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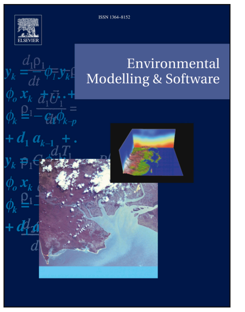

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Multivariate overall and dependence trend tests, applied to hydrology

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CRediT authorship contribution statement

Dorsaf Goutali: Conceptualization, Formal analysis, Methodology, Software, Validation, Writing – original draft, Writing - Review & Editing. **Fateh Chebana:** Conceptualization, Methodology, Supervision, Validation, Writing – review & editing

Abstract

Given climate change, trend detection is gaining increasing attention in the context of multivariate frequency analysis. In this paper, we propose new statistical tests for multivariate trend detection. The first one, a multivariate overall trend (MOT) test, is designed to detect trend in all components of the multivariate distribution (margins and dependence structure) whereas the second test is a multivariate dependence trend (MDT) test focusing on detecting trend in the dependence structure. A simulation study is used to evaluate the performance of the proposed tests. Results show that the proposed MOT test performs well when trend is present in margins, in the dependence structure and/or in both. Likewise, results of the proposed MDT test indicate an interesting power when the trend is in the dependence structure. Moreover, an application to a real dataset is provided. Performing the proposed tests with the univariate tests provides a complete overview of trend detection.

Keywords: Trend, Hydrology, Multivariate, Non-stationarity, Copula, dependence structure.

Highlights

- Two multivariate trend tests for multivariate hydrological series are proposed.
- New multivariate overall trend (MOT) test dealing with trend in all the components of the whole multivariate distribution.
- New multivariate dependence trend (MDT) test focuses on trend in the dependence structure.
- Vast simulation study is considered to evaluate the performance of the tests.
- The developed tests show high performance, with increasing power observed as the trend slope and sample size increase..

Software and/or data availability

Software:

- The code used for developing the multivariate trend tests and the simulation study scenarios, implemented in the R language, can be found on GitHub at the following link: https://github.com/GOUD05/Multivariate-Trend-Tests.git
- Repository creator: Dorsaf Goutali.
- Creation date: 2024.
- Contact Information: Dorsaf.goutali@inrs.ca.
- Program Language: R version 4.1.3 (64bit).
- Required Software: R (Download from https://cran.r-project.org/), RStudio (Download from https://www.rstudio.com/).
- Cost: free.
- Required R Packages:
  - copula https://cran.r project.org/web/packages/copula/index.html,
  - Kendall , https://cran.r-project.org/web/packages/Kendall/index.html),
  - resample , https://cran.r-project.org/web/packages/resample/index.html,
  - VGAM: https://cran.r-project.org/web/packages/VGAM/index.html,
  - openxlsx: https://cran.r-project.org/web/packages/openxlsx/index.html,
  - gtools: https://cran.r-project.org/web/packages/gtools/index.html.
- Used Hardware: Computer with Windows 10, Intel i5 8th Gen processor 8 GB RAM, 256 GB storage.

Data:

- This study relies on the generation of synthetic data as a requisite part of the methodology to conduct simulations study. The provided code on GitHub generates data and simultaneously calculates the performance of the tests. The data used in the illustrative applications will be available on request.

1. Introduction

Hydrological frequency analysis (HFA) is widely used for modeling extreme hydro-meteorological events like floods, droughts, and storms (e.g. Hamed & Rao, 1998). Such events are often identified by correlated features, such as peak, volume, and duration for floods (e.g. Chebana & Ouarda, 2021; Grimaldi & Serinaldi, 2006). These dependent features highlight the need for a multivariate HFA approach, supported by various studies (e.g. Genest & Chebana, 2017; Li *et al.*, 2019; Requena *et al.*, 2013). Univariate HFA can provide only limited assessment of extreme events and their probability of occurrence (e.g. Chebana & Ouarda, 2011; Joyce *et al.*, 2018).

Commonly, HFA is based on the assumptions of stationarity, homogeneity, and serial independence. In the multivariate context, checking these assumptions, particularly stationarity, attracted less attention compared to modeling (e.g. Chebana & Ouarda, 2021; Gu *et al.*, 2018). Ignoring the testing step of these assumptions can lead to inaccurate results and potentially wrong decisions (e.g. Chebana *et al.*, 2013). Indeed, this step contributes to the choice of the appropriate model, which should integrate possible trends in some or all components of the multivariate distribution (margins and dependence structure). The stationarity assumption has long been compromised by climate change and human activities such as deforestation, and overuse of extraction from surface water and ground water (e.g. Milly *et al.*, 2008; Tan & Gan, 2015; Vidrio-Sahagún *et al.*, 2024). Related to theoretical considerations, it is no longer valid to believe that the design flood is always stationary (e.g. Aissia *et al.*, 2014; Kang *et al.*, 2019; Milly *et al.*, 2008). Therefore, in recent years, increasing attention has been paid to hydrological designs under non-stationarity (NS) conditions and particularly in the multivariate setting (e.g. Chebana & Ouarda, 2021; Li *et al.*, 2016; Zhang *et al.*, 2022).

A wide variety of parametric and non-parametric tests has been employed for trend detection (e.g. De Luca & Napolitano, 2023). The Mann-Kendall (MK) and the Spearman rank order correlation

Table 1: Overview of existing tests for trend in univariate and multivariate framework

(SR) tests are among the most non-parametric considered univariate trend tests (e.g. Chong *et al.*, 2022; Conover, 1980; Kendall, 1975; Ouarda *et al.*, 2018). In addition, Chebana et al. (2013) presented an overview of the available multivariate extensions of the univariate MK and SR tests. Being non-parametric and powerful is the main advantage of these multivariate tests. However, the latter were initially developed and designed for water quality analysis even though they have been directly employed later in HFA. Moreover, these multivariate tests are essentially based on their univariate counterparts (component-wise tests), do not take into account the dependence between the variables, and cannot identify the affected component . On the other hand, it seems that testing for trends in the dependence structure has not been explored yet.. Furthermore, upon reviewing the literature, it appears that there are no recently developed trend tests and recent studies (e.g. Chebana & Ouarda, 2021; Chebana *et al.*, 2013; Jalili Pirani & Najafi, 2020; Kang *et al.*, 2019; Karahacane *et al.*, 2020; Modarres, 2018; Xu *et al.*, 2023) consider multivariate tests reviewed by Chebana *et al.* (2013). In Table 1 the univariate and multivariate trend tests are summarised including their advantages and drawbacks.

In order to overcome the drawbacks of the multivariate trend tests, the objective of the present paper is to propose two multivariate trend tests. The first proposed test is a multivariate overall trend (MOT) test dealing with trend in all the components of the whole multivariate distribution (margins and the dependence structure). The second proposed one, a multivariate dependence trend (MDT) test, focuses on trend in the dependence structure. Therefore, the proposed tests, along with the existing univariate trend tests, allow dealing with the multivariate distribution as whole as well as its components.

Tests		Advantages	Drawbacks	Some references
Univariate tests	Mann-Kendall (MK) Spearman's rho (SR)	• Both tests have been recommended by the World Meteorological Organization as standard nonparametric procedures • Powerful • Robustness against missing values and outliers • Making very few assumptions • Detect increasing decreasing trend • Simple to apply	• The existence of positive autocorrelation in the data increases the probability of detecting trends when actually none exist, and vice versa • Inability to detect non-monotonic trend structures	Mann (1945); Yue *et al.* (2002) Bihrat and Bayazit (2003) Yue and Pilon (2004) Rutkowska (2015) Wang *et al.* (2020) Hamed and Rao (1998)
Multivariate component wise tests	Covariance-Inversion test (CIT) Covariance-Eigenvalue test (CET) Covariance Sum test (CST)	• Non-parametric tests do not make any assumption or precondition about the models • Detect increasing/decreasing trends • Simple to apply	• Designed for water quality analysis and not for hydrological fields, existing comparisons and evaluations of these tests are often based on scenarios that do not align with the hydrological context (e.g. sample size, distributions) • Essentially based on their univariate counterparts (component-wise tests) • Simple combinations of univariate tests and do not take into account the dependence between the variables • Cannot identify the affected components	Dietz and Killeen (1981) Hirsch and Slack (1984) Lettenmaier (1988) Loftis *et al.* (1991) Smith *et al.* (1993) Thas *et al.* (1998) Chebana *et al.* (2013)

The developed tests, MOT and MDT, are based on multivariate extension of Kendall's τ and not on combinations of univariate statistic tests. A simulation study to evaluate and compare the performances of the proposed tests is presented. The proposed tests are general and can be considered in other contexts and applications dealing with trends.

The paper is organized as follows. A brief theoretical background, related to the developed tests, is presented in Section 2. The proposed statistical tests for trend are described in Section 3. The simulation study to evaluate the performance of the tests is given in Section 4. The conclusions are reported to Section 5.

2. Available multivariate trend tests

In this section, we briefly present the available univariate and multivariate tests for trend. In statistical hydrology, mainly two non-parametric rank-based statistical tests are considered, namely the MK and SR tests. Even though, they have the same aim and similar performance, the univariate SR tests are less employed than MK ones (e.g. Sneyers, 1990; Yue *et al.*, 2002). More details about multivariate SR tests are provided in Chebana *et al.* (2013). In the following, we focus on presenting MK tests. Either in the univariate or multivariate settings, the null hypothesis of no trend TR is $H_0 : TR = 0$ against the general alternative hypothesis of a monotonic trend $H_1 : TR \neq 0$ and there exists at least a component u such that $TR^{(u)}$ is monotonic (e.g. Chebana *et al.*, 2013).

The univariate MK test is the most used test to detect monotonic univariate trends. Given a data series $(x_1, x_2, , \dots, x_n)$ of length n, the MK test statistic is given by

$$M = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sgn\left(x_j - x_i\right) \quad (1)$$

where x_j and x_i are both values in the series, and *sgn* (.) is a sign function:

$$sgn\,(x) = -1 \text{ if } x < 0, \qquad = 0 \text{ if } x = 0, \qquad = 1 \text{ if } x > 0 \quad (2)$$

Under H_0, the test statistic M has asymptotically normal distribution with mean $E(M) = 0$ and

$$Var(M) = \frac{n(n-1)(2n+5)}{18} \quad (3)$$

Multivariate extensions of the univariate MK tests have been established to analyze multivariate trends in the hydrological context. Table 2 gives an overview of the main properties of those existing multivariate MK tests covering their expression and the asymptotic distributions.

