mascon product is correlated with estimated volume in unmonitored reservoirs (d), with the volume stored in the three monitored reservoirs (e), and with the unmonitored and monitored reservoirs volume combined (Surface Water Storage, f).

occurs between the two scenarios (blue rectangle). Negative VD in the ARS are associated with positive values in the LRS: there is a clear impact of the small reservoirs on the volume stored in the main reservoir. During these periods, the volume stored in the DNR would have been enough to mitigate the hydrological impacts of these drought events in the monitored reservoirs. In the bottom left part of this figure there is again a proximity pattern between the two scenarios (red rectangle), indicating limited impact of the small reservoirs. However, this time associated with an intense water stress situation (extreme negative VD for both scenarios). Storage was so low that the little water stored in unmonitored reservoirs during this period would not have been sufficient to directly mitigate the hydrological impacts.

The most important result that can be extracted from this figure is that there is a threshold at which a reservoir will enter a phase most likely to be affected by small upstream reservoirs during the occurrence or continuity of drought events. This threshold is the lower limit of the region in Figure 6 where the VD values of the All Reservoirs Scenario are negative while those of the Large Reservoirs Scenario are positive. This means that the unmonitored reservoirs are not yet in a critical storage situation. For the Riacho do Sangue Dam this threshold is  $-0.2$  in the All Reservoirs Scenario which can be seen to be associated with positive VD values in the Large Reservoirs Scenario.

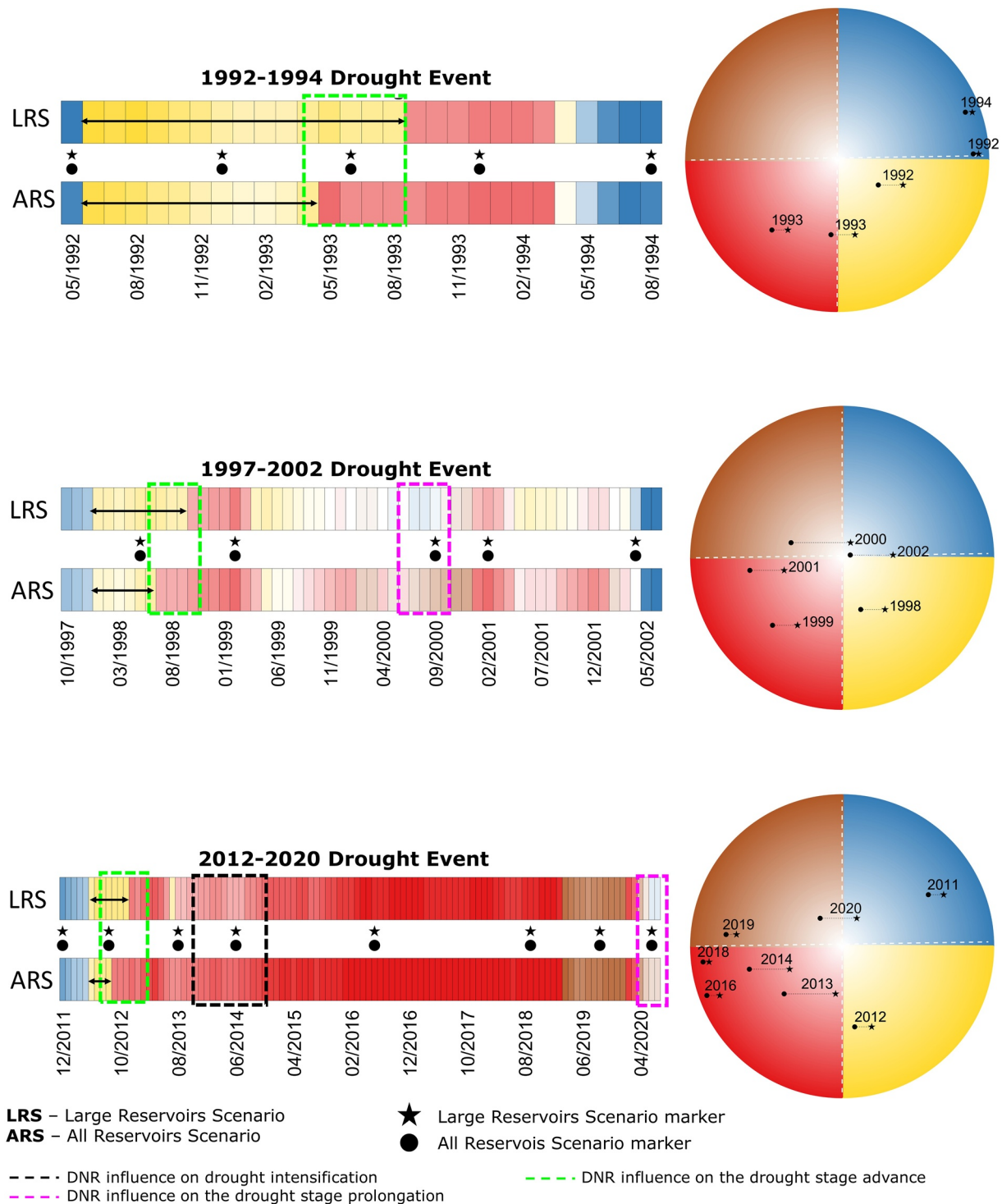
We conducted and evaluated a Drought Cycle Analysis for the three most intense recent drought events, identified using this method, 1992–1994, 1997–2002 and 2012–2020 (Figure 7). The horizontal bars of this figure represent the time series on the monthly scale of the results related to Drought Cycle Analysis (2.3.1) for both scenarios of each of the three drought events. The colors printed in each rectangle of the horizontal bars align with the



**Figure 6.** Scatterplot between the Volume Deviation of the two scenarios associated to the SPI. The colored rectangles (red, blue, and green, discussed in the main text) indicate zones of influence of the small reservoirs in the DNR on the intensification and evolution of drought events.

