

Non-Parametric Trend Tests and Change-Point Detection

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Contents

1	Trend detection	1
1.1	Mann-Kendall Test	1
1.2	Seasonal Mann-Kendall Test	3
1.3	Correlated Seasonal Mann-Kendall Test	4
1.4	Partial Mann-Kendall Test	4
1.5	Partial correlation trend test	5
2	Magnitude of trend	5
2.1	Sen's slope	5
2.2	Seasonal Sen's slope	6
3	Change-point detection	7
3.1	Pettitt's test	7

1 Trend detection

1.1 Mann-Kendall Test

The non-parametric Mann-Kendall test is commonly employed to detect monotonic trends in series of environmental data, climate data or hydrological data. The null hypothesis, H_0 , is that the data come from a population with independent realizations and are identically distributed. The alternative hypothesis, H_A , is that the data follow a monotonic trend. The Mann-Kendall test statistic is calculated according to :

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^n \text{sgn}(X_j - X_k) \quad (1)$$

with

$$\text{sgn}(x) = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{if } x = 0 \\ -1 & \text{if } x < 0 \end{cases} \quad (2)$$

The mean of S is $E[S] = 0$ and the variance σ^2 is

$$\sigma^2 = \left\{ n(n-1)(2n+5) - \sum_{j=1}^p t_j(t_j-1)(2t_j+5) \right\} / 18 \quad (3)$$

where p is the number of the tied groups in the data set and t_j is the number of data points in the j th tied group. The statistic S is approximately normal distributed provided that the following Z-transformation is employed:

$$Z = \begin{cases} \frac{S-1}{\sigma} & \text{if } S > 0 \\ 0 & \text{if } S = 0 \\ \frac{S+1}{\sigma} & \text{if } S < 0 \end{cases} \quad (4)$$

The statistic S is closely related to Kendall's τ as given by:

$$\tau = \frac{S}{D} \quad (5)$$

where

$$D = \left[\frac{1}{2}n(n-1) - \frac{1}{2} \sum_{j=1}^p t_j(t_j-1) \right]^{1/2} \left[\frac{1}{2}n(n-1) \right]^{1/2} \quad (6)$$

The univariate Mann-Kendall test is invoked as follows:

```
> require(trend)
> data(maxau)
> Q <- maxau[, "Q"]
> mk.test(Q)
```

Mann-Kendall Test

```
two-sided homogeneity test
H0: S = 0 (no trend)
HA: S != 0 (monotonic trend)
```

```
Statistics for total series
   S varS   Z   tau pvalue
1 -144 10450 -1.4 -0.145 0.16185
```

1.2 Seasonal Mann-Kendall Test

The Mann-Kendall statistic for the g th season is calculated as:

$$S_g = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(X_{jg} - X_{ig}), \quad g = 1, 2, \dots, m \quad (7)$$

According to Hirsch *et al.* (1982), the seasonal Mann-Kendall statistic, \hat{S} , for the entire series is calculated according to

$$\hat{S} = \sum_{g=1}^m S_g \quad (8)$$

For further information, the reader is referred to Hipel and McLeod (1994, p. 866-869) and Hirsch *et al.* (1982). The seasonal Mann-Kendall test is conducted as follows:

```
> require(trend)
> smk.test(nottem)
```

Seasonal Mann-Kendall Test without correlation

```
two-sided homogeneity test
H0: S = 0 (no trend)
HA: S != 0 (monotonic trend)
```

```
Statistics for individual seasons
      S varS   Z   tau  pvalue
1   -7 944.3 -0.2 -0.037 0.8198092
2    3 949.0  0.1  0.016 0.9224214
3    1 949.0  0.0  0.005 0.9741041
4   31 947.0  1.0  0.163 0.3137596
5  -23 944.3 -0.7 -0.121 0.4541863
6   45 949.0  1.5  0.237 0.1440808
7   -9 949.0 -0.3 -0.047 0.7701701
8   80 946.0  2.6  0.421 0.0092946
9   67 944.3  2.2  0.353 0.0292368
10  -2 946.0 -0.1 -0.011 0.9481536
11  59 947.0  1.9  0.311 0.0552071
12 -21 949.0 -0.7 -0.111 0.4954357
```

```
Statistics for total series
      S varS   Z   tau  pvalue
1  224 11364  2.1  0.098 0.035617
```

Only the temperature data in Nottingham for August ($S = 80$, $p = 0.009$) as well as for September ($S = 67$, $p = 0.029$) show a significant ($p < 0.05$) positive trend

according to the seasonal Mann-Kendall test. Thus, the global trend for the entire series is significant ($S = 224$, $p = 0.036$).

1.3 Correlated Seasonal Mann-Kendall Test

The correlated seasonal Mann-Kendall test can be employed, if the data are corelated with e.g. the pre-ceeding months. For further information the reader is referred to Hipel and McLoed (1994, p. 869-871).

```
> require(trend)
> csmk.test(nottem)
```

Seasonal Mann-Kendall Test with correlations

```
two-sided homogeinity test
H0: S = 0 (no trend, seasons are correlated)
HA: S != 0 (monotonic trend)
```

```
Statistics for total series
      S      varS      Z  pvalue
1 224 19663.33 1.6 0.11017
```

1.4 Partial Mann-Kendall Test

This test can be conducted in the presence of co-variates. For full information, the reader is referred to Libiseller and Grimvall (2002).

