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Flood trends and variability in the Mekong river

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Abstract

Annual maximum discharge is analyzed in the Mekong river in Southeast Asia with regard to average flood trends and variability during the 20th century. Data from four gauging stations downstream of Vientiane, Laos, were used, covering two distinct hydrological regions within the Mekong basin. These time series span through over 70 years and are the longest daily discharge time series available in the region. The methods used, Mann Kendal test (MK), ordinary least squares with resampling (OLS) and non-stationary general extreme value function (NSGEV), are first tested in a Monte Carlo experiment, in order to evaluate their detection power in presence of changing variance in the time series. The time series are generated using the general extreme value function with linearly varying scale and location parameter. NSGEV outperforms MK and OLS, both because it incurred in less type II errors, but also because it allows for a more complete description of the trends, allowing to separate trends in average and in variability

Results from MK, OLS and NSGEV agreed on trends in average flood behaviour. However, the introduction of a time-varying scale parameter in the NSGEV allowed to isolate flood variability from the average flood trend and to have a more complete view of the changes. Overall, results showed an increasing likelihood of extreme floods during the last half of the century, although the probability of an average flood decreased during the same period. The variance, estimated with the wavelet power spectrum as a function of time, allowed to identify a period of enhanced variance in the last quarter of the 20th century, which confirmed the results of the NSGEV.

We conclude that the initial absence of detected positive trends in the hydrological time series was a methodological misconception due to over-simplistic models.

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1 Introduction

Detecting trends in hydrological variables has been given emphasis in recent years, due to an increasing scientific consensus on anthropogenic climate change. Indeed, climatic mechanisms are being triggered that increase the potential for intense precipitation around the world (Kundzewicz and Schellnhuber, 2004) and particularly in Asia (Cruz et al., 2007). However, this change is considered not to be spatially or temporally uniform: different studies show significant increases in extreme precipitation and discharge in many countries (Petrow and Merz, 2009; Robson, 2002; Kunkel et al., 1999), whereas many others do not find evidence on this regard (Robson et al., 1998; Svensson et al., 2006; Kundzewicz et al., 2005; Mudelsee et al., 2003). Nevertheless, global climate models claim that climate change would drive higher precipitation and river discharge (Nijssen et al., 2001; Palmer and Räisänen, 2002; IDAG, 2005).

Although Katz and Brown (1992) proves the importance of change in variability (also referred to as the scale parameter of certain statistical distributions), and despite the existence of several frequency models in the literature that take non-stationarity of the scale parameter into account (see Khaliq et al., 2006, for a review), studies have seldom tried to detect a trend in this parameter (Strupczewski et al., 2001). Indeed, we are not even acquainted with the effect that change in variability produces in usual average flood trend detection tests.

A first approach to variability in the flood regime of the Mekong river, our case study, motivated a deeper investigation on how trend detection methods are affected by a time-dependent change in variance. The methods, some of them not explicitly taking into account change in variance, were chosen mainly because of their simple underlying concepts, widespread use and for being fundamentally different: the ordinary least squares with statistical significance obtained from resampling (OLS), the Mann-Kendall test (MK) and the non-stationary general extreme value function (NSGEV) with location parameter as a linear covariate. Investigating the result of trend detection tests in presence of time-varying variability suits a Monte Carlo experiment well. We generate many

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synthetic time series with *a priori* knowledge of their variance based on the general extreme value function and try to detect a trend with the aforementioned methods. These methods are conceptually different and each of them focus on different definitions of what a trend is, yielding different responses to a change in variance.

Another important aspect of variability is its link to vulnerability on the societal level. One of the drivers of vulnerability is variability and change in the environmental conditions (Turner et al., 2003), and the probability of exposure to stress or perturbations of the system is a part of the vulnerability equation (Luers et al., 2003; Adger, 2006). Therefore, methods for identifying periods of enhanced variability are crucial to contextualize and provide a quantitative background to vulnerability assessments in the field. Additionally, a framework that assumes a non-stationary approach to frequency analysis is necessary to quantify the change in the probability of an extreme event. That is accomplished in this work by using the wavelet power spectrum and the NSGEV model, respectively.

Further motivating our work is a general public consensus on an increase in the flood damage and risk during the last century in the Mekong basin (Campbell, 2007; Käkönen, 2008), although the scarce published studies that attempt to identify trends in river discharge or precipitation point to a negative trend (Campbell, 2007; Lu and Siew, 2006). Model output and theoretical research also point to a future increase of flood events in the region due to climate change (Hoanh et al., 2003). Even disregarding anthropogenic climate change, trends are expected, as an effect of an interannual to decadal organization in climate (Black, 2002) as well as changes in monsoon intensity over centennial to millennial timescales (Zhang et al., 2008).