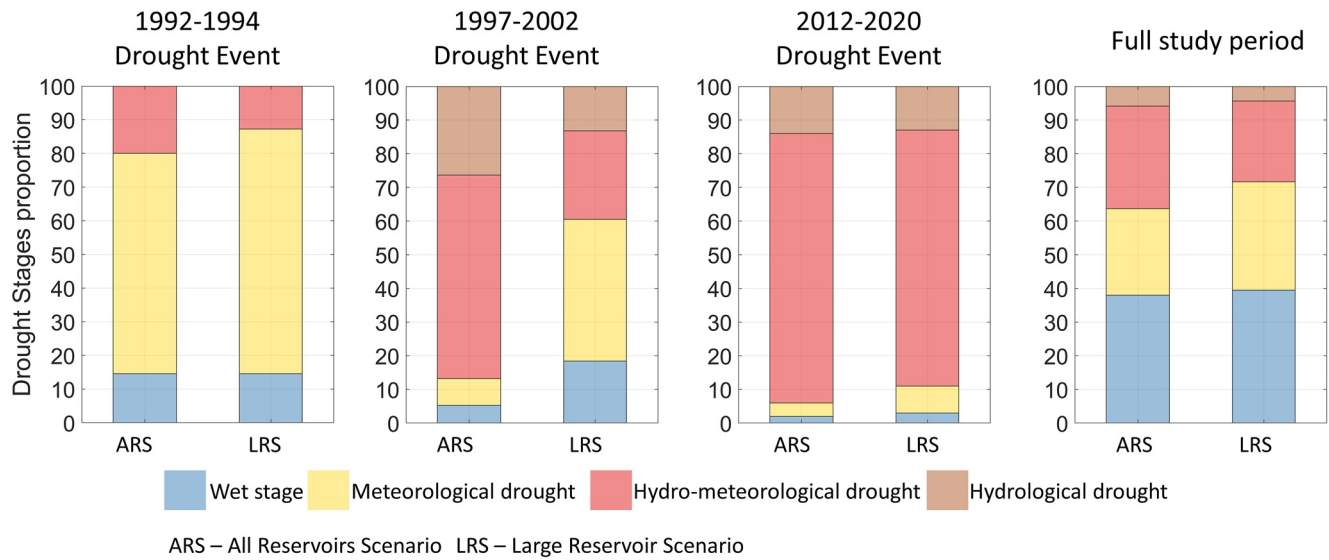
colors in the Drought Wheel (Figure 4) and indicate in which drought stage the scenario is for a particular month. Through these results it is possible to observe the influence of reservoirs on the intensification and evolution of drought events. The Drought Cycle Analysis method allows to identify the interval between the onset of a precipitation deficit and the occurrence of hydrological drought (impacts). This can be done by counting the number of continuous months (rectangles of the horizontal bars in Figure 7) of the meteorological drought stage (yellow colors) prior to the emergence of the drought-hydrometeorological stage (red colors), indicated by the black arrows in Figure 7. For example, in the ARScenario for the 1992–1994 drought event, the lag between the onset of the precipitation deficit and the occurrence of hydrological impacts is 11 months, while for the 2012–2020 event this lag was only 4 months. The difference in lags between the analyzed scenarios indicates the effect that a DNR can cause. Prolongation of drought impacts due to the DNR is identified when the drought stage of the LRS is





**Figure 7.** Results of the Drought Cycle Analysis for three distinct drought events. The colors of the horizontal bars align with the colors in the Drought Wheel, indicating the drought stage for a particular month. The black circle and star in between the horizontal bars indicate time periods that are indicated inside the Drought wheel itself. For instance in the top figure, the circle and star for 05/1992 corresponds to 1992 indicated inside the wheel. The distance between the circle and the star is the difference between both scenarios, thereby demonstrating the impact of the small reservoirs in the DNR on volume deviation.

less intense than in the ARS for the same month. It can be seen that, in general, the presence of the DNR caused an earlier onset of hydrological impacts (red and brown colors) of 3–4 months indicated by the green rectangles, and an extension of these impacts by at least 2 months in the 2012–2020 event indicated by the purple rectangle.



**Figure 8.** Proportion of time that the system is in each drought stage over the three main drought events (1992–1994, 1997–2002, 2012–2020) and the complete study period for the two scenarios.

When, for a particular month, it is observed that the same color was registered in both scenarios, though with different shades, this indicates that the DNR influence the intensity of the drought stage (black rectangles in upper and lower drought events).

As described in Section 2.3.1, drought events can evolve to cover all quadrants of the Drought Wheel. To facilitate the observation of this effect, as well as to present another way to visualize the influence of the DNR, we selected periods of each event and showed them directly in the Drought Wheel. The Drought Cycle Analysis is based on the combination of a precipitation index (SPI) which does not vary between the scenarios and a water storage index (VD) which does vary between both scenarios. The vertical axis of the Drought Wheel is related to the SPI and as both scenarios have the same value for this index, each pair of observations will always be horizontally aligned. A greater horizontal distance between the markers indicates a greater influence of the DNR on drought evolution.

We also evaluated the fraction of time that the system is in a particular drought stage, for the different drought events as well as for the whole study period (Figure 8). The difference between both scenarios demonstrate the impact of the DNS. It is shown that the small reservoirs can prolongate and advance drought, because the small reservoirs alter the temporal proportion of each drought stage. For example, for the 1997–2002 event in the All Reservoirs Scenario (ARS, representing the actual situation), approximately 60% of the time the system was in a hydro-meteorological drought, and 26% of the time in a hydrological drought when small reservoirs are present. This means that the hydrological impacts lasted for 86% of the time. Comparing this with the scenario without the DNR (the Large Reservoir Scenario, LRS), only about 25% of the period was in hydro-meteorological drought and 13% was in hydrological drought, that is, the hydrological impacts lasted only 38% of the time. In this case, the DNR almost doubled the duration of hydrological impacts. In general, the hydrological impacts in the ARS scenario lasted about 36% over the whole studied period, while in the LRS scenario this was only 28%. Thus, the presence of the DNR can lead to a 30% increase in duration of the hydrological impacts.

To capture some of the uncertainty associated with our volume estimation of the small reservoirs, we have analyzed the sensitivity of our results in Figure 8 to a 20% variation in the estimated volume stored in the DNR (minus 10%, plus 10%). The outcomes show that hydrological-drought duration would still increase relative to scenario where no DNR is assumed, by 12% and 45% for the cases of minus 10% and plus 10%, respectively.

