

TREND AND STATIONARITY ANALYSIS FOR STREAMFLOW PROCESSES OF RIVERS IN WESTERN EUROPE IN THE 20TH CENTURY

W. Wang^{1,2}, P.H.A.J.M. Van Gelder² and J.K. Vrijling²

¹ Faculty of Water Resources and Environment, Hohai University, Nanjing, 210098, China,
w.wang@126.com.

² Faculty of Civil Engineering & Geosciences, Section of Hydraulic Engineering, Delft University of Technology, 2600 GA Delft, Netherlands.

Abstract

Streamflow processes of seven major rivers at 7 stations in western Europe are investigated for trend and nonstationarity. Trend analyses with Mann-Kendall test show that there is no trend in annual mean discharge. Only one annual maximum flow series exhibits significant trend (Rhine, upward). There are one minimum flow series which exhibit significant downward (Maas) and seven that exhibit upward trend (Danube, Elbe, Thames and Weser). Monthly flow series are examined with seasonal Kendall test, but no trend is found. Nonstationarity is tested with ADF test (Dickey and Fuller, 1979) and KPSS test (Kwiatkowski *et al.*, 1992). All annual streamflow series and most monthly streamflow series appear to be significantly stationary. Two out of the 7 daily series are stationary while other daily series are basically nonstationary. The results imply that despite the context of global warming, the streamflow processes in western Europe are generally not significantly impacted.

Keywords: ADF test; KPSS test; Mann-Kendall test; stationarity; streamflow time series; trend.

INTRODUCTION

Many hydrological time series exhibit trending behavior or nonstationarity in the mean. An important hydrological modelling task (e.g. fitting an ARMA model) is to determine if there is the existence of any trend in the data and how to achieve stationarity when the data is nonstationary. On the other hand, the possible effects of global warming on water resources have been the topic of many recent studies (Lettenmaier *et al.*, 1999). Thus, detecting the trend and stationarity in a hydrologic time series may help us to understand the possible links between hydrological processes and global environment changes.

Many studies have been carried out to investigate the possible trends in the streamflow processes as well as other hydrological processes in Canada (Zhang *et al.*, 2001; Burn and Hag Elnur, 2002), United States (Lins and Slack, 1999; McCabe and Wolock, 2002). While many studies have explored the climate change in Europe (Grieser *et al.*, 2002), relatively fewer studies have explored the streamflow trends over European countries. Robson *et al.* (1998) found no evidence of any major impact of climatic change on flood behavior in the UK. Van Gelder *et al.* (2000) found no evidence of a possible upward trend in annual average discharges of the Rhine River. De Wit *et al.* (2001) investigated the discharge records in Belgium, and found that the average annual and seasonal discharges have hardly changed over the last century. However, the maximum daily winter discharges seem to have increased, whereas the minimum summer discharges seem to have increased. At the same time, some significant trends have been detected on a local scale. For instance, in Western Scotland, Mansell (1997) showed an increase in streamflow due to an important increase of winter rainfall coupled to a change in rainfall structure with a higher concentration of periods of rain. Pfister *et al.* (2000) show that the contribution of the westerly

atmospheric circulation lead to an increase in winter rainfall intensity and duration, which has induced a significant increase in the winter maximum daily storm flow in the Alzette River basin in Luxembourg since the 1970s.

Although these studies have explored the trends of hydrologic processes for some local regions, their extrapolation to a regional or continental scale remains uncertain, because the factors acting on streamflow trends on a basin scale are not necessarily similar to those acting on a regional or continental scale (Pfister *et al.*, 2000). Furthermore, it is very difficult to detect whether a trend in a hydrologic sequence is significant or whether it is part of an oscillation (Matalas, 1997). In this paper, the trend of several rivers in western Europe is investigated with the non-parametric Mann-Kendall method, and the stationarity is examined with the Dickey-Fuller unit root test (Dickey and Fuller, 1979) and KPSS test (Kwiatkowski *et al.*, 1992), which originate from econometrics.

DATA USED

To study the possible change of streamflow processes in western Europe in the 20th century, we choose streamflow processes of 7 major rivers at 7 stations, which basically temporally span the whole century and are spatially and evenly located in western Europe to the north of Alps. The description of the 7 streamflow processes are listed in Table 1. Daily discharge data are provided by the Global Runoff Data Center (GRDC), which are available on the website <http://grdc.bafg.de/>. The daily data are aggregated to monthly and annual data by taking the average of each month and each calendar year. The annual maximum daily average discharge and minimum daily average discharge as well as their corresponding timing are obtained according to the water year of each streamflow process.