For all the tests presented in Table 2, let $M^{(u)}$ be the univariate MK test statistic for the observed time series $X_i^{(u)}, i = 1, \dots, n$ and component $u = 1, \dots, d$. For a given u, $M^{(u)}$ is defined as:

$$M^{(u)} = \sum_{1 \le i \le j \le n} sgn\left(x_j^{(u)} - x_i^{(u)}\right) \quad (4)$$

Under the null hypothesis H_0 of no trend, $M^{(u)}$ is asymptotically d-dimensional normal with zero mean and covariance matrix $C_M = (C_{u,v})_{u,v=1,\dots,d}$ with $C_{u,v} = cov(M^{(u)}, M^{(v)})$ which is estimated by

$$\hat{C}_{u,v} = \frac{t_{u,v} + r_{u,v}}{3} \text{ for } u \neq v \tag{5}$$

where

$$t_{u,v} = \sum_{1 \le i \le j \le n} sgn\left(\left(x_j^{(u)} - x_i^{(u)}\right)\left(x_j^{(v)} - x_i^{(v)}\right)\right) \tag{6}$$

$$r_{u,v} = \sum_{i,j,k=1}^{n} sgn\left(\left(x_k^{(u)} - x_j^{(u)}\right)\left(x_k^{(v)} - x_i^{(v)}\right)\right) \tag{7}$$

Table 2: Summary of the available multivariate MK-based trend tests

Expression of the test statistic	Asymptotic distribution under H$_0$ and decision rule
Covariance Inversion test (CIT) $D = M' C_M^{-1} M$ (8) where C_M^{-1} is the inverse matrix of C_M	• It is asymptotically $\chi^2(q)$ distributed under H_0, where q is the rank of the matrix $1 \le q \le d$. • The null hypothesis is rejected: if the value of D exceeds the critical threshold determined according to $\chi^2(q)$ distribution quantile, depending on the fixed significance level α.
Covariance Sum test (CST) $H = \sum_{u=1}^{d} M^{(u)}$ (9)	• The statistic H is asymptotically normal under H_0, with mean E(H) = 0 and variance: $var(H) = \sum_{u=1}^{d} var\,(M^{u}) + 2 \sum_{v=1,u=1}^{d,v-1} C_{u,v}$ (10) where $C_{u,v} = \text{cov}\,(M^{(u)}, M^{(v)})$ (11) with an estimator as given in (5) • The null hypothesis is rejected: similar to CIT
Covariance Eigenvalue test (CET) $L = \sum_{u=1}^{d} (M^{(u)})^2$ (12)	• The statistic$(M^{(u)})$ for $u=1,\dots,d$ are asymptotically normally distributed with zero mean and the approximate variance is $\sigma^2 = var\,(M^{(u)})$ as in (3) • If $(M^{(u)}$ are independent, The statistic L would be asymptotically $\sigma^2\chi^2(q)$- distibuted under H_0 where q is the rank of the covariance matrix as given in (5)

Notations: n is the sample size and d is the dimension or the number of components. More details about multivariate tests are provided in Chebana *et al.* (2013)

3. Proposed multivariate trend tests

To overcome the drawbacks mentioned above, the developed multivariate tests rely on two main aspects. The first one is the multivariate extension of the rank correlation coefficient Kendall's τ. This idea draws from Kendall's τ relationship with the univariate MK trend test statistic. The second ingredient is the moving window technique over the dependence.

Kendall's τ and univariate MK test

Kendall's τ is defined, in the bivariate and usual case, as the difference between the probabilities of concordance and discordance between two variables *X* and *Y* respectively with series x_1 , x_2 ...x_n and $y_1, y_2, \ldots, y_n$ (e.g. Kendall & Gibbons, 1990):

$$\tau(X,Y)_n = \frac{2}{n(n-1)} \sum_{(i<j)} sgn\left(x_j - x_i\right)\left(y_j - y_i\right) \tag{13}$$

Hence, the statistic of the univariate MK test statistic is a particular case of Kendall's τ (e.g. Dietz & Killeen, 1981; Hamed & Rao, 1998). Indeed, Kendall's τ has also been used to test the significance of trends in univariate data if the values in *Y* are replaced by *T* the time order of the time series *X*, i.e. *T = 1, 2,..., n*,. In that case, the test is called as Mann-Kendall test and the equations in (1) and (13) become the same (e.g. Hamed & Rao, 1998; Hirsch & Slack, 1984). Therefore, in an analogous way, the multivariate proposed test statistics are based on multivariate extension of Kendall's τ.

Kendall's τ in *d*-dimension and the proposed tests

In the literature, two extensions of Kendall's τ have been proposed in higher dimensions (e.g. Genest *et al.*, 2011). Consider a random vector *X* taking values in $\mathbb{R}^d$ with cdf $H(\mathrm{x}) = \mathbb{P}(\mathrm{X} \leq \mathrm{x})$ and continuous marginal distribution $F_1, \ldots, F_d$. Referring to Joe (1990), the first option of *d*-variate version of Kendall's τ for *H* is defined by:

$$\tau_{\mathrm{d}}(X) = \frac{2^d \mathbb{E}_H\{H(X)\} - 1}{2^{d-1} - 1} \tag{14}$$

where $\mathbb{E}_H$ denotes the expectation with respect to *H*. Note that $\mathbb{E}_H\{H(X)\} = \mathbb{E}_C\{C\,(\mathrm{U})\}$, where *C* is the copula of *H* and $U = (F_1\,(X_1), \ldots, F_d\,(X_d))$. The second option was established by Kendall and Smith (1940). It is defined as the average value of Kendall's τ taken over all possible pairs (X_r, X_s), with $r, s = 1, \ldots, d$ and $r \neq s$, viz. and $H_{r,s}$ is the bivariate cdf of (X_r, X_s):

$$t_d(X) = \frac{1}{d(d-1)} \sum_{r \neq s} \tau\ (X_r, X_s) \tag{15}$$

To develop the proposed tests, we used the *d*-variate extension given in the first option in (14). Indeed, this extension has the advantage to be expressed in terms of copulas. The use of copula allows to take into account the whole dependence structure instead of only dependence between pairs as in (16) (e.g. Genest *et al.*, 2011; Li *et al.*, 2011). Further, Nelsen (1996) mentioned that when $d = 3$, both extensions (14) and (15) coincide leading to:

$$\tau_3 = \mathrm{t}_3 = \frac{1}{3}\{\tau\,(X_1, X_2) + \tau\,(X_1, X_3) + \tau\,(X_2, X_3)\} \tag{16}$$

In our developed tests, the moving window technique has been employed in order to take into account the dependence evolution according to time. Indeed, contrary to the margins, the evolution of the dependence structure cannot be directly seen (e.g. Chebana & Ouarda, 2021). Moreover, the result of Kendall's τ between two series is a single value that represents the strength of the dependence and not the evolution of the dependence structure over time. Consequently, in order to bring out the aspect of the trend in dependence, Kendall's τ should be used in a series. This has been achieved by employing a moving window technique. The chosen window size, denoted *s*, should be selected in a way to be neither too large nor too small, in order to perform reliable analysis and adequate number of values for the identification of the dependence structure (e.g. Bender *et al.*, 2014; Chebana *et al.*, 2013).

Based on multivariate extension of Kendall's τ τ_3 in equation (16) developed by Joe (1990), let's substitute X_1 with *X*, X_2 with *Y*, and replace X_3 with the time order *T = 1, 2,..., n,*. Let τ_n denote the empirical version of bivariate Kendall's τ. In this context, we introduce the first proposed test statistic, T_{MOT} is given by:

$$T_{MOT} = \frac{1}{3}\left(\tau_n(X,T)^2 + \tau_n(Y,T)^2 + \tau_n(\tau_{nw}(X,Y),T')^2\right) \tag{17}$$

where τ_{nw} is the series of the empirical Kendall's τ obtained through moving window for corresponding series *X* and *Y* (see Figure 1). T' is the new series of time order that has the same length of τ_{nw}. Note that the length *q* of the obtained series τ_{nw} is related to the sample size *n* and the width *s* of the window as *q* = *n* – *s* + 1. Choosing the size of *s* involves a trade-off. On one hand, a small *s* increases the number of rolling window series *q* for reliable analysis. On the other hand, a large *s* is necessary to have a sufficient number of values to identify the dependence structure, but this might decrease *q* (e.g. Bender *et al.*, 2014; Chebana & Ouarda, 2021). In addition, the selection of the width *s* of the windows is a common challenge to various tests (e.g. Bücher *et al.*, 2019; Chebana, 2022). To the best of our knowledge, and considering the existing literature, formal statistical inference procedures specifically designed to address this purpose appear to be not clearly established (e.g. Bücher *et al.*, 2019; Kojadinovic & Yan, 2011).

Note that the window step in the moving windows shifts point-by-point in this study. Previous studies by Vidrio-Sahagún and He (2022) have shown that a potential bias is introduced due to the fact that data points located in the center of the series would be counted more times than those located at the bounds, thereby exerting a significant influence on the estimates.

We employed the square of each term in order to avoid them cancelling each other or reduce the final value of the statistics. This is similar when passing from the test CST in (10) to the test in (12). This test is designed to test overall trend in a multivariate series. Indeed, the first two terms

$\tau_n(X,T)^2$ and $\tau_n\,(Y,T)^2$ focus on the univariate trends in the variables *X* and *Y*, respectively, with respect to the time order *T*. However, the last term $\tau_n\,(\tau_{nw}(X,Y),T')^2$ introduces a distinctive multivariate perspective by considering the Kendall's τ between *X* and *Y* with a moving window applied through T'. Unlike other available multivariate trend tests, this term allows to integrate the dependence between the variables in the proposed test. Hence, the developed overall multivariate trend test T_{MOT} considers the trend both in margins and in the dependence structure.

In order to focus on the trend in the dependence structure, the following multivariate dependence trend (T_{MDT}) test is proposed:

$$T_{MDT} = \tau_n\,(\tau_{nw}(X,Y),T') \tag{18}$$

It represents the last term in (17) dealing only with dependence.