## 4. Discussion

### 4.1. Volume Estimation of Unmonitored Reservoirs

The first results obtained in this study were related to the estimation of the volume stored in the Dense Network of (small) Reservoirs (DNR). The validation of these results is challenging as there are no observational data for the overwhelming majority of (small) reservoirs in the study area. However, evaluation is necessary because these results are crucial for the subsequent analyses and conclusions regarding the potential impact of these structures on the evolution and intensification of drought events. The lack of observational data lead to the selection of two indirect evaluation methods:

1. We correlated the total volume stored in the DNR with the total volume stored in the monitored reservoirs. It was expected that these variables would show a high correlation since the hydro-meteorological processes responsible for the recharge of these structures are the same. The rivers in the study area are intermittent, that is, stream drainage flow ceases during the dry season which increases the potential for water loss through infiltration and evaporation. The consequence is that there is an interruption in surface runoff connectivity. This hydrological process is crucial to understand the potential hydrological impacts that small reservoirs can have, since the return of the watershed surface runoff connectivity increases the recharge of large reservoirs and is achieved only when these small reservoirs are full. Hence, there is a strong cause-and-effect relationship between the small reservoirs being full and an increase in the recharge of the large reservoirs. Therefore, a high correlation between these two variables is an indication that the dynamics of estimated storage in the DNR was plausible. During the wet season, the monitored show well-defined interannual seasonality of the stored volume, that is, in general they present similar and homogeneous patterns of recharge and emptying throughout this period. In the drier years, a more persistent and prominent pattern of depletion is observed, associated with lower volumes that can still be retained by unmonitored reservoirs. Thus, the low volumes stored in monitored reservoirs during the driest years would be closer to the stored volume in unmonitored reservoirs and should therefore lead to a higher correlation compared to wet years. Although in general high correlations were found between the estimated volume storage in the monitored reservoirs and the DNR ( $R^2 > 0.89$ ), the highest value was indeed found for the driest years, which confirms our assumption and endorses that the dynamics of the estimated storage in the unmonitored reservoirs was plausible.
2. We attempted to show that the estimation of the total volume stored in the DNR was consistent with remotely sensed water storage. We conducted a series of correlation analyses between total storage in the DNR added to the storage in the monitored reservoirs and the Terrestrial Water Storage (TWS) defined from the GRACE and GRACE-FO missions. The volume stored in the monitored reservoirs had a higher correlation ( $R^2$  close to 0.85) with these remote sensing products than the unmonitored reservoirs, however, the highest value was obtained when the monitored and unmonitored (small) volumes were combined.

In addition to the limitations of the DNR volume estimation method and precision of the TWS products, the fact that the Riacho do Sangue watershed (1368 km<sup>2</sup>) is almost half the size of the GRACE/GRACE-FO pixel (2500 km<sup>2</sup>) may explain why not a perfect correlation ( $R^2 = 1$ ) was found. There are possibly thousands of reservoirs that are not part of the study area, but are part of the GRACE/GRACE-FO pixel and therefore should be accounted for in the SWS calculation. If these reservoirs had been considered in the indirect validation using the TWS products, we would possibly have found a more significant increase in the correlation between SWS and TWS.

Furthermore, we assume that the 2294 unmonitored reservoirs that are part of the study area and were not accounted for because their maximum surface water extent is less than the Landsat pixel area (see Section 2.2.1) do not contribute significantly to the increase in the uncertainties of our results. The maximum volume stored in these reservoirs (considering the Molle equation, see Section 2.2.3) would be less than 1.5% of the total storage capacity of the 1138 unmonitored reservoirs that were considered in this study, even if the surface water extent of these small uncounted reservoirs were equal to a Landsat pixel (900 m<sup>2</sup>).

Another source of uncertainty that could have contributed to the low increase in the correlation between TWS and SWS is the accuracy of the method for identifying water pixels (see Section 2.2.2.). We used fixed thresholds for water identification with the Modified Normalized Difference Water Index (MNDWI) and Short Wave Infrared band (SWIR). A detailed analysis of the water detection sensitivity of this index through dynamic threshold

definition methods (e.g., Z. Du et al., 2014; Ji et al., 2009; Otsu, 1979; Pan et al., 2020) could improve the results presented in this study. Nevertheless, we consider that these results, in addition to the indications that our estimation of the volume stored in DNR is satisfactorily plausible, raise more questions beyond the scope of this study which can be addressed in future research. Possible future directions are: Is it possible to use surface water storage information to downscale GRACE/GRACE-FO products? Is it possible to use GRACE/GRACE-FO products directly or indirectly (e.g., combined with socio-hydrological models) to estimate the volume stored in reservoirs in drought-prone regions with similar physical characteristics to those of the Riacho do Sangue watershed? Answering these scientific questions could improve the understanding of the socio-hydrological dynamics of semi-arid environments, which would be useful to improve water resource management in such regions.

#### 4.2. Drought Event Attribution

The Drought Cycle Analysis method has the advantage of considering not only a meteorological index for drought monitoring, but also information directly related to the impact that drought can cause, within this study addressing hydrological impacts. This method can easily be adapted for the study of vegetation droughts (which are not the subject of this study) by choosing a more suitable precipitation-based index time scale for this kind of drought, and by using an index related to vegetation conditions for the horizontal axis.

The index on the horizontal axes should always be tailored to the specific application. Some of the large reservoirs in Ceará and the semi-arid region of Brazil are oversized, that is, their maximum storage capacity is greater than what would be expected based on the hydro-meteorological conditions of the region. Thus, they are rarely completely full and because of this, the volume deviation as defined here based on half of the storage capacity, should not be applied in these situations. We recommend using another hydrological index or to find a value that better represents the median volume of these reservoirs, and to calculate the deviation in volume deviation based on this value. We used the Volume Deviation (VD) from half of the total capacity of the Riacho do Sangue reservoir as a proxy for the storage situation of the study area, since this is the largest and most important reservoir of this region. Furthermore, this information is a socio-hydrological variable, as its variation relies on human demand and the presence of upstream small reservoirs, in addition to the climatic conditions. Therefore, when we consider a socio-hydrological variable that captures the impact that a drought event can cause, what we can actually achieve is an analysis of drought as a hybrid disaster, that is, those that have natural and anthropogenic components (Monte et al., 2020). This differs from many studies that only use meteorological drought indices (e.g., SPI, percent of normal precipitation, K Index) to analyze drought events (Kchouk et al., 2021). These indices characterize the occurrence of precipitation deficit, but without actually associating it to human activities or environmental demands.

Furthermore, the Drought Cycle Analysis method divides a drought event into four possible stages (see Section 2.3.1), which allows for detailed analysis of the progression and intensification of this disaster over time. Through this method it is possible to identify in a more precise way when a precipitation deficit starts to cause impacts. This information can be used by decision makers to determine triggers for short-term preparedness and mitigating measures. Figure 6 confirms that this delay is significant since it can be seen that the most negative values of SPI did not occur concomitantly with the most negative values of the VD. Analyzing the drought events in Figure 8, it can be seen that this lag ranged between 3 and 6 months for the Riacho do Sangue watershed. The comparison of scenarios related to the existence (ARS) or not (LRS) of a DNR can be used to attribute the causes of the drought events. Our results indicate that the high concentration of small reservoirs structures can induce and modify drought events. This is useful to determine whether decision makers should focus on strategies to adapt to natural conditions or mitigate the human actions that are inducing the occurrence of droughts (Van Loon, Stahl, et al., 2016; Van Loon, Gleeson, et al., 2016).

