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Hulsman, Petra; Savenije, Hubert H.G.; Hrachowitz, Markus

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Satellite-based drought analysis in the Zambezi River Basin: Was the 2019 drought the most extreme in several decades as locally perceived?

Petra Hulsman *, Hubert H.G. Savenije, Markus Hrachowitz

Water Resources Section, Faculty of Civil Engineering and Geosciences, Delft University of Technology, Stevinweg 1, 2628 CN, Delft, the Netherlands

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ABSTRACT

Study region: The study area is the river basin upstream of the Kariba dam located in the Zambezi River at the border of Zambia and Zimbabwe.

Study focus: During the dry season of 2019 in Sub-Saharan Africa, extremely low water levels occurred in the Zambezi. According to news media, locals perceived this drought as the worst in several decades. We analyzed the 2019 drought in the Zambezi River Basin upstream of the Kariba dam to determine whether it indeed was the longest, most intense, and severe drought, in terms of precipitation, total water storage and reservoir water level observations over recent decades.

New hydrological insights for the region: Data analysis indicates that the 2019 drought indeed had the lowest basin-averaged annual rainfall, most severe local rainfall deficit in the north of the basin, and lowest reservoir level since 1995. However, the rainfall deficit was more severe in 2002, both basin-wide and locally in the south of the basin. The total storage deficit was more severe in 2004, both basin-wide and locally in the central part of the basin. However, as the available storage data did not cover the entire deficit for 2019, its final duration and severity remain unknown. Therefore, it depends on the drought characteristic, hydrological variable, and location within the basin, whether the 2019 drought was indeed the most extreme over recent decades.

1. Introduction

During the dry season of 2019 in Sub-Saharan Africa, extremely low river water levels were observed. This was especially visible in the Zambezi River at Victoria Falls. Extremely low water levels were also observed in the reservoir upstream of the Kariba hydropower dam, which was down to 10% of usable water for hydro-power generation. According to locals and the news media, this resulted in frequent power cuts of up to 18 h per day for at least 3 months starting in November 2020 (Carlowicz, 2019; Matiashe, 2019; Tshili, 2019). 250 km further upstream of the Kariba Reservoir, the Victoria Falls, which is known as one of the biggest waterfalls in the world, was reduced from a 1.7 km wide falls to multiple small waterfalls (Childs, 2019; Henson, 2019).

The Zambezi River Basin is characterized by one distinct wet and one dry season. It exhibits high temporal and spatial variability in water availability and demand such that the dry season demand frequently exceeds water availability, resulting in water stressed areas.

* Corresponding author.
E-mail address: p.hulsman@tudelft.nl (P. Hulsman).

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In 1995 and 2005, severe droughts in multiple Sub-Saharan countries caused reduced crop production (Libanda et al., 2019; The World Bank, 2010). Between 2000 and 2009, about 12.5 million people were affected by droughts in Mozambique, Zambia and Zimbabwe (ZAMCOM et al., 2015). However, according to popular news media, locals perceived the drought in 2019 as the worst in several decades (Brown, 2019; Edel, 2019) or even a century (Carlowicz, 2019; Henson, 2019).

Drought is one of the most damaging natural hazards in the world with widespread impacts on society, economy, and ecology (Mishra and Singh, 2010; Van Loon, 2015). In general, droughts are classified into meteorological droughts related to precipitation deficits, hydrological droughts related to water deficits on the (sub-) surface, and groundwater droughts related to decreased groundwater levels (Mishra and Singh, 2010; Van Loon et al., 2014; Wilhite and Glantz, 1985). Many previous studies have focused for example on 1) quantifying and predicting droughts in terms of intensity, duration, severity or spatial extent using drought indices (Bayissa et al., 2018; Hao and Singh, 2015; Hellwig and Stahl, 2018; Kumar et al., 2016; Naresh Kumar et al., 2009; Van Loon et al., 2017), 2) analysing the impact of drought on society, economy or ecology (Haile et al., 2019; He et al., 2019; Mishra and Singh, 2010; Stahl et al., 2016), and 3) analysing the influence of climate-change, human modifications or catchment characteristics on droughts (Firoz et al., 2018; Haile et al., 2019; Roodari et al., 2020; Van Loon and Laaha, 2015; Van Loon et al., 2016). Some of these studies focused on analysing droughts in Sub-Saharan regions such as the Zambezi River Basin (e.g. Dutra et al., 2013; Thomas et al., 2014; Tirivarombo and Hughes, 2011).

In addition, previous studies illustrated discrepancies between people's perception of dry conditions and data analyses results (e.g. Foguesatto et al., 2020; Simelton et al., 2013; Solano-Hernandez et al., 2020). For instance, Foguesatto et al. (2020) showed multiple farmers in Africa and Asia perceived decreased rainfall amounts, which was not reflected in meteorological records. They argued that these discrepancies can often be a result of economic and psychological stress factors. In another study, Taylor et al. (1988) showed that farmers in the United States remembered the most recent drought and individual extreme drought events, but largely forgot intermediate droughts. Similarly, Viglione et al. (2014) and Collenteur et al. (2015) illustrated that the memory of specific flood events decreases in time, affecting community actions. In addition, Di Baldassarre et al. (2017) and Albertini et al. (2020) provide evidence that the lack of preparation for droughts after extreme flood events can intensify the resulting impacts. In several Sub-Saharan countries, there was an extreme flood event due to the tropical cyclones Idai and Kenneth in March and April 2019 (United Nations Office for the Coordination of Humanitarian Affairs (OCHA), 2019), which thus may have impacted the local perception of the 2019 drought in the Zambezi River Basin.

Many previous studies compared local perceptions of drought events to rainfall observations (e.g. Giordano et al., 2013; Iqbal et al., 2018; Osgood et al., 2018; Ovuka and Lindqvist, 2000; Solano-Hernandez et al., 2020). However, these studies did not incorporate satellite-based total water storage and reservoir water level observations to provide additional information on drought events. In addition, the drought of 2019 in the Zambezi River Basin has not yet been fully analyzed as it occurred recently. Therefore, the objective of this study was to analyze the drought of 2019 in the Zambezi River Basin upstream of the Kariba Reservoir using multiple satellite observations to determine whether it was indeed the most extreme drought in at least 20 years as perceived by locals.