The purpose of this work is to evaluate whether there is a trend in average flood and in flood variability on four stations along the Mekong river and evaluate how such a change in variance might affect the power of usual trend detection tests.

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2 Data and geographical extent

The present study analyzes the only available long daily discharge time series in river Mekong. These are available for Vientiane (1913–2000), Thakhek (1924–2000), Pakse (1923–2000) and Kratie (1924–2007). The time series were trimmed to the size of their intersection (1924–2000). The data was provided by Southern Institute of Water Resources Research in Ho Chi Minh City, Vietnam. The daily discharge is estimated by the use of a rating curve and daily water level readings. Discharge measurements do not exist for the years before 1960 and therefore the values here presented were estimated using the rating curves from 1960 on. For Pakse, for example, a set of discharge measurements are available about every ten years, from 1960 until 2000, when measurements are taken with more modern equipment. Different rating curves present differences of, at most, $5 \times 10^3 \text{ m}^3 \text{ s}^{-1}$, where the average annual maximum discharge is about $38 \times 10^3 \text{ m}^3 \text{ s}^{-1}$, and the evolution of the rating curve over time is not monotonic, meaning that there isn't one unique tendency in the cross-section or flood dynamics that influence discharge along time. Special care should be paid to Kratie, where rating curves only exist for the 1960s and after 2000. However, the data was allegedly corrected and gaps were filled based on the station of Stung Treng, about 100 km upstream (MRC, 2004).

The flood index used was the annual maximum discharge series (AMAX), obtained from daily discharge. This describes well and simply the flood hydrograph, which every year depends on the same forcing mechanisms and arrives roughly at the same time.

The Mekong river lies in Southeast Asia and its $800\,000 \text{ km}^2$ catchment is shared by China, Myanmar, Thailand, Laos, Cambodia and Vietnam (Fig. 1). In China, the river flows on the Tibetan plateau, mainly fed by snow melting in spring and receiving a small proportion of monsoon precipitation. The Yunnan (so is called this region) component makes up for 16% of the whole annual volume (MRC, 2005). In the lower basin, the Mekong may still be divided into three main reaches: from the Chinese border to the beginning of the eastern highlands on the Laos-Vietnam border (more or less near

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Vientiane), from there to Kratie and from Kratie on to the delta. The main differences concern the flood generation during the monsoon season, the first reach being mainly fed by moisture from the bay of Bengal (thus related with the Indian monsoon), the second being fed by strong orographic precipitation from westerly air masses that cross Indochina until they meet the eastern highlands (Delgado et al., 2009), and finally the third sharing the same source of moisture as the second, but not generating much runoff due to flat topography. These two moisture sources have both different forcing large scale atmospheric circulation patterns and onset times.

3 Methods

We start by a methodological definition of the different types of trends we are aiming at. As we are using different methods that detect trends in different aspects of the data, we separate two groups of trends: an *average flood trend*, which is a change in a statistic related to or describing the expected value of the time series, may it be the mean, the location parameter of the underlying distribution or another related parameter; and a *trend in flood variability*, which may be detected by an estimation of average variance on a given year or of the changes in the scale parameter of the underlying distribution.

Three methods were used to estimate average trends in the time series (as in Zhang et al., 2004): linear regression in a least squares sense, an inappropriate but straightforward and often used method for detecting trends in extreme values, the Mann-Kendall test (Kendall, 1938), a powerful non-parametric trend test, for every kind of time series, and the non-stationary general extreme value model (Coles, 2001), a parametric statistical test that accounts for the skewness of the data.

Assessing the significance of a linear regression as an estimate for a trend was done following the resampling methodology given by Kundzewicz and Robson (2004). According to this method, a time series with a trend is represented by

$$x(t) = b_1 + b_2 t + \epsilon_t \quad (1)$$

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where b_1 and b_2 are estimated by the method of the least squares and ϵ_t is the deviation of the trend line to the time series. If ϵ_t is normally distributed, x_t is the given time series and t is the time. ϵ_t is often not normally distributed and does not even have a symmetric distribution in the case of climate variables. We use this method nevertheless as a reference, because it is easy to use and often adopted in trend assessments.

The Mann-Kendall test (Kendall, 1938) is a non-parametric statistical test that evaluates whether there is a trend in a time series x_t of size n . x_t is compared with its successors x_{t+i} . C is the sum of all the results of the comparison, being 1 when $x_{t+i} > x_t$, -1 if $x_{t+i} < x_t$ and 0 if $x_{t+i} = x_t$. We then compute

$$C^* = \frac{C}{\sqrt{n(n-1)(2n+5)/18}} \quad (2)$$

As C^* is normally distributed with mean 0 and standard deviation 1, it is possible to compute the statistical significance of rejecting the null hypothesis of the time series not having a trend.