Table 1. Description of streamflow data used in this study.

River	Station	Country	Period	Upstream area (km ²)	Latitude	Longitude	Elevation (m)	Mean Discharge (m ³ /s)
Danube	Achleiten	Austria	1901-1990	76653	48.582	13.504	288	1420
Elbe (Labe)	Decin	Czech republic	1901-1990	51104	50.79	14.23	120	304
Inn	Wasserburg	Germany	1901-1980	11983	48.059	12.233	-	353
Maas	Borgharen	Belgium	1911-1990	21300	50.87	5.72	40	247
Rhine	Cologne	Germany	1901-1997	144232	50.94	6.96	35	2094
Thames	Kingston	United Kingdom	1901-1995	9948	51.8	-0.8	5	66.3
Weser	Vlotho	Germany	1901-1994	17618	52.176	8.862	42	172

TREND ANALYSIS

The purpose of a trend test is to determine whether the values of a series generally increase or decrease. Non-parametric trend detection methods are less sensitive to outliers (extremes) than are parametric statistics, such as Pearson's correlation coefficient. In addition, a nonparametric test can test for a trend in a time series without specifying whether the trend is linear or nonlinear. Therefore, a rank-based nonparametric method, the Mann-Kendall's test, is applied in this study to annual and monthly series.

Trend test based on annual streamflow

The trend test for annual series gives us an overall view of the change in streamflow processes.

Mann-Kendall test. Kendall (1938) proposed a measure τ_{au} to measure the strength of the monotonic relationship between x and y . Mann (1945) suggested using the test for significance of Kendall's τ_{au} ,

where one of the variables is time as a test for trend. The test is well known as Mann-Kendall's test (referred to as MK test hereafter), which is powerful for uncovering deterministic trends. Under the null hypothesis H_0 , that a series $\{x_1, \dots, x_N\}$ come from a population where the random variables are independent and identically distributed, the MK test statistic is

$$S = \sum_{i=1}^{N-1} \sum_{j=i+1}^N \text{sgn}(x_j - x_i) \quad (1)$$

where,

$$\text{sgn}(x) = \begin{cases} +1, & x > 0 \\ 0, & x = 0 \\ -1, & x < 0 \end{cases}$$

And τ is estimated as:

$$\tau = \frac{2S}{N(N-1)} \quad (2)$$

Kendall (1975) showed that the variance of S , $\text{Var}(S)$, for the situation where there may be ties (i.e., equal values) in the x values, is given by

$$\sigma_s^2 = \frac{1}{18} \left[N(N-1)(2N+5) - \sum_{i=1}^m t_i(t_i-1)(2t_i+5) \right] \quad (3)$$

where,

m : is the number of tied groups in the data set and

t_i : is the number of data points in the i th tied group.

Under the null hypothesis, the quantity z defined in the following equation is approximately standard normally distributed even for the sample size $N = 10$:

$$z = \begin{cases} (S-1)/\sigma_s & \text{if } S > 0 \\ 0 & \text{if } S = 0 \\ (S+1)/\sigma_s & \text{if } S < 0 \end{cases} \quad (4)$$

It has been found that positive serial correlation inflates the variance of the MK statistic S and hence increases the possibility of rejecting the null hypothesis of no trend (von Storch, 1995). In order to reduce the impact of serial correlation, it is common to prewhiten the time series by removing serial correlation from the series through $y_t = x_t - \phi x_{t-1}$, where y_t is the prewhitened series value, x_t is the original time series value, and ϕ is the estimated lag 1 serial correlation coefficient.

Mann-Kendall test results. The trend of the annual maximum and minimum daily average discharge as well as their timing are analyzed with MK test. Because annual mean discharge sequences usually exhibit serial dependence, therefore, they are prewhitened. But annual maxima and minima series are basically uncorrelated, so prewhitening is not necessary. The MK test results are displayed in Table 2.

Results of this analysis indicate no increasing or decreasing trends in annual mean discharges of all the rivers. However, trend is present in some annual maximum and minimum flows. Out of 7 maximum flow series, one series, Rhine at Cologne, exhibits a significant increase. No maximum flow series exhibit significant downward trend. In contrast, most minimum flow series exhibit significant downward (Maas) or upward trend (Danube, Elbe, Thames and Weser). The timing of maximum flow exhibits no significant change, but the timing of minimum streamflow at 3 sites has significant change. The occurrence of minimum streamflow of the Danube gets earlier, whereas the minimum flows of Maas and Weser come later.