2. Site description

The Zambezi River, the fourth longest river in Africa, is shared by the countries Zambia (42% of the basin area), Angola (18%), Zimbabwe (16%), Mozambique (12%), Malawi (7.5%), Tanzania (2%), Botswana (1.5%), and Namibia (1%) (Kling et al., 2014). The river has a basin area of 1.37 million km^2, is about 2 660 km long, and has an average discharge of 4 134 m^3 s^{-1} at the outlet in Mozambique (The World Bank, 2010). There is a distinct wet season from September – April and dry season from May – August. In this semi-arid basin, the potential evaporation (2000 mm year^{-1}) exceeds the precipitation (1000 mm year^{-1}), especially during dry seasons (Schleiss and Matos, 2016). Two large hydropower dams are located in the main Zambezi River which are the Cahora Bassa Dam (2075 MW) in Mozambique and further upstream the Kariba Dam (2130 MW) at the border of Zambia and Zimbabwe. The latter is one of the main power sources for both countries according to the local power supply companies (Kesselring, 2017). The maximum water depth above the minimum operating level in the Kariba Reservoir is 13 m according to the Zambezi River Authority (http://www.zambezira.org/).

Table 1
Data used in this study.

	Time-period	Time resolution	Spatial resolution	Location	Product Name	Source/Reference
Precipitation	1992–2020	Monthly	0.05°	Kariba Basin (22,848 grid cells)	CHIRPS	Version 2 (Funk et al., 2014)
Total water storage anomalies	2002–2020	Monthly	0.5°	Kariba Basin (229 grid cells)	GRACE	Pre-processed by JPL (Version RL05_1.DSTvSCS1411) https://grace.jpl.nasa.gov/ (Landerer and Swenson, 2012; Swenson, 2012; Swenson and Wahr, 2006)
Temperature	1992 – 2020	Monthly	0.25°	Kariba Reservoir (9 grid cells)	ERA5	5th generation ECMWF atmospheric reanalysis dataset (Copernicus Climate Change Service (C3S), 2017)
Evaporation	2009 –2020	Monthly	250 m	Kariba Basin ($11.4 \cdot 10^6$ grid cells)	WaPOR	WaPOR V2 Level 1 (FAO, 2018; FAO and IHE Delft, 2019)
Altimetry	1992–2020	10–35 days	n/a	Kariba Reservoir	DAHITI	https://dahiti.dgfi.tum.de/en/ (Schwatke et al., 2015)

3. Data availability

In this study, satellite observations were used to estimate precipitation, total water storage anomalies, actual and potential evaporation, and reservoir water levels (Table 1) as the available ground observations were very limited within the Zambezi River Basin (e.g. Hulsman et al., 2020). Monthly precipitation data was obtained from Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) and monthly actual evaporation from Water Productivity Open-access portal (WaPOR). As WaPOR was only available since 2009 (Table 1), monthly satellite-based temperature data obtained from 5th generation ECMWF atmospheric reanalysis dataset (ERA5) and averaged over the Kariba Reservoir were used to estimate the potential evaporation with the Hargreaves method (Hargreaves and Allen, 2003; Hargreaves and Samani, 1985) which was assumed to be equal to the total actual evaporation from this open water body.

Total water storage anomaly observations were obtained from the Gravity Recovery and Climate Experiment (GRACE). GRACE observations describe variations in the Earths' gravity field, which are related to regional mass changes that are dominated by terrestrial water storage variations (Landerer and Swenson, 2012; Swenson, 2012). Readily available and pre-processed GRACE observations were generated by Jet Propulsion Laboratory (JPL) and downloaded from the GRACE Tellus website (https://grace.jpl.nasa.gov/). The JPL pre-processed the data to remove atmospheric mass changes, systematic errors and noise, and subtract the 2004–2009 time-mean baseline to obtain total water storage anomalies (Landerer and Swenson, 2012; Swenson and Wahr, 2006; Wahr et al., 1998). Note, that GRACE observations were missing for several months among which July 2017 – May 2018 and August – September 2018 since the GRACE mission was ended in October 2017 and the mission GRACE-Follow-on (GRACE-FO) was launched in May 2018 (Kornfeld et al., 2019).

Satellite-based lake water levels, i.e. altimetry observations, were extracted from the platform Database for Hydrological Time Series of Inland Waters (DAHITI) for the Kariba Reservoir. Altimetry observations estimate the water level relative to a reference ellipsoid. The distance between the satellite and earth surface is estimated by sending a radar signal in nadir direction towards the earth and measuring the time difference between sending and receiving the reflected signal. With this distance and the known satellite position, the surface level relative to a reference ellipsoid is estimated (Calmant et al., 2008; Łyszkowicz and Bernatowicz, 2017). At the Kariba Reservoir, the following satellite missions were used to create a time-series: Envisat, Jason-1/2/3, and Topex/Poseidon (Schwatke et al., 2015). Depending on the satellite mission, the temporal resolution is 10 and 35 days (CNES, Accessed 2018; ESA, 2018; Schwatke et al., 2015).

In this study, the temporal variability of remotely sensed precipitation, total water storage, actual and potential evaporation, and reservoir water levels at Kariba were compared for the time-period 1992 – 2020. As GRACE and WaPOR data were only available since 2002 and 2009 respectively, any comparison with these variables comprised the time-period 2002–2020 and 2009–2020, respectively. Annual values for the precipitation and evaporation were calculated from monthly observations considering hydrological years starting in August, rather than calendar years. There were no discharge data available in the vicinity of the Kariba Reservoir after 2018 in the global discharge database Global Runoff Data Centre (GRDC), so this variable was not included in this study.

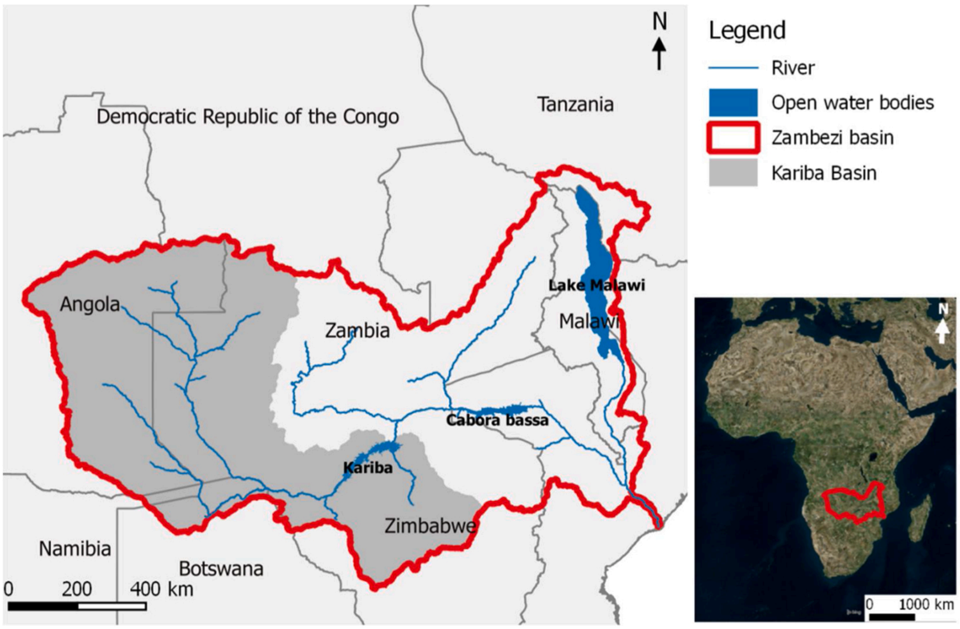

Fig. 1. Map of the Zambezi River Basin and the basin area upstream of the Kariba Reservoir now called "Kariba Basin".

