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Evaluating the BFAST method to detect and characterise changing trends in water time series: A case study on the impact of droughts on the Mediterranean climate

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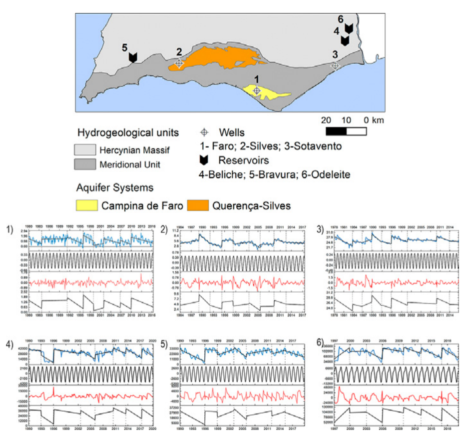
HIGHLIGHTS

- BFAST allowed detection of abrupt and gradual changes in the freshwater resources.
- BFAST enabled the detection and quantification of recovery and drawdown periods.
- BFAST identified trends in groundwater and surface water due to weather fluctuations.
- BFAST assessed impact of water management on both surface and groundwater resources.

GRAPHICAL ABSTRACT



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ABSTRACT

Mediterranean climate regions are facing increased aridity conditions and water scarcity, thus needing integrated management of water resources. Detecting and characterising changes in water resources over time is the natural first step towards identifying the drivers of these changes and understanding the mechanism of change. The aim of this study is to evaluate the potential of Breaks For Additive Seasonal and Trend (BFAST) method to identify gradual (trend) and abrupt (step- change) changes in the freshwater resources time series over a long-term period. This research shows an alternative to the Pettitt's test, LOESS (locally estimated scatterplot smoothing) filter, Mann–Kendall trend test among other common methods for change detection in hydrological data, and paves the way for further scientific investigation related to climate variability and its influence on water resources. We used the monthly accumulated stored water in three reservoirs, the monthly groundwater levels of three hydrological settings and a standardized precipitation index to show BFAST performance. BFAST was successfully applied, enabling: (1) assessment of the suitability of past management decisions when tackling drought events; (2) detection of recovery and drawdown periods (duration and magnitude values) of accumulated stored water in reservoirs and groundwater

Abbreviations: BFAST, Breaks for Additive Season and Trend; LOESS, locally estimated scatterplot smoothing; (CF), Campina de Faro; (MS), Meridional Rim of Sotavento; (MOSUM), Moving sum; (OLS), Ordinary least squares; (QS), Querença-Silves; (SPI), Standartized Precipitation Index; (STL), Seasonal Trend decomposition using Loess.

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bodies after wet and dry periods; 3) measurement of resilience to drought conditions; (4) establishment of similarities/differences in trends between different reservoirs and groundwater bodies with regard to drought events.

1. Introduction

The Mediterranean region and Portugal mainland are being faced with increasing aridity conditions (Sousa et al., 2011; Vicente-Serrano et al., 2014) that fit well into predicted future climate trends, with higher frequency and intensity of droughts and floods in regions already prone to these extreme weather events (IPCC, 2018, 2019). A resulting decrease in water resources is foreseen that will seriously affect the availability of freshwater resources for drinking and irrigation purposes (Hiscock et al., 2008). Climate variability, in general, and precipitation variability, in particular, can have substantial effects on the rate of aquifer recharge (Green et al., 2011) and the availability of surface water resources stored in dammed reservoirs (Deng et al., 2020).

Sustainable groundwater management requires the evaluation of groundwater resources to ensure a balance between abstraction and groundwater recharge. Water resource availability is dependent on interannual short-term climate fluctuations (e.g. precipitation and evapotranspiration), but also on long-term changes such as climate change (Pinto et al., 2021). Furthermore, abrupt changes, such as those resulting from floods or overexploitation, or gradual changes resulting from modifications in land cover, management, as well as socio-economic drivers (Antunes Aghsaei et al., 2020; Lian et al., 2020; Mendes and Ribeiro, 2014) can influence fluctuations in groundwater levels and surface water reserves. Traditionally, different problems related to hydrology have been addressed applying machine learning for predictive modelling (Adnan et al., 2021; Cardenas-Martinez et al., 2021; Mendes et al., 2021; Pandey et al., 2020), numerical models (Casillas-Trasvina et al., 2019; dos Santos et al., 2019; Sondermann and de Oliveira, 2021), and statistical methods (Młyński et al., 2021; Peña-Angulo et al., 2020; Vicente-Serrano et al., 2019; Zeleňáková et al., 2017) among others.

The establishment of gradual or abrupt changes of temporal hydrological dynamics can help to establish and identify any probable causes, e.g. to distinguish natural climate variability from anthropogenic changes, especially if supported by descriptive characteristics, such as drought indices or climate teleconnections (Anyah et al., 2018; Secci et al., 2021; Wang et al., 2021; Xu et al., 2021). Parametric approaches require features to follow specific statistical distributions, such as a normal distribution, and they are very sensitive to outliers. Non-parametric approaches do not require any prior assumption about the distributional characteristics of the samples (Teegavarapu, 2019).

The non-parametric Mann–Kendall trend test (Gilbert, 1987) is widely used in hydrology, since it is simple, outlier-resistant and can handle missing values or values that are below detection limits. However, this method can only be used in the case of monotonic trends and it assumes that sample data are serially independent. Block bootstrapping (Carlstein, 1986a; Kunsch, 1989a) will be used to overcome the serial dependence enabling the checking the robustness of the trend assessment.

On the other hand, LOESS (locally estimated scatterplot smoothing) is less outlier-resistant, but allows examination of both monotonic and non-monotonic trends (Cleveland and Devlin, 1988). LOESS is recommended for assessing statistically significant trends at the groundwater bodies level, within the scope of the European Union River Basin Management Plans (Grath et al., 2001). Although, abrupt and gradual changes can co-exist (Sharma et al., 2016), these two abovementioned tests cannot detect abrupt changes, since it assumes that the trend component varies smoothly. The Pettitt's Test (Pettitt, 1979) is widely used in hydroclimatological studies for addressing abrupt change or a step change within the time series, allowing the detection of a single shift at an unknown time *t* (Mallakpour and Villarini, 2016).

