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Technical Note: Why Methods Matter. A Guidance for Data-based Climate and Hydrological Change Assessments

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Abstract: *An important topic of the journal "Integrated Water Resources Management in Central Asia" will be the assessment of past and future changes in climate and water resources in Central Asia. This technical note aims at providing guidance for sound data-based assessment of changes to be published in this journal. The main requirements for achieving credible results are (1) the use of consistent data series, (2) the selection of appropriate change detection methods, and (3) the discussion of the results, their uncertainties and limitations. Using an example of trend analysis, it is exemplarily shown how inhomogeneities in a data series, the selection of start and end points, the applied methods, and temporal aggregation may affect the results of change studies.*

Keywords: data analysis, uncertainty, hydrometeorology, climate

Introduction

The assessment of climate change and its impact on water resources is one of the major topics in water research in Central Asia. Many studies on this topic have been published in the past two decades. For an overview, readers are referred to previously published review papers which try to piece together the findings of different studies to an overall picture (Sorg et al., 2012; Savoskul and Smakhtin, 2013; Unger-Shayesteh et al., 2013). However, these reviews have faced a major obstacle when synthesizing the findings of previous publications: the methodological approaches are quite diverse and often not well documented which hampers any comparison and overall conclusions are difficult to make. This technical note aims at (1) demonstrating the effects of different methods and data sets on the findings about climate and hydrological change and at (2) establishing guidance for change studies to be published in this new journal.

Basic Concepts

The following basic concepts should be considered in the design of any change analysis.

1.1. Variability versus change

Due to its highly continental position in the mid-latitudes, hydrometeorological state variables in many areas of Central Asia exhibit a substantial natural variability on the intra-annual and inter-annual scale. This variability should not be confused with "change", and in many studies, it may be a challenge to disentangle both factors. Thus, it is crucial for any change assessment that longer time periods are investigated based on homogenous data sets. Typically, depending on the study site and the investigated variable, 10 to 30 years of observations are recommended to infer an "average" condition, i.e. the climate state for the selected period (WMO, 2011). For change assessment, Kundzewicz and Robson (2000) recommend to use at least 50 years of observations.

WMO (2011) defines climate change as "a statistically significant variation in either the average state of the climate or in its variability, persisting for an extended period, typically decades or longer". Similarly, this applies also to hydrological change. With regard to the "average state", it should be noted, that many hydrometeorological variables (e.g. precipitation and river discharge on a daily time scale) do not follow a symmetric distribution, i.e. their distributions are typically highly skewed. This implies that the arithmetic mean is not always the adequate descriptor of the central tendency of the data set. In such cases, the median, i.e. the value separating the higher 50 % from the lower 50 % of the observations in the data set, is a more appropriate statistics (WMO, 2011, chapter 4) and has the additional advantage of being more robust against outliers. Spatial and/or temporal aggregation of observations usually leads to more symmetric distributions at the expense of losing information on the variability.

Many phenomena are not driven by the average state of the climate system but by its variability on a seasonal or even daily time scale. For instance, glacier melt can be described better by changes in the temperatures at a sub-seasonal scale than by mean annual temperature changes. To investigate changes in floods and low flows, the high and low percentiles of river discharge need to be considered. Thus, the temporal scale and the statistical metrics of the investigated variables should be carefully selected, particularly, if aiming for interpretation of the results.

1.2. Uncertainty

Any climatological and hydrological measurement is associated with uncertainty (WMO, 2008 / BMO, 2011). Different sources contribute to the overall uncertainty of a measurement, among them the accuracy of the sensor, the precision of the measurement, but also systematic errors in the measurement procedure (e.g. precipitation undercatch due to wind), data reporting errors, and the spatial and temporal limitations of the measurement (i.e. the representativeness). During data processing, the uncertainties propagate and new sources of uncertainty are introduced (e.g. due to assumptions underlying certain statistical inferences, selection of statistical measures and study periods, etc.). Hence, any study on climate and hydrological change should discuss how much confidence we can put into the data and results of the change assessment. This is of particular importance for informed decision making.