4. Approach

The temporal variability of all individual variables was analyzed and compared using basin-averaged time-series for the gridded observations considering the basin upstream of the Kariba hydropower dam (dark grey area in Fig. 1). Potential evaporation at Kariba Reservoir, however, was averaged over the open water body. During this analysis, basin-averaged actual evaporation was calculated as this variable directly influences the total water storage. Similarly, potential evaporation at Kariba Reservoir was included in this analysis since it influences the reservoir water levels. The precipitation, actual evaporation, and potential evaporation time-series were analyzed on an annual timescale to detect multi-annual changes. In contrast, GRACE and altimetry observations were analyzed on the same timescale for which the data was available to use as much data as possible for the drought analysis and as both variables account for effects of preceding months. In addition, multiple drought indices were calculated using precipitation, GRACE and altimetry data as explained in Section 4.1. With these indices, the associated drought severities, durations, and intensities were estimated and analyzed as explained in Section 4.2. Then, the spatial variability of the minimum deficit index, drought intensity and severity were compared for the most severe drought and the 2019 drought with respect to precipitation and GRACE.

4.1. Drought indices

Remotely sensed precipitation data was used to estimate the Standardized Precipitation Index (SPI; McKee et al., 1993), which is typically used to quantify meteorological droughts. The SPI was calculated for each month using monthly precipitation time-series accumulated over the 12 preceding months to reflect short- and long-term effects. This time-series was fitted to the Gamma probability density function to compute the corresponding cumulative distribution function which was then transformed to a normal distribution function to estimate SPI values. This approach was applied to the basin-averaged precipitation time-series and to each individual grid cell. For the latter, each grid cell was fitted to the Gamma probability density function separately.

Total water storage observations according to GRACE were used to estimate the GRACE-based Total Storage Deficit Index (TSDI; Nie et al., 2018). This was calculated by first estimating the Total Storage Deficit (TSD) using Eq.1 to remove seasonal variations to allow comparisons of TSD between different seasons, and then standardizing TSD using Eq.2 to obtain TSDI (Nie et al., 2018):

$$\mathrm{TSD}_{ij} = \frac{S_{ij} - S_{\mathrm{avg},j}}{S_{\mathrm{max},j} - S_{\mathrm{min},j}} \tag{1}$$

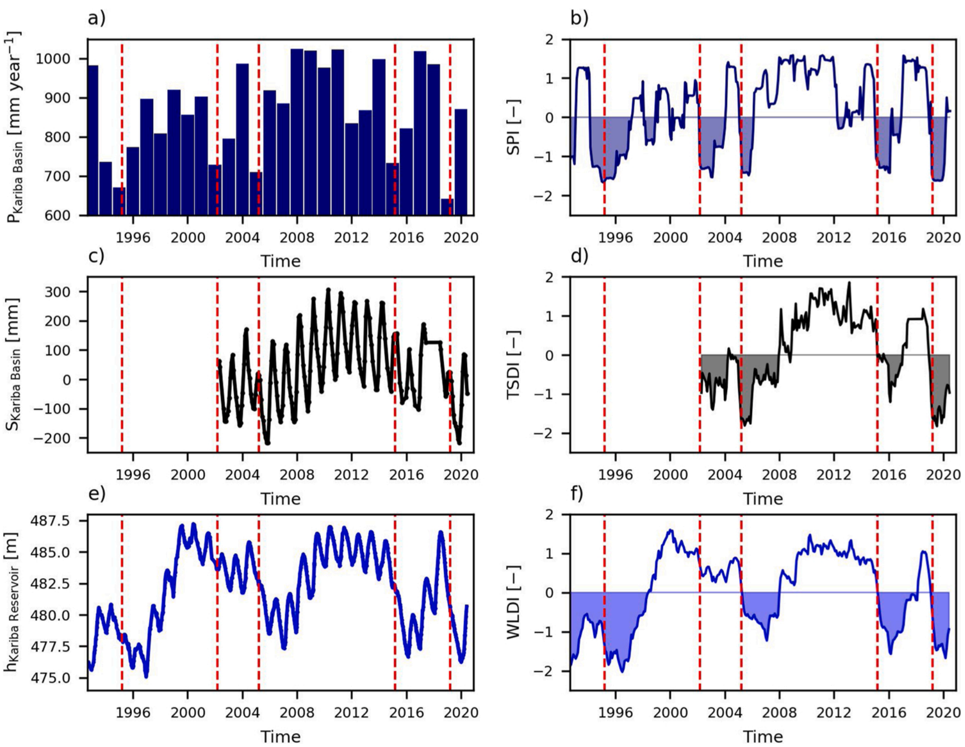

Fig. 2. a) Basin-averaged annual precipitation, b) monthly SPI (Standardized Precipitation Index), c) basin-averaged monthly total water storage anomalies, d) monthly TSDI (Total Storage Deficit Index), e) altimetry observations at Kariba Reservoir, and f) 10 – 35 day WLDI (Water-Level Deficit Index). The red dashed lines mark the dates 15 March 1995, 2002, 2005, 2015 and 2019 which were chosen visually to mark several extremely dry years.

$$\mathrm{TSDI}_{ij} = \frac{\mathrm{TSD}_{ij} - \mu}{\sigma} \tag{2}$$

With S_{ij} [mm] total water storage in month j and year i, $S_{avg,j}$ [mm] long-term mean total water storage for month j, $S_{max,j}$ [mm] long-term maximum total water storage for month j, $S_{min,j}$ [mm] long-term minimum total water storage for month j, μ [-] mean of TSD [-] and σ [-] standard deviation of TSD. The TSDI was estimated using basin-averaged total water storage time-series and gridded data for all months for which data was available.

Reservoir altimetry observations were used to estimate the corresponding drought index which was called Water-Level Deficit Index (WLDI) in this study. This index was calculated for all data points for which data was available. For this purpose, Eqs.1 and 2 were used similar to the calculation of GRACE-based TSDI as reservoir water level and total water storage observations both already account for effects of preceding months. That is why the altimetry and GRACE time-series were not accumulated when calculating the corresponding drought indices as done when estimating SPI (Bloomfield and Marchant, 2013; Van Loon et al., 2017).