It is important to note that even during extreme and long-lasting drought events (e.g., 2012–2020) there is not a complete absence of precipitation but an anomalous decrease in precipitation levels (Figure 3b). The spatio-temporal distribution of rain can also influence drought conditions; precipitation can occur over a short time period and only in a small area. This demonstrates the high relevance of understanding the socio-hydrological dynamics of the study area. Human-induced drought events due to the presence of a high concentration of small reservoirs can occur during a meteorological drought, when there is still enough precipitation to recharge these structures but not the main water reservoir of the study area. We attributed that as the cause of the 1997–2002 event, since in the All Reservoirs Scenario (ARS) of this event we observed the development of the four drought stages, while



in the LRS (assuming an absence of the small reservoirs) there was mainly a smooth oscillation between meteorological drought and short periods of hydrological drought.

In the study area, the vast majority of reservoirs in the DNR are small, informal and unmonitored. It is known that these structures aim to meet the demands of the respective users only in the short term. Therefore, these reservoirs need to recharge more water during the rainy season than the human and evaporative demands of the dry season, in order to maintain water security. The effect of prolonged droughts results in changes in the water balance of the small reservoirs, to a situation where they are always empty (or partially empty) during the recharge period. In addition, these structures only release water downstream when they are completely full and overflow; coming from an empty situation, it therefore requires longer or more intense periods of precipitation to reach this point. This process, events associated with a high concentration of small reservoirs, can cause human-modified drought, in which the partial or complete emptying of these structures for long periods delays the recharge of the main storage of the study area. The consequence is an increase in the hysteresis of the hydrological system (decrease in resilience) and intensification of drought events, since the little water retained in these structures could otherwise lessen the hydrological impacts. We attributed that the periods 1992–1994 and 2012–2020 were predominantly human-modified drought events, since a high similarity was observed between the ARS and LRS mainly for hydro-meteorological and hydrological drought stages of these events (e.g., black rectangles Figure 8).

Conceptually, it is possible that a single event can be attributed both as human-modified and human-induced drought, as was the case for the 2012–2020 event. At the beginning of this period the DNR induced the occurrence of the hydro-meteorological drought over at least 3 months. The human-modification can be noticed at the end of this event in which, due to the intensification of the precipitation deficit, there was a significant reduction in the volume stored in the small reservoirs. This resulted in the persistence of the hydrological impacts. At the end of the Large Reservoirs Scenario of this event, the wet period began at least 2 months earlier than in the ARS. Overall, the hydrological impacts (hydrological drought plus hydro-meteorological drought periods) lasted about 30% longer due to the presence of the high concentration of small reservoirs, and this duration could almost double for specific drought events, such as the 1997–2002 drought event.

The prolongation of hydrological impacts directly affects water availability, aggravating drought impacts. On the short term, impacts are mitigated through emergency policies. For the Riacho do Sangue basin, these measures are related to water supply programs by water trucks, construction of cisterns and income transfer programs, which in general present high financial costs for society (Marengo, Alves, et al., 2017; Marengo, Torres, & Alves, 2017). In the mid to long term, societal pressure may arise to increase storage capacity in order to sustain water security during future drought events. Meeting this demand can be achieved through governmental efforts to build large public reservoirs. However, it is more common that the expansion of storage capacity is conducted by individual initiatives, related to building new small reservoirs. The methods presented in this study can be used as complementary tool to minimize the vicious cycle of the effect of small reservoirs. Estimating the amount of water stored in these structures using remote sensing products provides practical and low cost information relevant to more efficient water resource management, since it reveals the real situation of the analyzed hydrological system. In addition, the comparison of the two scenarios (Figure 6) can be used for reservoir management. It can be applied for determination of operating rules to prevent the reservoir from entering a stage where its filling would take longer due to the empty condition of the small reservoirs upstream. This information is particularly useful because it helps in the development of contingency plans for the management of large reservoirs during drought events.

This study does not aim to bring discussions about the societal benefits or negatives of the presence of small unmonitored reservoirs in a region. In the context of the Riacho do Sangue watershed, and in the Brazilian semi-arid region in general, these structures are strongly linked to the history, culture, and productive practices of tens of thousands of subsistence farmers who mostly depend on this water source to survive. Therefore, it is important to emphasize that the idea behind the Large Reservoirs Scenario is purely hypothetical and we do not make any recommendation of policies aimed at removing or limiting the use of these kind of reservoirs.

## 5. Conclusions

This study analyzed the role of a Dense Network of (small) Reservoirs (DNR) in the evolution of drought events. The case study was the Riacho do Sangue watershed, located in the semi-arid region of Brazil. The volume stored in these structures was estimated using remote sensing products combined with an empirically based equation. The analysis of the DNR effect was conducted through a new and innovative Drought Cycle Analysis method, which tracks the simultaneous (non)occurrence of precipitation and hydrological deficits and associates this with four drought stages. This method is a useful and simple approach for a better understanding of drought evolution and therefore provides relevant information to improve drought and water management at the watershed level. The influence of small informal reservoirs on these processes was evaluated by comparing a scenario that represents the current situation in the study area and one in which it is considered that the dense network of small reservoirs never existed. The results showed that the small reservoirs can not only intensify the hydrological impacts, but also lead to an earlier drought onset of 3–4 months, and a delay in the recovery of the drought event with at least 2 months.

In response to the frequent occurrence of meteorological drought, the local population has constructed small reservoirs as a coping mechanism. Our results indicate that a high concentration of such structures can induce and modify drought events, mainly with regard to extending hydro-meteorological and hydrological droughts. On the other hand, we also showed that these structures increase the amount of water retained in the study area (although not optimized and managed) and their absence would impose an overall decrease in the cumulative storage in the hydrological system due to the release of water downstream. We showed that a large number of small reservoirs acutely influences water storage of a hydrological system and this should be taken into account in water resources management. The lack of information regarding small unmonitored reservoirs need not hinder their consideration in water resources management, since we showed that it is possible to estimate the volume stored in the DNR using mainly remote sensing products. We also show that the methods presented in this study can be used for the management of large reservoirs considering the storage situation of small unmonitored reservoirs, which can reduce the vulnerability of a region to the occurrence of hydro-meteorological and hydrological droughts.