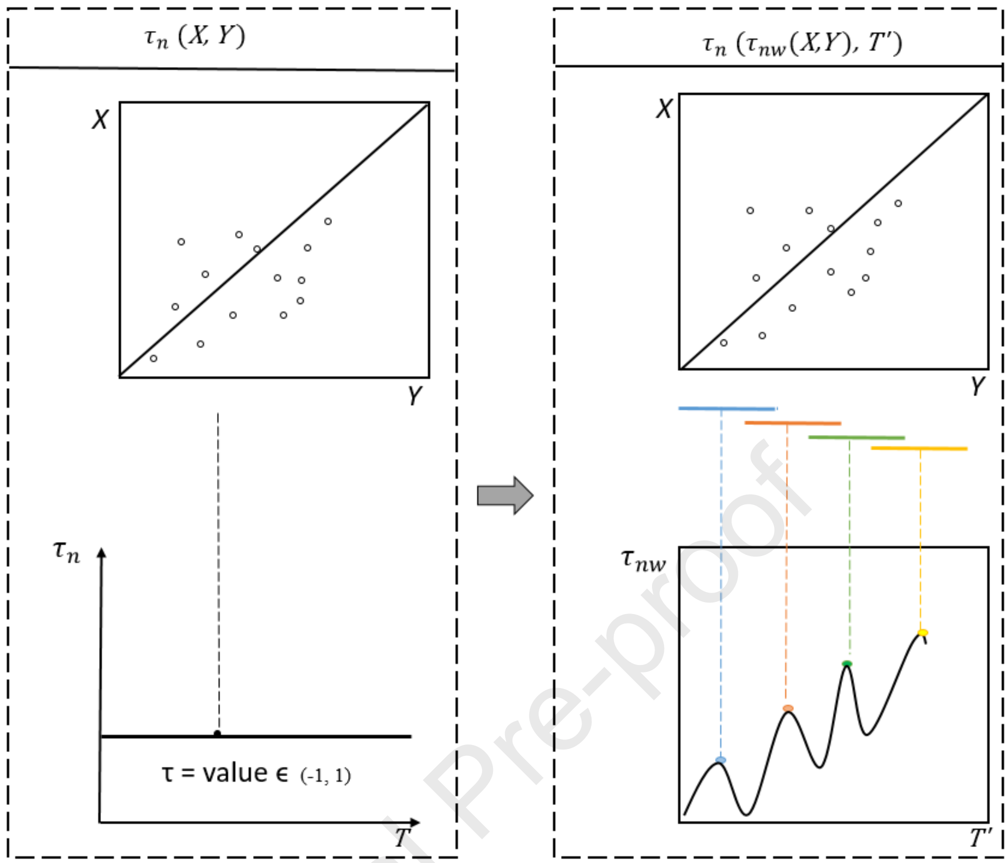

Figure 1: Illustration of evolution of the dependence structure obtained through moving windows for corresponding series X and Y

To evaluate the *p-values* corresponding to the proposed tests, the bootstrap procedure is considered (e.g. Good, 2005). The asymptotic distribution of the proposed statistics is beyond the framework of this paper since the distributions of these statistics T_{MOT} and T_{MDT} under the null hypothesis depend on the unknown copula. Moreover, asymptotic results could be inappropriate in the context of HFA, and other fields dealing with extreme values, since the series are usually very short (e.g. Nasr & Chebana, 2019; Rutkowska, 2015).

The methodology of the proposed tests is based on two well-known notions in statistics and applications, i.e. Kendall's τ extension and the moving window technique. Regarding the moving window technique, used to integrate the evolution of the dependence structure, it has been considered in other studies for different reasons, such as in econometrics (e.g. Selvin *et al.*, 2017), in finance (e.g. Siami-Namini & Namin, 2018), in medicine (e.g. Dinh *et al.*, 1999) and in statistic (e.g. Genest & Rémillard, 2004).

The proposed tests have several conceptual advantages (along with their performance presented below). Indeed, they allow overcoming some drawbacks of the existing multivariate tests (Table 1). In fact, the proposed overall statistic test T_{MOT} is designed to detect the trend in different components (both margins and dependence structure) and it is not componentwise. The second proposed test T_{MDT} is constructed to focus on detecting trend in dependence structure. Then, the use of the proposed tests T_{MOT} and T_{MDT}, along with the univariate testing for each margin, provides an attractive and complete procedure for testing trend in the multivariate framework. Even though the proposed tests are introduced and evaluated as part of multivariate HFA, they can be considered in other fields and application dealing with multivariate trends such as economics, finance, medicine, and climatology. It is important to recall that these tests are designed to test *monotonic* trends only.

4. Simulation study

A Monte Carlo simulation study is conducted to evaluate the performance of the proposed multivariate trend tests (e.g. Hirsch *et al.*, 2015; Hirsch & Slack, 1984) and compare them with the existing multivariate tests. Since the test CST has already lower performance compared than those of CIT and CET (e.g. Modarres, 2018), then CST test is not considered. In addition, CET test is the one recommended among the available multivariate ones (e.g. Chebana & Ouarda, 2021; Chebana *et al.*, 2013; Lettenmaier, 1988; Modarres, 2018).

4.1 Simulation design

Given that a multivariate distribution can be composed of margins and dependence structure, a trend can affect these components in different ways. Therefore, we considered the following scenarios for the bivariate case:

a) Trend only in the dependence structure
b) Trend only in one margin
c) Trend in both margins with the same direction (increasing)
d) Trend in both margins with different directions
e) Trend in both margins and also in the dependence structure.

The above scenarios were considered in different levels and values in order to evaluate the possible effects on the performances of the considered trend tests with different factors (direction and magnitudes of the trend, degrees of dependence and sample size).

Data are generated from representative margins and copulas in hydrometeorology analyses to evaluate the performance of the considered tests (e.g. Nasr & Chebana, 2019; Salvadori & De Michele, 2010; Zhang & Singh, 2006). The employed copulas are in two groups: Archimedean (Clayton, Frank, Joe and Gumbel), and Extreme-Value (Galambos and Husler-Reiss).

.Even though, a large number of univariate distributions are available, the generalized extreme value (GEV), lognormal (LN2) and three-parameter lognormal (LN3) have been those developed in non-stationarity hydrological framework (e.g. Chebana & Ouarda, 2021). In this study, we have opted for the GEV as the marginal distribution as by previous studies (e.g. El Adlouni *et al.*, 2007; Gado, 2016).

The GEV distribution is parameterized with location (μ), scale (σ), and shape (ξ) parameters. As in previous studies, the non-stationary aspect is introduced by allowing the location parameter to be linear function of time (μ_t), while keeping the scale and shape parameters constant (μ_0 + μ_1t, σ, ξ) where *t* is the time order.

In this study, the location parameter that characterize the non-stationarity are selected to have weak trends, a condition frequently observed in hydrometeorological series (e.g. El Adlouni *et al.*, 2007; Gado, 2016). As in Gado (2016), the location parameter was chosen in the range of -0.3 ≤ μ_1≤ +0.5 and $\mu_0 = 0$ in order to test the sensitivity of the proposed tests to the values of a variety of trends. The scale and shape parameters were fixed at σ=1 and ξ= -0.1 respectively (e.g. El Adlouni *et al.*, 2007). Other values of the shape parameter, such as -0.3 as considered by El Adlouni *et al.* (2007), have been checked. The obtained results showed no significant changes leading to similar conclusions (for space limitations, those results are not presented).Note that, given the main contribution of the present study is in the multivariate framework, the focus is not on univariate aspects (e.g. selection of marginal distributions and their parameters).

In order to consider trend in the dependence structure, we generated random samples from time-dependent copula C_t where the corresponding parameter θ_t in terms of Kendall's τ τ_t is assumed to be linear with respect to time, similarly to Nasri *et al.* (2019). Each copula has a specific parameter range and related to Kendall's τ (e.g. Chebana, 2022). On the other hand, in the majority of flood events, the Kendall's τ is between 0.3 and 0.8 (e.g. Nasr & Chebana, 2019; Requena *et al.*, 2013; Zhang & Singh, 2007). Hence, we considered three values of $\tau =$ 0.2, 0.6, 0.8, representing weak, moderate, and strong dependence respectively.

Different factors could affect the performance of a trend test, either univariate or multivariate, specifically the sample size *n* and magnitudes of the trend (e.g. Bihrat & Bayazit, 2003; Lettenmaier, 1988; Rutkowska, 2015; Yue *et al.*, 2002). Moreover, the proposed tests could be affected by dependence strength and copula type (e.g. Quessy *et al.*, 2013). Hydrologic series are usually characterized by small sample sizes. Hence, we considered sample sizes of n =30, 50 and 100 as in other studies (e.g. Barth *et al.*, 2017; Nasr & Chebana, 2019; Santhosh & Srinivas, 2013). Since the size s of the rolling window series is related to the sample size n (e.g. Chebana & Ouarda, 2021), the window size s is selected respectively as s = 10, 15, 20 for n = 30, 50, 100 similarly to Nasr and Chebana (2019). This is short enough to have large rolling window series and lengthy enough to have an adequate number of values for identifying the dependence structure (e.g. Bender *et al.*, 2014). While the challenge of choosing the size s of moving windows is common to other tests in the literature, formal statistical inference procedures for this purpose are lacking in the literature (e.g. Kojadinovic & Yan, 2011). However, Bücher et al. (2019) discussed this matter and suggest, considering values such as s = 2, 3, or 4 and depending on the ultimate interest, one might also consider choosing s differently. Chebana and Ouarda (2021) consider s =12 for 27-sample size. In the case of Bender *et al.* (2014), the time window length is set to s = 50 years for 191 years. It is important to note that, across all scenarios, N_{sim} =1000 samples are generated to ensure stable results. Preliminary trials were conducted to assess convergence, and stability in results was achieved with N_{sim} =1000 samples. Note that, no significant differences have been observed with other values greater than $N_{sim} = 1000$ such as N_{sim} = 5000.The first kind error, or nominal level, α is set to the usual value $\alpha = 5\%$. To compare the considered tests, we evaluate their ability to estimate α as well as to quantify their power (1-β). Figure 2 summaries the conducted simulation study.

4.2 Simulation results

This section presents the obtained results of simulation study by estimating the nominal level and evaluation the power of the considered tests.

Figure 2: Diagram of the simulation study

4.2.1. Nominal level estimation

This section reports the estimates $\hat{\boldsymbol{\alpha}}$ of α for the proposed tests T_{MOT} , T_{MDT} along with the

Table 3: First type error estimates (%) by the proposed multivariate tests (T_{MOT},T_{MDT}) and the existing ones (CIT, CET)

multivariate existing tests CIT and CET for different factors: sample sizes, dependence strengths and different copula types as presented in Table 3. From Table 3, we observe that the proposed tests T_{MOT} and T_{MDT} provide estimates $\hat{\boldsymbol{\alpha}}$ close to the selected significance level α = 5 % for different factors. The first type error should be close to the chosen significance level α to be exact which is the main advantage of proposed tests.

Results from Table 3 show that the proposed tests T_{MOT} and T_{MDT} are generally not sensitive to different factors. First, it can be seen that the proposed tests are almost insensitive to the copula type regarding the estimation of α. Indeed, as an example, for T_{MOT} and T_{MDT} tests, $\hat{\boldsymbol{\alpha}}$ is respectively in the range 3.8-5.9%, and 3.8-5.5%, for $\tau = 0.6$ and $n = 50$ for different copula type.

Regarding the dependence strength, for a given sample size, it has almost no effect on the estimation of α by T_{MOT} and T_{MDT} tests. As an example, when considering the Frank copula with $n = 50$, the estimation ranges between 3.5-4.5% for T_{MOT} and 3.9-5.3% for T_{MDT}, for different values of τ. We have similar results regarding the effect of the sample size n. For example, considering a dependence strength τ of 0.6 and employing the Clayton copula, estimated $\hat{\boldsymbol{\alpha}}$ for T_{MOT} ranges from 5.1-5.9%, and for T_{MDT}, it varies between 3.8-5.0% across different sample sizes.

As we can see under H_0, the results presented in Table 3 indicate that existing multivariate CIT and CET tests lead to estimates $\hat{\boldsymbol{\alpha}}$ close to the selected significance level α = 5 % for different factors (in the range 3.1-6.6%). Not that, in the context of water quality, Lettenmaier (1988) found that CIT and CET tests provide under-estimations of the nominal values.

4.2.2. Power evaluation

In this section, we examine the power of the proposed tests in detecting the trend in the margins and dependence structure (combined or separately).