Data Basis

1.3. Station Data

Climate and hydrological change detection relies on observational data sets which meet the following requirements (Unger-Shayesteh et al., 2013):

- The station data should be homogeneous (or be homogenized by the investigator). Inhomogeneities may arise due to changes in station location or surroundings, changes in the measurement techniques or in reporting times. For details on changes in measurement techniques readers are referred to Groisman et al. (1991) for precipitation and National Climate Data Center (2003) for air temperature. WMO (2003) suggests a number of homogeneity tests and discusses homogenization approaches. Example 1 below demonstrates how unconsidered inhomogeneities may distort the results of a change assessment.
- Known errors such as coding/typing errors should be corrected. This includes also the correction for systematic measurement errors such as the precipitation gauge undercatch due to wind and solid precipitation. Groisman and Rankova (2001) discuss correction factors with focus on measurement techniques used in the former USSR.
- Station data should be representative for the phenomenon under investigation. Observations are affected by many factors such as the station location (e.g. elevation, exposure) or the station surroundings (e.g. increasing urbanization, irrigated areas). Depending on the research question, data of specific stations may not be able to reveal the phenomenon of interest, especially if the assessment is based on comparison of data from stations affected by different factors.

1.4. Gridded Data Sets

Many climate change impact studies – particularly in the field of hydrology and geoecology – require spatially explicit climate estimates. During the past two decades, global gridded climate data sets have increasingly become available which promise an additional data basis in data-scarce regions such as Central Asia. Here we give a brief overview about available data sets, their advantages and disadvantages, without any claim to completeness. Based on the method of generation, gridded climate data can be grouped into three categories: (1) gridded observational data sets, (2) satellite based estimates and (3) reanalysis products, all of them giving rise to specific strengths and weaknesses. Gridding algorithms utilize traditional interpolation or geostatistical methods in order to generate spatially comprehensive fields of near surface variables from station observations. Widely applied datasets are e.g. CRU (Harris et al., 2014), worldclim (Hijmans et al., 2005), APHRODITE (Yatagai et al., 2012), GPCC (Schneider et al., 2015). The quality of these data sets highly depends on the number of stations considered. Several studies evaluated global precipitation estimates for Central Asia (for an overview see Unger-Shayesteh et al., 2013). They found that the GPCC Full Data Reanalysis and APHRODITE data performed best, most likely due to a larger number of records involved. This was recently confirmed by Malsy et al. (2015).

Gridded observations usually have a spatial resolution of 0.5° lat/long or less, however most of the algorithms only consider latitude, longitude and elevation as independent predictor variables, resulting in a negligence of important topo-climatic processes, such as wind- and leeward slope positions and the associated spatial variability of precipitation rates in high mountain environments (Soria-Auza et al., 2010). Additionally, the utilized observational data sets are spatially biased (most of the stations are located at lower elevations), which leads to under-representation of the high mountain regions (Gerlitz et al., 2014). Thus, particular very high-resolution climate estimates such as worldclim should be handled with care. Since gridded observations are based on meteorological records, the methodological limitations of station data should likewise be considered for gridded data sets. It is highly recommended to evaluate the homogeneity and representativeness of the data set prior its application for climate impact assessment.

Gridded climate data based on satellite observations mainly process radar images, infrared and passive micro-wave observations in order to detect cloud top temperatures and the optical thickness of the atmosphere, and to parameterize local or regional scale precipitation amounts. The parametrizations are usually calibrated for specific regions and thus might not be spatially and temporally persistent. Moreover, the fact that most regions are only captured by satellite images once or twice a day, might result in loosing short-term precipitation events. Thus, state of the art satellite estimates such as TRMM (Huffman et al., 2007) and GPCP (Adler et al., 2012) additionally assimilate station observations. Guo et al. (2015) found that the gauge corrected version of TRMM adequately represents the spatial and temporal precipitation variability over Central Asia, while the satellite-only data set tends to highly overestimate the precipitation amounts. Since satellite data are only available after 1980, those data sets are usually not suitable for the estimation of climatic trends.