Overall, this research provides an approach that is helpful for water managers in drought-prone regions with a dense network of small unmonitored and unmanaged reservoirs. While these small reservoirs are invaluable for the livelihoods of smallholder farmers, this study shows that they do adversely impact water storage in large reservoirs and consequently prolong hydrological droughts at the basin scale.

## Data Availability Statement

The precipitation data used in this study is available in the Climate Hazards Center website (<https://www.chc.ucsb.edu/data>) and is cited in this paper. The time series of the water volume stored in the three monitored reservoirs, the list of Landsat images that were used in the Section 2.2, the location of the small unmonitored reservoirs identified by FUNCEME, and the shapefile of the Riacho do Sangue watershed are available online via <https://www.hydroshare.org/resource/b9a832201b304f8696b9bd708ccfb770>.

## References

- Abileah, R., Vignudelli, S., & Scozzari, A. (2011). *A completely remote sensing approach to monitoring reservoirs water* (Vol. 17).
- Annor, F. O., van de Giesen, N., Liebe, J., van de Zaag, P., Tilmant, A., & Odai, S. N. (2009). Delineation of small reservoirs using radar imagery in a semi-arid environment: A case study in the upper east region of Ghana. *Physics and Chemistry of the Earth, Parts A/B/C*, 34(4–5), 309–315. <https://doi.org/10.1016/j.pce.2008.08.005>
- Arvor, D., Daher, F. R. G., Briand, D., Dufour, S., Rollet, A.-J., Simões, M., & Ferraz, R. P. D. (2018). Monitoring thirty years of small water reservoirs proliferation in the southern Brazilian Amazon with Landsat time series. *ISPRS Journal of Photogrammetry and Remote Sensing*, 145, 225–237. <https://doi.org/10.1016/j.isprsjprs.2018.03.015>
- Avisse, N., Tilmant, A., Müller, M. F., & Zhang, H. (2017). Monitoring small reservoirs storage from satellite remote sensing in inaccessible areas (preprint). *Water Resources Management/Remote Sensing and GIS*. <https://doi.org/10.5194/hess-2017-373>
- Berg, M. D., Popescu, S. C., Wilcox, B. P., Angerer, J. P., Rhodes, E. C., McAlister, J., & Fox, W. E. (2016). Small farm ponds: Overlooked features with important impacts on watershed sediment transport. *JAWRA Journal of the American Water Resources Association*, 52(1), 67–76. <https://doi.org/10.1111/1752-1688.12369>
- Biemans, H., Haddeland, I., Kabat, P., Ludwig, F., Hutjes, R. W. A., Heinke, J., et al. (2011). Impact of reservoirs on river discharge and irrigation water supply during the 20th century. *Water Resources Research*, 47(3). <https://doi.org/10.1029/2009WR008929>
- Bronstert, A., de Araújo, J.-C., Batalla, R. J., Costa, A. C., Delgado, J. M., Francke, T., et al. (2014). Process-based modelling of erosion, sediment transport and reservoir siltation in mesoscale semi-arid catchments. *Journal of Soils and Sediments*, 14(12), 2001–2018. <https://doi.org/10.1007/s11368-014-0994-1>

## Acknowledgments

The authors would like to thank the FUNCEME water resources team, which directly provided us with the observational data used in this research, even though they are freely available from the portal <http://www.hidro.ce.gov.br/>. This work is part of the research program Joint SDG Research Initiative with project number W07.30318.016, which is (partly) financed by the Dutch Research Council (NWO) and the Interdisciplinary Research and Education Fund (INREF) of Wageningen University, the Netherlands.