Table 2. Mann-Kendall tests on annual series.

Series		Danube	Inn	Elbe	Maas	Rhine	Thames	Weser
Annual mean	tau	0.0000	-0.0597	0.0225	-0.0834	0.0777	0.0158	0.0392
	z statistic	0.0000	-0.7747	0.3063	-1.0837	1.1124	0.2221	0.5498
	p-value	1.0000	0.4385	0.7593	0.2785	0.2660	0.8242	0.5825
Annual maximum	tau	-0.0442	0.0038	-0.0624	0.0409	0.1615	0.0757	-0.0526
	z statistic	-0.6171	0.0457	-0.8678	0.5292	2.3407	1.0836	-0.7480
	p-value	0.5372	0.9635	0.3855	0.5967	0.0192*	0.2786	0.4545
Annual minimum	tau	0.1451	-0.0639	0.3763	-0.3234	0.1103	0.1942	0.1851
	z statistic	2.0216	-0.8356	5.2499	-4.2476	1.5893	2.7892	2.6264
	p-value	0.0432*	0.4034	0.0000*	0.0000*	0.1120	0.0053*	0.0086*
Timing of maximum	tau	-0.0337	-0.0348	0.1194	0.1574	-0.0006	-0.1064	0.0737
	z statistic	-0.4697	-0.4530	1.6626	2.0493	-0.0062	-1.5243	1.0486
	p-value	0.6385	0.6506	0.0964	0.0404	0.9950	0.1274	0.2943
Timing of minimum	tau	-0.1438	-0.1063	-0.0105	0.2316	-0.0246	0.0936	0.1501
	z statistic	-2.0044	-1.3923	-0.1429	3.0378	-0.3514	1.3410	2.1276
	p-value	0.0450*	0.1638	0.8864	0.0024*	0.7253	0.1799	0.0334*

Null hypothesis: tau = 0. An asterisk indicates that trend is significant at 5%.

Trend test for monthly series

To examine the possible changes occur in smaller timescale, we need to investigate the monthly flow series. Monthly streamflows usually exhibit strong seasonality. A modification of Kendall's test, referred to as the seasonal Kendall test (Hirsch *et al.*, 1982; Hirsch and Slack, 1984), is used here.

Seasonal Kendall test. The seasonal Kendall test accounts for seasonality by computing the MK test on each of p seasons separately, and then combining the results. Compute the following overall statistic S' :

$$S' = \sum_{j=1}^p S_j$$

where,

S_j : is simply the MK S-statistic (Equation 1) for season j ($j = 1, 2, \dots, p$).

When no serial dependence exhibit in the time series, the variance of S' is defined as $\sigma_{S'}^2 = \sum_{j=1}^p \text{Var}(S_j)$.

When serial correlation is present, as in the case of monthly streamflow processes, the variance of S' is defined as

$$\sigma_{S'}^2 = \sum_{j=1}^p \text{Var}(S_j) + \sum_{g=1}^{p-1} \sum_{h=g+1}^p \sigma_{gh}$$

where,

σ_{gh} : denotes the covariance between the Kendall statistic for season g and the Kendall statistic for season h .

Then the quantity z' defined in the following equation is approximately standard normally distributed:

$$z' = \begin{cases} (S' - 1) / \sigma_{S'} & \text{if } S' > 0 \\ 0 & \text{if } S' = 0 \\ (S' + 1) / \sigma_{S'} & \text{if } S' < 0 \end{cases} \quad (5)$$

The overall tau is the weighted average of the p seasonal τ 's, defined as

$$\tau = \frac{\sum_{j=1}^p n_j \tau_j}{\sum_{j=1}^p n_j}$$

where,

τ_j : is the *tau* for season j , estimated with Equation 2, and

n_j : denotes the number of observations without missing values for season j .

Seasonal Kendall test is appropriate for testing for trend in each season when the trend is always in the same direction across all seasons. However, the trend may have different directions in different seasons. Van Belle and Hughes (1984) suggest using the following statistic to test for heterogeneity in trend

$$Het = \sum_{j=1}^p z_j^2 - p\bar{z}^2 \quad (6)$$

where,

z_j : denotes the *z*-statistic for the j th season computed as $z_j = \frac{S_j - E(S_j)}{(Var(S_j))^{1/2}}$, and $\bar{z} = \frac{1}{p} \sum_{j=1}^p z_j$.

