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Article *in* Journal of Hydrology · July 2019

DOI: 10.1016/j.jhydrol.2019.123973

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Journal of Hydrology 577 (2019) 123973

Contents lists available at ScienceDirect

Journal of Hydrology

journal homepage: www.elsevier.com/locate/jhydrol

Research papers

Comparison of different methods for detecting change points in hydroclimatic time series

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ARTICLE INFO

This manuscript was handled by A. Bardossy, Editor-in-Chief, with the assistance of Fateh Chebana, Associate Editor

Keywords:
Change point
Hydrological variability
Detection
Time series analysis
Nonstationary

ABSTRACT

An abrupt change is an important manifestation of hydroclimatic variability. Accurate detection of change points is a critical issue in hydroclimatic and climate change studies. In the article, we evaluated the performances of 12 methods (including both parametric and non-parametric) for detecting change points in hydroclimatic time series by considering the influences of eight major factors. Different methods exhibited different efficiencies and eight of the methods performed better which are recommended for application. Furthermore, the mean values of series and locations of change points were found to have little influence on the detection of change points. However, for a time series with smaller variance but bigger skewness and larger difference in the mean values before and after the change point, the abrupt changes can be more easily and accurately detected. Detection of change points in shorter series would have larger uncertainty. Based on the Monte-Carlo experiments, the efficiency of each method was quantified and its capability was quantitatively clarified. Detection of abrupt changes in precipitation over Southwest China showed that the Indian monsoon had a dominant influence on precipitation in the regions south of 30°N and west of 110°E. Since 2007 the Indian monsoon has maintained a weakening pattern, causing a decrease in precipitation on the Yunnan-Guizhou Plateau, which is one of the main causes of frequently occurring droughts. Results of this study can be a useful reference for choosing a method to detect change points in hydroclimate time series, and be an important complement for the detection and attribution of hydroclimatic variability.

1. Introduction

Hydrological analysis and design are fundamental in water-resources engineering practice (Favre et al., 2004; Raghunath, 2006; Kao and Govindaraju, 2007). Climatic and hydrological processes are usually assumed stationary, and observed hydroclimatic data are generally assumed to satisfy the consistency condition (Beighley and Moglen, 2003; Renard and Lang, 2007; Sang et al., 2010). Therefore, many methods of hydrological analysis and design are based on the stationary and consistency assumptions (Xu and Singh, 2004). However, the hydroclimatic system has been exhibiting significant variability over recent decades, perhaps due to the impacts of global change (Allen et al., 2002; Trenberth et al., 2014). In particular, streamflow regimes in many basins worldwide have been changing because of the profound influence of human activities, including water infrastructures, channel modifications, drainage works, as well as land use and cover changes (Milly et al., 2008; Sang and Yang, 2017). Statistically, probability distributions of hydroclimatic data and their parameters are changing (López and Francés, 2013; Cheng et al., 2014). How to detect the changed signals in the hydroclimatic system is of great socio-economic significance (Diffenbaugh et al., 2008; IPCC, 2013) and remains a challenge.

An abrupt change is a phenomenon frequently encountered in hydroclimate studies. It usually presents some physical process that causes an rapid switch or change from one mode of behavior to another (Thorne et al., 2005), as an important manifestation of hydroclimatic variability, for it intuitively reflects the changed signals in many situations (McCabe and Wolock, 2002; Wilby and Harris, 2006; McCuen, 2016). Another well-known example is the abrupt increase (or decrease) in streamflow and water level in rivers due to dams and other

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https://doi.org/10.1016/j.jhydrol.2019.123973
Received 14 February 2019; Received in revised form 25 May 2019; Accepted 19 July 2019
Available online 21 July 2019

water-retaining constructions (Zhang et al., 2014; Tongal et al., 2017; Stosic et al., 2016).

There are many methods for detecting abrupt change points in hydroclimatic time series. These methods, with different mathematical hypotheses and scopes of application, can be divided into two types: parametric and non-parametric tests (Kendall et al., 1999). When using parametric tests, such as moving *T*-test (Welch, 1947) and moving *F*-test (Jackson et al., 2016), a proper probability distribution should be preset and its statistical parameters should be estimated from observed data (Geisser and Johnson, 2006). Non-parametric tests, such as Mann-Kendall test (Kisi and Ay, 2014) and Pettitt test (Pettitt, 1979), need not to postulate any probability distribution and thus perform better compared with parametric tests.

All methods for the detection of change points in time series have advantages and disadvantages (Lloyd et al., 2014; Jeon et al., 2016; Turner et al., 2016), and they may not suffice to meet practical needs. For example, the moving average method is suitable for detecting the change point at around the middle of a time series but performs poorly for the change point that is close to either of the two endpoints (Nigro et al., 2014). The Mann-Kendall test is commonly used for detecting change points but would be unreliable when there are several change points in a time series (Gocic and Trajkovic, 2013). The rescaled range analysis method mainly depends on the difference between a time series before the change point and that after the change point (Mandelbrot and Wallis, 1969). Generally, change points detected by a method are often not as reliable as expected, and results vary with the methods used. Hence, the reliability of detected abrupt changes in a hydroclimatic time series may be suspect, which may lead to an unreasonable evaluation of global change impacts and biased hydrological design values. However, efficiency and applicability of different methods for detecting change points are not clearly clarified, and how to accurately detect change points in a hydroclimatic time series still remains a challenge.

The objective of this study therefore is to evaluate the efficiencies of the twelve methods that are used widely for the detection of change points, aiming at providing guidelines for choosing a proper method. To that end, the capabilities of these methods are first clarified through Monte-Carlo experiments, where the influences of eight factors are considered. After that, these methods are used to detect the variability and abrupt changes of annual precipitation in Southwest China, and their relationship with the climatic variability is investigated. The conclusions are given finally.

2. Methods for detection of change points

Twelve methods that are used widely for the detection of change points were considered here, with the aim to compare their performances and improve the accuracy of detection results. These methods included: moving F-test, moving T-test, Lee-Heghinian Bayesian method (Lee and Heghinian, 1977), ordered clustering method, rescaled range analysis method, Brown-Forsythe test (Brown and Forsythe, 1974), moving rank sum test, moving runs test, optimal dimidiate partitioning method, Mann-Kendall test, Bayesian analysis method (Perreault et al., 2000a,b), and Pettitt test. Their abbreviations and applicable conditions are briefly listed in Table 1.

3. Comparison of different methods

3.1. Factors influencing detection of change point

In order to quantitatively evaluate the performances of different methods, the factors which influence the detection of change points in hydroclimatic time series should be first specified. Considering a general situation of hydrological variability, for a time series X_t ($t = 1,2,\ldots,n_t$) with a length of n_t, it is assumed that there is one abrupt change at an unknown time point n_1 ($n_1 < n_t$), which is to be estimated by using

Table 1
Average efficiencies of 12 methods used widely for the detection of abrupt change points in time series. The results are obtained from Monte-Carlo experiments.