- Collischonn, B., Paiva, R., Collischonn, W., Meirelles, F., Schettini, E., & Fan, F. (2011). Modelagem Hidrológica de Uma Bacia com Uso Intensivo de Água: Caso do Rio Quaraí-RS. *Revista Brasileira de Recursos Hídricos*, 16(4), 119–133. <https://doi.org/10.21168/rbrh.v16n4.p119-133>
- Craig, I. P. (2008). *Loss of storage water through evaporation with particular reference to arid and semi-arid zone pastoralism in Australia*. Desert Knowledge CRC.
- Cunha, A. P. M., Alvalá, R. C., Nobre, C. A., & Carvalho, M. A. (2015). Monitoring vegetative drought dynamics in the Brazilian semiarid region. *Agricultural and Forest Meteorology*, 214, 494–505. <https://doi.org/10.1016/j.agrformet.2015.09.010>
- de Araújo, J. C., & Bronstert, A. (2016). A method to assess hydrological drought in semi-arid environments and its application to the Jaguaribe River basin, Brazil. *Water International*, 41(2), 213–230. <https://doi.org/10.1080/02508060.2015.1113077>
- Deng, Z., Sun, Y., Zhang, K., Qiu, Q., & Sun, W. (2020). A water identification method basing on grayscale Landsat 8 OLI images. *Geocarto International*, 35(7), 700–710. <https://doi.org/10.1080/10106049.2018.1552324>
- Di Baldassarre, G., Wanders, N., AghaKouchak, A., Kuil, L., Rangelcroft, S., Veldkamp, T. I. E., et al. (2018). Water shortages worsened by reservoir effects. *Nature Sustainability*, 1(11), 617–622. <https://doi.org/10.1038/s41893-018-0159-0>
- Du, Y., Zhang, Y., Ling, F., Wang, Q., Li, W., & Li, X. (2016). Water bodies' mapping from sentinel-2 imagery with modified normalized difference water index at 10-m spatial resolution produced by sharpening the SWIR band. *Remote Sensing*, 8(4), 354. <https://doi.org/10.3390/rs8040354>
- Du, Z., Li, W., Zhou, D., Tian, L., Ling, F., Wang, H., et al. (2014). Analysis of Landsat-8 OLI imagery for land surface water mapping. *Remote Sensing Letters*, 5(7), 672–681. <https://doi.org/10.1080/2150704X.2014.960606>
- Fontenele, S. de B., Mendonça, L. A. R., de Araújo, J. C., Santiago, M. M. F., & de Brito Gonçalves, J. Y. (2014). Relationship between hydrogeological parameters for data-scarce regions: The case of the araripe sedimentary basin, Brazil. *Environmental Earth Sciences*, 71(2), 885–894. <https://doi.org/10.1007/s12665-013-2491-z>
- Fowler, K., Morden, R., Lowe, L., & Nathan, R. (2015). Advances in assessing the impact of hillside farm dams on streamflow. *Australian Journal of Water Resources*, 19(2), 96–108. <https://doi.org/10.1080/13241583.2015.1116182>
- Frantz, D., Haß, E., Uhl, A., Stoffels, J., & Hill, J. (2018). Improvement of the Fmask algorithm for Sentinel-2 images: Separating clouds from bright surfaces based on parallax effects. *Remote Sensing of Environment*, 215, 471–481. <https://doi.org/10.1016/j.rse.2018.04.046>
- FUNCEME. (2021). *Mapeamento das barragens dos pequenos reservatórios d'água situados nos Estado do Ceará*, (p. 10). Fortaleza.
- Funk, C., Verdin, A., Michaelsen, J., Peterson, P., Pedreros, D., & Husak, G. (2015). *A global satellite assisted precipitation climatology*, (p. 25). Discussion Paper.
- Gallego-Elvira, B., Baille, A., Martin-Gorritz, B., Maestre-Valero, J. F., & Martinez-Alvarez, V. (2010). Energy balance and evaporation loss of an irrigation reservoir equipped with a suspended cover in a semiarid climate (southeastern Spain). *Hydrological Processes*, 25(11). <https://doi.org/10.1002/hyp.7929>
- Getirana, A. (2016). Extreme water deficit in Brazil detected from space. *Journal of Hydrometeorology*, 17(2), 591–599. <https://doi.org/10.1175/JHM-D-15-0096.1>
- Guntner, A. (2002). *LARGE-SCALE hydrological modelling IN the semi-arid north-east of Brazil*, (p. 154).
- Guttman, N. B. (1999). Accepting the standardized precipitation index: A calculation Algorithm1. *JAWRA Journal of the American Water Resources Association*, 35(2), 311–322. <https://doi.org/10.1111/j.1752-1688.1999.tb03592.x>
- Habets, F., Molénat, J., Carluer, N., Douez, O., & Leenhardt, D. (2018). The cumulative impacts of small reservoirs on hydrology: A review. *The Science of the Total Environment*, 643, 850–867. <https://doi.org/10.1016/j.scitotenv.2018.06.188>
- Habets, F., Philippe, E., Martin, E., David, C. H., & Leseur, F. (2014). Small farm dams: Impact on river flows and sustainability in a context of climate change. *Hydrology and Earth System Sciences*, 18(10), 4207–4222. <https://doi.org/10.5194/hess-18-4207-2014>
- Hughes, D. A., & Mantel, S. K. (2010). Estimating the uncertainty in simulating the impacts of small farm dams on streamflow regimes in South Africa. *Hydrological Sciences Journal*, 55(4), 578–592. <https://doi.org/10.1080/02626667.2010.484903>
- Ji, L., Zhang, L., & Wylie, B. (2009). Analysis of dynamic thresholds for the normalized difference water index. *Photogrammetric Engineering & Remote Sensing*, 75(11), 1307–1317. <https://doi.org/10.14358/PERS.75.11.1307>
- Kchouk, S., Melsen, L. A., Walker, D. W., & van Oel, P. R. (2021). A geography of drought indices: Mismatch between indicators of drought and its impacts on water- and food securities. *Natural Hazards Earth System Science Discussion* [in press]. <https://doi.org/10.5194/nhess-2021-152>
- Krol, M. S., & Bronstert, A. (2007). Regional integrated modelling of climate change impacts on natural resources and resource usage in semi-arid Northeast Brazil. *Environmental Modelling & Software*, 22(2), 259–268. <https://doi.org/10.1016/j.envsoft.2005.07.022>
- Lasage, R., Aerts, J. C. J. H., Verburg, P. H., & Sileshi, A. S. (2015). The role of small scale sand dams in securing water supply under climate change in Ethiopia. *Mitigation and Adaptation Strategies for Global Change*, 20(2), 317–339. <https://doi.org/10.1007/s11027-013-9493-8>
- Li, B., Rodell, M., Kumar, S., Beaudoin, H. K., Getirana, A., Zaitchik, B. F., et al. (2019). Global GRACE data assimilation for groundwater and drought monitoring: Advances and challenges. *Water Resources Research*, 55(9), 7564–7586. <https://doi.org/10.1029/2018WR024618>
- Liebe, J., van de Giesen, N., & Andreini, M. (2005). Estimation of small reservoir storage capacities in a semi-arid environment. *Physics and Chemistry of the Earth, Parts A/B/C*, 30(6–7), 448–454. <https://doi.org/10.1016/j.pce.2005.06.011>
- Lima Neto, I. E., Wiegand, M. C., & de Araújo, J. C. (2011). Sediment redistribution due to a dense reservoir network in a large semi-arid Brazilian basin. *Hydrological Sciences Journal*, 56(2), 319–333. <https://doi.org/10.1080/02626667.2011.553616>
- Lowe, L., Nathan, R., & Morden, R. (2005). Assessing the impact of farm dams on streamflows, Part II: Regional characterisation. *Australian Journal of Water Resources*, 9(1), 13–26. <https://doi.org/10.1080/13241583.2005.11465260>
- Malveira, V. T. C., Araújo, J. C. de, & Güntner, A. (2012). Hydrological impact of a high-density reservoir network in semiarid northeastern Brazil. *Journal of Hydrologic Engineering*, 17(1), 109–117. [https://doi.org/10.1061/\(ASCE\)HE.1943-5584.0000404](https://doi.org/10.1061/(ASCE)HE.1943-5584.0000404)
- Mamede, G. L., Araujo, N. A. M., Schneider, C. M., de Araujo, J. C., & Herrmann, H. J. (2012). Overspill avalanching in a dense reservoir network. *Proceedings of the National Academy of Sciences*, 109(19), 7191–7195. <https://doi.org/10.1073/pnas.1200398109>
- Mamede, G. L., Guentner, A., Medeiros, P. H. A., de Araújo, J. C., & Bronstert, A. (2018). Modeling the effect of multiple reservoirs on water and sediment dynamics in a semiarid catchment in Brazil. *Journal of Hydrologic Engineering*, 23(12), 05018020. [https://doi.org/10.1061/\(ASCE\)HE.1943-5584.0001701](https://doi.org/10.1061/(ASCE)HE.1943-5584.0001701)
- Marengo, J. A., Alves, L. M., Alvala, R. C. S., Cunha, A. P., Brito, S., & Moraes, O. L. L. (2017). Climatic characteristics of the 2010–2016 drought in the semiarid Northeast Brazil region. *Anais da Academia Brasileira de Ciências*, 90 (2 suppl 1). <https://doi.org/10.1590/0001-3765201720170206>
- Marengo, J. A., Cunha, A. P. M. A., Nobre, C. A., Ribeiro Neto, G. G., Magalhaes, A. R., Torres, R. R., et al. (2020). Assessing drought in the drylands of northeast Brazil under regional warming exceeding 4°C. *Natural Hazards*, 103, 2589–2611. <https://doi.org/10.1007/s11069-020-04097-3>
- Marengo, J. A., Torres, R. R., & Alves, L. M. (2017). Drought in Northeast Brazil—Past, present, and future. *Theoretical and Applied Climatology*, 129(3–4), 1189–1200. <https://doi.org/10.1007/s00704-016-1840-8>