Test	Copula under H_0	$\tau = 0.2$			$\tau = 0.6$			$\tau = 0.8$		
		n =30	n =50	n =100	n =30	n =50	n =100	n =30	n = 50	n =100
T_{MOT}	**Clayton**	4.0	4.9	5.6	5.9	5.2	5.1	3.2	5.6	3.9
	Frank	4.9	4.5	4.6	4.5	4.5	6.1	4.6	3.5	4.5
	Joe	4.7	5.2	4.9	6.1	5.9	4.8	4.3	4.3	4.4
	Gumbel	5.8	3.9	5.4	3.8	4.9	4.7	3.8	4.7	5.0
	Galambos	4.6	4.7	6.3	4.9	4.4	4.5	4.9	4.9	4.1
	Husler-Reiss	4.2	5.1	4.9	3.3	3.8	5.5	2.9	4.4	5.4
T_{MDT}	**Clayton**	5.3	4.7	4.8	5.0	3,8	3.9	3.9	3.5	6.0
	Frank	4.8	5.3	4.3	3.4	4.1	4.0	3.6	3.9	6.5
	Joe	4.2	5.2	5.4	3.6	5.4	5.4	3.6	4.5	4.8
	Gumbel	3.9	4.9	3.9	4.4	4.4	4.2	3.6	4.0	5.3
	Galambos	4.2	5.3	4.5	4.4	5.5	5.2	4.9	4.2	3.7
	Husler-Reiss	4.3	5.2	4.7	4.5	4.9	4.6	4.3	5.6	4.4
CIT	**Clayton**	4.6	6.1	6.1	4.2	5.2	5.3	4.7	4.8	4.5
	Frank	3.1	3.7	5.9	5.5	5.7	3.9	3.5	4.4	6.0
	Joe	5.1	4.7	5.5	4.9	4.8	5.3	4.6	4.4	5.8
	Gumbel	4.6	5.1	4.9	4.1	5.3	5.2	5.6	4.4	5.7
	Galambos	4.7	4.6	4.6	6.1	5.4	5.4	4.9	5.3	4.7
	Husler-Reiss	5.7	5.3	6.0	3.8	4.5	5.4	3.9	4.4	5.9
CET	**Clayton**	5.1	6.3	5.7	4.6	4.9	5.5	5.8	5.3	3.7
	Frank	3.1	4.6	6.1	5.5	6.6	3.9	4.7	5.3	4.5
	Joe	5.5	4.2	4.9	5.1	5.2	6.1	5.5	4.1	5.0
	Gumbel	5.3	5.6	4.9	4.2	5.7	5.0	4.5	4.8	5.4
	Galambos	5.4	5.2	4.3	6.0	5.0	6.5	4.4	5.9	4.8
	Husler-Reiss	6.0	6.0	5.9	5.2	5.9	3.8	4.4	5.9	5.8

a) Trend in the dependence only

The power of the proposed tests in detecting the trend in the dependence structure is studied. Results for different sample sizes, different copulas and dependence strengths, are displayed in Table 4. One can see overall from Table 4 that the proposed tests T_{MOT} and T_{MDT} stand out with high power, in contrast to the CIT and CET tests.

From Table 4, one first notes that the type of the copulas and dependence strength seems to have little influence on the power of the T_{MOT} and T_{MDT} tests; it is rather the sample size that have a significant impact. Indeed, we can see that the power of the tests T_{MOT} and T_{MDT} is increasing with the sample size. For instance, for T_{MOT} test with Clayton copula, the power increases from 37.0% when $n = 30$ to 94.7% when $n = 100$ (similarly for T_{MDT} from 36.7 % to 95.5%). These results align with the results from other tests, which also observed that power increase with the sample size (e.g. Hirsch *et al.*, 1982).

It is also of interest to note that the power of T_{MOT} and T_{MDT} has less variability regarding copula type. For instance, for T_{MOT} test with $n = 50$, powers are 66.6% and 64.4% when considering Clayton copula and Frank copula respectively. As another example, in the T_{MDT} test with $n = 100$, the powers are 95.5% for the Clayton copula 94.8% for the Galambos copula. These values are considerably high. Moreover, the power of T_{MOT} and T_{MDT}, remains well regardless of the trend direction in the dependence structure. No significant differences were observed in the powers when considering various trend directions. For the sake of simplicity and brevity, the results pertaining to the decreasing trend direction are not presented.

Overall, with some exceptions, both proposed tests lead to similar powers. According to the sample size, the power is low values (roughly 30 to 45%), moderate (55 to 67%) to very high (88 to 95%). In trend or non-stationarity studies, it is important and appropriate to have n as high as possible. Hence, the proposed tests are adapted to this context.

In the comparison of performance between the proposed tests(T_{MOT} ,T_{MDT}) and the existing tests CIT and CET, a notable observation is that the latter exhibit inability to detect any trend in the dependence structure across all examined scenarios. For instance, for CET test, the power estimate

Table 4: Power estimates (%) of the proposed tests (T_{MOT}, T_{MDT}) and existing tests (CIT, CET)-trend in in the dependence structure

consistently ranges between 3.8%-8.8%, close to those in Table 3. These very low values are expected since these tests ignore the dependence structure explicitly in their construction.

Sample size	Test	Archimedean				ExtremeValue	
		Clayton	Frank	Joe	Gumbel*	Galambos	Husler-Reiss
n=30	T_{MOT}	**37.0**	**38.3**	**41.9**	**36.3**	**43.2**	**32.2**
	T_{MDT}	**36.7**	**35.0**	**43.9**	**37.6**	**45.6**	**31.5**
	CIT	8.8	4.0	6.5	5.2	6.1	5.1
	CET	6.8	4.7	8.0	4.7	4.9	4.7
n=50	T_{MOT}	**66.6**	**64.4**	**64.1**	**59.6**	**67.2**	**55.6**
	T_{MDT}	**67.2**	**59.1**	**65.5**	**59.7**	**67.5**	**56.1**
	CIT	6.9	5.5	7.3	4.9	4.8	4.9
	CET	6.0	5.1	6.6	4.6	3.8	3.9
n=100	T_{MOT}	**94.7**	**92.3**	**92.3**	**90.1**	**95.3**	**87.5**
	T_{MDT}	**95.5**	**92.1**	**94.7**	**88.3**	**94.8**	**88.3**
	CIT	5.4	5.2	6.3	5.5	5.5	4.3
	CET	5.0	4.3	6.2	5.3	4.2	3.8

This table presents the power of the proposed test at significance level α=5%, for different scenarios. The Gumbel* copula belongs both to the class of Archimedean and extreme value copulas

b) Power evaluation: trend in one margin only

The results corresponding to this scenario are presented in Table 5. Since in this section we are only interested in the marginal distributions, we consider only two families of copula (Clayton and Galambos) with fixed Kendall's τ, $\tau = 0.6$.

Table 5 show higher powers of the statistical test T_{MOT} as both the sample size and the trend slope increase, eventually reaching 100%. These high power values demonstrate the efficacy of T_{MOT} in detecting trends in one margin. From Table 5, we can see that the impact of sample size *n* on the power. For a given slope of location parameter μ_{t} and a copula, the power increases with *n*. For instance, we consider the case with a location parameter slope $\mu_1 = 0.1$, generated from a Clayton copula. In this case, the power of the T_{MOT} test rises notably from 17.5% at $n = 30$ to 100% at $n = 100$. These high powers, highlighting the effectiveness of the T_{MOT} test in detecting trend within one margin. In addition, no differences in growth are observed between different copulas. For example, for n =100 and τ = 0.6, powers of T_{MOT} tests are 100% for Clayton and Galambos copulas.

Table 5 shows also high powers of the T_{MOT} test, particularly when the trend slope increases. Indeed, for sample size n =50 and Galambos copula, power estimates of the T_{MOT} test increase from 42.2% to 100% when slope μ_1 passes from 0.1 to 0.3. This finding is expected and it is in agreement with the literature dealing with univariate trend (e.g. Yue *et al.*, 2002). Moreover, from Table 5, when considering a Galambos copula with n = 100, the T_{MOT} test demonstrates very high powers, reaching 100% for both increasing trend (μ_1 = 0.1) and decreasing trend (μ_1 = -0.1). This result demonstrates the effectiveness of the T_{MOT} test, highlighting its ability to capture trends in margins irrespective of their direction.

Results from Table 5 show that the proposed test T_{MDT} is not able to detect any trend in margins. In all cases, the power estimates are less than 3.7%. This is not surprising since this test is intended to capture trend only in dependence structure.

Table 5: Power estimates (%) of the proposed tests (T_{MOT}, T_{MDT}) and existing tests (CIT, CET)-trend in one margin only

Test	Copula	τ = 0.6											
		μ_1 = 0.1t			μ_1 = 0.3t			μ_1 = 0.5t			μ_1 = -0.1t		
		n=30	n=50	n=100	n=30	n=50	n=100	n=30	n=50	n=100	n=30	n=50	n=100
T_{MOT}	Clayton	**17.5**	**40.8**	**100**	**96.6**	**100**	**100**	**100**	**100**	**100**	**17.0**	**39.4**	**100**
	Galambos	**15.0**	**42.2**	**100**	**96.0**	**100**	**100**	**100**	**100**	**100**	**17.3**	**42.5**	**100**
T_{MDT}	Clayton	2.9	2.8	3.1	1.1	0.8	0.6	0.4	0.4	0.0	3.7	1.9	1.6
	Galambos	2.9	2.1	1.3	0.6	0.6	0.0	0.5	0.3	0.1	2.6	2.2	2.1
CIT	Clayton	99.9	100	100	100	100	100	100	100	100	99.7	100	100
	Galambos	100	100	100	100	100	100	100	100	100	100	100	100

CET	Clayton	94.3	100	100	100	100	100	100	100	100	94.4	100	100
	Galambos	94.0	100	100	100	100	100	100	100	100	93.7	100	100

This table presents the power of the proposed test at significance level α=5%

As part of comparison, Table 5 reports also the performance for the existing CIT and CET tests. Through Table 5, those tests have high power values almost always 100%. These high power values of CIT and CET tests are different from the literature (e.g. Hirsch & Slack, 1984; Lettenmaier, 1988). This can be attributed to distinct simulation conditions. Initially developed for monthly water quality data, the CET and CIT tests are not specifically adapted for hydrological data, as in our case. The primary purpose of these tests is the detection of trends in time series, not the frequency analysis of hydrological data. This dissimilarity in objectives and context introduces several differences in simulation conditions. For instance, Hirsch and Slack (1984) and Lettenmaier (1988) based their analyses on sample sizes ranging from 5 to 20, with a slope value from 0.0065 to 0.05, specifically chosen to match the features of water quality time series. When we applied some of these features (n = 20, slope = 0.05), the power of the CET test decreased significantly to 11%.

c) Power evaluation: trend in both margins

We present the power values here when trend is present in both margins. Table 6 shows that except T_{MDT}, the power of all tests is very high and can reach 100%. The high power of the developed multivariate T_{MOT} test clearly emphasizes its effectiveness in detecting trends in both margins. Moreover, T_{MOT} power significantly increases with n. For instance, with a Galambos copula and slopes μ_1 = -0.1 and μ_2 = -0.1, the power values for the T_{MOT} test increase from 56.4% at n = 30 to a 100% at n = 100.