Method	Abbreviation	Type	Applicable conditions	Average efficiency C_i
Moving runs test	MRT	Non-parametric	The data does not need to follow normal distribution or homogeneity of variances Wanner et al. (2002)	0.550
Moving rank sum test	MRS	Non-parametric	The relative location of two sub-data sets before and after the change point should be known Ansari and Bradley (1960)	0.361
Lee-Heghinian's Bayesian method	LHB	Non-parametric	The data should follow the Gaussian distribution and the prior distribution of abrupt change should be uniform distribution Zhou et al. (2012)	0.310
Moving T-test	MTT	Parametric	The two sub-data sets before and after the change point can have different mean values, but their variance values should be equal Buishand (1984)	0.307
Ordered clustering method	OCM	Parametric	The data should have no significant trend Chen et al. (2011)	0.307
Bayesian analysis method	BYS	Non-parametric	The data is assumed as following a distribution in the exponential family Jo et al. (2016)	0.307
Brown-Forsythe test	BFT	Parametric	There is no requirement for data length, probabilistic distribution or variance difference between two sub-data sets Shoemaker (2003)	0.294
Pettitt test	PET	Non-parametric	The data is distribution-free and resistant to the presence of outliers, but the results would be better when the time series represents the central part of the distribution Mallakpour and Villarini (2016)	0.280
Moving F-test	MFT	Parametric	The data is assumed as following the normal distribution, which highly influences the testing results Shoemaker (2003)	0.129
Rescaled range analysis	RST	Parametric	It performs good for the times series with positive correlations and long data lengths Bassingthwaighte and Raymond (1994)	0.040
Mann-Kendall test	MKT	Non-parametric	The data should be serially independent Yue and Wang (2002)	0.087
Optimal information dimidiate partitioning method	ODP	Non-parametric	The data should have a high signal-to-noise value Goodwell and Kumar (2017)	0.011

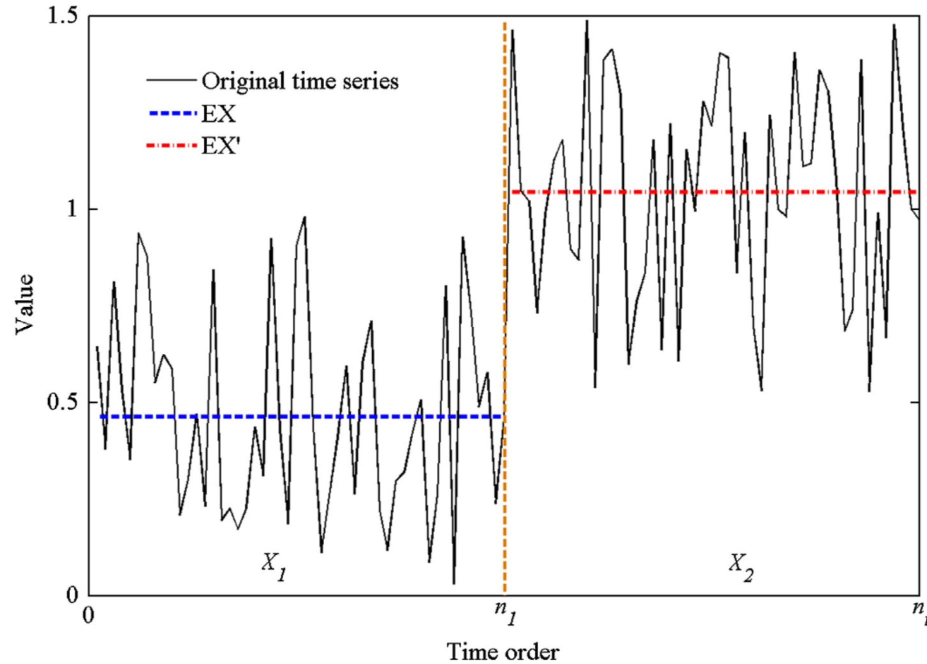

Fig. 1. Diagrammatic sketch showing general situation of abrupt change point in a time series.

the twelve methods. The sub-series before and after the change point n_1 is denoted as X_1 and X_2 (Fig. 1), which follow a certain probability distribution:

$$X_1 \sim \mathrm{PDF}(\mathrm{EX}, \mathrm{Cv}, \mathrm{Cs})$$
$$X_2 \sim \mathrm{PDF}(\mathrm{EX}', \mathrm{Cv2}', \mathrm{Cs2}') \tag{1}$$

where PDF means the probability density function; *EX* (*EX*'), *Cv* (*Cv*'), *Cs* (*Cs*') are the mean value, coefficient of variation, and coefficient of skewness of the series X_1 (X_2). From Eq. (1), it is seen that eight factors would influence the detection of change point at n_1, that is, the length n_1 of X_1, length n_t -n_1 of X_2, *EX*, *Cv*, *Cs*, *EX*', *Cv*', and *Cs*'. To more clearly describe the difference between X_1 and X_2, some factors can be transformed to:

$$\theta_1 = (EX' - EX)/EX$$
$$\theta_2 = (Cv' - Cv)/Cv$$
$$\theta_3 = (Cs' - Cs)/Cs \tag{2}$$

where θ_1 describes the relative difference between *EX* and *EX*'; θ_2 describes the relative difference between *Cv* and *Cv*'; and θ_3 describes the relative difference between *Cs* and *Cs*'. The eight new factors are then denoted as n_t, n_1/n_t, *EX*, *Cv*, *Cs*, θ_1, θ_2, θ_3, and their influences on the detection of a change point can be more conveniently evaluated.

3.2. Design of MC experiments for investigating the influences of eight factors

Monte-Carlo (MC) experiments were done to investigate the influences of the above eight factors on the performances of 12 methods given in Table 1. The specific steps are described as follows:

(1) Set a group of values for parameter n_t, n_1/n_t, *EX*, *Cv*, *Cs*, θ_1, θ_2, θ_3, and generate synthetic series with the total number of *N* ($N = 10{,}000$ here). Each synthetic series includes the same change point.
(2) Use the *i*th ($i = 1, 2, \ldots, 12$) method in Table 1 to detect the change point in the *j*th ($j = 1, 2, \ldots, 10{,}000$) synthetic series, and evaluate the efficiency R_{ij} of the result using the following equation:

$$R_{ij} = \begin{cases} 1, & \frac{|n_{ij} - n_1|}{n_t} \le \delta_1 \\ 0, & \frac{|n_{ij} - n_1|}{n_t} > \delta_1 \end{cases}, \quad i = 1, 2, \ldots, 12;\ j = 1, 2, \ldots, 10000 \tag{3}$$

where n_1 is the change point preset, and n_{ij} is the change point in the *j*th synthetic series detected by the *i*th method; n_t is the length of synthetic series; and δ_1 is a threshold used to quantify the difference between n_1 and n_{ij}. A method succeeds if the estimation n_{ij} is close to the true point n_1, with the criterion of $(n_{ij} - n_1)/\ n_1 < \delta_1$. Here δ_1 was set as 0.01 for the MC experiments;

(3) The efficiency of each method was described as C_i, $i = 1, 2, \ldots, 12$:

$$C_i = \frac{1}{N}\sum_{j=1}^{N} R_{ij} \times 100\backslash\% \tag{4}$$

$$S_i^2 = \frac{1}{N}\sum_{j=1}^{N} (R_{ij} - C_i)^2 \tag{5}$$

where S_i^2 is the variance of the R_{ij} result and was used to describe its uncertainty.

(4) Reset the *k*th group of values for eight parameters in step (1), and repeat the steps (1–3) to investigate the variation of methods' efficiency with parameter values.