The third class of gridded climate data are reanalysis data products. The datasets such as ERA-Interim (Berrisford et al., 2009), NCEP/NCAR (Kalnay et al., 1996) or MERRA (Rienecker et al., 2011) are widely applied in data sparse regions. These data products result from global climate models merged with in situ observations and remote sensing data using data assimilation approaches. The combination of physically based climate models and atmospheric observations enables the estimation of large-scale weather and climate conditions for recent decades. Particularly the fact, that reanalysis products provide a comprehensive set of physically consistent variables is an advantage for many climate impact investigations. Several studies indicate that reanalysis products, especially ERA-Interim, sufficiently simulate the spatial and temporal climate variability over Central and High Asia (Schiemann et al., 2008; Wang & Zeng, 2012; Bao & Zhang, 2013), although some studies show that temperature trends are mostly underestimated by reanalysis products (Hasson et al., 2015; Frauenfeld et al., 2005). Moreover, depending on the assimilation approach, reanalysis data products may be less suitable for the analysis of long-term changes due to different number of stations and satellite data

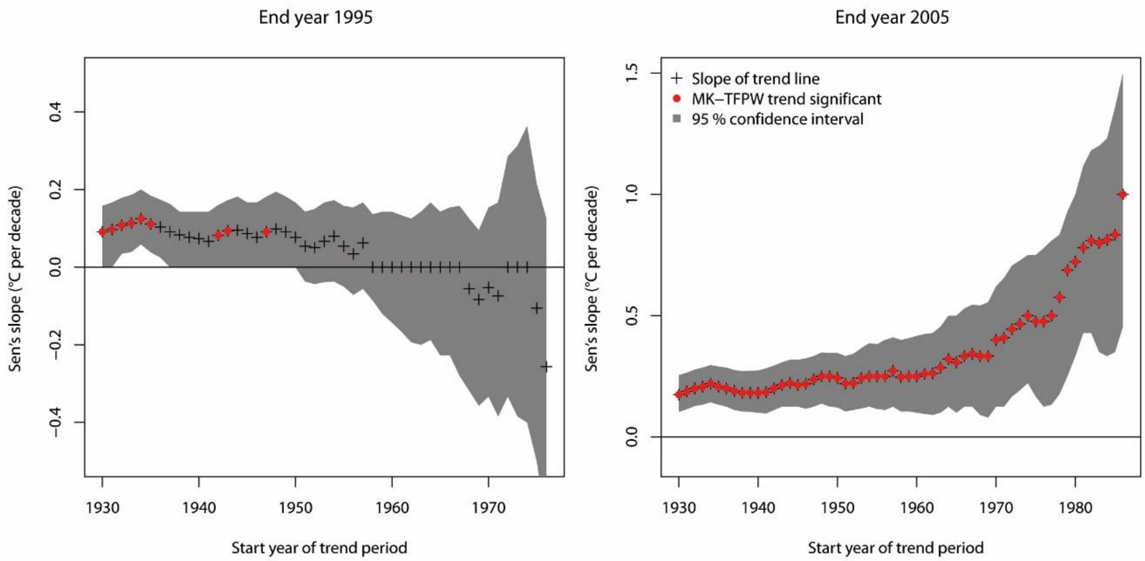
products assimilated into them. The latter causes inconsistencies and may corrupt actual trends (Bengtsson et al., 2004). Also the topographic heterogeneity in high mountain regions is not captured by state of the art climate reanalysis products due to their limited spatial resolution of 1 to 2.5° lat/long. Thus, reanalysis products are only representative for large regions (extending over several hundred kilometers). On the regional to local scale, reanalysis products are usually characterized by a systematic bias due to the simplified topography and thus are not reliable without a subsequent statistical or dynamical downscaling processing step (Gerlitz et al., 2015; Gerlitz et al., 2014).
We recommend selecting suitable gridded climate data sets, depending on the research target, the spatial extent and the topographic characteristics of the target area. The weaknesses of different gridded climate estimates (temporal inconsistency, low resolution) should eventually be considered for the interpretation of research results.

Examples

In the following section, selected examples shall demonstrate how data and methods affect the results of trend analyses at Central Asian monitoring stations.