The NSGEV function was used following the methodology in Coles (2001). This model is an extended parametrization of the general extreme value function (GEV), a combination of three families of extreme value distribution, Gumbel, Fréchet and Weibull (Jenkinson, 1955). The cumulative GEV distribution function is written as:

$$F(x) = \begin{cases} \exp \left[- \left(1 - \frac{\xi}{\sigma} (x - \mu) \right)^{\frac{1}{\xi}} \right] & \text{if } \xi \neq 0 \\ \exp \left[- \exp \left(- \frac{(x - \mu)}{\sigma} \right) \right] & \text{if } \xi = 0 \end{cases} \quad (3)$$

where x is the random variable and the rest are the distribution parameters, which are fit to the sample with the maximum likelihood criterium. According to this parametrization, the location (μ , which defines the position of the function with regard to the origin) and scale parameter (σ , which defines the spread of the distribution) are made time-dependent following a desired function. The shape parameter (ξ , defining additional

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shape characteristics of the function) is left constant. At a first stage, we used linear time varying location and scale parameters to compare with other methods. Then, we make these parameters vary quadratically and evaluate if this introduces significant improvements on the statistical model. If yes, we accept it as a trend, otherwise we keep the linear case. This explicitly accounts for changes in average and variance over time, as seen in the example shown in Fig. 2a for Pakse, yielding a different probability distribution each year (tails grow fatter with time). A first approach consisted of a linear parametrization:

$$\mu(t) = \mu_0 + \mu_1 t \quad (4)$$

$$\sigma(t) = \sigma_0 + \sigma_1 t \quad (5)$$

A second degree time-dependence was investigated for one of the parameters:

$$\mu(t) = \mu_0 + \mu_1 t + \mu_2 t^2 \quad (6)$$

$$\sigma(t) = \sigma_0 + \sigma_1 t + \sigma_2 t^2 \quad (7)$$

The second degree extension is important, because it accounts for the change in the sign of the trend, which may occur at the time scale analyzed. Accepting more than one maximum or minimum would mean that we would be considering a cycle and not a trend (Wu et al., 2007), so higher degree co-variation was not considered, also due to problems in the convergence of the estimation method.

To find the best fit of the parameter set to the sample, the maximum likelihood criterion is used. Instead of the location and scale parameter, the whole expressions of $\mu(t)$ and $\sigma(t)$ are inserted in the likelihood function:

$$L = \prod_{t=1}^n \sigma(t)^{-1} \exp \left[- \left(1 - \xi \frac{x(t) - \mu(t)}{\sigma(t)} \right)^{\frac{1}{\xi}} \right] \times \left(1 - \xi \frac{x(t) - \mu(t)}{\sigma(t)} \right)^{\frac{1}{\xi} + 1} \quad (8)$$

where $x(t)$ is the element of the time series corresponding to time t .

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Both the linear and second degree model are a generalization of the stationary GEV. They necessarily yield a set of parameters that are at least as good as the particular case of $\sigma_1=0$ and $\mu_1=0$. However, if the results are very similar to the stationary case, it can be argued that the differences were obtained by chance and not due to an improvement in the description of non-stationarity. Therefore, a likelihood ratio test is used to raise confidence in the model. Let M_0 be a submodel of model M_1 , stationary and non-stationary, respectively, whose log-likelihood is l_0 and l_1 . The log-likelihood ratio is given by:

$$T=2(l_1-l_0) \quad (9)$$

where T is χ_q^2 distributed, and q is the difference between the number of free parameters in M_1 and M_0 . We will reject M_0 at α significance level, if the integral of the χ_q^2 distribution from zero to T is greater than α .

After obtaining a statistically significant model, reference values are established for the stationary case with the GEV distribution. For the probability of an average flood, we use the probability of exceeding the mean flood according to the stationary GEV fitted for the sample. For a measure of variability we use the probability of 20 year return period discharge of the sample, when estimated with a stationary GEV model. Note that the return period is given by

$$R=\frac{1}{1-F(x)} \quad (10)$$

where $F(x)$ is the cumulative probability from Eq. 3.

The goodness of fit of the NSGEV may be also visually inspected by plotting a diagnostic. Two types are given in Coles (2001): a residual probability plot and a residual quantile plot. Both diagnostic plots represent standardized variables: first the modeled probability against the mean rank plotting positions and second the observed discharges against the modeled discharge corresponding to the respective mean rank plotting position. These are presented in Fig. 2b and c as an example.

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The estimation of variance against time is done with the wavelet power spectrum (WPS) (Torrence and Compo, 1998), which is the absolute value up to the power of 2 of the wavelet transform. The wavelet transform may be described as a correlation coefficient between the time series and a given and well known function that slides over the time domain and is scaled to account for different frequencies. A coefficient is therefore given for every scale and time step, building a two dimensional plot. The present work uses a *Morlet* wavelet, which is a complex valued, nonorthogonal function.