Table 6 demonstrates also the impact of the trend direction between both margins on the power of T_{MOT}. Regardless of whether the trend is increasing or decreasing, the T_{MOT} test exhibits high power. As an example, when examining different trend directions for both margins with location parameters set at μ_1 =0.3, μ_2 =-0.3, and considering Clayton copulas, the power remains at a high level of 100% across all sample sizes *n*. This high power demonstrates the effectiveness of the T_{MOT} test in detecting trends across both margins under diverse directions.

Table 6: Power estimates (%) of the proposed tests (T_{MOT}, T_{MDT}) and existing tests (CIT, CET)-trend in both margins

Table 6 provides also insights about the effect of the trend slope on the power on the power of the proposed tests. In fact, the proposed test T_{MOT} performs clearly better when the slope of trend increases. As an example, considering $n = 30$ and Clayton copula, the test power increases from 53.2% if slope are μ_1 = -0.1, μ_2 = -0.1 to 100 % when the slopes are μ_1 = 0.3, μ_2 = 0.3.

The powers here increased (except for the T_{MDT}) compared to Table 5 specifically for T_{MOT}. The reason is that we have additional component with trend in the margins. Moreover, T_{MDT} as designed and expected, is not detecting such a trend. CET and CIT continue to slowly increasing to reach 100% in all cases which similar to the previous case (Table 5). However, importantly, T_{MOT} is adapted to the situation with an increase that is realistic. The reason that tests, except T_{MDT}, reach 100% is that the trend in the margins is dominating the non-trend in the dependence (e.g. Bender *et al.*, 2014).

As part of comparison, the two classical tests CIT and CET are able to detect the trend in both marginal distributions with a high performance =100% in all cases. These obtained results are different from the literature and the reasons are explained in the previous case (trend in one margin only). As anticipated, Table 6 affirms that the proposed statistic T_{MDT} is not able to detect any trend in both margins, aligning with its specific design focused on capturing trend solely within the dependence structure. In all instances, the powers remain below 7.8%.

Test	Copula	τ = 0.6											
		μ_1 = -0.1t μ_2 = -0.1t			μ_1 = 0.3t μ_2 =-0.3t			μ_1 = 0.3t μ_2 = -0.1t			μ_1 =0.3t μ_2 = 0.3t		
		n=30	n=50	n=100	n=30	n=50	n=100	n=30	n=50	n=100	n=30	n=50	n=100
T_{MOT}	Clayton	**53.2**	**99.8**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**
	Galambos	56.4	100	100	97.0	100	100	99.9	100	100	100	100	100
T_{MDT}	Clayton	3.2	5.1	5.4	3.6	0.1	6,8	2.4	1.3	0.5	3.4	4.8	5.5
	Galambos	4.9	4.6	5.2	1.5	0.3	7.8	1.7	1.4	1.7	5.0	4.2	5.2
CIT	Clayton	100	100	100	100	100	100	100	100	100	100	100	100
	Galambos	100	100	100	100	100	100	100	100	100	100	100	100
CET	Clayton	100	100	100	100	100	100	100	100	100	100	100	100
	Galambos	100	100	100	100	100	100	100	100	100	100	100	100

This table presents the power of the proposed test at significance level α=5%

d) Power evaluation: trend in both margins and dependence

In this case, we considered a large number of possibilities since all the components of the bivariate distribution have trends. Note that similar results are obtained when examining either an increasing or a decreasing trend in the dependence structure, as well as for the direction of the trend (increasing/decreasing) in both margins. For the sake of brevity, we do not present all the results.

Form, results highlight the high power of the T_{MOT} tests across various copulas and sample sizes. Notably, the T_{MOT} test exhibits high performance, reaching 100% power even with weak slopes and short sample sizes.

Notably, as shown in Table 7, similar to the preceding scenario, the performance of trend T_{MOT} tests is influenced by the sample size. Specifically, a larger sample size correlates with higher power. This observation is most apparent for a very weak slope $\mu_t =$ -0.1 for both margins. As an example, considering Gumbel copula, the test power increases from 83.9 % for a sample size $n =$ 30 to 100% when $n =$100. These powers are considerably high. In this instance, the presence of trends in all components (margins and dependence structure) leads to a rapid increase in performance compared to the previous Tables (Table 5 and Table 6).

Moreover, the power of T_{MOT} increases with the slope of the trend. For instance, considering Husler-Reiss copula with n = 30, the power is 88.6% when μ_1 = -0.1, μ_2 = -0.1 and increases to 100% when μ_1 = 0.3, μ_2 = 0.3. However, no significant differences were found between powers when considering different copulas. Indeed, as an example, for n = 30 and μ_1 = -0.1, μ_2 = -0.1, the test power is between 83.9% and 94.0% for all different copulas.

From Table 7, we can see also that power of T_{MOT} is very high when considering the same trend direction in margins and dependence. As an example, from Table 7 when considering time-varying location parameters for $\mu_1 = 0.3$, $\mu_2 = 0.3$t, and increasing trend in dependence structure, the power is always 100%. Further, it can be seen from the same Table 7 that power estimates of the proposed test T_{MOT} is not sensitive to the different direction of trend between both margins and dependence. For instance, when both margins exhibit a decreasing trend (μ_1 =-0.1, μ_2 =-0.1) and the dependence shows an increasing trend, the power ranges from 83.9% to 100% across different sample sizes n and copula types. Moreover, it is important to emphasise that the proposed statistic T_{MOT} performs well in detecting trend even when considering different directions between both margins. For instance, for time-varying location parameters of μ_1 = 0.3, μ_2 = -0.3, and increasing trend in dependence structure, the power estimates are 100% for all different sample size and copulas. This is because of the terms in the test T_{MOT} are squared to avoid cancelling the trend with different signs. Through Table 7, considering overall test T_{MOT} it is very important to note that the powers are around 100% in the majority of simulation cases. The first column is the only one that does not reach 100% for the different copula types. Indeed, the power range between 83.9% and 94% when $n = 30$. This is because this column represents the lowest slope (-0.1). This is a high results despite the weak slopes of marginal distributions were chosen according to the hydrological flood context and only the location parameter (μ_t) is assumed to be a linear function of time.

Table 7: Power estimates (%) of the proposed tests T_{MOT} and T_{MDT} − trend in both margins and the dependence structure

Test	Copula	μ_1 = -0.1t μ_2 = -0.1t			μ_1 = 0.3t μ_2 = 0.3t			μ_1 = 0.5t μ_2 = 0.3t			μ_1 = 0.3t μ_2 = -0.3t		
		***n*= 30**	***n*= 50**	***n*= 100**	***n*= 30**	***n*= 50**	***n*= 100**	***n*= 30**	***n*= 50**	***n*= 100**	***n*= 30**	***n*= 50**	***n*= 100**
T_{MOT}	Clayton	93.1	99.8	100	100	100	100	100	100	100	100	100	100
	Frank	94.0	100	100	100	100	100	100	100	100	100	100	100
	Joe	92.0	100	100	100	100	100	100	100	100	100	100	100
	Gumbel	83.9	100	100	100	100	100	100	100	100	100	100	100
	Galambos	92.4	100	100	100	100	100	100	100	100	100	100	100
	Husler-Reiss	88.6	100	100	100	100	100	100	100	100	100	100	100
T_{MDT}	Clayton	25.4	37.6	70.5	26.5	34.9	78.4	11.0	20.2	50.4	7.2	9.6	15.4
	Frank	31.4	59.3	91.8	22.7	36.3	79.8	14.2	22.4	54.1	8.4	10.3	19.6
	Joe	30.4	58.6	93.7	26.5	47.8	84.5	18.7	28.4	61.7	7.2	11.5	11.5
	Gumbel	34.9	55.4	92.1	29,5	49.4	89.1	16.4	27.8	59.5	7.8	12.1	17.8
	Galambos	29.8	63.3	95.2	37.6	60.8	95.0	14.0	25.3	62.6	6.5	11.3	14.4
	Husler-Reiss	21.7	47.8	89.0	28.3	47.7	90.3	13.5	23.9	54.3	5.7	10.1	15.7

This table presents the power of the proposed test at significance level α=5%

Regarding the second proposed test, T_{MDT}, as observed in Table 7, we can see that the power substantially increases with a higher sample size, specifically reaching up to 95.2% when the sample size is elevated to *n* = 100. For example, generated data from a Gumbel copula and a slope $\mu_1 = 0.3$, $\mu_2 = 0.3$ and trend in dependence structure, the test power increase from 29.5% for a series of length $n = 30$ to 89.1% when n =100. It is also important to note that exceptions are observed concerning T_{MDT}. Table 7 reveals that the T_{MDT} test's power increases as the slope of both margins decreases. For instance, with the Clayton copula and $n = 50$, the test power increases from 50.4% when the location parameters are set to $\mu_1 = 0.5$ and $\mu_2 = 0.3$ to 78.4% when $\mu_1 = 0.3$ and $\mu_2 = 0.3$. Moreover, T_{MDT} test's performance is better when the directions of the margins are the same compared to case where they differ. For example, considering the Frank copula and $n = 50$, the power estimates increase from 10.3% when location parameters are set to $\mu_1 = 0.3$, $\mu_2 = -0.3$ to 36.3% when $\mu_1 = 0.3$, $\mu_2 = 0.3$. This exceptions on results can be explained by the fact that incorporating trends in the margins can dilute or mask the trend in the dependence, especially when the trend in the margins is stronger than the trend in the dependence (e.g. Bender *et al.*, 2014).

In order to have an overview of the power of the proposed tests, T_{MOT} test performs well, especially with more data and stronger trends. It is flexible, width different trend directions. However, T_{MDT}'s power varies more, improving with larger sample sizes but sometimes decreasing with stronger trends in margins. The T_{MDT} test seems to have some exception associated with varying directions in margins trends. Comparatively, existing tests (CIT and CET) have high powers when trends are only in margins but fall short in spotting trends in the dependence. This highlights the importance of T_{MOT} and T_{MDT}, which consider both margins and dependence for a more complete picture.

Note that the performance of the existing multivariate tests CIT and CET is not interesting in this scenario (trend in both margins and dependence). Notably, Table 4 demonstrate that both CIT and CET do not identify any trend in the dependence structure. This demonstrates that current existing multivariate tests fall short in capturing trends across the entire system, encompassing both margins and the dependence structure. In particular, they neglect to discern whether a trend is present or absent in the dependence structure.

It is important to extract information from different tables (4, 5, 6, and 7) in order to quantify the trend in all components. We chose Clayton copula and slope of trend equal to -0.1 for both margins. Considering T_{MOT} test, powers of the cases of trend in both margins and dependence are higher than in trend on the only the dependence or only in the margins. This can be explained by the fact that the higher the trend in terms of the number components, the higher the power will be.