3.3. Influence of each factor on detection of change point

Through the MC experiments explained above, the influences of eight factors (n_t, n_1/n_t, *EX*, *Cv*, *Cs*, θ_1, θ_2, θ_3) on the efficiency of the 12 methods were analyzed, as discussed below.

(1) Influence of n_t. Here the Pearson-III (P-III) probability distribution, as applied commonly in hydrological design in China, was used to generate the synthetic series. The values of six parameters were set as: $EX = 1000$, $Cv = 0.5$, $Cs = 2$, θ_1=1, θ_2=0, θ_3=0, and the position of change point was set at the middle of synthetic series, that is, n_1/n_t=0.5. Then, the data length (i.e., parameter n_t) was increased from 50 to 500, with a length interval of 50, to investigate its influence on the efficiency of each method. Fig. 2 shows performances

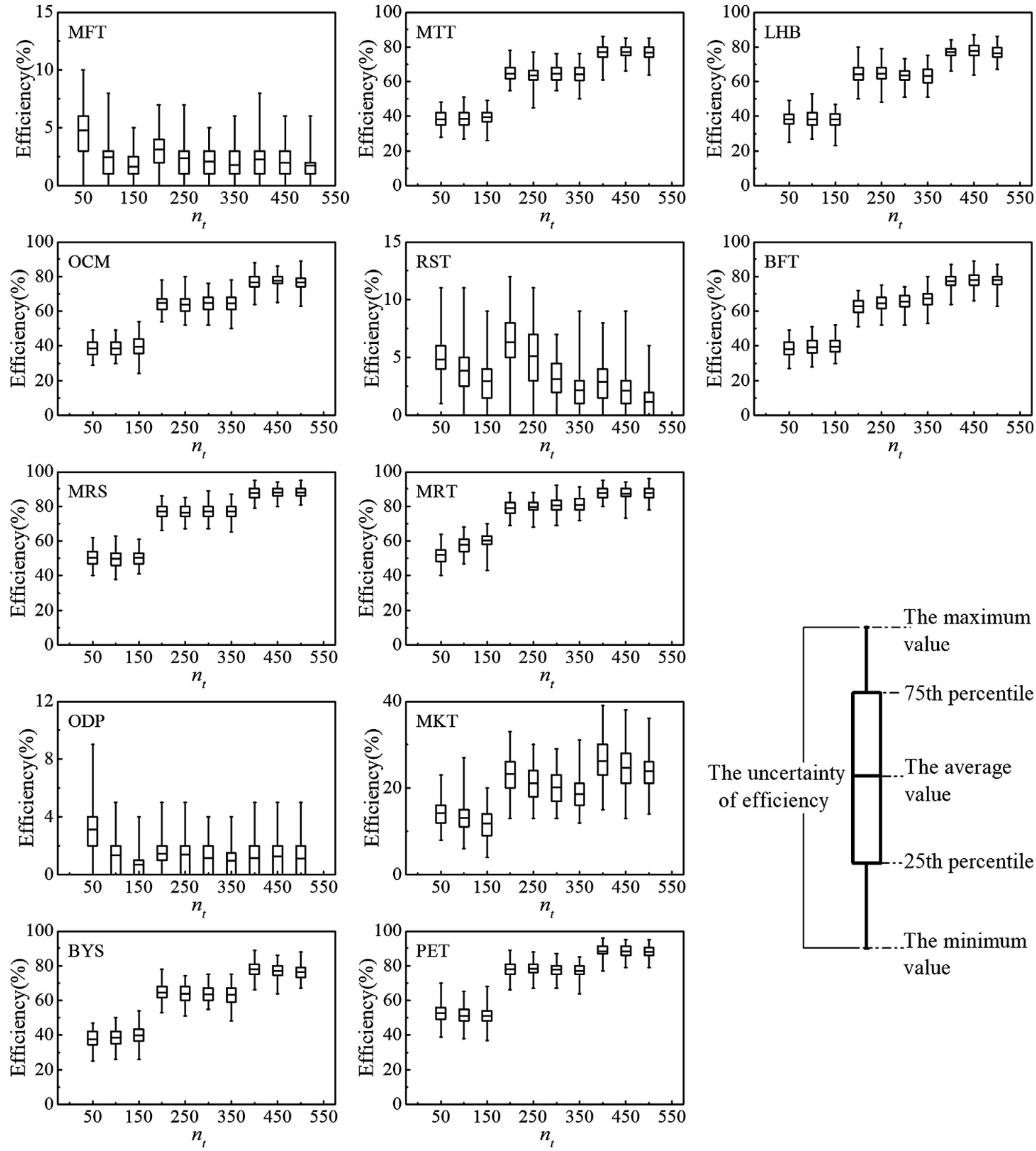

Fig. 2. Variation of the efficiencies of 12 methods with the increase of series length n_t. The results are obtained from the synthetic series, which follow the Pearson-III probability distribution and have the parameters $n_1/n_t = 0.5$, $EX = 1000$, $Cv = 0.5$, $Cs = 2$, $\theta_1=1$, $\theta_2=0$, $\theta_3=0$.

of these methods. The influence of data length n_t on these methods is obviously different. Among them, MFT, RST, and ODP performed poorly for any length, with an efficiency smaller than 10%. The results of MKT were also not as good as expected no matter the length, with an efficiency smaller than 30%. Comparatively, the other eight methods (MTT, LHB, OCM, BFT, MRS, MRT, BYS and PET) performed much better, and PET performed the best, with an efficiency bigger than 40%.

It is thus seen that the data length has a big influence on the detection of a change point. The efficiency of the eight methods with satisfactory performance can be divided into three parts, corresponding to the data length < 200, 200–400, and > 400, respectively. Their efficiency was similar in each part, but increased with the data length. The efficiency was higher than 70% for the data length bigger than 400. Note that the noncontinuous variation of methods' efficiency is due to the threshold $\delta_1 = 0.01$ preset. Interestingly, it was found that the efficiency of each method for a smaller length had a bigger uncertainty, described by the height of box in Fig. 2, and the change point in a time series with a longer length can be more easily detected. Considering that the result for a certain data length had similar uncertainty for each method, it was not considered again in the following discussion. The