The BFAST (Breaks for Additive Season and Trend) method was developed to identify gradual and abrupt changes, allowing the detection of multiple breakpoints, while explicitly considering seasonal variations (Verbesselt et al., 2010a). BFAST permits characterisation of the time, magnitude and direction of change, flagging disturbance events in groundwater and surface water resources. The B-FAST method can identify gradual and multiple abrupt changes in a time series, but it has rarely been used in hydrological applications as few exceptions can be found in the literature. For instance, Liu et al. (2021) used BFAST to evaluate the trends of runoff change in the upper and middle reaches of the Yellow River, Coladello et al. (2020) to assess the over-abundance of aquatic macrophytes in tropical reservoirs and, Deng et al. (2020) to identify and supplement newly impounded reservoirs during 2000–2018 in the Yellow River.

The aim of this work is to evaluate the potential of BFAST to quantify the impacts of disturbance events, such as droughts periods, on groundwater and surface water resources. The specific objectives are to: (1) Detect abrupt changes such as hydrological droughts in the seasonal and trend components of piezometric levels and accumulated stored water in dammed reservoirs in a Mediterranean climate region; (2) Identify trends in groundwater and surface water due to weather fluctuations, discerning these from effects induced by human activities such as overexploitation of groundwater resources or the filling of a reservoir; and (3) Compare the performance of the BFAST method with that of the Pettitt test and Mann-Kendall.

2. Methods and data

2.1. Water resources

The southernmost region of mainland Portugal, named Algarve (with 16 municipalities and around a resident population of 467,475; CENSUS, 2021) (Fig. 1), has high urban pressures along the coastline, which began with the tourism boom in the 1960s. Along with tourism, the expansion of irrigated agriculture also started during the 60's, leading to an exponential rise in water demand. Since 1990, Algarve has expanded its provision and range of golf courses (nowadays around 39), and facilities extensively (Barros et al., 2010). Public water supply, with an volume of 69.5 hm^3 (in 2018) comes from surface-water sources (76 %) and groundwater (24 %). Public water supply is characterized by a strong seasonality, with water consumption in the summer months being more than one and a half times the average annual consumption.

Groundwater was the dominant source for public water supply, irrigated farming and golf courses until the end of the 20th century (Stigter et al., 2009), which led to a severe decrease in the piezometric levels in the majority of the aquifers located in the coastal zones (Maia and Silva, 2009; Mendes and Ribeiro, 2014). Nowadays, groundwater remains the primary water source for irrigated farming ($\approx$ 68 %) and golf courses ($\approx$ 65 %). Surface water represents around 40 % of the total water consumption in this region (APA, 2016).

The Bravura and Beliche dams were built in the late 1950s and in the 1980s (Fig. 1), respectively, to cope with water shortages in months with the greatest tourist influx (June to September) (Antunes do Carmo, 2019; Carriço et al., 2014). In 2002, >80 % of the total public supply was sustained by surface water after the construction of the Odeleite dam in late 1990's and the rehabilitation of the Beliche and Bravura dams (Table 1). The Odeleite and Beliche reservoirs have a storage capacity of 117 hm^3 and 47.6 hm^3, respectively. These two dams were connected through a tunnel, constituting a unique water supply system. The Odeleite-Beliche system is located in the Guadiana river basin, and serves the irrigation and water consumption needs of the eastern part of the study region. Odeleite and Beliche have, respectively, an average annual precipitation of 722 mm and 644 mm.

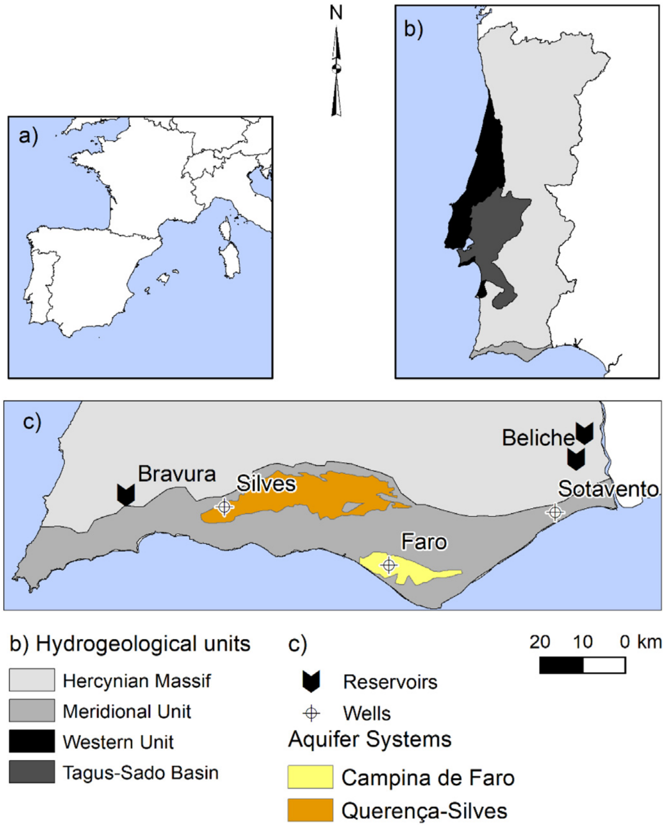

Fig. 1. a) Location of Portugal in Europe; b) the four major hydrogeological units and; location of the six water wells (the three reservoirs, Bravura, Beliche and Sotavento) and the three wells (Sotavento, Silves e Faro) and the two aquifer systems.