4.2. Drought characteristics

The three individual drought indices were used to characterize droughts in terms of minimum deficit index, drought duration, intensity, and severity. The minimum deficit index ($DI_{min,\theta}$) is the lowest index value in a drought for drought index θ. The drought duration $D_{D,\theta}$ [months] was defined as the number of consecutive months with θ below zero, drought intensity $D_{I,\theta}$ [month^{-1}] as average θ over consecutive months with θ below zero, and drought severity $D_{S,\theta}$ [-] as the accumulated θ over consecutive months with θ below zero (Huang et al., 2016). This was applied for all drought indices used in this study such that θ = SPI, TSDI or WLDI.

5. Results

5.1. Precipitation

The annual precipitation varied between 642 mm year^{-1} in 2019, and 1024 mm year^{-1} in 2008 (Fig. 2a). In other words, in 2019 the annual rainfall was lowest since at least 27 years, which was the duration of the available rainfall data. Considerably low rainfall amounts were also observed in 1995 (670 mm year^{-1}), 2002 (728 mm year^{-1}), 2005 (710 mm year^{-1}) and 2015 (733 mm year^{-1}). Consecutive wet years with above average rainfall amounts (871 mm year^{-1}) were observed in 2006–2011 and 2017–2018, whereas in 1997–2001 the annual rainfall amounts were more than 800 mm year^{-1} (Fig. 2a).

According to the precipitation-based drought index SPI, there have been multiple droughts in the Kariba Basin (colored areas in Fig. 2b) of which five droughts are characterized by SPI_{min} < -1.5 (Table 2) and can hence be classified as "severe meteorological drought" according to the drought categories as defined by McKee et al. (1993). These droughts started in 1994, 2002, 2005 and 2019. Their minimum deficit indices were $DI_{min,SPI}$ = -1.5 – -1.7, their severities were $D_{S,SPI}$ = -14.1 – -44.0, their durations were $D_{D,SPI}$ = 13–37 months, and their intensities were $D_{I,SPI}$ = -1.0 – -1.5 month^{-1} (Table 2). Based on these results, the longest and most severe meteorological drought with the lowest deficit index occurred in 1994 ($D_{D,SPI}$ = 37 months, $D_{S,SPI}$ = -44.0, and $DI_{min,SPI}$ = -1.7),

Table 2
Overview of drought characteristics according to precipitation, GRACE and altimetry data including minimum Deficit Index (DI_{min}), duration (D_D), intensity (D_I) and severity (D_S) for all droughts with D_D > 6 months. Bold numbers indicate droughts with $DI_{min} \leq -1.5$. Note that the data for the GRACE and altimetry based deficit in 2019 was incomplete as it continued after June 2020, the end of the time-series. In other words, the corresponding deficit indices remained below zero until the end of the time-series.

Variable	Start of drought	End of drought	DI_{min} [-]	D_D [months]	D_I [month^{-1}]	D_S [-]
Precipitation	Jan 1992	Jan 1993	−1.3	13	−1.0	−13.6
	Mar 1994	**Mar 1997**	**−1.7**	**37**	**−1.2**	**−44.0**
	Feb 1998	Nov 1998	−0.7	10	−0.5	−5.2
	Apr 2000	Nov 2000	−0.3	8	−0.1	−0.9
	Mar 2002	**Jan 2004**	**−1.5**	**23**	**−1.0**	**−24.0**
	Feb 2005	**Feb 2006**	**−1.5**	**13**	**−1.1**	**−14.1**
	Apr 2012	Oct 2012	−0.3	7	−0.2	−1.6
	Jan 2015	Mar 2016	−1.4	15	−1.1	−16.6
	May 2016	Dec 2016	−0.6	8	−0.4	−3.3
	Mar 2019	**Mar 2020**	**−1.6**	**13**	**−1.5**	**−19.0**
GRACE	Apr 2002	Mar 2004	−1.4	24	−0.8	−16.8
	Aug 2004	**Dec 2007**	**−1.8**	**41**	**−0.8**	**−32.9**
	Sep 2015	Dec 2016	−1.2	16	−0.6	−6.4
	Dec 2018	**Jun 2020***	**−1.8**	**19**	**−1.3**	**−23.7**
Altimetry	**Sep 1992**	**May 1998**	**−2.0**	**69**	**−1.2**	**−79.6**
	May 2005	Jan 2008	−1.2	33	−0.7	−22.4
	Apr 2015	**Feb 2018**	**−1.6**	**35**	**−0.7**	**−25.3**
	Feb 2019	**Jun 2020***	**−1.7**	**17**	**−1.2**	**−20.1**

whereas the most intense drought was in 2019 ($D_{I,SPI}$ = -1.5 month^{-1}, Table 2).

5.2. Total water storage

The total water storage varied seasonally and on average 271 mm. In contrast, the long-term the annual minimum storage varied between −217 mm and 26 mm (Fig. 2c). In 2005 and 2019, the total water storage decreased to −217 mm and −215 mm, respectively, which were both dry years when considering the annual rainfall (710 mm year^{-1} and 642 mm year^{-1}, respectively). The decreased total water storage in 2019 was likely also a result of the above average actual total evaporation in the basin (1030 mm year^{-1}, Fig. 3a), resulting in increased water releases from the soil and hence decreased total water storage values. In contrast, the total water storage remained relatively high in 2015 despite the low rainfall (733 mm year^{-1}) with an annual minimum storage of −80 mm (Fig. 2a and c). During that year, the basin-averaged annual evaporation was below average (902 mm year^{-1}, Fig. 3a), resulting in less water being released from the (sub-) surface and hence higher total water storage values. Therefore, the high total water storage in 2015 can plausibly be due to the below average actual evaporation.

According to the GRACE-based TSDI, water storage deficits occurred multiple times. The droughts starting in 2004 and 2018 had $TSDI_{min} < -1.5$ (Table 2 and Fig. 2d). Their minimum deficit indices were equal to $DI_{min,TSDI} = -1.8$, their drought severities were $D_{S,TSDI}$ = −23.7 – −32.9, their durations were $D_{D,TSDI}$ = 19–41 months, and their intensities were $D_{I,TSDI}$ = -0.8 – −1.3 month^{-1}. In contrast to these droughts, the low rainfall in 2015 did not result in TSDI < −1.5. Based on these results, the longest and most severe drought in total water storage occurred in 2004 ($D_{D,TSDI}$ = 41 months, and $D_{S,TSDI}$ = −32.9), whereas the most intense total storage related drought began in 2019 ($D_{I,TSDI}$ = −1.3 month^{-1}, Table 2). Note the TSDI remained below zero towards the end of the available time-series in June 2020 (Fig. 2d), meaning the total storage deficit was still ongoing, thereby affecting the final duration, severity, and intensity for this specific drought.