Computing the average variance over the time domain is also given by the wavelet. If we integrate the power spectrum with respect to the scales, we obtain for each year the localized variance over a chosen scale range. This is an useful tool for validating the NSGEV in terms of variability, as it explicitly shows the changes in variance over time.

Synthetic annual maximum discharge time series are generated without simulating the annual cycle or modeling the temporal occurrence of flood peak. The reason is that the annual cycle is very stable, defined by the monsoon precipitation that arrives approximately at the same time of the year (MRC, 2005). The same may be said about the flood season. More than one flood peak per year can occur, but always within the same flood season, close to the maximum, and they are imposed on the annual flood hydrograph, which is unique for any given year and similar in shape between different years. The annual maximum discharge is able to represent the magnitude of the flood hydrograph.

The chosen distribution for the generation of the synthetic annual maximum discharge time series is the general extreme value (GEV) distribution with time varying location and scale parameter, which are the analogues to mean and variance of a normal distribution. As we intend to simulate a natural trend in both mean and variance, we let μ and σ , location and scale parameter, respectively, vary linearly with time, like in Eqs. 4 and 5. We choose Pakse as a reference station and use its NSGEV parameters as a baseline. The location parameter is taken from the fit of the NSGEV function

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to Pakse and different scale parameter trends are generated based on the one found for Pakse: we start with no trend and increase it by $\sigma_1^{\text{Pakse}}/5$ until $2\sigma_1^{\text{Pakse}}$, where σ_1^{Pakse} is about 1.15% of σ_0^{Pakse} (the lower index identifies the term in Eq. 5). For the location parameter, μ_1^{Pakse} is about 0.07% of μ_0^{Pakse} . Note that this trend is within the smallest tested by Zhang et al. (2004). The only restrictions for the synthetic time series are that each data point may not be greater than 1.5 times the maximum historical discharge and not lower than half the minimum recorded AMAX. Figure 3 shows the diagnostic plot of the random generation of the set of time series, where all the generated points appear to have the same underlying distribution (the modeled quantiles are similar enough to generated empirical quantiles).

The three trend detection methods, OLS, MK and NSGEV with one covariate at a time (first keeping the scale parameter constant and then the location parameter), are applied to the 1000 synthetic time series. Results are presented and discussed in Sect. 4.

4 Results and discussion

4.1 Trend detection with changing variance

Figure 4 shows the number of detected positive and negative trends among the 1000 trials for each of the positive scale parameter rate of change (Eq. 5), given a constant negative trend in the location parameter. A first observation is that NSGEV is the most powerful method to detect a trend in average flood ($\mu(-)$ in Fig. 4), except in the case of constant scale parameter. In second comes MK and finally OLS. Their performance for constant scale parameter was 64%, 53% and 47% for MK, NSGEV and OLS, which is greater than in Zhang et al. (2004), because of different significance levels. However, it is also seen that all the methods loose power in detecting the negative average trend, when the samples are driven with a strong positive scale parameter trend. For example, MK detects 3 times less negative trends in the presence of a strong

trend in the scale parameter than it would with a constant scale parameter, whereas OLS more than 4 times less. This means that regarding average trends, an error of type II (failure to detect an existing trend) is more likely to occur in the presence of a strong trend in the scale parameter.

5 A second result may be derived from the scale parameter. We observe that, with a stronger trend in the scale parameter, the OLS and MK tests become weaker. These two tests, contrary to NSGEV, even detect a number of positive trends in some cases (*OLS(+)* and *MK(+)* in Fig. 4). The reason for that may be that the partial derivative of the GEV cumulative distribution function with regard to σ , $\partial F/\partial\sigma$, when $x>\mu$, is always
10 greater than the derivative for $x<\mu$. This means that the likelihood of randomly generating values greater than μ increases faster with σ , than the likelihood of randomly generating values lower than μ . By other words, although both tails increase with an increment in the scale parameter, the right tail increases more. OLS detects this more evidently than MK, because it uses the magnitude of x_j , making the method more sensitive to extreme values, whereas MK computes only the relative position of each x_j to
15 all the other values.

Thirdly, detecting a trend in the scale parameter with NSGEV appears to be free of problems. The power of the NSGEV increases with a steeper trend in the scale parameter. A great improvement was achieved by computing the NSGEV simultaneously with
20 two covariates, instead of running it twice, for each of the covariates. This improvement was not included in the figure.