The Bravura reservoir (storage capacity of 32.33 hm^3) and two other reservoirs (Arade and Funcho) supplied the western part alone until construction of the Odelouca dam, with the capacity of these three storage reservoirs being lower than the Odeleite-Beliche system (Maia and Silva, 2009). The Bravura reservoir is located in Odeáxere river basin and has an average annual precipitation of 821 mm.

The severe drought that occurred in 2004–2005 caused a major water shortage in these storage reservoirs, with water use restriction measures being imposed for the agriculture sector. This issue was addressed by reactivating some municipal boreholes that had previously been abandoned. Additionally, new boreholes located in the western part of the Querença-Silves (QS) aquifer system (Fig. 1) were used (Maia and Silva, 2009). The QS aquifer system is the largest (324 km^2) and the most important groundwater resource (mean yield of 11.1 l/ s) in the region (Stigter et al., 2009). This aquifer system is comprised of karstified carbonate rock and has a significant recharge (long-term mean annual recharge of approximately 111 hm^3/year) (ARH Algarve, 2012a; Hugman et al., 2013; Nicolau, 2002). Its western sector has a small (approximately 1.5 %) hydraulic gradient, a predominant E–W flow direction and discharge occurs at Estombar springs located near the mouth of the Arade river (Almeida et al., 2000; Neves et al., 2016; Stigter et al., 2009). The Campina de Faro (CF) multi-aquifer system (Fig. 1) is composed of three aquifer systems: the deeper Cretaceous limestone/marls, the overlying Miocene sandy limestone aquifer system, and the sand and gravel Plio-Quaternary upper aquifer. This latter aquifer system is located in the centre and south, with an average thickness of 50 m, and can be considered phreatic (Stigter et al., 2006). Recharge occurs directly via precipitation and is approximately 9.95 hm^3/year, which is the same as the estimated available resources (ARH Algarve, 2012). The Meridional Rim of Sotavento (MS) has a low productivity and is composed of biocalcarenites and sands. The mean annual recharge is 11.08 hm^3/year with mean available resources of 9.97 hm^3/year. These three groundwater bodies (where two of the three are aquifer systems) mirror distinct hydrogeological settings with quick response to precipitation events. Three piezometers located at the Querença-Silves aquifer system (QS), Campina de Faro aquifer system (CF) and Meridional Rim of the Sotavento groundwater body (MS) were selected (Table 1), each with good data quality (i.e. good length and integrity of water level records), as well as three dammed reservoirs (Bravura, Beliche and Odeleite; Table 1), in order to illustrate the advantages of using BFAST for detecting both gradual and abrupt changes in the trend component.

2.2. Climate

The Algarve region has a warm-summer Mediterranean climate (Csa) under the Köppen-Geiger classification, with a well marked dry summer with nearly five-month-long. 64 % of the precipitation falls between November and February, with a low mean annual precipitation of around 500 mm/year (1981–2010 climate normal). The highest monthly accumulated precipitation occurrs in December (115.6 mm) followed by November (83.5 mm). The rivers show typically seasonality, with high winter discharges and low summer discharges, generally resulting of the seasonality of the rainfall exacerbated by the high tempertures of the summer months (Guerreiro et al., 2017). The daily average temperature ranges between 12 °C (January) and 24 °C (July and August). The average number of tropical nights (i.e., days with low temperatures over 20 °C) for the summer months are 18 days (June), 8.6 days (July), 8.7 days (August) and 4.8 days (September) (IPMA, 2021). Due to the orography, coastal areas receive on average <70 % of precipitation than northern areas, making the south coast one of the aridest regions on the Portuguese mainland (Neves et al., 2019). Only the Querença-Silves aquifer is located at the foothills of the Serra do Caldeirão, one of the rainiest regions in the Algarve (mean annual precipitation around 1000 mm), where episodes of heavy rainfall are most frequent and torrential nature (Fragoso and Gomes, 2008).

2.3. Standardized Precipitation Index (SPI)

The standartized Precipitation Index (SPI; Mckee et al., 1993) is one of the drought indices that is extensively used worldwide since is easy to

Table 1
Location of water points.

ID Database	Name	Coordinates WGS 84		Altitude (m)	Surface (S)/Groundwater (G) body	Data Source
		N	W			
600/134	Sotavento	37.17	−7.56	33.51	G- Meridional Rim of Sotavento (MS)	https://snirh.apambiente.pt
610/167	Faro	37.06	−8.00	4.13	G- Campina de Faro (CF)	https://snirh.apambiente.pt
595/215	Silves	37.18	−8.44	63.76	G- Querença-Silves (QS)	https://snirh.apambiente.pt
Odeleite	Odeleite	37.33	−7.52	47.00	S- Guadiana river basin	https://snirh.apambiente.pt
Beliche	Beliche	37.28	−7.51	39.00	S- Guadiana river basin	https://snirh.apambiente.pt
Bravura	Bravura	37.20	−8.70	96.00	S- Ribeiras do Algarve	https://snirh.apambiente.pt

calculate, is effective in analysing wet-dry periods/cycles and, only requires precipitation as an input parameter (WMO, 2012). Calculation of the SPI is based on the long-term precipitation data for a certain period. SPI values are units of standard deviation from the long-term mean, allowing the SPI to be used to compare any precipitation anomalies for any location and for any number of time scales. When calculated for longer periods, the SPI is more related to hydrological droughts with low frequency. The 14-month SPI was used because SPIs of these longuer timescales are usually tied to streamflows, reservoir levels, and groundwater levels (WMO, 2012). In this study, it serves as an indicator for reduced reservoirs and groundwater recharge. The 14-month SPI values were classified according to seven categories: extremely dry (Min $\leq$ SPI $\leq$ -2.0), very dry ($-2.0 <$ SPI $\leq$ -1.5), moderately dry ($-1.5 <$ SPI $\leq$ -1.0), normal precipitation ($-1.0 <$ SPI $\leq$ 1.0), moderately wet (1.0 $<$ SPI $\leq$ 1.5), very wet (1.5 $<$ SPI $\leq$ 2) and extremely wet (2.0 $<$ SPI $\leq$ Max) (EDO, 2020).