Under the null hypothesis of no trend in any season, the statistic defined in Equation (6) is approximately distributed as a chi-square random variable with $p - 1$ degrees of freedom.

Seasonal Kendall test results. The 7 monthly streamflow processes are tested for trend with the seasonal Kendall test which allows for the serial dependence. And the homogeneity of trend is also tested. The results are shown in Table 3. The results give the same as conclusion as the test for annual series, that is, there is no increasing or decreasing trend in monthly mean flows. Only the monthly streamflow of Maas may exhibit weak trend because the p-value is only slightly larger than 0.05. Meanwhile, it is found that there is no significant trend heterogeneity for each month.

Table 3. Seasonal Kendall tests on monthly series.

Streamflow	<i>tau</i>	<i>z'</i> statistic	trend p-value	<i>Het</i> p-value
Danube	-0.0084	-0.2010	0.8407	0.2558
Elbe	0.0600	1.4102	0.1585	0.4341
Inn	-0.0150	-0.3646	0.7154	0.1879
Maas	-0.0884	-1.8951	0.0581	0.1305
Rhine	0.0359	0.8370	0.4026	0.7966
Thames	0.0634	1.3903	0.1644	0.6260
Wesser	0.0482	1.0849	0.2780	0.1384

Null hypothesis for trend test: $\tauau = 0$

Null hypothesis for trend homogeneity test: τau of all seasons are equal to 0

STATIONARITY TEST

While the purpose of a trend test is to determine whether the values of a series have a general increase or decrease with the time increase, the purpose of stationarity test is to determine whether the mean values and variances of a series vary with time. Almost all methods of time series analysis, traditional linear or nonlinear, must assume some kind of stationarity. It is thus necessary to test for stationarity for the justification of using certain models. On the other hand, sometimes the investigation of nonstationarity may give us some insights into the underlying physical mechanism. Therefore, testing for stationarity is an important topic of time series analysis in many areas of science.

There are roughly two groups of methods for testing stationarity. The first group is based on ideas of analyzing the statistical differences of different segments of the time series (e.g. Chen and Rao, 2002). If the observed variations in a certain parameter of different segments are found to be significant, that is,

outside the expected statistical fluctuations, the time series is regarded as nonstationary. Another group of stationarity tests is based on statistics for the full sequence. We adopt the second approach here.

The stationarity test is carried out with two methods, one is the augmented Dickey-Fuller (ADF) unit root test first proposed by Dickey and Fuller (1979) and modified by Said and Dickey (1984), which tests for the presence of unit roots in the series (difference stationarity); another is KPSS test proposed by Kwiatkowski *et al.* (1992), which tests for the stationarity around a deterministic trend (trend stationarity) and the stationarity around a fixed level (level stationarity). KPSS test can also be modified to be used as a unit root test, but it is shown by Shin and Schmidt (1992) that the KPSS statistic, designed for use as a test of stationarity, is not as good a unit root test as other standard test. In particular, its power is noticeably less than the power of the Dickey-Fuller test (or other similar tests) against stationary alternatives.

ADF test. Dickey-Fuller unit-root tests are conducted through Ordinary Least Square (OLS) estimation of regression models incorporating either an intercept or a linear trend. Consider the AR(1) model

$$x_t = \rho x_{t-1} + \varepsilon_t, t = 1; 2; \dots, N \quad (7)$$

where,

$$x_0 = 0,$$

$$|\rho| \leq 1, \text{ and}$$

ε_t : is a real valued sequence of independent random variables with mean zero and variance σ^2 .

If $\rho = 1$, the process $\{x_t\}$ is nonstationary and it is known as a random walk process. In contrast, if $|\rho| < 1$, the process $\{x_t\}$ is stationary. The maximum likelihood estimator of ρ is the least squares estimator

$$\hat{\rho} = \left(\sum_{t=2}^N x_{t-1}^2 \right)^{-1} \sum_{t=2}^N x_t x_{t-1}$$

The statistic for testing the null hypothesis that $\rho = 1$ is based on the usual OLS (ordinary least square) t test of this hypothesis

$$t = \frac{\hat{\rho} - 1}{\hat{\sigma}_{\hat{\rho}}} \quad (8)$$

where,

$\hat{\sigma}_{\hat{\rho}}$: is the usual OLS standard error for the estimated coefficient.