Although we used the 90% significance level for all the methods, this does not mean that we can trust the results equally, due to the fact that statistical significance was computed following three different methods. On the same line, the results must be
25 interpreted according to the method used, because each of them is conceptually different. For example, it is expected that OLS places a greater weight on greater magnitudes than NSGEV: the method is based on gaussian assumptions, whereas the sample that it is applied to has more frequent high peaks than it had if it was driven from a normal distribution, given GEV's heavy tail. Regarding MK, we cannot expect

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to cover the change in the frequency of extreme high floods, which itself may induce a significant perception of a trend, because it places the same weight on an upper percentile value as on a median value. This affects its ability to incorporate the more frequent occurrence of extremes, which is well described by the NSGEV, for example.

5 In summary, the different methods focus on different aspects of the time series, which means that the user should be aware of each method's limitations. As it will be seen in the application to the case study, the use of NSGEV allows the study of both different sets of magnitudes: we can focus on which percentile of the time series we want to analyze and estimate its change over time, for example greater magnitudes of the time
10 series or average values. Moreover, it allows to perform both a trend detection test and a frequency analysis.

We learn from this exercise that different methods are affected differently by a change in variance in the time series. Namely, the power of detection of an average trend decreases greatly for MK and OLS, to a level where they incurred in a type II error in most
15 of the test trials. OLS even detects more positive trends than negative when the trend in scale parameter is about σ_1^{Pakse} , probably due to being based on a normal distribution, when the data is clearly non-normal. When suspecting changes in variance, NSGEV should be used, as it explicitly accounts for change in the scale and location parameter. Even considering only location parameter, it was by far the best method tested.

20 Results from trend detection should be considered with caution and always validated with another method. Further, and equally important, a possible change in variance should be considered, as it can affect the trend detection results even with high significance levels, as shown in this section. Simple methods are available that give an idea of the change in variance of the time series over time. Computing a moving window variance or the average variance obtained from the wavelet power spectrum (Torrence and Compo, 1998) are straightforward choices, although in the case of skewed
25 datasets, as normally meteorological and hydrological data are, the NSGEV could be a better option.

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4.2 Flood trends in the Mekong river

A summary of the trend analysis to four stations on the Mekong river is presented in Table 1, where the results of MK, OLS and NSGEV with linear varying covariates are shown. A first inspection reveals apparent consensual results: a negative trend is affecting all four stations. Only in Pakse there is some uncertainty regarding the trend, because it is not statistically significant. This may be due to the fact that it has the strongest scale parameter trend, identified by NSGEV, which, according to the results of the previous section, conducts to higher incidence of type II error. However, when we distinguish trend in the average flood and trend in variability, we obtain different conclusions regarding how we see the flood regime of the Mekong during the 20th century. This is analyzed with respect to trends in flood variability in Sect. 4.3.

Table 1 shows overall agreement between methods in detecting average flood trends: MK, OLS and NSGEV all detect negative average flood trends in all the stations. This contrasts with public and local managers' perceptions as stated in Campbell (2007) and with the hypothesis of a strengthening Southwest monsoon. We know, however, that average flood trend detection methods like OLS and MK do not capture what may be the most interesting aspect of change in the flood regime: variability (Katz and Brown, 1992; Kundzewicz and Schellnhuber, 2004). Indeed, for greater flood magnitudes, modeled by NSGEV with two covariates (the linear case for both parameters), the trends are ascendant for Thakhek and Pakse. This means that the flood regime became more variable during the 20th century. Extremely high flood events were experienced more often than before, although intercalated with years of below-average flooding. Therefore, in present and according to the NSGEV model, the probability of experiencing a greater than average flood in Thakhek and Pakse is greater than before. This is an interesting result, not only because it matches projections from regional and global climate models, but also because it adds on the discussion of trend detection: within certain hydrological systems, MK, OLS or NSGEV with varying location parameter may not fully describe change in the flood regime.

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But why doesn't Vientiane present the same behaviour? The answer lies probably on the regions of influence of the two components of the monsoon (Sect. 4.3): the Indian monsoon (IM) and the East Asian monsoon (EAM). Vientiane receives its flood waters from moisture entering the continent through the bay of Bengal and from melting of snow in the Tibetan plateau. Downstream of Vientiane, the contribution from the highlands on the border between Laos and Vietnam is dominant (MRC, 2005), where the flood generation is linked in the north with a combination of EAM and IM and in the south predominantly with EAM (Delgado et al., 2009).

Variability trend in Kratie does not match Pakse and Thakhek. Indeed, a light negative linear change in the scale parameter was found to be significant, although this was the only station where a second degree trend in the scale parameter of the NSGEV proved to be significant. Although generally not useful, because of the difficult convergence when searching for a solution to the likelihood function, it yielded this time a significant likelihood ratio, when compared to the linear case. The analysis of this trend is done in Sect. 4.3, where it is also compared with other measures of variability.

When focusing on average flood trends, the three methods seem to agree that floods decreased on average over the 20th century. However, the scale parameter obtained by the NSGEV model presents a significant trend, revealing that the underlying distribution may be changing in a way that may affect extremes differently than it affects average floods. This is discussed in the next section.