1.5. Example 1: Trend in mean annual air temperature at the Tien Shan station – the effect of data inhomogeneities

Unger-Shayesteh et al. (2013) demonstrated the sensitivity of trend estimations to the selection of the start and end year. They conducted a Mann-Kendall trend analysis for mean annual air temperature data at the Tien Shan monitoring station. As is obvious from Figure 1, the calculated trends depend substantially on the selected study periods. The start and end years do not only affect the statistical significance of the trend but also its direction and magnitude (Figure 1a).
In the case of the Tien Shan station, an inhomogeneity in the data series substantially adds to this effect (Figure 1b). A conventional manually operated station was in operation until 1996 when it was relocated and replaced by a new automatic weather station (see Unger-Shayesteh et al., 2013, supplement 1). As is evident from Figure 1, the blending of air temperature data provided by the manual station with data from the automatic weather station after 1997 without homogenization results in high temperature trends over the whole study period (Figure 1b). This should not be interpreted as temperature change but is first of all an effect of the inconsistent data series.



(a) Effect of selected period (b) Effect of data inhomogeneity

Figure 1. Trend in mean annual air temperature at the Tien Shan station. (a): For the end year 1995. (b): For the end year 2005 (i.e. after station relocation). Red points mark the trend significance at the respective start year. The black crosses and the area shaded in grey give the Sen slope as the trend estimator and its 95 % confidence interval (computed using R and the package zyp).
(Reprinted from Global and Planetary Change, Vol. 110, Part A, Unger-Shayesteh et al., 2013, Copyright (2013), with permission from Elsevier)

1.6. Example 2: Trends in monthly streamflow at gauge Naryn – The effect of the selected method

Studying hydrological change over the past decades in the Naryn basin, we investigate if the gauge Naryn shows a trend in streamflow values over time. Monthly observations for 76 years are available from Kyrgyzhydromet, the operator of the Naryn gauge. We would like to use the full data set (912 observations, see Figure 2) for the trend assessment and look for an overall trend in the series.