2.4. Methods to evaluate the temporal behaviour of time series

The Mann-Kendall test (Kendall, 1955; Mann, 1945) is a non-parametric trend test, widely used in hydrology. The Mann-Kendall test is based on the calculation of Kendall's tau measure of association between two samples, which is itself based on the ranks with the samples. This test requires the data to be independent, meaning that a positive/negative serial correlation might affect the power of the test, rejecting or accepting the null hypothesis (H_0) of monotonic trend absence even if true (Fatichi et al., 2009). For instance, a positive serial correlation among the observations can be perceived by the test as the data having a trend, even in the absence of a trend (error of type I; Cox and Stuart, 1955). Non-parametric bootstrap strategies such as block bootstrapping (Carlstein, 1986b; Kunsch, 1989b) can be used to cope with the serial dependence, breaking the data set into smaller chunks for sampling purposes that might wreck any correlations that exist in the larger data set (Arteche, 2021; WCAP, 2004). By separating the observations in blocks far enough, in time, they are nearly uncorrelated and can be treated as exchangeable, if the time series has length n and can be factored as $n = b * l$, where b and l are integers (Chernick and LaBudde, 2014). Using block bootstrap (Canty and Ripley, 2021), time-series data will be first deseasonalized, and then block bootstrap will run with a fixed block length (l) equal to 12 and a (b) number of blocks for the assessment of a Mean Mann Kendall Tau, i.e., trend component.

Seasonal Trend decomposition using Loess (STL) was proposed by Cleveland et al. (1990), and it is a filtering procedure for decomposing a seasonal time series at a period v into three components: trend (T_v), seasonal (S_v) and remainder (R_v) (or irregular or error), for $v = 1$ *to* N:

$$Y_v = T_v + S_v + R_v \tag{1}$$

STL consists of an inner loop nested inside an outer loop (in the case of STL robustness estimation). If Y_v indicates no non-Gaussian behaviour (i.e. aberrant behaviour on S_v and T_v), then only the inner loop is used. The STL algorithm (Verbesselt et al., 2015) is tuned using six parameters: $n_{(p)}-$ number of observations in each cycle of the seasonal component related to periodicity; $n_{(i)}-$ number of passes through the inner loop; $n_{(0)}$: number of robust interactions of the outer loop, e.g. if robustness is not needed then: $n_{(0)} = 0$; $n_{(l)}-$ smoothing parameter for the low-pass filter, e.g. if robustness is not needed then: $n_{(i)} = 2$; $n_{(t)}-$ smoothing parameter for the trend component; and $n_{(s)}-$ smoothing parameter for the seasonal component. Selecting the first four parameters is straightforward since they are based on empirical rules/default values and can be selected in an automated way. The $n_{(s)}$ is always odd and its choice can be ambiguous as it depends on the expert knowledge of the characteristics of the data being analysed. Nevertheless, STL considers subseries of values at each position of the seasonal cycle (called cycle-subseries), revealing changes in timing, amplitude and variance that occur in the seasonal cycle (Sellinger et al., 2008). However, STL assumes that the T_v and S_v components change slowly and smoothly, and does not permit the detection of abrupt changes within the time series (Verbesselt et al., 2010a).

Pettitt's test (Pettitt, 1979) is a rank based nonparametric statistical test method for determining a shift (i.e., change point) in the mean of a time series. Pettitt's test can be used to detect the statistical significance and position of an abrupt change or a step change in the time series. Traditionally, this test has been assumed to be less sensitive to outliers and skewed distribution. The null hypothesis (H_0) of the test is that, when arbitrarily splitting the sample into two segments, there is no change in the mean value of each segment (Xie et al., 2014). Pettitt's test normally only allows detection of a unique changing point in a time series. The Pettitt test uses the Mann-Whitney U test to find a single change point in the median of a series and returns a p-value for the change point (Pettitt, 1979).

All the aforementioned statistical methods are most frequently used in hydrological studies and can either assess the trend or an abrupt change. This work presents the BFAST method, which is commonly used in remote sensing studies (Verbesselt et al., 2010a), but not in hydrological field, and has some advantages, as it allows the smooth and abrupt changes detection of time series. BFAST is an additive decomposition model like STL (Eq. (1)) that iteratively fits a seasonal model (S_v) and a piecewise linear trend (T_v). T_v is determined with m breakpoints $\upsilon_1^*, \ldots, \upsilon_m^*$, with defined $\upsilon_0^* = 0$ *and* $\upsilon_{m+1}^* = N$, and corresponding segment-specific intercept α_j and slope β_j, such as:

$$\begin{aligned} &T_v = \alpha_j + \beta_j v \\ &\upsilon_{j-1}^* < v \leq \upsilon_j^*, \text{where } j = 1, \ldots, m. \end{aligned} \tag{2}$$

This way, the trend component has every time series segment fixed between breakpoints, but can differ across breakpoints. The magnitude of an abrupt change at a breakpoint is derived by the diffrence between T_v at υ_{j-1}^* and υ_j^*, such as (Verbesselt et al., 2010a):

$$Magnitude = (\alpha_{j-1} - \alpha_j) + \left(\beta_{j-1} - \beta_j\right) t \tag{3}$$

A harmonic seasonal pattern (S_v) is calculated with p breakpoints $\upsilon_1^\#, \ldots, \upsilon_p^\#$ with defined $\upsilon_0^\# = 0$ *and* $\upsilon_{p+1}^\# = N$, and corresponding segment-specific harmonic $a_{i,\ k}$ and phase $\delta_{i,\ k}$, for K harmonic terms ($k = 1, 2, 3$) and frequency (f; e.g. $f = 12$ annual observations for monthly time series) (Verbesselt et al., 2010b):

$$\begin{aligned} &S_v = \sum_{k=1}^{K} \alpha_{i,k} \sin\left(\frac{2\pi k v}{f} + \delta_{i,k}\right) \\ &\upsilon_{i-1}^\# < v \leq \upsilon_i^\#, \text{where } i = 1, \ldots, p \end{aligned} \tag{4}$$

Hence, the seasonal component can be different for every time series segment comprised between two different breakpoints.