4.3 Trends in flood variability

Variability was assessed in two different ways. First, the NSGEV was fitted with free linearly varying location and scale parameters, just as in Sect. 4.2. Then, the same was done for second degree varying location and scale parameters. The linear NSGEV represents an increase of two in the parameterization of the GEV model and the quadratic NSGEV another increase of two of the linear case (two parameters are added when going from GEV to linear NSGEV and from linear NSGEV to quadratic NSGEV). The significance of the improvements obtained by this increase in parametrization were

assessed by the likelihood ratio, as explained in Coles (2001). The diagnostic plots for Pakse are presented, showing a fair fit of the linear NSGEV (Fig. 2b and c). Secondly, a more adaptive method is used, the wavelet power spectrum, that is able to outline both the dominant modes of variability and how they vary with time (Torrence and Compo, 1998). The power spectrum was computed for the whole scale domain showing periods of short term variability.

The results of the NSGEV regarding reference values (probability of exceedence of the 20 year return period and of the expected value/mean of the distribution according to the stationary GEV) are given against time in Fig. 5 and 6. Kratie was the only station where a second degree time dependence was significant and is therefore shown instead of the linear dependence. According to this model, the probability of exceeding $Q_{T=20}^{GEV}$ decreased in Vientiane during the 20th century by 0.12, whereas it increased 0.03 and 0.08 in Thakhek and Pakse. During the same period, the probability of an average flood was decreasing in all stations. This difference between Vientiane and the two downstream stations may be explained by the different hydrological regimes within the Mekong river, as described in Sect. 2 and MRC (2005): downstream of Vientiane, the contribution of the flow generated in the highlands on the Laos-Vietnam border start to affect the flood hydrograph, whereas upstream it is still mainly affected by the Yunnan component. Kratie presents an inflection point around the 1960s, when the probability of an extreme flood starts increasing until the end of the century by 0.05. The change of behaviour between Kratie and upstream stations may be explained with the important contribution of tributaries with their mouth between Pakse and Kratie, like the Se San and Se Kong (Tonle San and Tonle Kong in Cambodia).

The fact that in the beginning of the time series, the probability of an extreme flood is very high may be due to errors in rating curves, or filling of gaps in the record using an upstream station, as discussed previously. The NSGEV model fit was here driven by the high flows recorded in the early decades of the time series, which are difficult to validate, due to lack of other sources of data (for this region, reliable reanalysis climatic data is available only after 1950 and earlier tributary discharge records were not

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available). For the later 20th century, the discharge could be compared and validated with precipitation data, which suggests climatic causes for the increase in variability reported (Delgado et al., 2009). Indeed Wang et al. (2001) and Ho et al. (2004) show an enhancement of the western North Pacific monsoon index variance and typhoon activity in the 1980s, respectively.

The average variance obtained by integration of the wavelet power spectrum over the scale domain, presented in Fig. 7, confirms the result of NSGEV: a period of enhanced variance is observed in the last quarter of the 20th century for all stations except Vientiane. This enhancement is more evident in the two downstream stations of Pakse and Kratie, less evident in Thakhek and residual in Vientiane. The descending-ascending behaviour of variance in Kratie is reproduced by the probability of exceeding $Q_{T=20}$ shown in Fig. 5, due to the 2nd degree variation of the scale parameter of the NSGEV.

The separation between average flood trend and trend in flood variability by NSGEV proves to be more useful than usual trend detection methods like OLS or MK, as it provides a probabilistic interpretation of the trend, including describing the change in probability of occurrence of a certain flood. In this sense, although negative average flood trends in all stations are found, the theoretical probability of an extreme event, for example exceeding the 20-year return period, increases over time in the three downstream stations Thakhek, Pakse and Kratie, at least in the last years of the 20th century (Fig. 5).

5 Conclusions

Usual methods of trend detection like linear regression (OLS) and Mann-Kendall test (MK) proved to loose detection power in presence of changes in variance. In a Monte Carlo experiment it was shown that the introduction of a trend in the scale parameter made the number of detected trends drop to less than half with MK and less than a quarter with OLS. Therefore, the number of type II errors increases with increasing trends in the scale parameter. The use of NSGEV is advantageous both because of its

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power of detection in presence of changing variance and because it allows to detect trends in different flood magnitudes with a probabilistic approach.

In what concerns river Mekong, although it is clear that average magnitude floods have a negative trend, we showed that variability is increasing, both shown by an increase in variance and by a positive trend in the scale parameter of a fitted NSGEV model, for stations downstream Vientiane. According to the fitted distribution, the increase in the theoretical probability of extreme floods is driven by the scale parameter. In this conceptualization, both very large floods and very small floods increase in frequency, with a decrease in frequency of average floods. This motivates further research on the causes and temporal scale of this variability change.