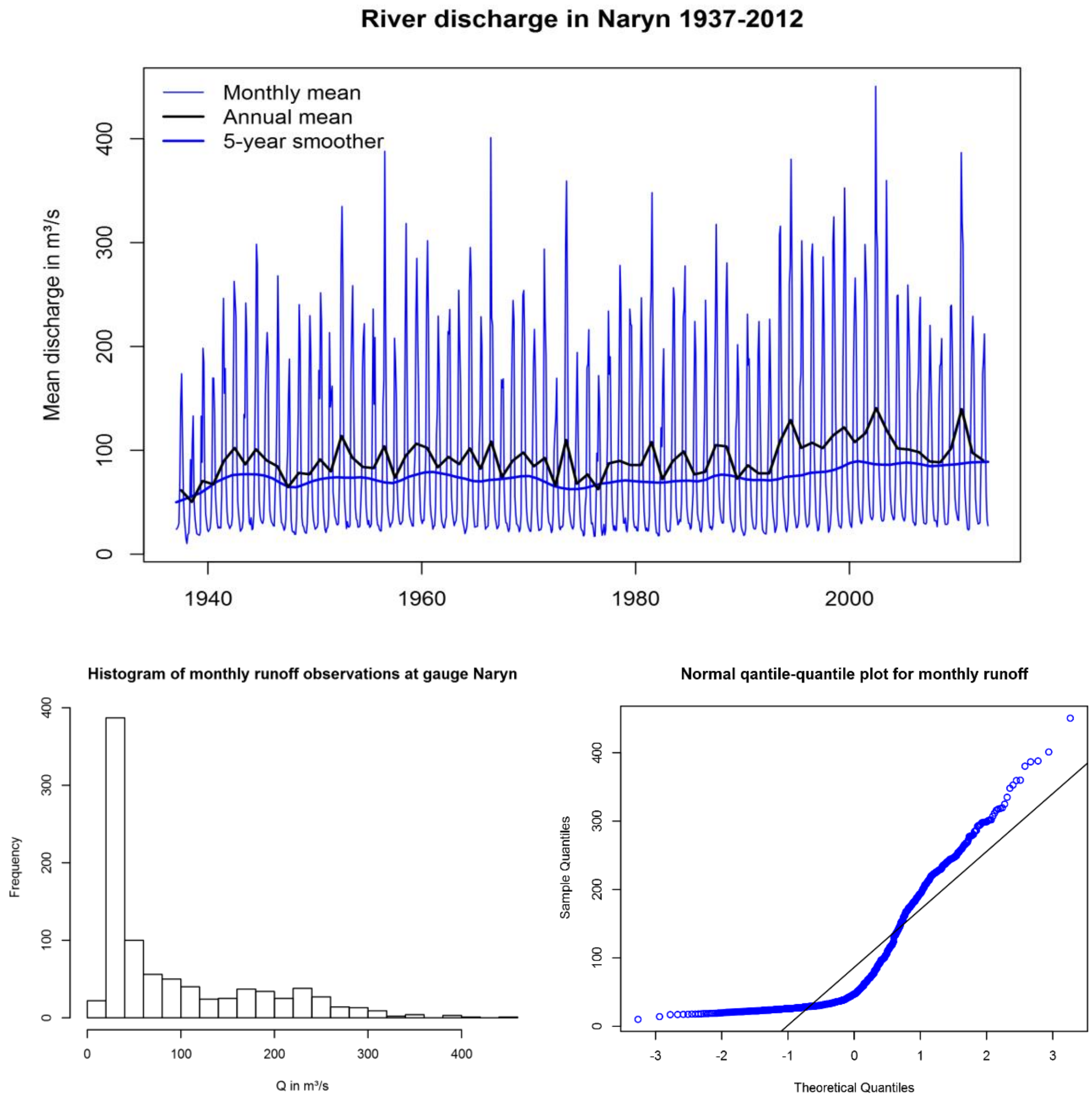


Figure 2. Time series of mean monthly and annual river runoff at the gauge Naryn for the period 1937-2012. The monthly series is plotted with the series of mean annual runoff and a locally-weighted polynomial regression line with 5-year smoother (upper panel).
Analytical plots to check for the distribution of the monthly runoff data (lower panel).

As most hydrological time series, the observations of mean monthly river runoff at the Naryn gauge do not follow a Gaussian normal distribution. Instead, the distribution of the data is strongly positively skewed and has a heavy tail towards runoff maxima (Figure 2). This implies that statistical inference methods relying on the normal distribution assumption cannot give meaningful results. In addition, the monthly series shows a strong seasonality which results in a high autocorrelation at lag 1 (with AR(1) = 0.7) and at lags of multiples of 12 (AR(m·12) > 0.5) over the whole observation period.

For trend analysis, we first deseasonalize the data series by subtracting the long-term monthly median from each individual monthly runoff observation. The median was chosen as the data is not symmetrically distributed, and thus the median is a more robust estimation of the central value than the mean. The resulting anomalies show a symmetric distribution with still distinct tails and a remaining lag-1 autocorrelation AR(1) of 0.4.

Following the recommendation by Kundzewicz and Robson (2000) to use several statistical tests which are not too similar, we perform various tests to check for an overall trend in the data series. Table 1 and Figure 3 give an overview on the applied methods and the results. The focus was on non-parametric methods which have no requirements regarding the statistical distribution of the data. An example is the Mann-Kendall trend test (Mann, 1945) widely used in environmental sciences in combination with Sen's slope (Sen, 1968) to assess trend significance and trend magnitude. As the original monthly observations contain a strong seasonal component we used the Seasonal Mann-Kendall trend test (Hirsch and Slack, 1984) to estimate the overall trend in the original series and check for its statistical significance. In addition, we applied the ordinary Mann-Kendall test to the original data series and used resampling schemes to assess the statistical significance of the trend. Resampling preserves the seasonal structure of the series by randomly choosing tied parts of the data with replacement ("bootstrap") or without replacement ("permutation"), computing the test statistics and comparing it to the test statistics of the original series. The resampling schemes used in our case in order to preserve the seasonal structure were (1) block bootstrap with a block-length of 12 months, (2) circular permutation ("time series design" after Simpson, 2015, which shifts the start and end points of the series), and (3) permutation with block lengths of 12 months ("plot design" after Simpson, 2015).