Dickey and Fuller (1979) derived the limiting distribution of the statistic t under the null hypothesis that $\rho = 1$, and tables of the percentiles of this distribution is available in Fuller (1976: 371-373). The test rejects $\rho = 1$ when t is “too negative”. The basic autoregressive unit root test can be augmented (referred to as ADF test) to accommodate general AR(p, q) models with unknown orders (Said and Dickey, 1984; Hamilton, 1994: 516-530). Said and Dickey (1984) show that the Dickey-Fuller procedure, which was originally developed for autoregressive representations of known order, remains valid asymptotically for a general ARIMA($p, 1, q$) process in which p and q are of unknown orders.

KPSS test. Let $\{x_t\}, t = 1, 2, \dots, N$, be the observed series for which we wish to test stationarity. Assume that we can decomposes the series into the sum of a deterministic trend, a random walk, and a stationary error with the following linear regression model

$$x_t = r_t + \beta t + \varepsilon_t \quad (9)$$

where,

r_t : is a random walk, i.e., $r_t = r_{t-1} + u_t$,

u_t : is iid $N(0, \sigma_u^2)$; βt is a deterministic trend, and

ε_t : is a stationary error.

To test in this model if x_t is a trend stationary process, namely, the series is stationary around a deterministic trend, the null hypothesis will be $\sigma_u^2 = 0$, which means that the intercept is a fixed element, against the alternative of a positive σ_u^2 . In another stationarity case, the level stationarity, namely, the series is stationary around a fixed level, the null hypothesis will be $\beta = 0$. So that, under the null hypothesis, in the case of trend stationary, the residuals e_t ($t = 1, 2, \dots, N$) are from the regression of x on an intercept and time trend, $e_t = \varepsilon_t$; whereas in the case of level stationarity, the residuals e_t are from a regression of x on intercept only, that is $e_t = x_t - \bar{x}$. Let the partial sum process of the e_t as $S_t = \sum_{j=1}^t e_j$, and σ^2 be the long-run variance of e_t , which is defined as $\sigma^2 = \lim N^{-1} E[S_N^2]$. The consistent estimator of σ^2 can be constructed from the residuals e_t by

$$\hat{\sigma}^2(p) = \frac{1}{N} \sum_{t=1}^N e_t^2 + \frac{2}{N} \sum_{j=1}^p w_j(p) \sum_{t=j+1}^N e_t e_{t-j} \quad (10)$$

where,

p : is the truncation lag, and

$w_j(p)$: is an optional weighting function that corresponds to the choice of a special window, e.g. Bartlett window $w_j(p) = 1 - j/(p+1)$.

Then, the KPSS test statistic is given by

$$KPSS = N^{-2} \sum_{t=1}^N S_t^2 / \hat{\sigma}^2(p) \quad (11)$$

The upper tail critical values of the asymptotic distribution of the KPSS statistic are given by Kwiatkowski *et al.* (1992).

Test results. Because on one hand both ADF and KPSS tests are based on linear regression, which has the normal distribution assumption; on the other hand, logarithmization can convert exponential trend possibly present in the data into a linear trend, therefore, it is common to take logs of the data before attempting to describe them with trend-stationary model or unit-root-process model (Hamilton, 1994: 438), and then applying ADF test and KPSS test (e.g. Gimeno *et al.*, 1999). In this study, the streamflow data are logarithmized before applying stationarity tests. Because the daily streamflow series of the Maas River has several zero discharges, we add 0.5 to all the discharges before taking logarithm. To eliminate possible impacts of seasonality present in the streamflow processes on the effectiveness of stationarity test, besides logarithmization, data are also deseasonalized. Deseasonalization is performed by subtracting the seasonal (daily or monthly) mean values and dividing by seasonal standard deviations.

An important practical issue for the implementation of the ADF and KPSS tests is the specification of the truncation lag value p . The KPSS test statistics are fairly sensitive to the choice of p , and in fact for every series the value of the test statistic decreases as p increases (Kwiatkowski *et al.*, 1992). If p is too small then the remaining serial correlation in the errors will bias the test. If p is too large, then the power of the test will suffer. In the work of some authors, such as Schwert (1989) and Kwiatkowski *et al.* (1992), the number of lag length is chosen as $p = \text{int}[x(N/100)^{1/4}]$, with $x = 4, 12$. Because the major concern when choosing an appropriate value of p is to take into account the serial correlation in the time series data, thus in our study, for daily and monthly series, we choose the value of p according to the orders of fitted AR models which are determined with Akaike Information Criterion (AIC). For annual series, we choose $p = 1$.