From Figure 3 we can see for $n = 30$ that the power of the T_{MOT}, test increases from 17.5% when trend in one margin, 53.2% when trend in both marginal distributions and to 93.1 % when trend in all components. This test allows a quantification of the trend since it detects it in all components unlike the multivariate existing tests. Through Figure 3, it is clear to see that T_{MDT} test performs well when a trend in dependence structure and in both components (margins and dependence structure). Moreover, we can see that the presence of the trend in the margins influences the performance of T_{MDT} test. For example, for n =100, Figure 3 show that the power of test increase from 70.5% when trend in both margins and dependence, to 95.5% when trend only in dependence structure. We note that CET test not able to detect the trend in the dependence structure. The high power of the CET is misleading and once a gain it ignores that there is no trend in the dependence. The proposed tests, although with lower power, provide realistic and representative results in detecting trends.

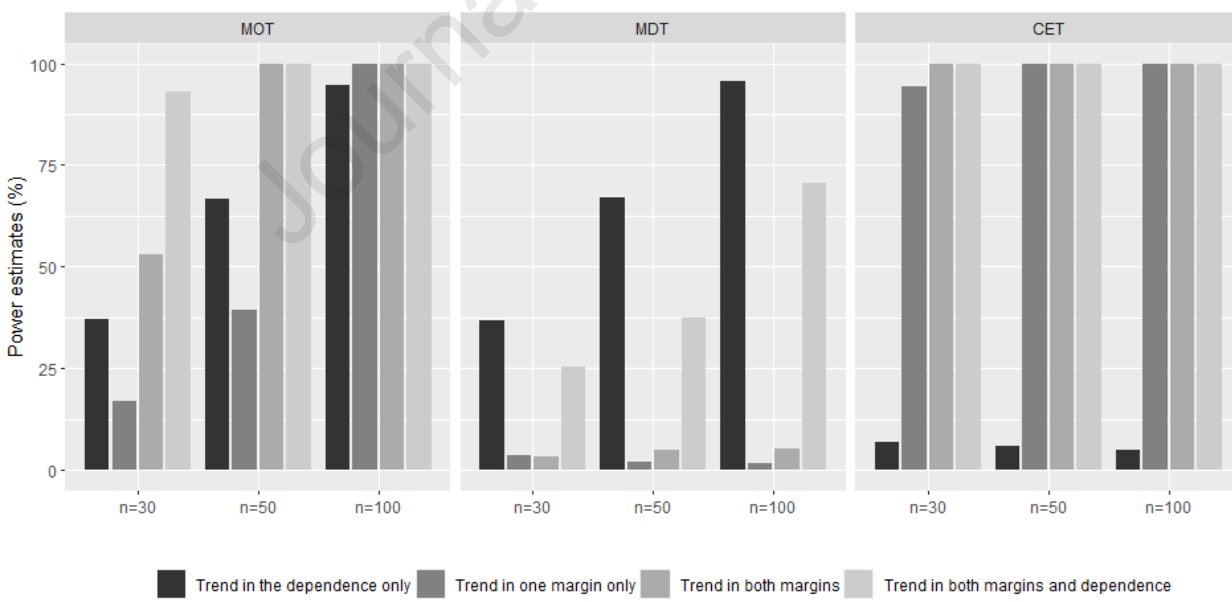

Figure 3: Quantification of trend by statistics T_{MOT}, T_{MDT} and CET test for Clayton copulas and slope of margins equal to -0.1.

5. Applications to Hydrological Data

In this section, the purpose is to assess the appropriateness of the proposed tests for practical use. We apply the developed and existing tests to three real-world hydrological datasets in Canada. They have been chosen to cover different affected components of trends. The first data series correspond to the Southwest Margaree River. The second data series correspond to the Long Creek stations. This station exhibits regulated flow regimes and located below Boundary dam Reservoir. Note that reservoir construction is one of the primary factors contributing to changes in the characteristics of natural river flow regimes (e.g. Ekka *et al.*, 2022). The same series was considered in Tan and Gan (2015) to study the contribution of human change impacts to changes in streamflow of Canada. The third data series correspond to Athabasca River. The same station has been previously employed in analysis of hydrological univariate trends and variability by numerous studies (e.g. Bawden *et al.*, 2014; Das *et al.*, 2020). Figure 4 and Table 8 present respectively the geographical location and general information about the considered stations.

Table 8: General information about the stations

Station name	Province	Station number	Period of records (years)	Part of RHBN*
Southwest Margaree River	Nova Scotia	01FB003	1960-2021 (61)	Yes
Long Creek near Estevan	Saskatchewan	05NB001	1970-2023 (53)	No
Athabasca River below Fort McMurray	Alberta	07DA001	1970-2021 (51)	Yes

* Reference Hydrometric Basin Network (RHBN), which consists of a set of stations with long records and minimal human impacts intended for climate change studies

Figure 4: Geographical location of stations 01FB003, 05NB001 and 07DA001

Based on hydrological literature, our emphasis is on the flood peak (Q) and volume (V) series (e.g. Gaál *et al.*, 2015). All the applications considered a significance level of 5%. The results are given in Table 9.

Table 9: Univariate and multivariate stationarity testing results

Station	Univariate MK test		Multivariate MK tests				
	Variable	**p-value**	**CST**	**CIT**	**CET***	**MOT**	**MDT**
01FB003	Q	0.627	0.668	0.528	0	**0.008**	**0.029**
	V	0.713					
05NB001	Q	**0.000052**	**0.00523**	**0.000040**	**1**	**0.026**	0.574
	V	**0.000011**					
07DA001	Q	**0.0184**	0,138	0,060	**1**	**0.017**	**0.037**
	V	**0.026**					

The bold character indicates the rejection of corresponding null hypothesis at the 5% level.* Note that, instead of the p-value, for the CET-test the conclusion is presented as: 1 if there is a trend, 0 if not, since this test is based on critical thresholds.

For station 01FB003, first, results show no trend detected in the margins (as confirmed from Figure 5). In addition, a significant trend in the dependence structure detected by the proposed MDT test, which is consistent with Figure 6. In contrast, the existing multivariate tests (CST, CIT and CET) were unable to detect the trend in the dependence structure. This confirms the efficacy of MDT in detecting trend in dependence structure. Furthermore, the MOT test also indicates a significant overall trend, which confirm its ability to detect trends some components (here in the dependence structure). Given that, this station is part of the RHBN, the presence of trends in the dependence structure is driven by climate changes. It is noteworthy that Burn and Whitfield (2023) have observed changes in the nival fraction at the same station.

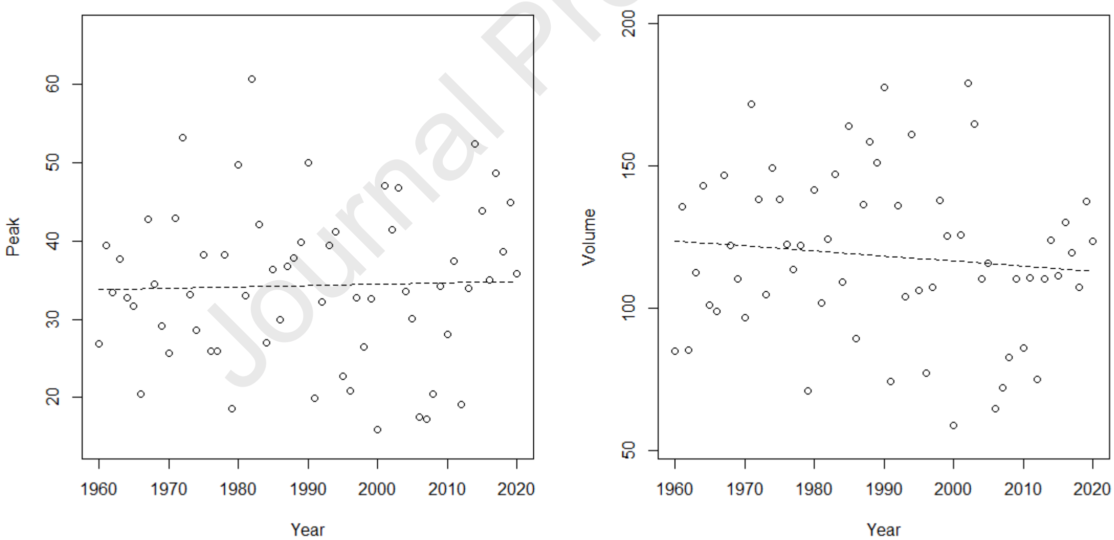

Figure 5: Plot of Peak, volume of the series Q (left) and V (right) with the associated regression lines (01FB003)

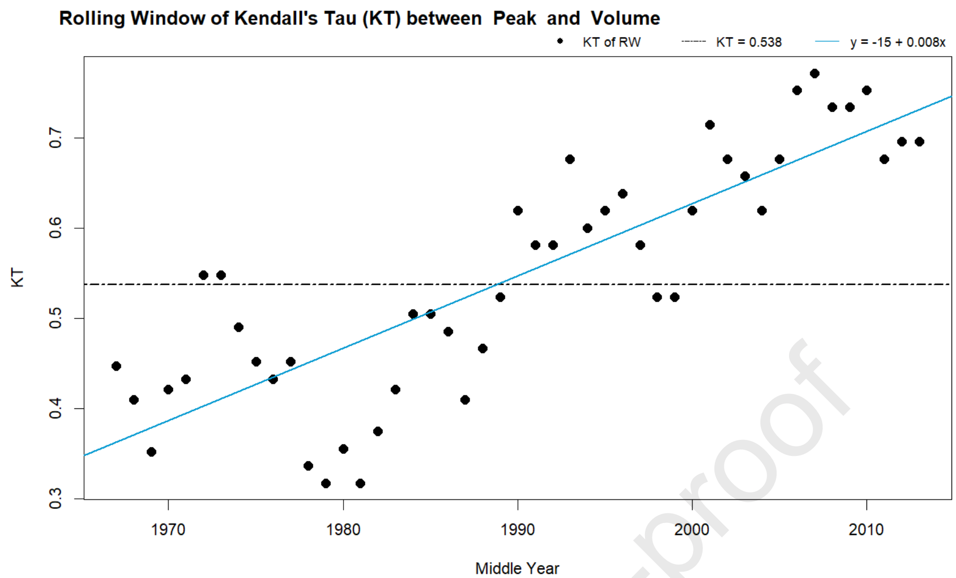

Figure 6: Plot of Peak, volume and rolling window of Kendall's τ (KT) between them against year (01FB003)

In station 05NB001, we observe that all multivariate existing tests are in agreement with a significant trend. The proposed multivariate test MOT also indicated overall trend. This can also be verified from Figure 7. Trends are also detected by MK univariate for each variable. Given that this station is non-RHBN and located below Boundary dam Reservoir, the observed trend detection in the margins may be attributed to anthropogenic activity and/or potential climate change impacts. It should be noted that no visually clear monotonic trend in the dependence structure is observable, as shown in Figure 8, as confirmed by the MDT test.