The segment decomposition model is not straightforward, as the number of required segments in the trend ($m + 1$) and seasonal ($p + 1$) components have to be determined. First, the ordinary least squares (OLS) residuals, based moving sum (MOSUM) test (Chu et al., 1995), is used to test whether one or more breakpoints occur. If the test is significant ($p <$ 0.05), the optimal position of breakpoints and the optimal number of breaks can be estimated by minimising the residual sum of squares, and minimising the Bayesian Information Criteria (BIC), respectively. The method starts the iteration decomposition by estimating a seasonal component $\widehat{S}_v$ from a standard season-trend decomposition, followed by the iterative estimation of the parameters until the number and position of the breakpoints are stable:

Step 1- the OLS-MOSUM is used to test the breakpoints of the trend component. If they occur, the number and position of these breakpoints ($\upsilon_1^*, \ldots, \upsilon_m^*$) are estimated using least squares from the seasonally adjusted data;
Step 2- a robust regression based on M-estimation is performed to estimate the α_j and β_j parameters, i.e. trend changes are estimated based on Eq. (2);

Step 3- the OLS-MOSUM is used to test the breakpoints of the season component. If they occur, the number and position of these breakpoints ($\upsilon_1^{\#}, \ldots, \upsilon_p^{\#}$) are estimated using least square from the seasonally adjusted data;

Step 4- a robust regression based on M-estimation is performed for the estimation of the $a_{i,k}$ and $\delta_{i,k}$ parameters, i.e. the seasonal changes based on Eq. (4).

Some limitations of this method have been reported in previous studies (Masiliūnas et al., 2021; Saxena et al., 2018): i) the time series must be completed without gaps; ii) the user has to choose a priori the number of breakpoints based on the duration and pattern of the time series; only the strongest breaks will be identified if the number of breaks in the time series is greater than the number of breaks specified by the user and; iii) the processing time can be high in the case of big data, as it needs to converge in both the seasonal and trend components.

All statistical analyses were performed in the R statistical environment (R Core Team, 2018).

3. Results and discussion

The widely used Mann-kendall test was performed to test monotonic trend. The monthly accumulated stored water in the three reservoirs showed non- statistical evidence of monotonic trend before and after the use of block bootstrap (Table 2). If the Mann-Kendall test was performed without considering the serial correlation of the time series, a false significant monotonic trend ($\alpha = 5$ %) would be detected in all three piezometers. Block bootstrap Mann-Kendall test was performed detecting non-monotonic behaviour of the trend for all-time series (Mean Mann Kendall Tau $\cong 0$), illustrating the need to examine within the hydrological time series both monotonic and non-monotonic trends.

The trend (i.e., smoth change) decomposed by BFAST and LOESS showed similar behaviour in each freshwater source (Fig. 2). The difference between these two methods lies in the fact that BFAST enables identifying several distinct time periods, quantifying the slope and its significance in each segment. Moreover 14 months SPI data were closely related to the behaviour of the trend of both freshwater sources.

Piezometers Sotavento (MS) and Faro (CF) presented a similar trend behaviour (LOESS, Fig. 1), following the dry/wet conditions (14-month SPI; Fig. 2), with valeys during the drought years and peaks during the wet years. Both piezometers (Sotavento and Faro) had two similar significant breakdates ($p < 0.05$) for groundwater levels in October/November 1983 and December 1995. The years of 1983 and 1995 were classified as drought years, ending these periods in October 1983 and December 1995, respectively. BFAST defined the biggest change of the trend component (recovery) from November to December 1995, where magnitudes of 4.71 m and 1.67 m, were respectively obtained for the piezometers Sotavento and Faro. From July 1995 to June 1996, piezometers Sotavento and Faro were highly correlated ($R^2 \cong 1$), presenting an upward trend (slope = 32 cm and slope = 10 cm, respectively). With regard to the piezometer Sotavento, a significant change point (i.e., at 95 % confidence level) in the mean value of piezometric series was detected by the Pettitt's test in December 1995 (Table 3), where the mean value increased from 25.8 m to 26.6 m. This change point also corresponds to the highest magnitude breakpoint detected by BFAST.

Concerning the piezometer Faro, the Pettitt's test detected the change point (i.e., a level shift) in May 1999 (Table 3), five months later than the breakpoint detected by BFAST in December 1998. According to Pettitt's test results, the mean went down from 1.32 m to 0.96 m.

Silves groundwater levels also closely reflected the SPI 14 months. During the period from January 1990 to December 1992, there was a drawdown of 1.69 m (1992 was a drought year with six months classified as severe drought, four months as moderate drought, and one month as extreme drought), followed by a negative slope of −1.21 m for the period of July 2003 to June 2006 (2005 was a drought year, with three months classified as a moderate drought, eight months as severe and one month as extreme). After the drought event of 2004/05, no recovery periods occurred in this piezometer (Fig. 2).