5.3. Reservoir water level

As illustrated in Fig. 2e, the water level in Kariba Reservoir changed both seasonally and inter-annually. While the seasonal variability was on average 2.8 m, the inter-annual variability ranged up to 10.2 m as the annual minima ranged between 475.1 m (1996) and 485.3 m (1999). The highest level was observed in 2000 (487.2 m) and the lowest in 1996 (475.1 m). During the dry season of 2019, the reservoir level decreased to 476.2 m before increasing again with the new rains. In other words, the lowest reservoir level was observed in 1996. The long-term variations in the altimetry often coincided with the annual precipitation amounts according to CHIRPS (Fig. 2a). For example, the water levels decreased significantly in 1995, 2005, 2015 and 2019 when the annual rainfall was low. Similarly, the water levels increased in 1997–1999, 2007–2011 and 2016–2018 during consecutively wet years (Fig. 2a and e). In contrast, the annual rainfall was lower in 2002 (728 mm year^{-1}) which was not reflected as strongly in the altimetry observations compared to the other dry years (Fig. 2a and e). This can be due to decreased outflow as a consequence of reservoir operation considerations or decreased evaporation from the open water body. However, in 2002, the evaporation was high (1320 mm year^{-1}) compared to preceding and following years (Fig. 3b). Therefore, the high altimetry observations in 2002, despite the low rainfall amount, were more likely a result of reservoir operation decisions.

According to the reservoir altimetry-based WLDI, significant water deficits continuing for more than a year started in 1992, 2005, 2015 and 2019 (colored areas in Fig. 2f). Their minimum deficit indices were $DI_{min,WLDI}$ = −1.6 to −2.0, their severities were $D_{S,WLDI}$ = −20.1 to −79.6, their durations were $D_{D,WLDI}$ = 17–69 months, and their intensities were $D_{I,WLDI}$ = −0.7 to −1.2 month^{-1} (Table 2). Based on these results, the longest, most severe and most intense deficit with the lowest deficit index occurred between 1992 and 1998 ($D_{D,WLDI}$ = 69 months, $D_{S,WLDI}$ = −79.6, $D_{I,WLDI}$ = −1.2 month^{-1}, and $DI_{min,WLDI}$ = −2.0, Table 2). Note, the WLDI remained below zero towards the end of the time-series in June 2020 (Fig. 2f) meaning the reservoir water deficit was still ongoing. Duration and severity of

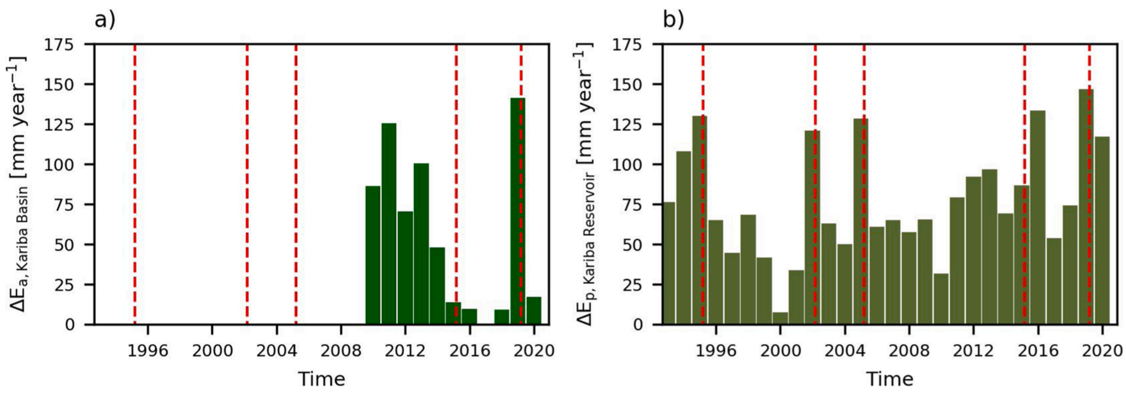

Fig. 3. Annual total a) actual evaporation for Kariba Basin; deviation from the minimum (888 mm year^{-1}) and b) potential evaporation for Kariba Reservoir; deviation from the minimum (1200 mm year^{-1}). The red dashed lines mark the dates 15 March 1995, 2002, 2005, 2015 and 2019, which were chosen visually based on Fig. 1 to mark several extremely dry years.

this specific drought as reported here are thus to be interpreted as lower bounds.

5.4. Spatial variability

In the previous sections, the basin-averaged drought characteristics were analyzed using precipitation, GRACE, and altimetry data. In this section, the spatial variability of the minimum deficit index, drought intensity and severity were compared for the most severe drought and the 2019 drought with respect to precipitation and GRACE for which gridded data was available. The most severe basin-averaged precipitation deficit occurred in 1994, while the most severe total water storage deficit occurred in 2004 (Table 2).

5.4.1. Precipitation

The precipitation deficit in 1994 resulted in a minimum index value of $DI_{min,SPI} = -0.6 - -1.9$ with low values in the central and western parts of the basin (Fig. 4a). In 2019, the minimum index value was $DI_{min,SPI} = 0.0$ to -1.9 with considerably more low values in the northern parts of the basin (Fig. 4b). Therefore, according to the minimum deficit index the drought was more extreme in 2019 or 1994 depending on the location within the basin (Fig. 4a and b).

The drought intensity was $D_{I,SPI} = -0.3$ to -1.6 month^{-1} in 1994 and exhibited pronounced spatial contrasts with the lowest values in the central parts of the basin (Fig. 5a). However, in 2019 the intensity was $D_{I,SPI} = 0.0$ to -1.8 month^{-1} with the lowest values in the north-west (Fig. 5b). Comparison between 1994 and 2019 further suggests that the 2019 drought was locally considerably more intense.

The drought severity in 1994 was $D_{S,SPI} = -5.4$ to -69.3 and with the lowest values in the central and southern parts of the basin (Fig. 6a). In 2019, the drought severity was $D_{S,SPI} = 0.0$ to -28.1 with the lowest values in the north-west of the basin (Fig. 6b). Therefore, the drought was significantly more severe in 1994 compared to 2019 throughout large parts of the basin, whereas in other regions in the north of the basin the drought was more severe in 2019.

It depended on the location within the basin whether or not the drought of 2019 was the most severe or intense in at least 20 years. In the northern part of the basin, the drought of 2019 was the most severe, intense and had the lowest deficit index values (Fig. 7a, c and e) for at least 20 years. However, in the southern parts of the basin the drought of 2019 was the most severe and had the lowest deficit index values in less than 10 years.