Another set of methods is applied to the series of monthly anomalies. The series of anomalies still contains a statistically significant lag 1 autocorrelation. As such an autocorrelation may lead to an overestimation of the trend; it is advisable to use pre-whitening approaches, which remove the lag-1 autocorrelation from the series in an iterative way. The trend is then computed for the resulting series without lag-1 autocorrelation.

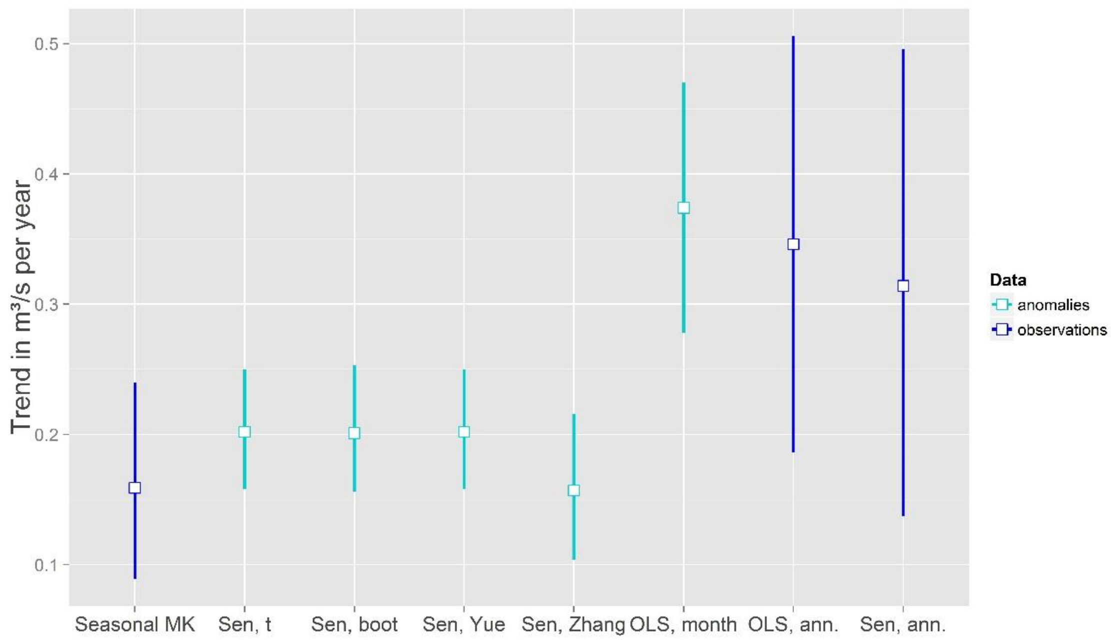


Figure 3. Trend results for the monthly and annual river runoff series at gauge Naryn and the period 1937-2012. All trends are statistically significant at the 1 % level. The lines mark the 95 % confidence interval of the trend magnitude. For comparison, the trends for the aggregated series of annual means are displayed in the two segments to the rights.

Table 1. Overview on trend tests applied to the river runoff series at gauge Naryn and their results.

Method	**Data**	**R package / function**	**Trend (95 % confidence interval), significance level α**	
Seasonal Mann-Kendall trend test corrected for serial dependence, Sen's slope	Monthly observations	EnvStats / kendallSeasonalTrendTest()	0.159 (0.089, 0.240)	0.01
Mann-Kendall trend test and Sen's slope	Monthly observations			
(a) Original test		Kendall / MannKendall()		0.01
(b) Trend-free pre-whitening after Yue et al., 2002		zyp / zyp.yuepilon()	0.135 (0.059, 0.223)	0.01
(c) Block bootstrap with bl=12, 1000 replications		Boot / tsboot()		0.01
(d) Permutation in blocks with bl=12, 1000		Permute()		0.01