We assume a correlation between concentration of suspended sediments (s) and flow at Maxau.

```
> data(maxau)
> s <- maxau[,"s"]; Q <- maxau[,"Q"]
> cor.test(s,Q, meth="spearman")
```

Spearman's rank correlation rho

```
data: s and Q
S = 10564, p-value = 0.0427
alternative hypothesis: true rho is not equal to 0
sample estimates:
      rho
0.3040843
```

As s is significantly positive related to flow, the partial Mann-Kendall test can be employed as follows.

```

> require(trend)
> data(maxau)
> s <- maxau["s"]; Q <- maxau["Q"]
> partial.mk.test(s,Q)

```

Partial Mann-Kendall trend test

```

data: t AND s . Q
Z = -3.597, p-value = 0.0003218
alternative hypothesis: true trend exists in series
sample estimates:
      S      varS
-350.6576 9503.2898

```

The test indicates a highly significant decreasing trend ($S = -350.7$, $p < 0.001$) of s , when Q is partialled out.

1.5 Partial correlation trend test

This test performs a partial correlation trend test with either the Pearson's or the Spearman's correlation coefficients ($r(tx.z)$). The magnitude of the linear / monotonic trend with time is computed while the impact of the co-variate is partialled out.

```

> require(trend)
> data(maxau)
> s <- maxau["s"]; Q <- maxau["Q"]
> partial.cor.trend.test(s,Q, "spearman")

```

Spearman's partial correlation trend test

```

data: t AND s . Q
t = -4.158, df = 43, p-value = 0.0001503
alternative hypothesis: true correlation is not equal to 0
sample estimates:
  r(ts.Q)
-0.5355055

```

Likewise to the partial Mann-Kendall test, the partial correlation trend test using Spearman's correlation coefficient indicates a highly significant decreasing trend ($r_{S(ts.Q)} = -0.536$, $n = 45$, $p < 0.001$) of s when Q is partialled out.

2 Magnitude of trend

2.1 Sen's slope

This test computes both the slope (i.e. linear rate of change) and intercept according to Sen's method. First, a set of linear slopes is calculated as follows:

$$d_k = \frac{X_j - X_i}{j - i} \quad (9)$$

for $(1 \leq i < j \leq n)$, where d is the slope, X denotes the variable, n is the number of data, and i, j are indices.

Sen's slope is then calculated as the median from all slopes: $b = \text{Median } d_k$. The intercepts are computed for each timestep t as given by

$$a_t = X_t - b * t \quad (10)$$

and the corresponding intercept is as well the median of all intercepts.

This function also computes the upper and lower confidence limits for sens slope.

```
> require(trend)
> s <- maxau["s"]
> sens.slope(s)
```

Sen's slope and intercept

```
slope: -0.2876
95 percent confidence intervall for slope
-0.1519 -0.4196
```

```
intercept: 31.8574
nr. of observations: 45
```

2.2 Seasonal Sen's slope

According to Hirsch *et al.* (1982) the seasonal Sen's slope is calculated as follows:

$$d_{ijk} = \frac{X_{ij} - x_{ik}}{j - k} \quad (11)$$

for each (x_{ij}, x_{ik}) pair $i = 1, 2, \dots, m$, where $1 \leq k < j \leq n_i$ and n_i is the number of known values in the i th season. The seasonal slope estimator is the median of the d_{ijk} values.

```
> require(trend)
> sea.sens.slope(nottem)
```

Seasonal Sen's slope and intercept

```
slope: 0.05
intercept: 42.1
nr. of observations: 240
```

3 Change-point detection

3.1 Pettitt's test

The approach after Pettitt (1979) is commonly applied to detect a single change-point in hydrological series or climate series with continuous data. It tests the H_0 : The T variables follow one or more distributions that have the same location parameter (no change), against the alternative: a change point exists. The non-parametric statistic is defined as:

$$K_T = \max |U_{t,T}|, \quad (12)$$

where

$$U_{t,T} = \sum_{i=1}^t \sum_{j=t+1}^T \text{sgn}(X_i - X_j) \quad (13)$$

The change-point of the series is located at K_T , provided that the statistic is significant. The significance probability of K_T is approximated for $p \leq 0.05$ with

$$p \simeq 2 \exp\left(\frac{-6 K_T^2}{T^3 + T^2}\right) \quad (14)$$

The Pettitt-test is conducted in such a way:

```
> require(trend)
> data(PagesData)
> pettitt.test(PagesData)
```

```
Pettitt's test for single change-point detection
```

```
data: PagesData
K = 232, p-value = 0.01456
alternative hypothesis: true change point is present in the series
sample estimates:
probable change point at tau
17
```

As given in the publication of Pettitt (1979) the change-point of Page's data is located at $t = 17$, with $K_T = 232$ and $p = 0.014$.

References

Hipel KW, McLoed AI (1994). *Time series modelling of water resources and environmental systems*. Elsevier, Amsterdam.

- Hirsch R, Slack J, Smith R (1982). “Techniques of Trend Analysis for Monthly Water Quality Data.” *Water Resour. Res.*, **18**, 107–121.
- Libiseller C, Grimvall A (2002). “Performance of partial Mann-Kendall tests for trend detection in the presence of covariates.” *Environmetrics*, **13**, 71–84. doi:10.1002/env.507.
- Pettitt AN (1979). “A non-parametric approach to the change-point problem.” *Appl. Statist.*, **28**, 126–135.