The stationarity test results are given in Table 4. Most monthly (except of the Maas) and annual series appear to be significantly stationary, since we cannot accept the unit root hypothesis with ADF test at 1% significance level and cannot reject the trend stationarity hypothesis and level stationarity hypothesis with KPSS test at the 5% level. For the Maas, monthly streamflow process is trend stationary at low significance level 1%, but not level stationary at 1% level. This indicates that there is weak trend

component, which has been shown by the seasonal Kendall test. After removing such a weak trend, the stationarity of the monthly streamflow series of the Maas is slightly improved, but still not significant enough for us to accept the null hypothesis of stationarity. Among the 7 daily flow series, two series pass level stationarity test (Danube and Inn) at significance level 10% and trend stationarity test at a lowerer level (2.5% for Danube, 1% for Inn). Other daily series either cannot pass the level stationarity or trend stationarity test at 1% level, or just pass at a very low significance level (1% for Rhine).

Table 4. Stationarity test results for streamflow series.

Station	Series	lag	KPSS level stationary statistic	p-value	KPSS trend stationary statistic	p-value	ADF unit roots statistic	p-value
Danube	Daily	44	0.1495	>0.1	0.1525	>0.025	-26.05	6.20E-99
	Monthly	6	0.0617	>0.1	0.0629	>0.1	-18.26	4.56E-51
	Annual	1	0.0347	>0.1	0.0335	>0.1	-8.465	7.02E-10
Elbe	Daily	27	1.5562	<0.01	0.3911	<0.01	-19.89	2.23E-68
	Monthly	6	0.2422	>0.1	0.0858	>0.1	-16.74	3.39E-45
	Annual	1	0.0639	>0.1	0.0522	>0.1	-6.479	1.86E-06
Inn	Daily	36	0.3093	>0.1	0.2133	>0.01	-40.19	7.66E-136
	Monthly	3	0.1015	>0.1	0.0958	>0.1	-17.25	2.42E-46
	Annual	1	0.1196	>0.1	0.0282	>0.1	-10.2	4.64E-07
Maas	Daily	43	2.5119	<0.01	0.4208	<0.01	-29.33	1.97E-112
	Monthly	3	0.914	<0.01	0.207	>0.01	-15.29	7.61E-39
	Annual	1	0.2323	>0.1	0.0736	>0.1	-7.146	3.70E-07
Rhine	Daily	40	0.5745	>0.01	0.2327	<0.01	-15.14	1.51E-43
	Monthly	4	0.2685	>0.1	0.1018	>0.1	-16.5	1.07E-44
	Annual	1	0.1868	>0.1	0.0475	>0.1	-8.706	1.79E-10
Thames	Daily	44	1.1312	<0.01	0.37	<0.01	-26.97	4.33E-103
	Monthly	4	0.3646	>0.05	0.1317	>0.05	-13.71	2.97E-33
	Annual	1	0.0948	>0.1	0.0599	>0.1	-7.869	5.50E-09
Weser	Daily	32	1.1439	<0.01	0.2268	<0.01	-18.95	1.87E-63
	Monthly	3	0.5287	>0.025	0.0924	>0.1	-16.14	4.50E-43
	Annual	1	0.1038	>0.1	0.045	>0.1	-7.264	6.96E-08

DISCUSSION

It has been observed (Houghton *et al.*, 2001) that average global surface temperature has increased by approximately $0.61 \pm 0.18^\circ\text{C}$ over 1901 to 2000, and corresponding Northern Hemisphere temperature change for 1901 to 2000 is $0.71 \pm 0.31^\circ\text{C}$. Most of this increase has occurred in two periods, from about 1910 to 1945 and since 1976, and the largest recent warming is in the winter extratropical Northern Hemisphere. Furthermore, there is a high level of consistency between changes in sea surface temperatures and near-surface land air temperatures across the land-ocean boundary over the 20th century. Grieser *et al.* (2002) investigated European monthly mean temperatures, and show that the temperature trends over Europe are mainly positive. At the same time, some research (Shorthouse and Arnell, 1999) has related European hydrological behaviour to the North Atlantic Oscillation (NAO), which presents a strong non-stationary behaviour (Pozo-Vázquez *et al.*, 2001) and strong decadal variability (Greatbatch, 2000).