permutations				
(e) Circular permutation		Permute()		0.05
Mann-Kendall trend test and Sen's slope	Monthly anomalies			
(a) Trend significance		Kendall / MannKendall()		0.01
(b) Sen slope confidence interval based on t statistics		zyp / zyp.sen()	0.202 (0.158, 0.250)	
(c) Bootstrapped Sen slope confidence interval, 5000 replications (BCa)		boot / boot(), ts(boot)	0.201 (0.156, 0.253)	
(d) Pre-whitening after Zhang et al., 2000		Zyp / zyp.zhang()	0.157 (0.104, 0.216)	0.01
(e) Trend-free pre-whitening after Yue et al., 2002		Zyp / zyp.yuepilon()	0.202 (0.158, 0.250)	0.01
Ordinary least squares regression	Monthly anomalies	Stats / lm()	0.374 (0.278, 0.470)	0.01
	Annual observations	Stats / lm()	0.346 (0.186, 0.506)	0.01
Mann-Kendall trend test and Sen's slope	Annual observations	zyp / zyp.sen	0.314 (0.137, 0.496)	0.01

It is evident that the trend magnitude is sensitive to the method used. The Sen slope estimator gives a trend magnitude of ≈ 0.2 m^3/s per year. The results for the different methods based on the Sen slope and monthly observations or anomalies are in good agreement, and their confidence intervals show considerable overlaps. However, the estimate based on ordinary least squares (OLS) regression yields a trend magnitude twice as much as the Sen slope. This might be an effect of the higher sensitivity of the OLS regression to extreme values at the beginning and end of the time series and to neglecting the autocorrelation still inherent in the series of anomalies. Generally, the Sen slope is less sensitive to outliers, i.e. is more robust compared to the OLS regression. It thus became state-of-the-art technique for trend analysis in combination with Mann-Kendall significance test in hydroclimatology and environmental sciences. Figure 3 also demonstrates that the trend magnitude for the temporally aggregated values, e.g. annual values, is higher than for the monthly values, because the variability in the annual data set is smaller. At the same time, the confidence interval / uncertainty gets bigger with aggregation, which is an effect of the smaller sample size.

1.7. Example 3: Trends in mean annual river discharge at gauge Naryn – the impact of the selected study period

As shown in Example 1 for the temperature at the Tien Shan station, the trend results vary with the selected start and end years (Figure 1). A useful technique to analyze trends and obtain a holistic picture of temporal changes considering different start and end-points is the so-called multiple trend plot (Figure 4). Applied to the mean annual river discharge at the Naryn station, the multiple trend analysis reveals negative trends in the period 1940s-1990s, while a positive trend sets in after the 1970s and is statistically significant at the 5% level.