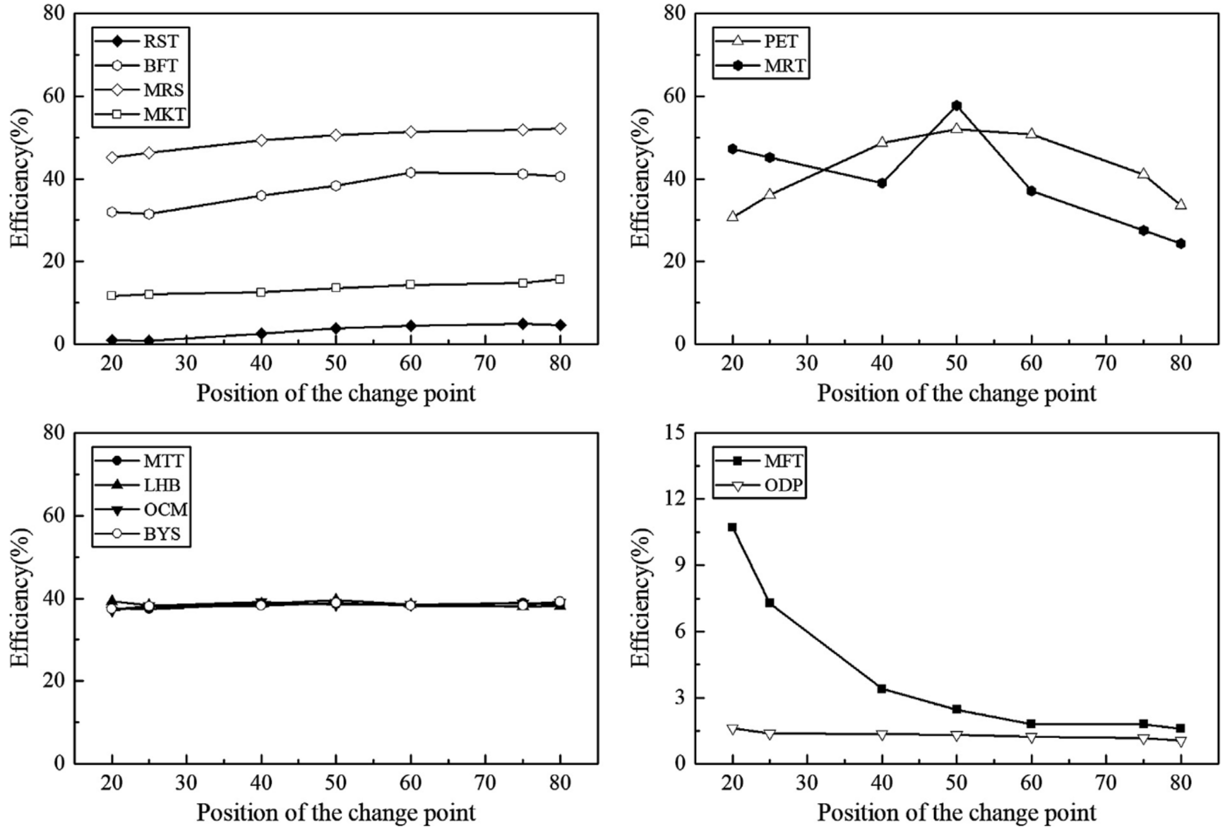

Fig. 3. Variation of the efficiencies of 12 methods with the movement (n_1/n_t) of change point in time series. The results are obtained from the synthetic series, which follow the Pearson-III probability distribution and have the parameters $n_t = 100$, $EX = 1000$, $Cv = 0.5$, $Cs = 2$, θ_1=1, θ_2=0, θ_3=0.

lengths of observed hydroclimatic time series are usually smaller than 100 years, and the results with shorter data lengths have worse efficiencies (in Fig. 2), thus the length of synthetic series was set as 100 to investigate the influence of other seven factors.

(2) Influence of n_1/n_t. The parameters were set as: $n_t = 100$, $EX = 1000$, $Cv = 0.5$, $Cs = 2$, θ_1=1, θ_2=0, θ_3=0, and parameter n_1/n_t was valued as 1/5, 1/4, 2/5, 1/2, 2/3, 3/5, 4/5, mainly to investigate its influence. Fig. 3 presents the results obtained from different methods, which can be divided into four types based on their different efficiencies. BFT, MRS, MKT, and RST were in the first type and their performances became better when the change point moved from the start-point to the endpoint of the series. When using PET and MRT in the second type, the best results appeared when the change point was in the middle of the series (i.e., $n_1/n_t = 0.5$), but the performance of the two methods became worse when the change point moved from the middle to the endpoint, especially for MRT. The MTT, OCM, LHB and BYS methods belonged to the third type, for which the results did not change with the position of change point but were stable. For the MFT and ODP method in the fourth type, the results were the worst and far away from the true results, with an efficiency < 10%.

(3) Influence of EX. The parameters were set as: $n_t = 100$, $n_1/n_t = 0.5$, $Cv = 0.5$, $Cs = 2$, θ_1=1, θ_2=0, θ_3=0, and the mean value EX of the sub-series before the change point was given different values, mainly to investigate its influence on the detection. Fig. 4 indicates that when the mean value increased from 0 to 5000 and other seven parameters were fixed at certain values, there were no obvious changes in the results obtained from different methods. It was found that the EX parameter had little influence on both the detection of change point and the efficiency of each method, and it need not to be considered in practical analysis. Following the general understanding of hydrological variability, it is known that the significance of abrupt change is mainly determined by the degree of relative difference between before and after the change point, but should have little relationship with the mean value of the series, explaining the reasonableness of the result in Fig. 4.

(4) Influence of Cv. The parameters were set as $n_t = 100$, $n_1 = 50$, $EX = 1000$, $Cs = 2$, θ_1=1, θ_2=0, θ_3=0, and the Cv parameter increased from 0 to 1.5 to investigate its influence. In Fig. 5, dramatic changes occur in the results of all methods, except for MFT, RST and OPD which kept their inferior performance and had an efficiency smaller than 10%. The efficiency of other nine methods (MTT, LHB, OCM, BFT, MRS, MRT, MKT, BYS, PET) similarly declined quickly with the increase of Cv value. This can be qualitatively explained as follows. If a time series shows a large variation (that is, large Cv value), the random component would occupy a large ratio in the original series and submerge the abrupt change occurring in the series, causing the difficulty in detecting the change point.

(5) Influence of Cs. The parameters were set as $n_1 = 50$, $EX = 1000$, $Cv = 0.5$, θ_1=1, θ_2=0, θ_3=0, and the Cs parameter increased from 0.5 to 3.0, to investigate its influence. In Fig. 6, the efficiency of the BFT, PET, MRS and MRT methods increased with the increase of Cs value. Comparatively, the efficiency of MKT, MTT, BYS, LHT and OCM kept stable, but again they exhibited inferior performance for any Cs value. It was found that big skew characteristics (i.e., big Cs value) of a time series would be favorable for the detection of change point, which can be explained as follows.

For a hydrological time series with more skew statistical characteristics (that is, bigger Cs value), the values at most of data points are more likely concentrated to its modal value but far from its mean value, causing more obvious difference between before and after the change point and the easier detection.