Differences between Vientiane and downstream stations were explained by the different origin of flood waters, coming in the first case mostly from rainfall and snowmelt on the upper Mekong basin, and in the second case from intense rainfall over the highlands on the Laos-Vietnam border. These two sources of runoff originate from two distinct atmospheric processes, having therefore different periods of enhancement.

The causes for the detected changes in variance are still unknown and probably range from changes on the landscape level to climate change. Regarding climate oscillations, a period of enhanced variance in the western North Pacific monsoon was identified in the literature, that matches the presented results. If these changes are an oscillation in the climate system or a permanent feature is also not known, and will not be understood by only analyzing instrumental records. Analyzing global climate model outputs with regard to variability and links between both monsoon components and precipitation over the Mekong basin would also be useful for understanding this.

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Table 1. Summary of the trend analysis of AMAX in the lower Mekong river. μ is the modeled location parameter, representing a trend in average flood and σ is the modeled scale parameter representing a trend in flood variability. “–” stands for negative trend and “+” for positive trend. Bold lettering indicates 90% statistical significance.

	Vientiane	Thakhek	Pakse	Kratie
OLS	–	–	–	–
Mann-Kendall	–	–	–	–
NSGEV	μ trend	–	–	–
	σ trend	–	+	+

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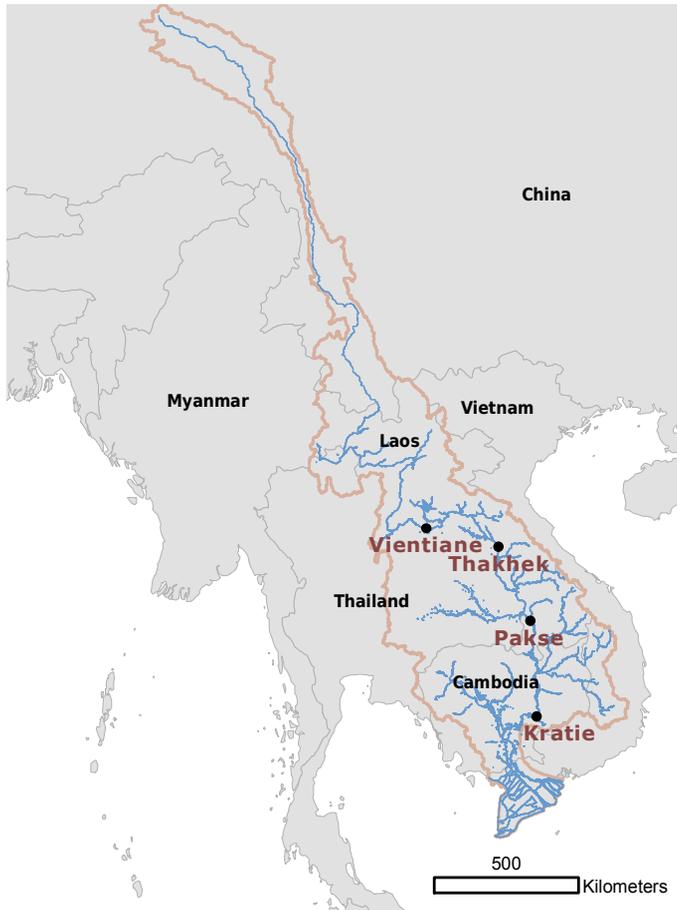


Fig. 1. Map showing part of Southeast Asia and main waterways (blue line) within the Mekong basin (delimited by the red line). Discharge gauges are marked with dark dots.

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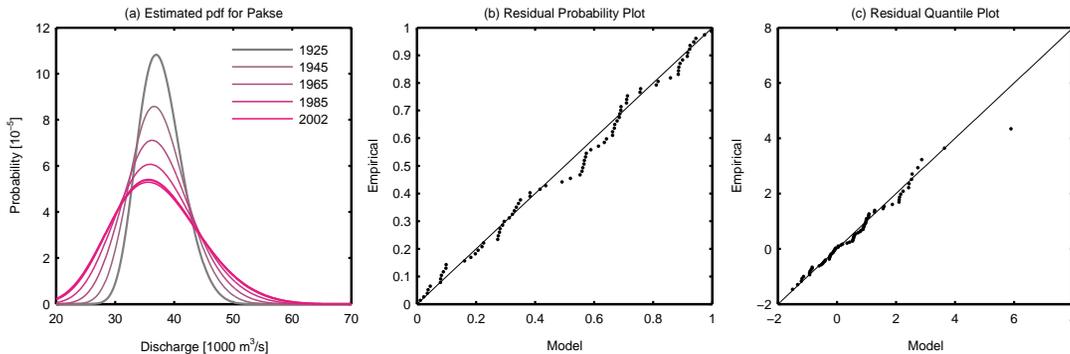


Fig. 2. (a) the estimated probability density function of AMAX for different years according to NSGEV. (b) the residual probability plot, presented as a diagnostic of the NSGEV model application. (c) same as (b) but for the residual quantile plot.