5.4.2. Total water storage

The GRACE-based minimum deficit index was $DI_{min,TSDI} = -1.2$ to -1.7 in 2004 with the lowest values in the western part of the basin (Fig. 4c). In 2019, the minimum deficit index was $DI_{min,TSDI} = -0.7$ to -1.7 with more high values in the central part of the basin compared to 2004 (Fig. 4d). As a result, according to the minimum deficit index, the drought was more extreme in 1994 or 2019 depending on the location within the basin (Fig. 4c and d).

The drought intensity was $D_{I,TSDI} = -0.7$ to -1.3 month^{-1} in 2004 with the lowest values in the south-east (Fig. 5c). However in

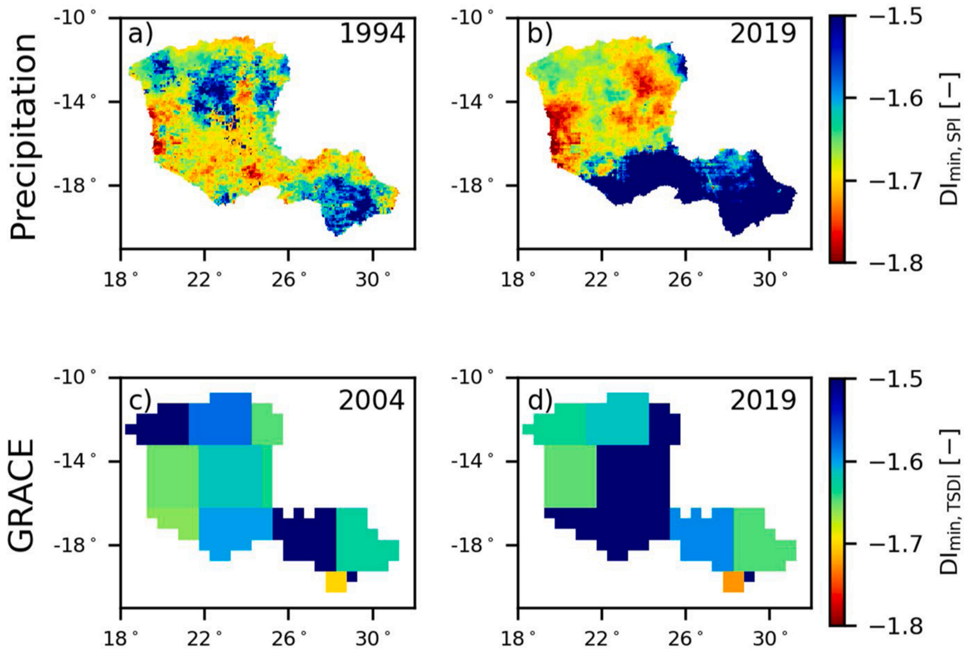

Fig. 4. Spatial variability of the minimum drought index according to the precipitation (a – b) and according to the total water storage (c – d) for the most severe drought according to precipitation (a) or GRACE (c), and the drought of 2019 (b and d).

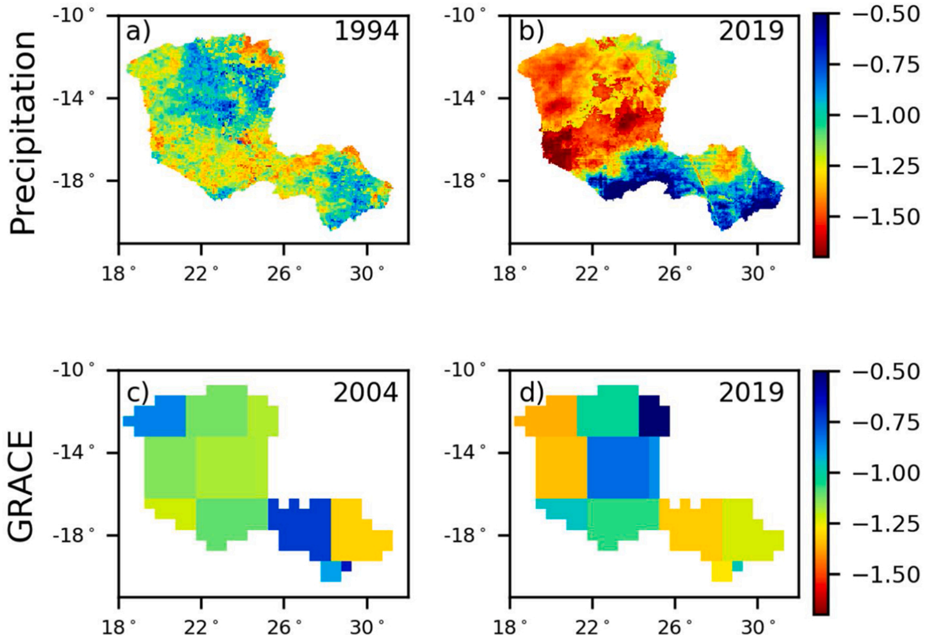

Fig. 5. Spatial variability of the drought intensity according to the precipitation (a – b) and according to the total water storage (c – d). The maps were temporally averaged considering the most severe drought according to precipitation (a) or GRACE (c), and the drought of 2019 (b and d).

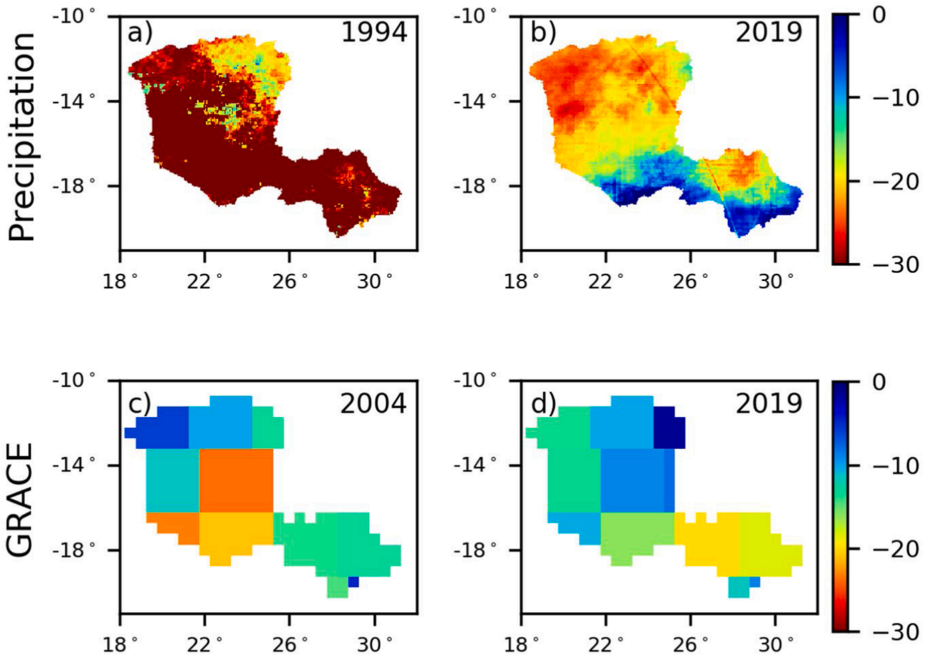

Fig. 6. Spatial variability of the drought severity according to the precipitation (a – b) and according to the total water storage (c – d). The maps were temporally averaged considering the most severe drought according to precipitation (a) or GRACE (c), and the drought of 2019 (b and d).