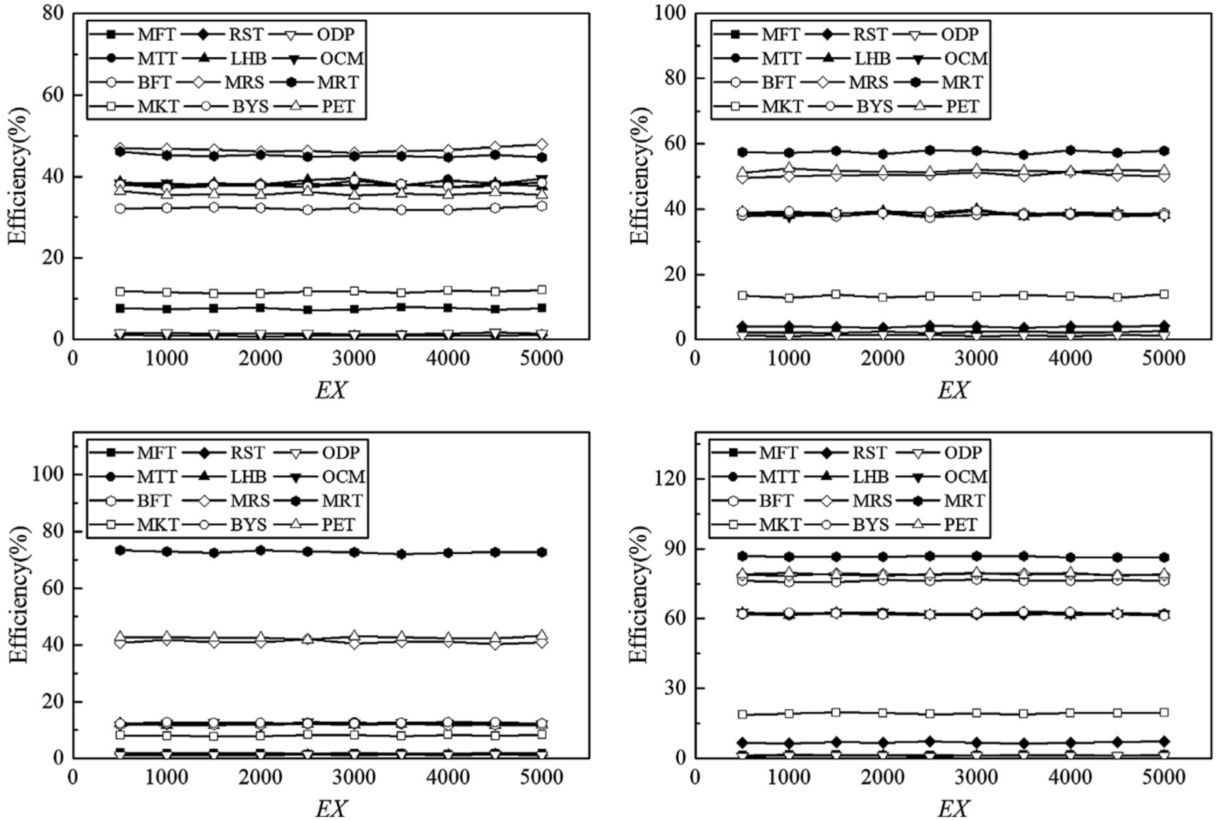

Fig. 4. Variation of the efficiencies of 12 methods with the increase of mean value *EX* of time series. The results are obtained from the synthetic series, which follow the Pearson-III probability distribution and have the parameters n_t = 100, n_1/n_t = 0.5, Cv = 0.5, Cs = 2, θ_1=1, θ_2=0, θ_3=0.

(6) Influence of θ_1. The six parameters were set as n_1 = 50, EX = 1000, Cv = 0.5, Cs = 2, θ_2=0, θ_3=0, and the θ_1 parameter was increased from 0 to 2.0 to investigate its influence. Results in Fig. 7 show that the efficiency of all methods became better with the increase of parameter θ_1, except for RST and ODP which kept their inferior performance. It is known that parameter θ_1 just reflects the difference of mean values before and after the change point in the original series, thus a bigger value of θ_1 indicates a more obvious abrupt change, and it would more easily be detected.

(7) Influence of θ_2. The parameters were set as n_1 = 50, EX = 1000, Cv = 0.5, Cs = 2, θ_1=1, θ_3=0, and the θ_2 parameter was increased from 0 to 1.5 to investigate its influence. In Fig. 8, the results obtained from the 12 methods showed different changes. To be specific, the result of MFT increased sharply, but that of MKT, MRS, BFT, OCM, LHB, MTT, BYS, and PET decreased. Interestingly, the efficiency of MRT fell first in the θ_2 range of 0–0.5 and then increased afterwards. The results of RST and OPD were as small as 0 and did not change for any θ_2 value. The increasing efficiency of MFT with θ_2 was due to its own basic idea, that is, MFT uses the *F* test to evaluate the significance between two variances; bigger θ_2 value means bigger difference in the variance of the two sub-series between before and after the change point, which would more easily be detected by MFT. Besides, the varying efficiency of MRT was mainly due to the first increase and then decrease in the number of runs when considering the P-III PDF.

(8) Influence of θ_3. The parameters were set as n_1 = 50, EX = 1000, Cv = 0.5, Cs = 2, θ_1=1, θ_2=0, and parameter $\theta_3$was increased from 0 to 2 to investigate its influence. In Fig. 9, the efficiency of MFT, RST and OCM was at low level and did not change with the increase of parameter θ_3; the efficiency of MKT just increased slightly.

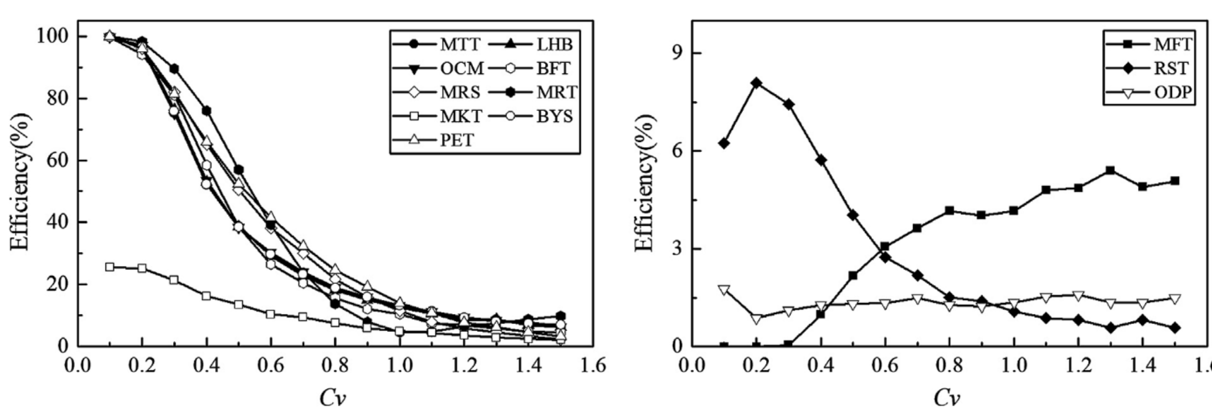

Fig. 5. Variation of the efficiencies of 12 methods with the increase of variation coefficient *Cv* of time series. The results are obtained from the synthetic series, which follow the Pearson-III probability distribution and have the parameters n_t = 100, n_1/n_t = 0.5, EX = 1000, Cs = 2, θ_1=1, θ_2=0, θ_3=0.