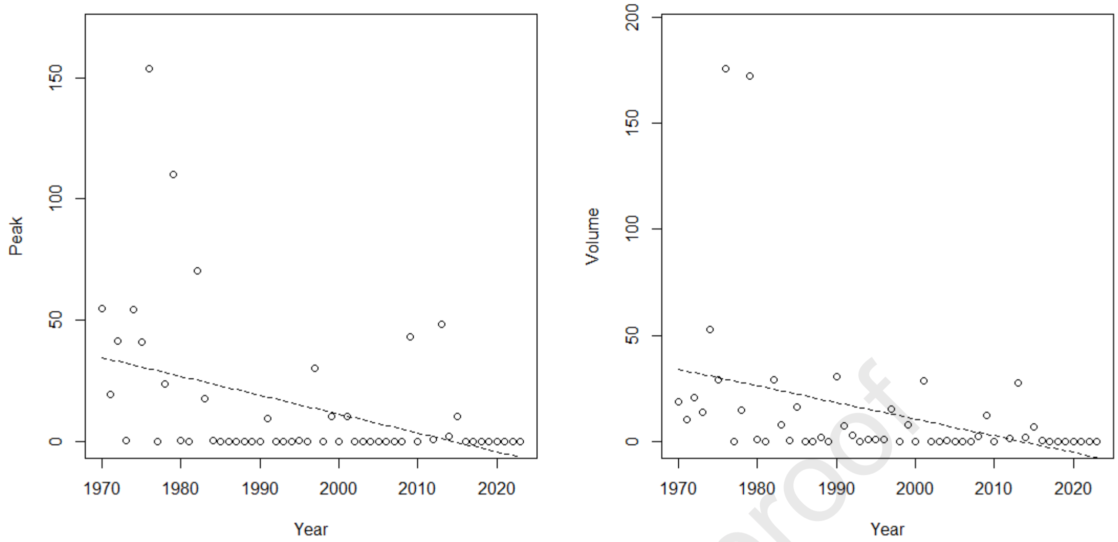

Figure 7: Plot of Peak, volume of the series Q (left) and V (right) with the associated regression lines (05NB001)

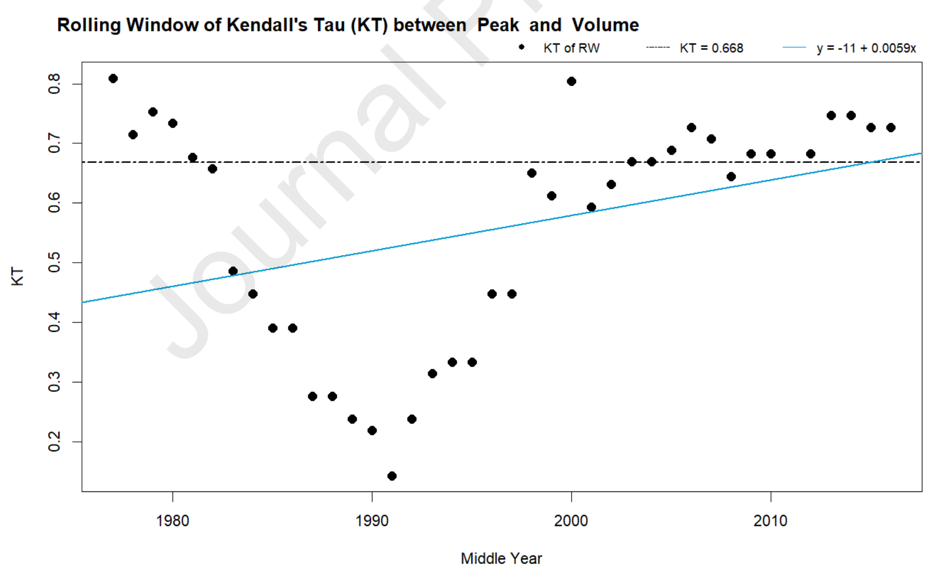

Figure 8: Plot of Peak, volume and rolling window of Kendall's τ (KT) between them against year (05NB001)

For 07DA001, we observe that the univariate MK test indicates the presence of trends in both variables simultaneously (as confirmed by Figure 9). Additionally, the MDT test detects a trend in the dependence structure, which can also be confirmed from Figure 10. The proposed multivariate MOT test confirms an overall multivariate trend. Among the existing multivariate tests, only CET detects the existence of a trend in the margins. The CIT statistic value is very close to the threshold. The CST test does not detect any trend. This confirms findings in the literature that the CST test has lower performance compared to CIT and CET (e.g. Modarres, 2018), and the CET test is recommended among the available multivariate tests (e.g. Chebana & Ouarda, 2021). This station is a part of the RHBN. Thus, the observed multivariate trends in the margins and dependence structure could be driven by climate change. Note that, recent decades have seen significant changes in the hydrological and meteorological conditions of the Athabasca River (e.g. Bawden *et al.*, 2014; Beltaos & Carter, 2009).

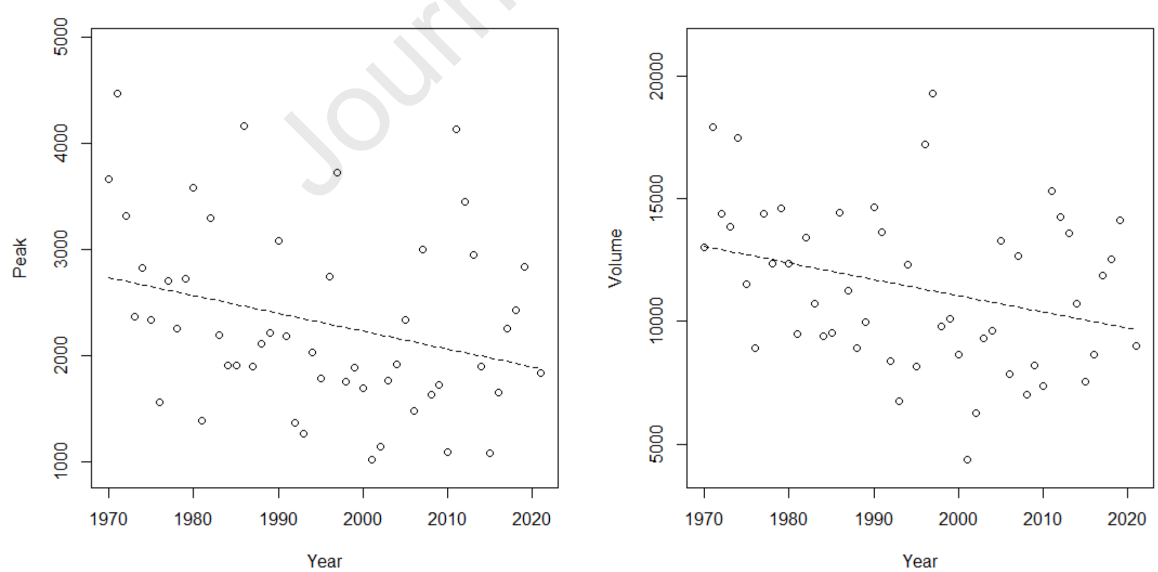

Figure 9: Plot of Peak, volume of the series Q (left) and V (right) with the associated regression lines (07DA001

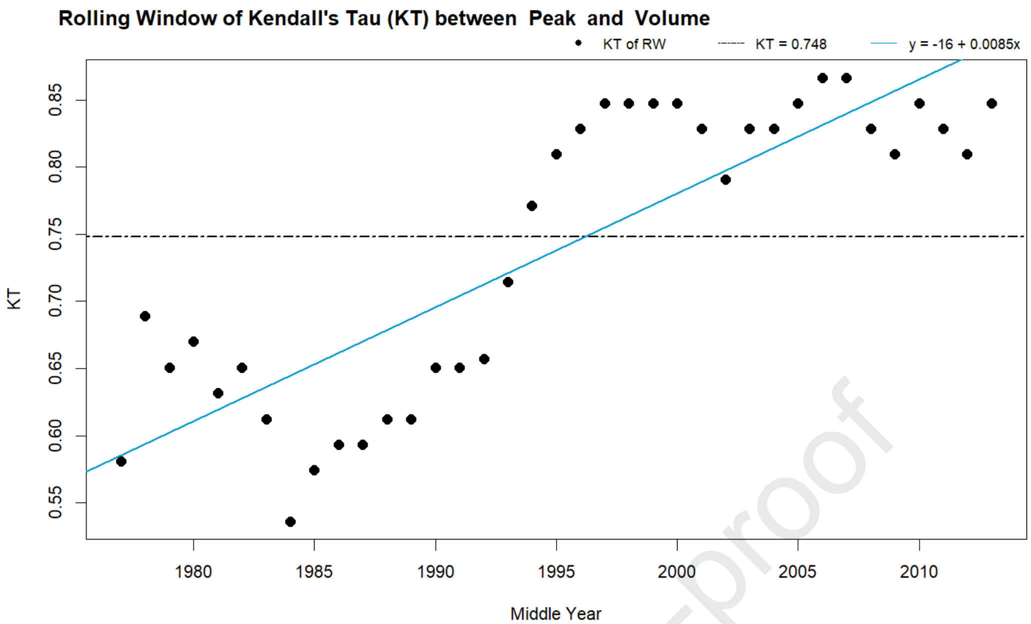

Figure 10: Plot of Peak, volume and rolling window of Kendall's τ (KT) between them against year (07DA001)

6. **Conclusions** and Perspectives

In the literature dealing with multivariate frequency analysis, in general, the stationarity assumption is not verified. This is in part due to the absence of powerful and effective tests. However, nowadays in climate and hydrological changing context, it is more and more important to consider multivariate tests that can detect non-stationarity either in the margins or in the dependence structure.

The aim of the present paper is to develop new tests for multivariate trend to fill a gap in the statistical and hydrological literature. The first test T_{MOT} is designed to detect trend in the affected component (margins and dependence), and the second test T_{MDT} is conceived to focus on trend in the dependence structure. In comparison to existing multivariate tests, simulation results show very promising performances in terms of first type error and power.

The proposed multivariate tests are adopted to hydrological context due to their good performance when the trend is very weak and the series is short, which often happens in hydrological series. The existing tests where not able to detect trend in the dependence structure alone or with the margins. The mutual application of the proposed tests T_{MDT} and T_{MOT} with univariate MK test provides an attractive procedure for testing multivariate trend and to discriminating its potential source.

In this paper, the proposed multivariate trend tests were theoretically justified and practically demonstrated through both a comprehensive simulation study and practical illustrative applications. However, certain limitations were observed for the developed tests. Indeed, they are designed for monotonic trends whereas other forms of trends may exist. Thus, for a more flexible trend detection, there is a need to advance the development of non-monotonic trend tests. Moreover, the presence of autocorrelation in the data can influence the outcomes of tests to detect trends. Consequently, Hamed and Rao (1998) proposed a modified univariate MK-test. Similarly, in the multivariate framework, it would of interest to develop multivariate trend tests suited for autocorrelated data.