- Martins, E., Nys, E. D., Molejón, C. Q., Biazeto, B., Silve, R. F. V., & Engle, N. (2015). *Monitor de Secas do Nordeste, em busca de um novo paradigma para a gestão de secas*. <https://doi.org/10.13140/rg.2.1.4238.8886>
- Martins, E. S. P. R., Coelho, C. A. S., Haarsma, R., Otto, F. E. L., King, A. D., Jan van Oldenborgh, G., et al. (2018). A multimethod attribution analysis of the prolonged northeast Brazil hydrometeorological drought (2012–16). *Bulletin of the American Meteorological Society*, 99(1), S65–S69. <https://doi.org/10.1175/BAMS-D-17-0102.1>
- Masek, J. G., Vermote, E. F., Saleous, N. E., Wolfe, R., Hall, F. G., Huemmrich, K. F., et al. (2006). A Landsat surface reflectance dataset for North America, 1990–2000. *IEEE Geoscience and Remote Sensing Letters*, 3(1), 68–72. <https://doi.org/10.1109/LGRS.2005.857030>
- McFeeters, S. K. (1996). The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features. *International Journal of Remote Sensing*, 17(7), 1425–1432. <https://doi.org/10.1080/01431169608948714>
- McKee, T. B., Doesken, N. J., & Kleist, J. (1993). The relationship of drought frequency and duration to time scales. *Proceedings of the 8th conference on applied climatology*, 17(22), 6.
- Medeiros, P. H. A., de Araújo, J. C., Mamede, G. L., Creutzfeldt, B., Güntner, A., & Bronstert, A. (2014). Connectivity of sediment transport in a semiarid environment: A synthesis for the upper Jaguaribe basin, Brazil. *Journal of Soils and Sediments*, 14(12), 1938–1948. <https://doi.org/10.1007/s11368-014-0988-z>
- Medeiros, P. H. A., Güntner, A., Francke, T., Mamede, G. L., & Carlos de Araújo, J. (2010). Modelling spatio-temporal patterns of sediment yield and connectivity in a semi-arid catchment with the WASA-SED model. *Hydrological Sciences Journal*, 55(4), 636–648. <https://doi.org/10.1080/02626661003780409>
- Melati, M. D., Fleischmann, A. S., Fan, F. M., Paiva, R. C. D., & Athayde, G. B. (2019). Estimates of groundwater depletion under extreme drought in the Brazilian semi-arid region using GRACE satellite data: Application for a small-scale aquifer. *Hydrogeology Journal*, 27(8), 2789–2802. <https://doi.org/10.1007/s10040-019-02065-1>
- Mialhe, F., Gunnell, Y., & Mering, C. (2008). Synoptic assessment of water resource variability in reservoirs by remote sensing: General approach and application to the runoff harvesting systems of south India: Assessing runoff harvesting potential IN India. *Water Resources Research*, 44(5). <https://doi.org/10.1029/2007WR006065>
- Molle, F. (1989). *Superintendencia do desenvolvimento do nordeste*. 25, 179.
- Molle, F. (1994). *Geometria dos pequenos açudes*. 29, 139.
- Monte, B. E. O., Goldenfum, J. A., Michel, G. P., & Cavalcanti, J. R. de A. (2020). Terminology of natural hazards and disasters: A review and the case of Brazil. *International Journal of Disaster Risk Reduction*, 101970. <https://doi.org/10.1016/j.ijdrr.2020.101970>
- Otsu, N. (1979). A threshold selection method from gray-level histograms. *IEEE Transactions on Systems, Man, and Cybernetics*, 9(1), 62–66. <https://doi.org/10.1109/TSMC.1979.4310076>
- Pan, F., Xi, X., & Wang, C. (2020). A comparative study of water indices and image classification algorithms for mapping inland surface water bodies using Landsat imagery. *Remote Sensing*, 12(10), 1611. <https://doi.org/10.3390/rs12101611>
- Paredes-Trejo, F. J., Barbosa, H. A., & Lakshmi Kumar, T. V. (2017). Validating CHIRPS-based satellite precipitation estimates in Northeast Brazil. *Journal of Arid Environments*, 139, 26–40. <https://doi.org/10.1016/j.jaridenv.2016.12.009>
- Pekel, J.-F., Cottam, A., Gorelick, N., & Belward, A. S. (2016). High-resolution mapping of global surface water and its long-term changes. *Nature*, 540(7633), 418–422. <https://doi.org/10.1038/nature20584>
- Peng, D., Guo, S., Liu, P., & Liu, T. (2006). Reservoir storage curve estimation based on remote sensing data. *Journal of Hydrologic Engineering*, 11(2), 165–172. [https://doi.org/10.1061/\(asce\)1084-0699\(2006\)11:2\(165\)](https://doi.org/10.1061/(asce)1084-0699(2006)11:2(165))
- Pereira, B., Medeiros, P., Francke, T., Ramalho, G., Foerster, S., & De Araújo, J. C. (2019). Assessment of the geometry and volumes of small surface water reservoirs by remote sensing in a semi-arid region with high reservoir density. *Hydrological Sciences Journal*, 64(1), 66–79. <https://doi.org/10.1080/02626667.2019.1566727>
- Pilz, T., Delgado, J. M., Voss, S., Vormoor, K., Francke, T., Costa, A. C., et al. (2019). Seasonal drought prediction for semiarid northeast Brazil: What is the added value of a process-based hydrological model? *Hydrology and Earth System Sciences*, 23(4), 1951–1971. <https://doi.org/10.5194/hess-23-1951-2019>
- Qiu, S., Zhu, Z., & He, B. (2019). Fmask 4.0: Improved cloud and cloud shadow detection in Landsats 4–8 and Sentinel-2 imagery. *Remote Sensing of Environment*, 231, 111205. <https://doi.org/10.1016/j.rse.2019.05.024>
- Rebouças, A. da C. (1997). Água na região nordeste: Desperdício e escassez. *Estudos Avançados*, 11(29), 127–154. <https://doi.org/10.1590/S0103-40141997000100007>
- Rodrigues, L. N., Sano, E. E., Steenhuis, T. S., & Passo, D. P. (2012). Estimation of small reservoir storage capacities with remote sensing in the Brazilian savannah region. *Water Resources Management*, 26(4), 873–882. <https://doi.org/10.1007/s11269-011-9941-8>
- Sawunoyama, T., Senzanje, A., & Mhizha, A. (2006). Estimation of small reservoir storage capacities in Limpopo River Basin using geographical information systems (GIS) and remotely sensed surface areas: Case of Mzingwane catchment. *Physics and Chemistry of the Earth, Parts A/B/C*, 31(15–16), 935–943. <https://doi.org/10.1016/j.pce.2006.08.008>
- Schwatke, C., Scherer, D., & Dettmering, D. (2019). Automated extraction of consistent time-variable water surfaces of lakes and reservoirs based on Landsat and sentinel-2. *Remote Sensing*, 11(9), 1010. <https://doi.org/10.3390/rs11091010>
- Tanny, J., Cohen, S., Assouline, S., Lange, F., Grava, A., Berger, D., et al. (2008). Evaporation from a small water reservoir: Direct measurements and estimates. *Journal of Hydrology*, 351(1–2), 218–229. <https://doi.org/10.1016/j.jhydrol.2007.12.012>
- Van Den Hoek, J., Getirana, A., Jung, H., Okeowo, M., & Lee, H. (2019). Monitoring reservoir drought dynamics with Landsat and radar/lidar altimetry time series in persistently cloudy eastern Brazil. *Remote Sensing*, 11(7), 827. <https://doi.org/10.3390/rs11070827>
- van Langen, S. C. H., Costa, A. C., Ribeiro Neto, G. G., & van Oel, P. R. (2021). Effect of a reservoir network on drought propagation in a semi-arid catchment in Brazil. *Hydrological Sciences Journal*, 66(10), 1567–1583. <https://doi.org/10.1080/02626667.2021.1955891>
- Van Loon, A. F., Gleeson, T., Clark, J., Van Dijk, A. I. J. M., Stahl, K., Hannaford, J., et al. (2016). Drought in the anthropocene. *Nature Geoscience*, 9(2), 89–91. <https://doi.org/10.1038/ngeo2646>
- Van Loon, A. F., Stahl, K., Di Baldassarre, G., Clark, J., Rangelcroft, S., Wanders, N., et al. (2016). Drought in a human-modified world: Reframing drought definitions, understanding, and analysis approaches. *Hydrology and Earth System Sciences*, 20(9), 3631–3650. <https://doi.org/10.5194/hess-20-3631-2016>
- van Oel, P. R., Krol, M. S., & Hoekstra, A. Y. (2011). Downstreamness: A concept to analyze basin closure. *Journal of Water Resources Planning and Management*, 137(5), 404–411. [https://doi.org/10.1061/\(ASCE\)WR.1943-5452.0000127](https://doi.org/10.1061/(ASCE)WR.1943-5452.0000127)
- Van Oel, P. R., Martins, E. S. P. R., Costa, A. C., Wanders, N., & van Lanen, H. A. J. (2018). Diagnosing drought using the downstreamness concept: The effect of reservoir networks on drought evolution. *Hydrological Sciences Journal*, 63(7), 979–990. <https://doi.org/10.1080/02626667.2018.1470632>
- Vanhof, V. & Kelly, R. (2019). Water storage estimation in ungauged small reservoirs with the TanDEM-X DEM and multi-source satellite observations. *Remote Sensing of Environment*, 235, 111437. <https://doi.org/10.1016/j.rse.2019.111437>