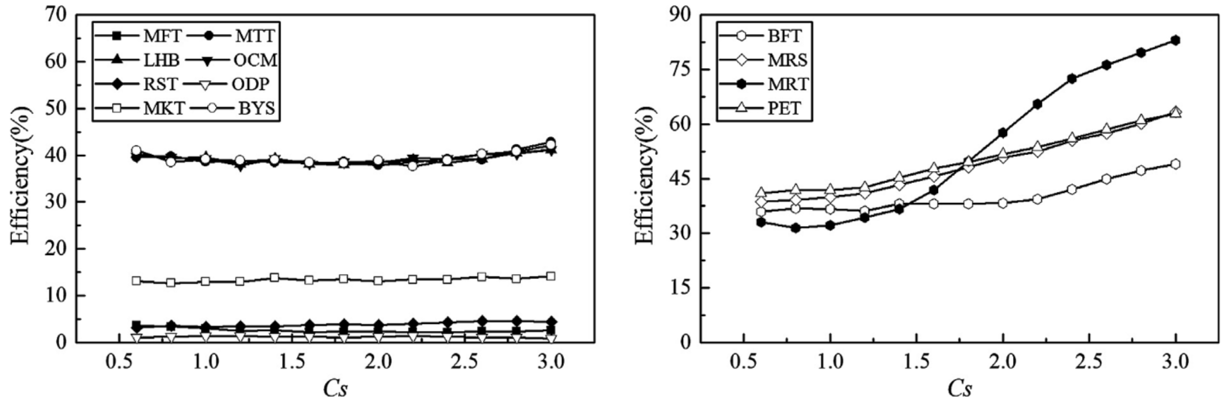

Fig. 6. Variation of the efficiencies of 12 methods with the increase of skewness coefficient *Cs* of time series. The results are obtained from the synthetic series, which follow the Pearson-III probability distribution and have the parameters n_t = 100, n_1/n_t = 0.5, EX = 1000, Cv = 0.5, θ_1=1, θ_2=0, θ_3=0.

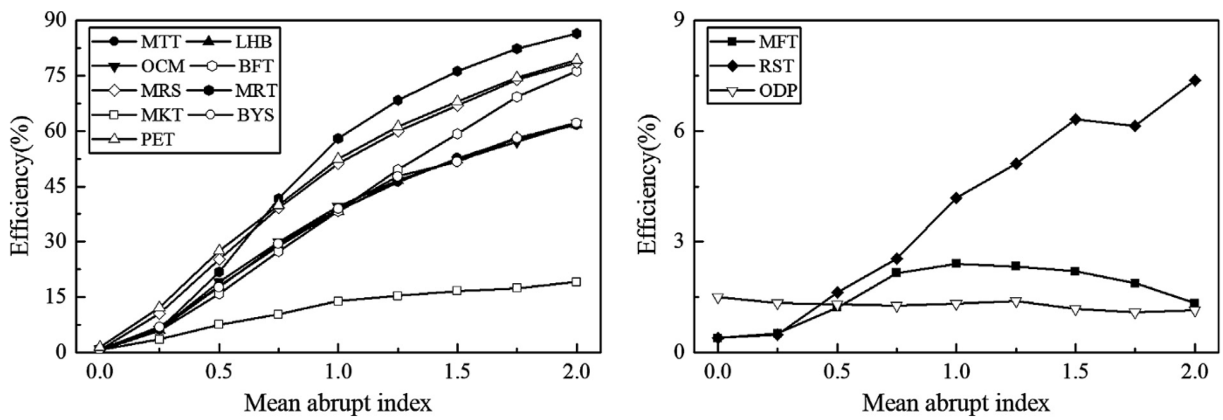

Fig. 7. Variation of the efficiencies of 12 methods with the increase of parameter θ_1 of time series. The results are obtained from the synthetic series, which follow the Pearson-III probability distribution and have the parameters n_t = 100, n_1/n_t = 0.5, EX = 1000, Cv = 0.5, Cs = 2, θ_2=0, θ_3=0.

Comparatively, the efficiency of other eight methods increased obviously with parameter θ_3. The result here was similar to that in Fig. 6, and the reason was also closely related to the modal value of series, as explained above.

3.4. Discussion of results

Overall, the above results of MC experiments indicated that the efficiency of the twelve methods was mainly influenced by the parameters θ_1, Cv and θ_2. When a time series had bigger θ_1 but smaller Cv and θ_2, its change point would more easily be detected. The Cs and θ_3 parameters also had an influence on the results, but the degree of influence was weaker than that of the former three factors. The change point in a time series with bigger Cs and θ_3 would more easily be detected. The EX and n_1/n_t parameters had little influence on the results. The n_1 parameter had little influence on the efficiency of these methods, but the results would have big uncertainty when parameter n_1 had smaller values. As a result, these factors should be carefully considered when choosing a proper method to detect change points in a hydroclimatic time series.

Besides, results also indicated different efficiencies of the 12 methods. The MFT, RST, MKT and ODP methods performed poorly,

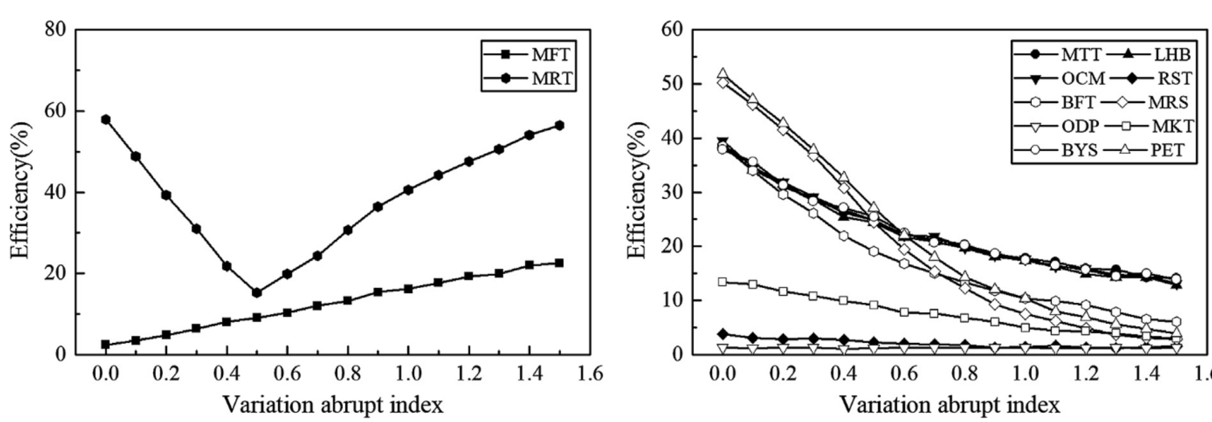

Fig. 8. Variation of the efficiencies of 12 methods with the increase of parameter θ_2 of time series. The results are obtained from the synthetic series, which follow the Pearson-III probability distribution and have the parameters n_t = 100, n_1/n_t = 0.5, EX = 1000, Cv = 0.5, Cs = 2, θ_1=1, θ_3=0.

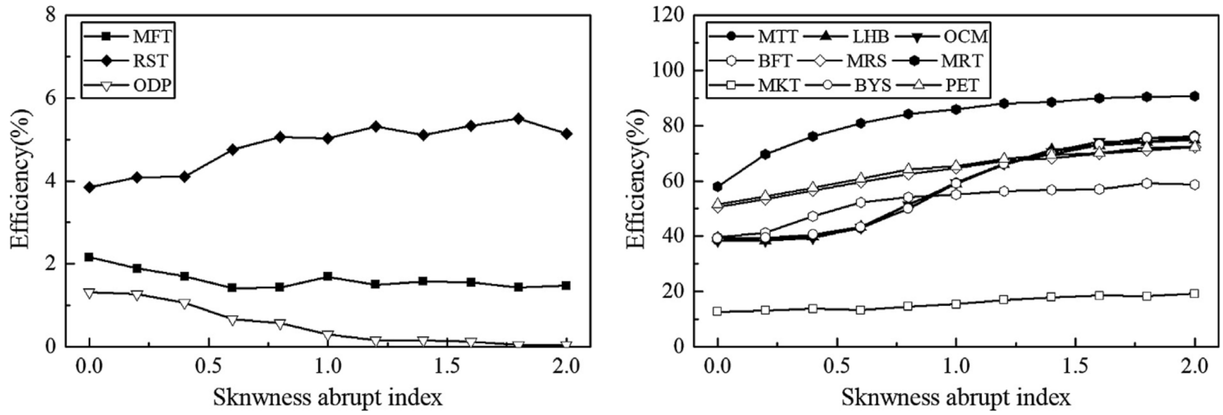

Fig. 9. Variation of the efficiencies of 12 methods with the increase of parameter θ_3 of time series. The results are obtained from the synthetic series, which follow the Pearson-III probability distribution and have the parameters $n_t = 100$, $n_1/n_t = 0.5$, $EX = 1000$, $Cv = 0.5$, $Cs = 2$, θ_1=1, θ_2=0.