However, with all these changes, according to the results from our study, streamflow processes on monthly and annual timescale are basically stationary and lack of any significant trend. This probably implies that streamflow processes in western Europe are not significantly influenced by global warming (if the warming indeed occurred). Albeit some daily flow processes are nonstationary, such nonstationarity on daily timescale is more likely to be caused by the change of human interventions, because rivers in western Europe usually strongly influenced by human activities, and such activities,

such as the operation of weirs, locks and pumps, may result in significant variations in discharges at short timescale. Even though we have detected that the Maas River has significant nonstationarity not only in daily streamflow but also in monthly streamflow, we cannot conclude that the nonstationarity is the result of climate change. The Dutch National Research Programme on Global Air Pollution and Climate Change workshop also states (de Wit, 2002) that one cannot tell whether the extremes of streamflow are the results of climate change.

The reasons that these streamflow processes in western Europe do not synchronize with global climate change may be two folded. First, temperature change may result in important changes in seasonal streamflow hydrographs for those river basins where snow plays an important role. In these systems, spring snowmelt peaks are reduced and winter flows increase, on average (Lettenmaier *et al.*, 1999). But the rivers we studied here have no or little dependence on snow melt water, therefore are little affected by temperature change. Second, streamflow processes are essentially dominated by precipitation processes. Although European hydrological behaviour is strongly influenced by NAO and NAO itself shows strong decadal variability, however, on one hand, although it has been found that NAO is related to the distribution of precipitation in some regions (e.g. Hurrel, 1995), it does not always result in the change of precipitation. For example, correlations between precipitation in Paris and the NAO index are not significant (Slonosky, 2002). On the other hand, the changes of streamflow processes caused by decadal variability of NAO may not be statistically significant enough to be detected in the long-term.

CONCLUSIONS

Streamflow processes of seven major rivers at 7 stations, which temporally span the 20th century and are spatially evenly located in western Europe to the north of Alps, are investigated for trend and nonstationarity. The trend of annual mean discharges, annual maximum daily discharges, annual minimum daily discharges and their timing are investigated with Mann-Kendall test. Results show that there is no trend in annual mean discharge. Only one annual maximum flow series exhibits significant upward trend (Rhine). There is one minimum flow series that exhibits significant downward (Maas) and seven that exhibit upward trend (Danube, Elbe, Thames and Weser). The timing of maximum flow exhibits no significant change, but the timing of minimum streamflow at 3 sites has significant change. The occurrence of minimum streamflow of the Danube gets earlier, whereas the minimum flows of Maas and Weser come later. Monthly flow series are examined with seasonal Kendall test, but no significant trend is found.

ADF test (Dickey and Fuller, 1979) and KPSS test (Kwiatkowski *et al.*, 1992) are used to test for nonstationarity. All annual streamflow series and most monthly streamflow series appear to be significantly stationary. But among the 7 daily flow series, two series pass the level stationarity test (Danube and Inn) at significance level 10% and trend stationarity test at a lowerer level (2.5% for Danube, 1% for Inn). Other daily series cannot pass neither the level stationarity nor trend stationarity test at 1% level, or just pass at a very low significance level (1% for Rhine). The results imply that despite the observed global warming, the streamflow processes in western Europe are generally not significantly impacted.

REFERENCES

- Burn D.H. and Hag Elnur M.A. (2002). Detection of hydrologic trends and variability. *Journal of Hydrology*, **255**, 107-122.
- Chen H.L. and Rao A.R. (2002). Testing hydrologic time series for stastionarity. *J Hydrol. Eng.*, **7**(2), 129-136
- de Wit M.J.M. (2001). *Effect of climate change on the hydrology of the river Meuse*. Report 104, Wageningen University Environmental Sciences, Netherlands.