- Wang, H., Li, X., Long, H., Qiao, Y., & Li, Y. (2011). Development and application of a simulation model for changes in land-use patterns under drought scenarios. *Computers & Geosciences*, *37*(7), 831–843. <https://doi.org/10.1016/j.cageo.2010.11.014>
- Watkins, M. M., Wiese, D. N., Yuan, D.-N., Boening, C., & Landerer, F. W. (2015). Improved methods for observing Earth's time variable mass distribution with GRACE using spherical cap mascons: Improved Gravity Observations from GRACE. *Journal of Geophysical Research: Solid Earth*, *120*(4), 2648–2671. <https://doi.org/10.1002/2014JB011547>
- World Meteorological Organization. (2012). *Standardized precipitation index user guide*.
- Wu, J., Chen, X., Yao, H., Gao, L., Chen, Y., & Liu, M. (2017). Non-linear relationship of hydrological drought responding to meteorological drought and impact of a large reservoir. *Journal of Hydrology*, *551*, 495–507. <https://doi.org/10.1016/j.jhydrol.2017.06.029>
- Xu, H. (2006). Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery. *International Journal of Remote Sensing*, *27*(14), 3025–3033. <https://doi.org/10.1080/01431160600589179>
- Zhang, H.-W. & Chen, H.-L. (2017). The application of modified normalized difference water index by leaf area index in the retrieval of regional drought monitoring. *DEStech Transactions on Engineering and Technology Research*. (sste). <https://doi.org/10.12783/dtetr/sste2016/6590>
- Zhang, S., Foerster, S., Medeiros, P., de Araújo, J. C., Motagh, M., & Waske, B. (2016). Bathymetric survey of water reservoirs in north-eastern Brazil based on TanDEM-X satellite data. *The Science of the Total Environment*, *571*, 575–593. <https://doi.org/10.1016/j.scitotenv.2016.07.024>
- Zhang, S., Gao, H., & Naz, B. S. (2014). Monitoring reservoir storage in South Asia from multisatellite remote sensing. *Water Resources Research*, *50*(11), 8927–8943. <https://doi.org/10.1002/2014WR015829>
- Zhu, Z., Wang, S., & Woodcock, C. E. (2015). Improvement and expansion of the Fmask algorithm: Cloud, cloud shadow, and snow detection for landsats 4–7, 8, and sentinel 2 images. *Remote Sensing of Environment*, *159*, 269–277. <https://doi.org/10.1016/j.rse.2014.12.014>
- Zhu, Z., & Woodcock, C. E. (2012). Object-based cloud and cloud shadow detection in Landsat imagery. *Remote Sensing of Environment*, *118*, 83–94. <https://doi.org/10.1016/j.rse.2011.10.028>