although the MFT method can perform slightly better facing larger values of parameter θ_2. Comparatively, the efficiencies of MTT, LHB, OCM, BFT, MRS, MRT, BYS and PET were better, and thus they are recommended for the detection of change point. The efficiency of each method estimated in this study (in Table 1) can be a useful reference for the choice of a method for the detection of change points in hydroclimatic time series. However, the detection of change points in hydrological time series is much more complex and difficult than that in synthetic series, because the influencing factors would mutually influence each other simultaneously. In practice, not only the efficiency of these methods but also their different performances under various practical situations should be considered. Thus these methods are further tested using a case study of observed dataset in the next section.

4. Abrupt changes in precipitation in Southwest China

Southwest China, covering the southeast Tibetan Plateau, is one of the regions that is sensitive to global climate change (Yao et al., 2012; Sang et al., 2013; Feng et al., 2014). Especially, the southeast Tibetan Plateau is well known as the “Asian water tower”, where many major Asian rivers, including the Yellow River, Yangtze River, Brahmaputra River, Mekong River and others, originate from (Lutz et al., 2014; Immerzeel et al., 2013). They provide a vital water source for hundreds of millions of people in China and Southeast Asia (Immerzeel et al., 2013; Zhang et al., 2016). Over recent years, global climate change has caused a change in the streamflow regimes of these major rivers (Zhang et al., 2013), and caused frequent occurrences of drought events in Southwest China. Knowledge about the variability of hydrological process and its response to the changing climate is thus critical for drought mitigation and sustainable water resources management in the region.

Following the water vapor fluxes (Sang et al., 2016), it is known that the precipitation process in Southwest China is mainly controlled by the Indian summer monsoon (ISM). ISM brings significant amounts of warm and wet air currents from the Indian Ocean and comes to Southwest China through the Bay of Bengal. Recent studies have indicated the weakening of Indian monsoon (Wu, 2005; Thompson et al., 2006). It can directly influence the precipitation variability in Southwest China, and would directly cause severe drought disasters and water resources shortages (Feng et al., 2014; Ji et al., 2015; Tan et al., 2017). However, it is still not clear when the ISM started its weakening pattern, and what influence it has on the precipitation variability and its spatial distribution in Southwest China. Accurate detection and attribution of abrupt changes in the precipitation in Southwest China is therefore a fundamental issue.

To clarify it, we used the twelve methods to detect abrupt changes in both the time series of ISM and precipitation in Southwest China, and compared the results for investigating the physical causes. For achieving the goal, we used the annual precipitation data measured at 144 meteorological stations in Southwest China (Fig. 11) and detected their change points. The ISM index used here is defined based on the convection near the Bay of Bengal, whose intensive activity is associated with two of the major precipitation maxima in the south Asian region (Wang and Fan, 1999), including Southwest China. All the precipitation and ISM data have the same observation period from 1961 to 2013.

The change point detected in the ISM time series is shown in Table 2. Among all the results, the change point of 2007 was detected by seven methods (MTT, LHB, OCM, RST, BFT, ODP, BYS). The change points obtained from MFT, MRT, MRS and PET were 2008 or 2006, just being close to 2007. As a result, it was thought that the abrupt change in the ISM process occurred in 2007, since then the Indian monsoon has a much smaller amplitude. The mean values of the ISM time series before and after 2007 were 0.160 and −0.964, respectively. Fig. 10 visually presents that the ISM time series kept stable in 1961–2007 but then obviously decreased, indicating its reliability.

The same practice was applied to the annual precipitation series. Results in Fig. 11 indicate that among all the 144 precipitation time series, the precipitation time series measured at 48 stations in the central area (i.e., the Yunnan-Guizhou Plateau within 100°–111°E and 22°–30°N) of Southwest China showed a decreasing pattern, with the abrupt decrease occurring around 2002–2008, being consistent with the abrupt decrease in 2007 in the ISM. The local difference of results can be due to the complex topography, geography and hydroclimate conditions in the area. Besides, the precipitation time series measured at eight stations at the boundary of Southwest China did not indicate significant abrupt changes at 5% significance level. It is thus thought that although the boundary of Southwest China is geographically closer to the Bay of Bengal, the weakening Indian monsoon has little influence on the precipitation in the local area, but the effect of weakening strengthens when moving inland. However, the precipitation time

Table 2
Abrupt change points in the time series of the Indian summer monsoon index detected by 12 methods.

Method	Method's efficiency	Abrupt change point identified	Method	Method's efficiency	Abrupt change point identified
MFT	0.129	2008	MRT	0.550	2008
MTT	0.307	2007	MRS	0.361	2006
LHB	0.310	2007	ODP	0.011	2007
OCM	0.307	2007	MKT	0.087	2005
RST	0.040	2007	BYS	0.307	2007
BFT	0.294	2007	PET	0.280	2006

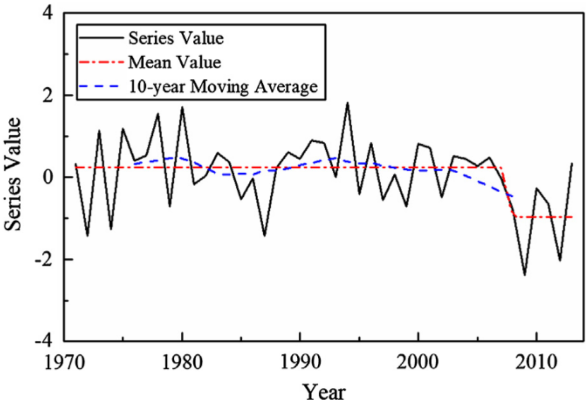

Fig. 10. Abrupt change point detected in the time series of Indian summer monsoon, and the mean values of series before and after the change point.

series measured north of 30°N on the whole showed no abrupt changes or even abrupt increase, differing from the abrupt decrease of precipitation south of 30°N.

A previous study (Yao et al., 2013) confirmed three distinct domains of climate condition in the Tibetan Plateau, associated with the influence of westerlies (north of 35°N), Indian monsoon (south of 30°N), and transition in between 30°N and 35°N respectively. The results of spatial pattern of abrupt changes in annual precipitation were consistent with previous studies. Hence, two important findings can be obtained here. The first is that the Indian monsoon directly controls the precipitation variability in the regions south of 30°N and west of 110°E in Southwest China, but its effect is weak in the local area of boundary. The other is that the weakening pattern of the Indian monsoon over the recent decade caused the decrease in precipitation on the Yunnan-Guizhou Plateau in Southwest China, which can be main reason for frequent occurrences of droughts.