The significant breakdates ($p < 0.05$) of November 1989, December 1992 and 1995, and January 2010 detected by BFAST in piezometer Sotavento were similar to those observed in piezometer Silves, although with a delay in 1989 (1 month), 1995 (2 months) and 2010 (2 months). Moreover, the piezometer Silves had also similar datebreaks of February 1996 and 1999, June 2006 and March 2010 to the piezometer Faro, albeit with a delay in 1995 and 1998 (2 months) and 2010 (3 months), and advancement in 2006 (4 months). Mallakpour and Villarini (2016) showed that the Pettitt test detects more easily a break if the variability of the data decreases. Observing Table 3, Sotavento was the piezometer with the lowest coefficient of variation (4.64 %). For this piezometer, the datebreak determined by the BFAST coincided with the breakpoint of the most significant magnitude detected by the BFAST.The majority of these breakpoints showed a connection between drought episodes (14 months SPI) and shifts in piezometric levels. As a result, the main drivers for the trend behaviour during these common periods could be related to climate variability. The most negative slopes of the three piezometers (Fig. 2) occurred during the period when groundwater assumed a relevant role in the Algarve region (i.e., until 1998; ARH Algarve, 2012), showing that the uptake of water intensified during the periods of drought. Some significant breakpoints were detected that could not be associated with climate variability, such as: December 2000 in piezometer Sotavento (slope of −0.69 m), December 1998 and 2001 (respectively, slopes of −0.38 m and 0.12 m) in piezometer Faro, and February 1999 and June 2006 (respectively, slopes of 0.19 m and 0.22 m) in piezometer Silves (Fig. 2). These breakpoints can be convincingly related to human activities. For instance, during the period of March 1996 and June 2003, the piezometer Silves showed two positive slopes (0.19 m and 0.22 m, respectively) related to a recovery period since, after the 2000s, surface water resources began to serve as the primary freshwater source (Fig. 2). However, due to the drought from 2003 to 2005 (Fig. 3), exploration of the Querença-Silves aquifer system resumed in October 2004 with an extraction rate of 500 l/s, which was halved in July 2005 due to a risk of saltwater intrusion (Do Ó and Monteiro, 2006).

Concerning the water accumulated at the end of the month, Beliche and Bravura reservoirs showed significant breakpoints in the trend in December of 1995, after the drought of 1995 (Fig. 3), with the highest turn of the trend component (recovery) from November to December

Table 2
Mann-kendall results of trend evaluation.

	Tau Kendall	Two-sided p-value	Block Bootstraping		Result H_0 ($\alpha = 5$ %)
			Mann Kendall Tau estimator standard error	Mean Mann Kendall Tau	
Sotavento	0.125	6.425E-05	0.0960	−0.0042	H_0 = not reject: Non- statistical evidence of monotonic trend
Faro	−0.132	4.07e-05	0.0863	−0.0026	H_0 = not reject: Non- statistical evidence of monotonic trend
Silves	0.130	0.00011	0.1096	0.0016	H_0 = not reject: Non- statistical evidence of monotonic trend
Odeleite	−0.065	0.10874	0.1092	−0.0084	H_0 = not reject: Non- statistical evidence of monotonic trend
Beliche	−0.077	0.03014	0.0983	−0.0063	H_0 = not reject: Non- statistical evidence of monotonic trend
Bravura	−0.023	0.52052	0.1059	−0.0052	H_0 = not reject: Non- statistical evidence of monotonic trend