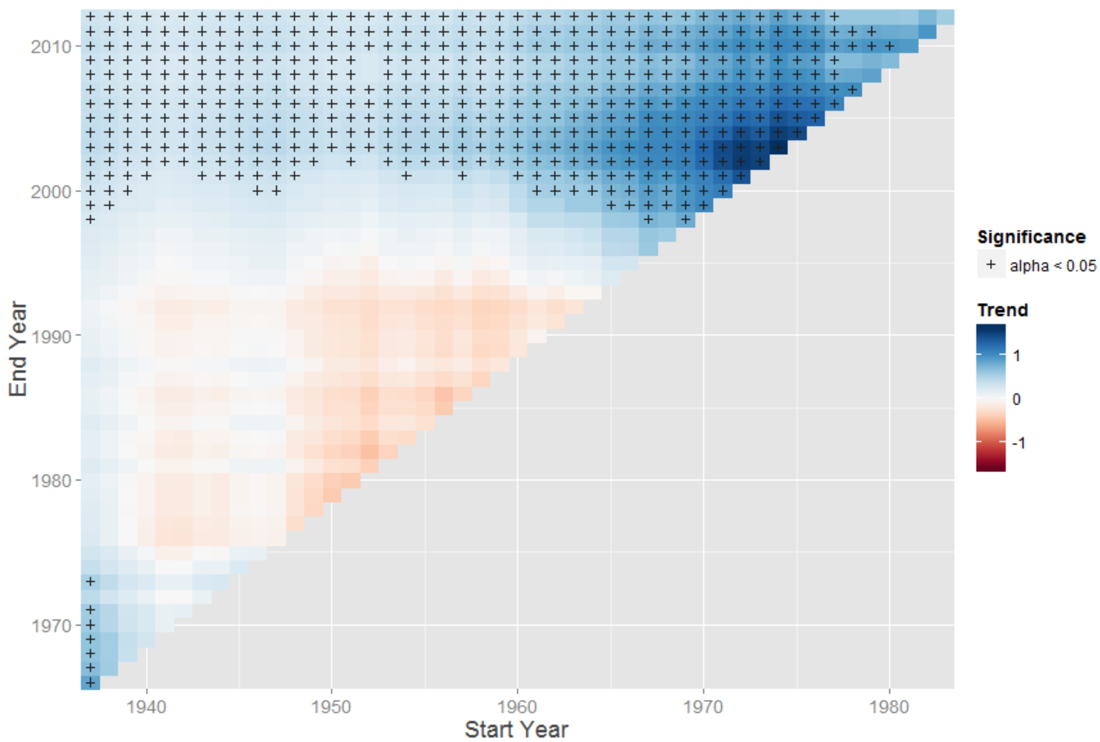


Figure 4. Temporal variation of trends in mean annual river discharge at the Naryn station. Trends were computed for a minimum of 30 years of observations. The trend magnitude is given by the Sen slope, the trend significance was calculated using the Mann-Kendall trend test with trend-free pre-whitening after Yue et al. (2002).

Conclusion

Although a detailed discussion of change assessment methods is out of scope of this technical note, the given examples demonstrate that the findings of climate and hydrological change studies are very sensitive to the underlying data sets and the selected methodological approaches. Thus, a description and discussion of the data used and methods applied is a basic requirement for any study to be published in this journal. This involves:

- Description of data sources and discussion of the representativeness, homogeneity and uncertainty of the underlying data set and its suitability for the study;
- Detailed description of methodological approaches, discussion of the limitations of the selected techniques, including checking the validity of preliminary assumptions (e.g. requirement of symmetrical distribution of data series in a statistical analysis);
- Discussion and if possible quantification of the uncertainty of the result.

The presented analysis should fulfill the criteria of reproducibility, meaning that the data and methods are described in a way making it possible for other scientists to follow and reproduce the results if necessary. This is a key prerequisite for transparent scientific inference and research progress.

Where possible, it is recommended to apply different methods and data sets to demonstrate the robustness of the findings, i.e. if one obtains consistent findings using different methodological approaches. Analytical plots such as the multiple-trend plots presented in Figures 1 and 3, or regional maps, may help in understanding the spatio-temporal variation of changes and underpin the robustness of the changes detected for a selected study period or study area.

When summarizing their results, authors should (1) avoid overgeneralization by considering natural spatio-temporal variability and (2) differentiate between indication, evidence and proof. Kundzewicz and Robson (2000) note that statistical tests provide evidence, not proof. Moreover, authors should exercise reasonable care when attributing the observed changes to specific drivers in other words, identifying physical reasons for detected changes. They should clearly differentiate between “soft” (logical but hypothetical) and “hard” attribution (Merz et al., 2012), with the latter ruling out other drivers of change. In fact, many drivers can act on the natural system, partly counteracting each other, and thus identification and quantification of the reasons for change are often much more complex than it may appear at first glance.

This technical note cannot provide an extensive review and detailed discussion of all available methods for climate and hydrological change assessment. For further information, readers are referred to the recent methodological handbooks and research articles. Useful guidance on change assessments is given by a number of open-access publications available on the Internet, among them WMO (2011/2014) and Kundzewicz and Robson (2000). For extensive change analyses, the use of statistical software packages is highly recommended, e.g. the open-source and freely available R software environment (www.r-project.org) with sophisticated user interfaces is available (e.g. www.rstudio.com). Trainings in R are increasingly offered from several international institutions and project consortia also in Central Asia.

Appendices

For reference, the R code used for this technical note is published in the supplements.

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