5. Conclusions

As an important complement for the detection and attribution of hydroclimatic variability, accurate detection of abrupt changes in hydroclimatic time series is critical for understanding the effects of climate change and human activities. Although there have been many methods for meeting the needs, they do not suffice to meet practical

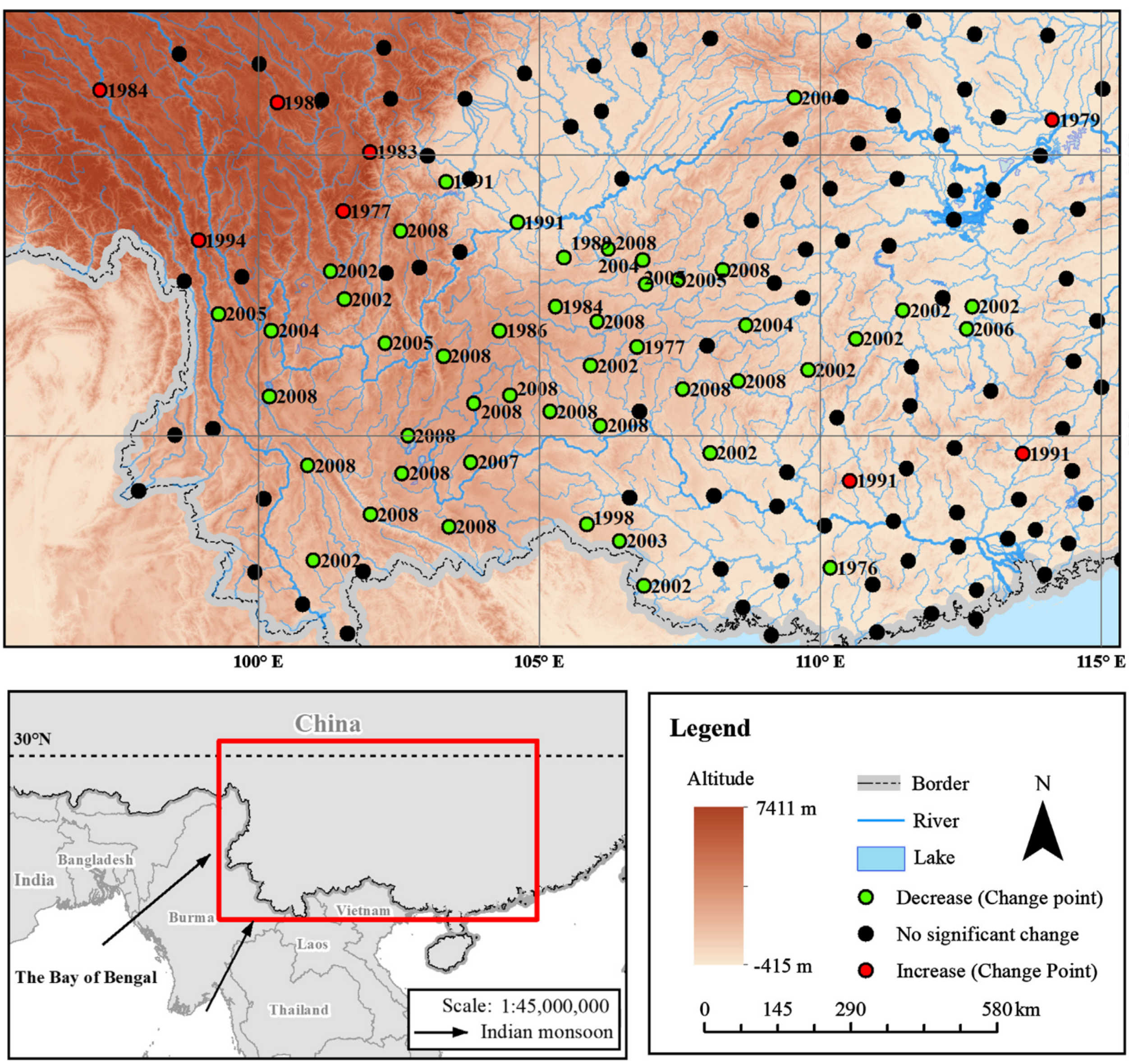

Fig. 11. Abrupt change points detected in the annual precipitation time series at measured at 144 stations in Southwest China.

needs due to limited applications. In this study, we compared the performances of 12 methods that are used widely for the detection of change points through Monte-Carlo experiments. We found that the MFT, RST, MKT and ODP methods had inferior performance. Comparatively, the MTT, LHB, OCM, BFT, MRS, MRT, BYS and PET methods performed better, and thus they are recommended for the detection of change points.

We also found that for those time series which have smaller variance (Cv and θ_2 in Figs. 5 and 8) but bigger difference in mean values before and after the change point (θ_1 in Fig. 7), the abrupt changes can be more easily and accurately detected; for the time series with big skew characteristics (Cs and θ_3 in Figs. 6 and 9), the abrupt changes can also be easily and accurately detected. However, the mean values (EX in Fig. 4) of time series and the location (n_1/n_t in Fig. 3) in the series have little influence on the detection of change points. For the time series with shorter length (n_1 in Fig. 2), the detection results of change points may have bigger uncertainty and thus should be carefully considered. Considering performances of these methods and the influences of the above factors, we quantified the efficiency of each method (Table 1), and emphasize the accuracy and reliability of the change points from the method with high efficiency.

We then used these methods to detect abrupt changes in precipitation in Southwest China, and further investigated its physical connection to the weakening Indian monsoon. Results indicate that the Indian monsoon directly controls the precipitation variability in the regions south of 30°N and west of 110°E in Southwest China, but its effect is weak in the local area of boundary (Fig. 11). Since 2007 the Indian monsoon has maintained its weakening pattern (Fig. 10), and causes the decrease in precipitation on the Yunnan-Guizhou Plateau, which may be the main reason for the frequent occurrence of droughts. If the Indian monsoon keeps the weakening effect, the droughts and water resources shortages in Southwest China would be inevitably aggravated, causing great difficulty to the socioeconomic development in local and surrounding regions. Therefore, more proactive and effective adaptation strategies should be implemented to handle the unfavorable situation.

Finally, it should be pointed out that characteristics of observed hydroclimatic data are complex, and the detection of change points in hydroclimatic time series is challenging. Both the complex variability of hydroclimatic process and the efficiencies of different methods should be carefully considered together. Especially, the physical causes of the abrupt changes in hydroclimatic process should be explored, based on which the reliable results of abrupt change in time series can be obtained.

Declaration of Competing Interest

None.

Acknowledgments

The authors gratefully acknowledged the valuable comments and suggestions given by the Editor and the anonymous reviewers. The data was obtained from the China Meteorological Data Sharing Service System (http://cdc.cma.gov.cn/) and the website: http://apdrc.soest.hawaii.edu/projects/monsoon/ismidx/ismidx-jja.txt. This project was financially supported by the National Natural Science Foundation of China (No. 91547205, 91647110, 51579181), the Strategic Priority Research Program of Chinese Academy of Sciences (No. XDA20060402), and the Youth Innovation Promotion Association CAS (No. 2017074).

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