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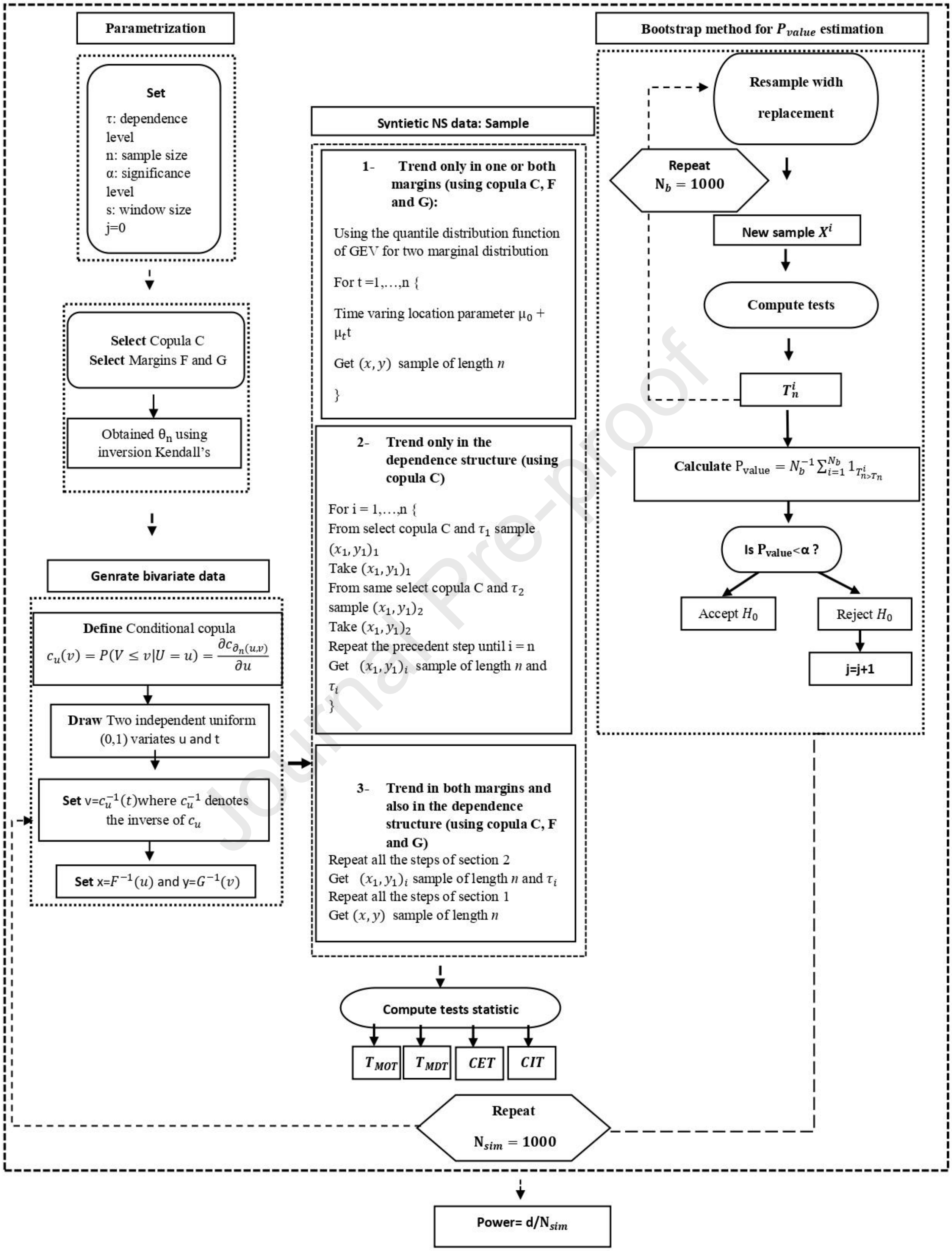

Figure 1: Diagram of the simulation study

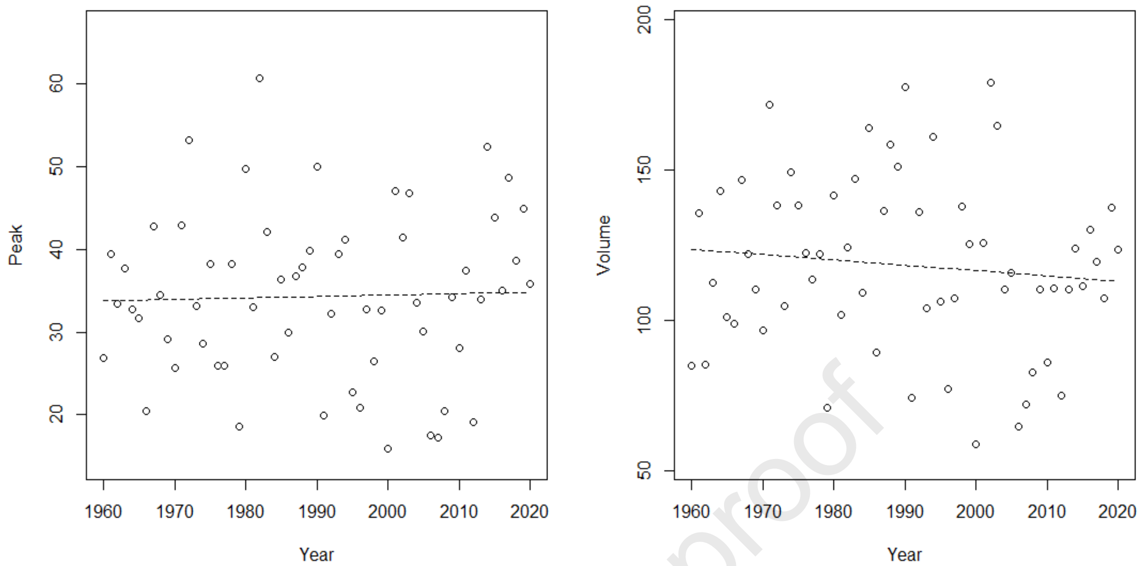

Figure 2: Plot of Peak, volume of the series Q (left) and V (right) with the associated regression lines (01FB003)

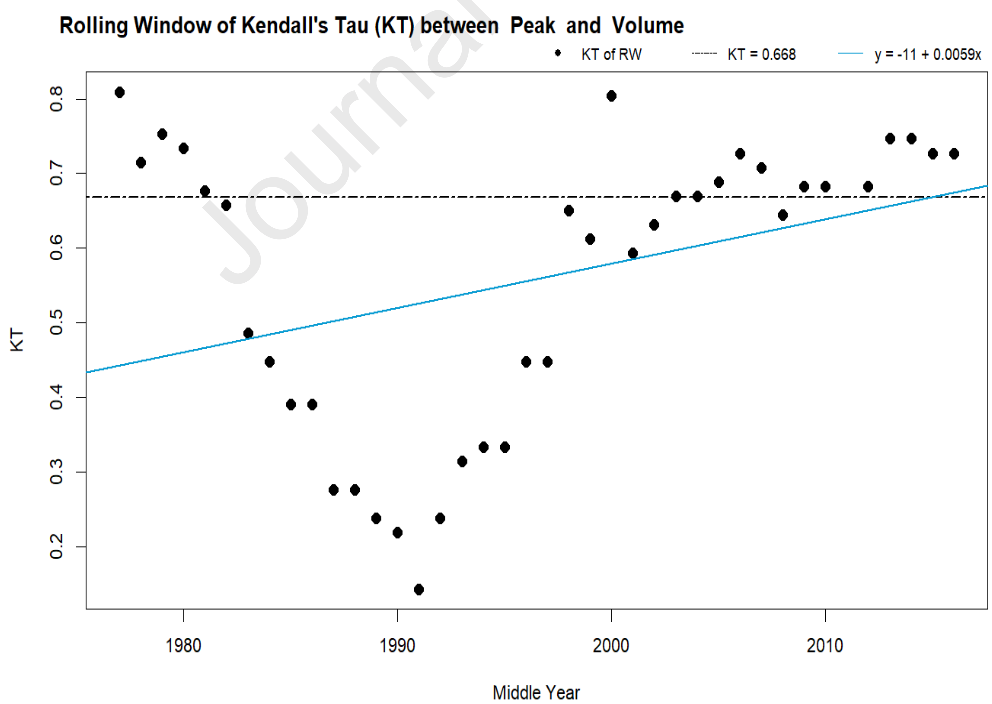

Figure 3: Plot of Peak, volume and rolling window of Kendall's τ (KT) between them against year (05NB001)

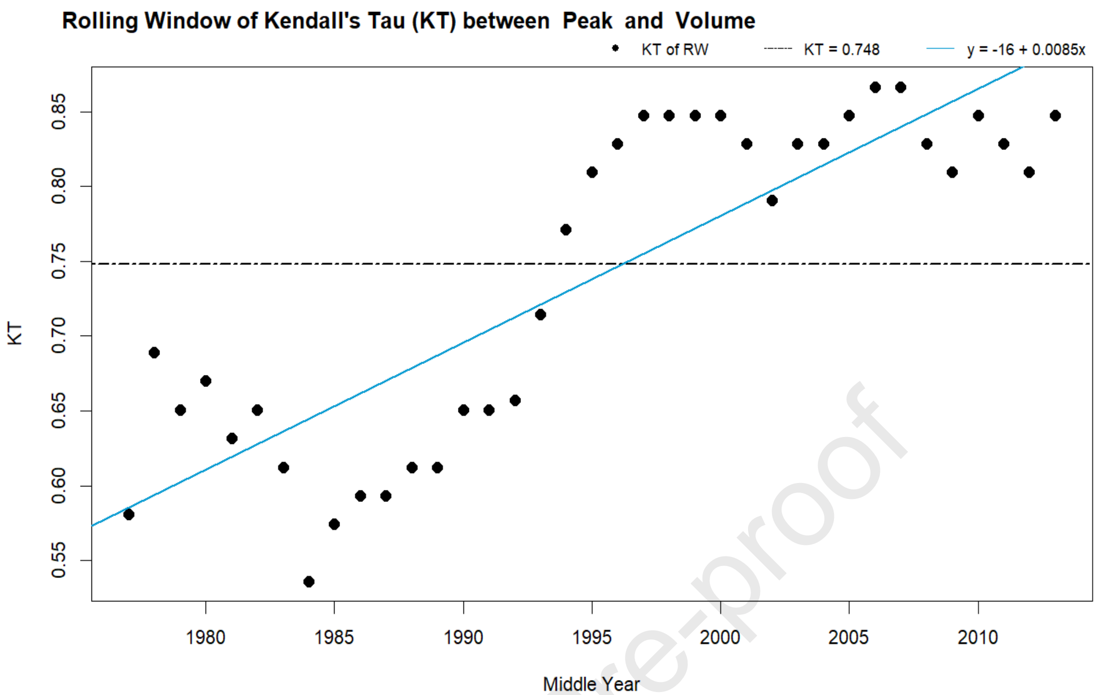

Figure 4: Plot of Peak, volume and rolling window of Kendall's τ (KT) between them against year (07DA001)

- Two multivariate trend tests for multivariate hydrological series are proposed.
- New multivariate overall trend (MOT) test dealing with trend in all the components of the whole multivariate distribution.
- New multivariate dependence trend (MDT) test focuses on trend in the dependence structure.
- Vast simulation study is considered to evaluate the performance of the tests.
- The developed tests show high performance, with increasing power observed as the trend slope and sample size increase.

Declaration of interests

☒ 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.

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