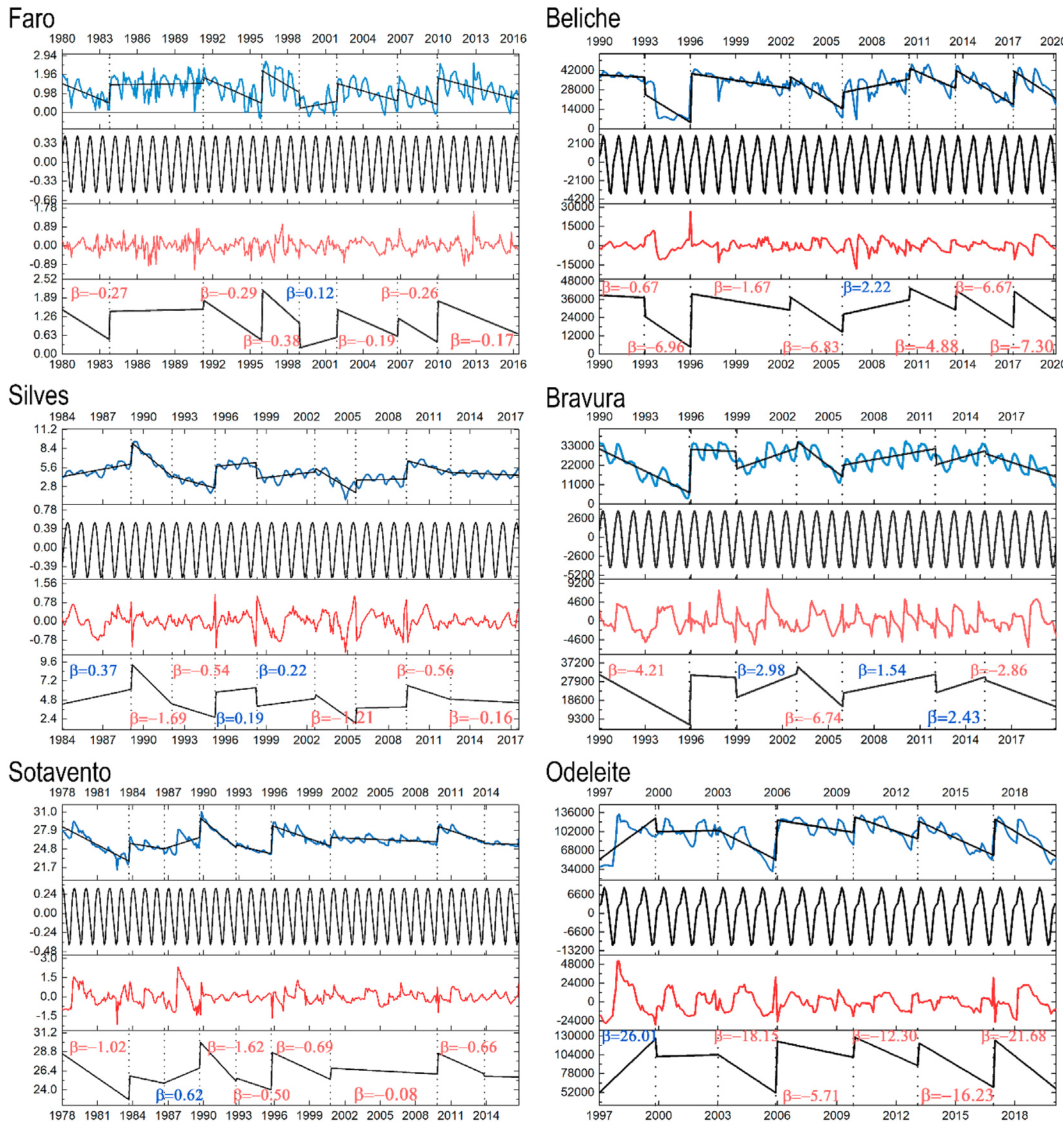

Fig. 2. Results of the BFAST application to hydrological series. Rectangle on the top:Trend resulting from BFAST (black line) and LOESS (blue line) for the piezometric levels (Silves, Sotavento and, Faro) and monthly accumulated stored water (Bravura, Beliche, and Odeleite); Rectangle at the middle (black line): Seasonal component resulting from BFAST; Rectangle at the middle (Red line): Remainder; Rectangle at the bottom: Trend resulting from BFAST with respective segments slopes (β) significant ($p < 0.05$).

1995 (i.e., magnitudes of 35.3 hm^3 and 24.7 hm^3, respectively). Regarding the water stored in the Beliche reservoir, Pettitt's test detected a lowering of the mean of the trend in March 1993, being detected a breakpoint by the BFAST three months earlier, i.e., December 1993 (Fig. 2). The Bravura reservoir exhibited negative slopes during a moderate drought between 1990 and 1995 (-4.21 hm^3) and a severe-to-extreme drought between 2003 and 2005 (-6.74 hm^3). All positive slopes can be related to normal precipitation periods, i.e. January 1999–December 2002 (slope = 2.98 hm^3) where 77 % of the months were normal and the early months were moderate drought (16.7 %), January 2006–January 2012 (slope = 1.54 hm^3) where approximately 85 % are normal years and, February 2012–April 2015 (slope = 2.43 hm^3), all classified as normal years (Fig. 2 and Fig. 3).

Odeleite dam was built after the two other dams in 1997, and BFAST signalized four breakdates (November 1999 and 2009, December 2005 and 2016, February 2013), that were, all related to drought episodes. During the study period, a significant positive slope (26 hm^3) was only found between December 1996 and November 1999 (during moderate drought; Fig. 3). This positive trend corresponded to the filling of the reservoir. The highest magnitude (in this case a lowering of storage levels) was in December of 2005 at the end of a severe drought period (≅18 hm^3) (Fig. 3). The Pettitt's test detected a significant point of change in the mean in August 2014 (Table 3), that could not be related to the breakpoints signalized by BFAST, and to drought periods Beliche showed a similar pattern of storage water levels, with breakdates for October 2005, February 2010 and 2013, and November 2016. These similarities are related to the fact that these two reservoirs constitute a unique system.

After the 2003–2006 drought, the first recovery period of the Bravura reservoir lasted approximately six years at 0.62 hm^3/month (January 2006 to January 2012), and Odeleite reservoir took four years and four

Table 3
Results of the Pettitt's test.

	Name	Two-sided *p*-value	Probable change point at time	Coefficient of variation (%)
Pettitt's test	Sotavento	4.628E-11	December 1995	4.64
	Faro	2.20E-16	May 1999	36.00
	Silves	1.71E-11	August 1992	24.46
	Odeleite	3.01E-07	August 2014	19.81
	Bravura	2.95E-07	March 1996	22.80
	Beliche	3.29E-05	March 1993	26.51