- Dickey D.A. and Fuller W.A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *J. Am. Stat. Assoc.* **74**, 423–431.
- Gimeno R., Manchado B. and Mínguez R. (1999). Stationarity tests for financial time series. *Physica A*, **269**(1), 72-78.
- Greatbatch R.J. (2000). The North Atlantic Oscillation. *Stoch. Env. Res. Risk Assess.* **14**, 213-242.
- Grieser J., Tromel S. and Schonwiese C.D. (2002). Statistical time series decomposition into significant components and application to European temperature. *Theor. Appl. Climatol.* **71**, 171-183.
- Hamilton J.D. (1994). *Time series analysis*. Princeton University Press, Princeton.
- Hirsch R.M. and Slack J.R. (1984). A nonparametric trend test for seasonal data with serial dependence. *Water Resources Research*, **20**(6), 727-732.
- Hirsch R.M., Slack J.R. and Smith R.A. (1982). Techniques of trend analysis for monthly water quality data. *Water Resources Research*, **18**(1), 107-121.
- Houghton J.T., Ding Y., Griggs D.J., Noguer M., van der Linden P.J., Dai X., Maskell K. and Johnson C.A. (2001). *Climate Change 2001: The Scientific Basis*. Cambridge University Press, 105-108
- Hurrell J.W., (1995). Decadal trends in the North Atlantic oscillation: Regional temperatures and precipitation. *Science*, **269**, 676–679.
- Kendall M.G. (1938). A new measure of rank correlation. *Biometrika*, **30**, 81-93.
- Kwiatkowski D., Phillips P.C.B., Schmidt P. and Shin Y. (1992). Testing the null of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? *J. Econometrics*, **54**, 159–178.
- Lettenmaier D.P., Wood A.W., Palmer R.N., Wood E.F. and Stakhiv E.Z. (1999). Water resources implications of global warming: A U.S. regional perspective. *Clim. Change*, **43**, 537-579.
- Lins H.F. and Slack J.R. (1999). Streamflow trends in the United States. *Geophysical Research Letters*, **26**(2), 227-230.
- Mann H.B. (1945). Nonparametric test against trend. *Econometrica*, **13**, 245-259.
- Mansell M.G. (1997). The effect of climate change on rainfall trends and flooding risk in the west of Scotland. *Nordic Hydrology*, **28**, 37–50.
- Matalas N.C. (1997). Stochastic hydrology in the context of climate change. *Climatic Change*, **37**, 89–101.
- McCabe G.J. and Wolock D.M. (2002). A step increase in streamflow in the conterminous United States. *Geophysical Research Letters*, **29**(24), 2185, doi:10.1029/2002GL015999.
- Pfister L., Humbert J. and Hoffmann L. (2000). Recent trends in rainfall-runoff characteristics in the Alzette river basin, Luxembourg. *Climatic Change*, **45**(2), 323 – 337.
- Pozo-Vázquez D., Esteban-Parra M.J., Rodrigo F.S. and Castro-Díez Y. (2001). A study of NAO variability and its possible non-linear influences on European surface temperature. *Climate Dynamics* **17**(9), 701-715.
- Robson A.J., Jones T.K., Reed D.W. and Bayliss A.C. (1998). A study of national trend and variation in UK floods. *Int. J. Climatol.* **18**, 165-182.
- Said S.E. and Dickey D. (1984). Testing for unit roots in autoregressive moving-average models with unknown order. *Biometrika*, **71**, 599-607.
- Schwert G.W. (1989). Tests for unit roots: a monte Carlo investigation. *Journal of Business and Economics Statistics*, **7**, 147-159
- Shin Y. and Schmidt P. (1992). The KPSS stationarity test as a unit root test. *Economic Letters*, **38**, 387-392.
- Shorthouse C. and Arnell N. (1999). The effects of climatic variability on spatial characteristics of European river flows. *Phys. Chem. Earth (B)*, **24**(1-2), 7-13.
- Slonosky V.C. (2002). Wet winters, dry summers? Three centuries of precipitation data from Paris. *Geophys. Res. Lett.* **29**(19), 1895, doi:10.1029/2001GL014302.
- van Belle G., and Hughes J.P. (1984). Nonparametric tests for trend in water quality. *Water Resources Research*, **20**(1), 127-136.
- van Gelder P., Kuzmin V. and Visser P. (2000). Analysis and statistical forecasting of trends of hydrological processes in climate changes. In: *Proceedings of the International Symposium on Flood Defence*, Vol. 1 (Toensmann F. and Koch M., Eds.), Kassel, Germany, pp D13-D22.

- von Storch H., (1995). Misuses of statistical analysis in climate research, In: *Analysis of Climate Variability: Applications of Statistical Techniques*, (Storch H.V. and Navarra A. Eds.), Springer-Verlag, New York, pp. 11– 26.
- Zhang X., Harvey K.D., Hogg W.D. and Uzyk R. (2001). Trends in Canadian streamflow. *Water Resources Research*, **37**(4), 987–998.