2019, it was $D_{I,TSDI} = -0.5$ to -1.4 month^{-1} with the lowest values in the north-west (Fig. 5d). Therefore, the drought was more intense in 2004 (for example south-east of the basin) or 2019 (for example north-west of the basin) depending on the location within the basin.

The drought severity was $D_{S,TSDI} = -4.6$ to -23.8 in 2004 with the lowest values in the central part of the basin (Fig. 6c). In 2019, the severity was $D_{S,TSDI} = -1.4$ to -19.9 with the lowest values in the south-east (Fig. 6d). Therefore, depending on the location within the basin, as of June 2020, the drought was more severe in 2004 in the central parts of the basin and in 2019 in the south-east of the

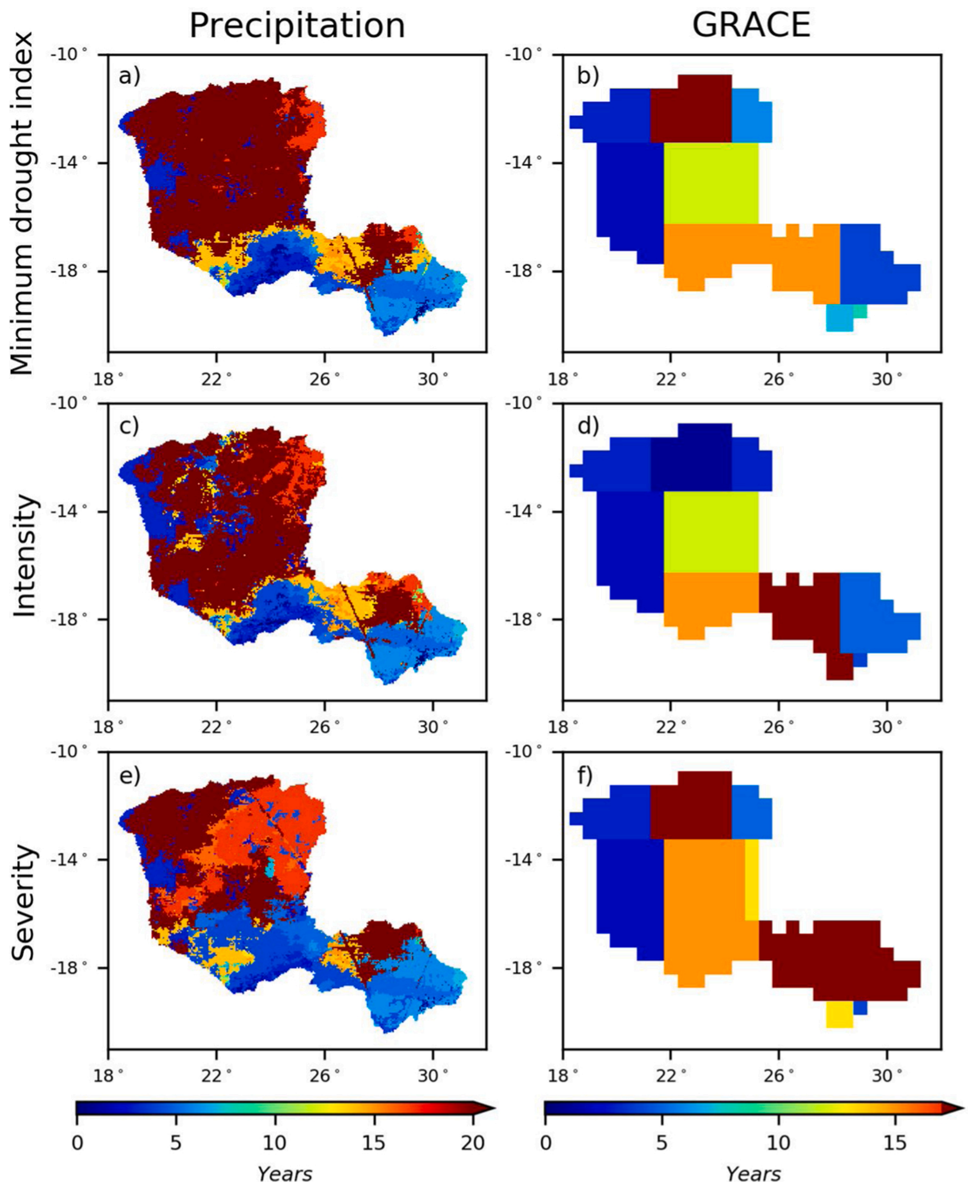

Fig. 7. Spatial variability of the number of years between the drought of 2019 and the most recent drought before 2019 with more extreme values based on the minimum deficit index (a and b), drought intensity (c and d) and drought severity (e and f) according to precipitation (a, c and e) or GRACE data (b, d and f). Grid cells where the drought of 2019 was the most severe as observed with satellite data are colored dark red.

basin.

Similar to precipitation-related drought, it depended on the location within the basin, as to whether or not the water storage-related drought of 2019 was the most severe and intense in at least 20 years. In the western parts of the basin the drought of 2019 was the most severe, intense and with the lowest deficit index values in less than 10 years (Fig. 7b, d and f). However, the drought of 2019 was the most severe and intense for at least 17 years (the duration of the available GRACE data) in the south of the basin.

6. Discussion

While locals perceived the drought of 2019 as the most severe in at least 20 years, data indicated this differed depending on the drought characteristic, hydrological variable, and the location within the basin. The drought of 2019 was characterized by the lowest basin-averaged annual rainfall for at least 27 years, the most intense rainfall deficit for at least 25 years, the most severe local rainfall deficit in the northern part of the basin for at least 20 years, and the lowest reservoir water level since 1995. This supports the local perception that the drought of 2019 was the most extreme in more than 20 years. However, the rainfall deficit was more severe in 2002 with respect to the basin-average and locally in the south of the basin. Also, reservoir water level deficit was more severe in 2015, and total storage deficit was more severe in 2004 with respect to the basin-average and locally in the south of the basin. This contradicts the local perception. However, the available data did not cover the entire water level and total storage deficit for 2019 such that the TSDI and WLDI remained below zero towards the end of the available time-series in June 2020. Thus, the final duration and severity of the drought of 2019 remains unknown.