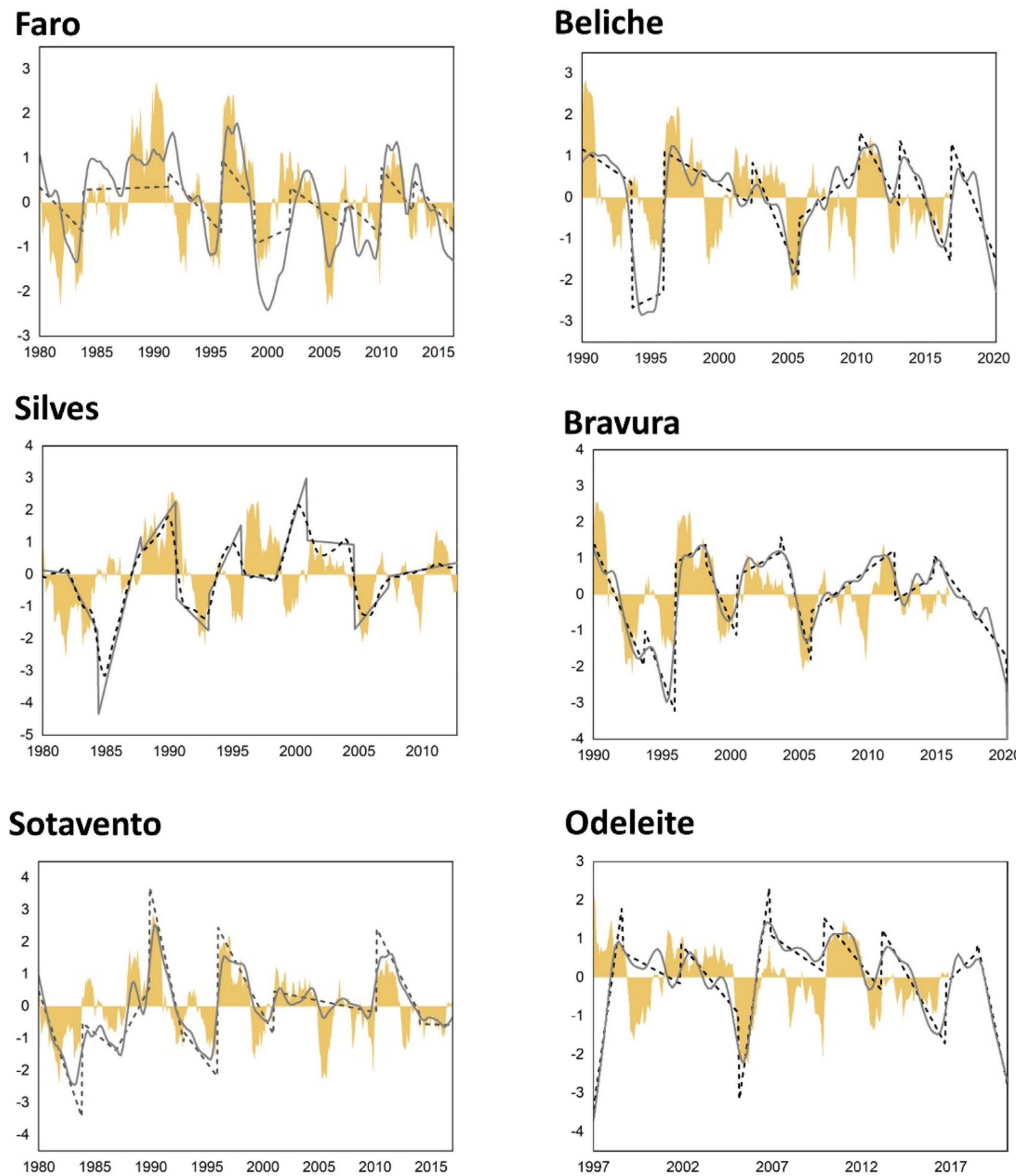

Fig. 3. *Z*-score values of the trends resulting from BFAST (dotted line) and LOESS (solid line), and 14 months SPI (Standardized Precipitation Index) (yellow area) for the z-score values of piezometric levels (Faro, Sotavento, and Silves) and z-score values of monthly accumulated stored water (Odeleite, Beliche, and Bravura).

months at 2.22 hm^3/month (November 2005 to February 2010). The BFAST method enabled the detection and quantification of recovery and drawdown periods, something that is not possible using common methods (LOESS, Pettitt's Test and Mann-Kendall Test). A correspondence was found between the mean change point detected by Pettitt's test and breakpoints detected by BFAST in all data, except for Beliche reservoir. This might be a consequence of data variability (Table 3) and the extension of the record which is the shortest of the three reservoirs (Fig. 2) (Mallakpour and Villarini, 2016).

Storage capacity, independent of the medium, had an influence on the resilience of water resources to drought conditions. For instance, both phreatic aquifers reacted quickly to weather conditions (14-month SPI), as the recovery periods matched to the end of drought periods and the upwards were related to the starting of the normal/wet period of rain. The detection of abrupt changes in the trend components of accumulated stored water in dammed reservoirs allowed us to establish relationships between similar trends. As expected, the Bravura reservoir followed the standard 14 month SPI more closely than the Odeleite-Beliche system as the latter is a unique system, located in two different locations. Moreover, Beliche reservoir, with its lower storage capacity, sometimes showed a delay or advance in the breakpoints of the trend when compared to the Odeleite reservoir. Nevertheless, some differences found between the trends of both reservoirs only occurred within one month.

None of the data (groundwater and surface water) showed seasonal breakpoints.

4. Conclusions

The performance of BFAST in detecting changing trends was evaluated in water resources over long-term period, (between 26 and 37 years). BFAST enabled robust detection of abrupt and gradual changes. The BFAST method outperformed the widely used Mann-Kendall and Pettitt tests in hydroclimatological studies, showing that monotonic trends and a single abrupt change are not adjustable to this type of data. The 14-

month SPI could be tied to reservoir storage levels and groundwater levels, showing BFAST some common datebreaks of surface water and groundwater resources (e.g., a common decline of the levels of the piezometers Silves and Sotavento and Beliche reservoir levels during the drought episode of 1992).

BFAST enabled assessment of the suitability of past management decisions when tackling drought events, showing, for instance, that during the period of 2003–2005, the three reservoirs demonstrated negative slopes (Beliche = -6.83 hm^3; Odeleite = -18.15 hm^3, and Bravura = -6.74 hm^3), where Odeleite (storage capacity of 117 hm^3) started showing this negative trend earlier in January 2003, followed by Bravura (storage capacity of 32.33 hm^3) in November 2003. This negative trend observed in the Odeleite storage volumes can be attributed to the fact that the severity of the hydrological drought was greater in that basin (i.e. the 14-month SPI classified six months as extreme drought) than that observed in Bravura (i.e. only one month was classified as extreme drought). Furthermore, Odeleite is located in a basin with average annual precipitation (722 mm/year) lower than observed in Bravura (821 mm/year). Piezometer Silves only showed a negative trend in July 2003, with this downward period ending in June 2006. This gap shows that the conjunctive use of groundwater and surface water resources was a good decision to reduce the effect of this drought, as there was a shortage of surface water resources.

In the Mediterranean region, drought events were found to increase substantially in summer. This fact can have a greater effect on society than the long-term rise in the average temperature, since adaption to weather extremes has to be faster. Quantification of the recovery and decline periods of water resources and their significance can help to establish mitigation measures for drought events. In the European Union, although it is not mandatory, the Drought Management Plan (EC, 2007) is a planning document that would benefit from the use of BFAST, since it can contribute to the establishment of a reliable early warning system based on hydrological indicators including stored surface reservoir volumes and aquifer water levels.

CRediT authorship contribution statement

Maria Paula Mendes: Conceptualization, Data curation, Research, Writing-original draft, Software **Victor Rodriguez-Galiano.**: Conceptualization, Methodology, Writing, Visualization, Reviewing and editing. **David Aragones-Borrego**: Software.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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