The water levels at Kariba Reservoir not only depended on precipitation, which largely dominates the inflow to the reservoir, but also on evaporation from the open water body and reservoir operation determining the amount of water leaving the reservoir. That is why low annual rainfall amounts do not necessarily result in low reservoir water levels. For example, reservoir operation is likely to explain the relatively high reservoir water levels in 2002 despite the very low rainfall and high evaporation in that year (Figs. 2a, 2e and 3b).

The results in this study are sensitive to uncertainties in the satellite observations. Previous studies illustrated satellite-based precipitation observations were sensitive to bias (Kimani et al., 2017; Le Coz and van de Giesen, 2020). Uncertainties in total water storage anomalies are a result of data (post-) processing including data smoothing using a radius of 300 km, which affects the spatial variability (Blazquez et al., 2018; Landerer and Swenson, 2012). Note that GRACE observations were missing for several months as mentioned in Section 3, which resulted in missing TSDI values and hence an irregular temporal pattern in Fig. 2c and d. Potential and actual evaporation data are prone to uncertainties related to the underlying estimation method and input data (Feng et al., 2019; Hobbins et al., 2008; Zhang et al., 2016). Altimetry uncertainties for open water bodies range between 0.04 m and 0.36 m depending on the lake size and climate conditions (Crétaux and Birkett, 2006; Schwatke et al., 2015). These uncertainties can affect long-term fluctuations in these variables. Therefore, we recommend that these satellite observations are tested against ground observations. This step was outside the scope of this study due to the limited in-situ data availability.

Previous studies have discussed various reasons for discrepancies between local perception of droughts and (satellite-based) observations. First, locals often perceive droughts through non-climatic factors such as reservoir water level or lack of electricity, which is more clearly visible compared to rainfall or total water storage amounts (Iqbal et al., 2018; Urquijo and De Stefano, 2016). Second, locals often remember most recent and extreme drought events, but forget intermediate droughts (Taylor et al., 1988). Third, local perceptions are often influenced by economic losses such as significant reductions in the expected crop production (Bola et al., 2014; Foguesatto et al., 2020; Meze-Hausken, 2004). Hence, farmers who experienced large crop failures often relate this to droughts even though the rainfall remained constant. They may also fail to take into account that they have expanded their crop production in the past such that the water demand increased.

In contrast to previous studies, this study illustrated the local perception was partially supported and partially contradicted by satellite observations depending on the drought characteristic, hydrological variable, and location within the basin. In other words, the simple statement "the drought of 2019 was the worst in several decades" mentioned in the news media (Brown, 2019; Edel, 2019) cannot be generalised. For example, locals in the west of the basin are more likely to consider the drought of 2019 as the most severe in at least 20 years if they mainly rely on rainwater (Fig. 7e) instead of groundwater sources (Fig. 7f). Note that monthly GRACE observations are dominated by slow processes which include changes in the groundwater system and seasonal variations in all storage components.

In future studies, it would be interesting to include local observations such as the inflow to Kariba Reservoir, reservoir operation, reservoir water levels, and precipitation data to validate satellite observations. In addition, the opinions of local experts who are familiar with the region and interview results on local perception should be included, as this may vary spatially and could depend on occupation or age. In this study, the SPI was calculated using 12 preceding months (Section 4.1) to identify extreme droughts, since short duration droughts of 3 or 6 months occur more frequently (Fig. 8). However, it would be interesting to analyze whether a different drought duration in the SPI calculation would reflect the local perception better at a specific location and, if so, why.

7. Conclusion

The objective of this study was to analyze the drought of 2019 in the Zambezi River Basin upstream of the Kariba Reservoir using multiple satellite observations to determine whether it was the most extreme drought in at least 20 years as locally perceived. For this purpose, we analyzed the drought duration, intensity, and severity, spatially averaged and locally, using precipitation, total water storage and reservoir water level observations. Data analysis indicated that the drought of 2019 was the most extreme for at least 24 years when considering the basin-averaged annual rainfall, local precipitation-based drought severity in the north of the basin, and reservoir water level. However, the 2019 drought was the most extreme only in recent decades when considering the basin-averaged drought severity according to the precipitation, total water storage and reservoir water level. Note that as the available data did not cover the entire water level and total storage deficit for 2019, the final duration and severity of the drought of 2019 remains unknown. Therefore, it depends on the drought characteristic, the hydrological variable considered, and the location within the basin, whether the drought of 2019 was indeed the most extreme over the last decades as perceived by local people.

Data availability

All satellite observations used in this study were obtained from publicly available online databases as described in Section 3 and Table 1. Processed data including basin-averaged time-series are available on https://doi.org/10.4121/13102274.v2.

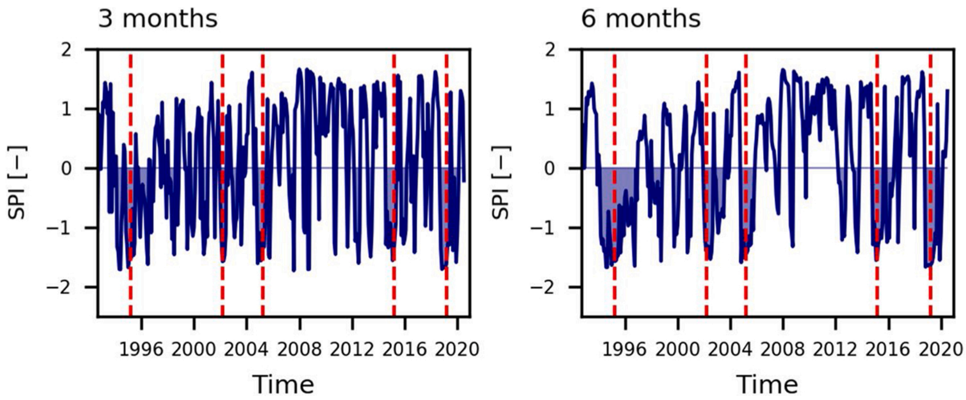

Fig. 8. Basin-averaged SPI using 3 or 6 preceding months.

CRediT authorship contribution statement

Petra Hulsman: Conceptualization, Methodology, Formal analysis, Writing - original draft. **Hubert H.G. Savenije:** Writing - review & editing. **Markus Hrachowitz:** Conceptualization, Methodology, Writing - original draft.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.ejrh.2021.100789.

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