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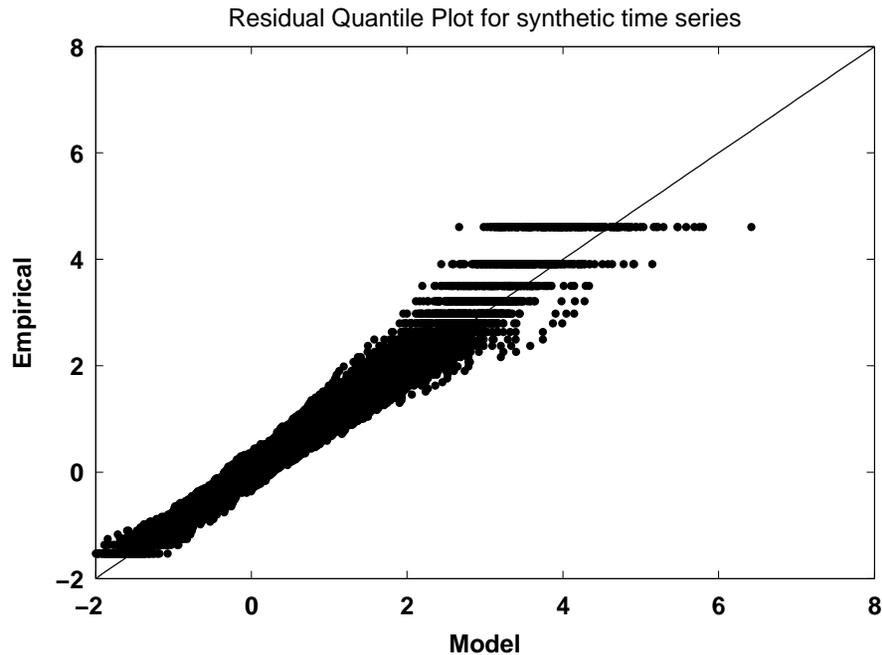


Fig. 3. The residual quantile plot of the 1000 time series generated. Shown are the transformed values of the generated samples against the theoretical value that they would have if each sample followed exactly a NSGEV distribution.

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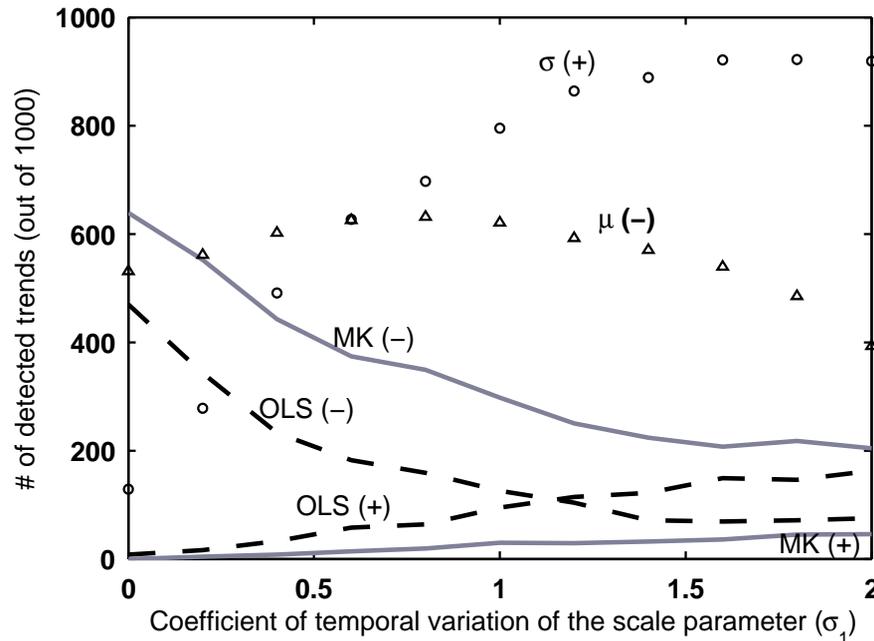


Fig. 4. Number of trends detected at a 90% significance level in the 1000 synthetic time series using OLS, MK and NSGEV. The time series were generated using the NSGEV model with a linear varying location and scale parameter. The different rates of change for the scale parameter were tested, which are given in the abscissa. μ refers to the detected trend in the location parameter and σ to the one in scale parameter derived by the NSGEV model. Plus and minus signs indicate positive and negative trend.

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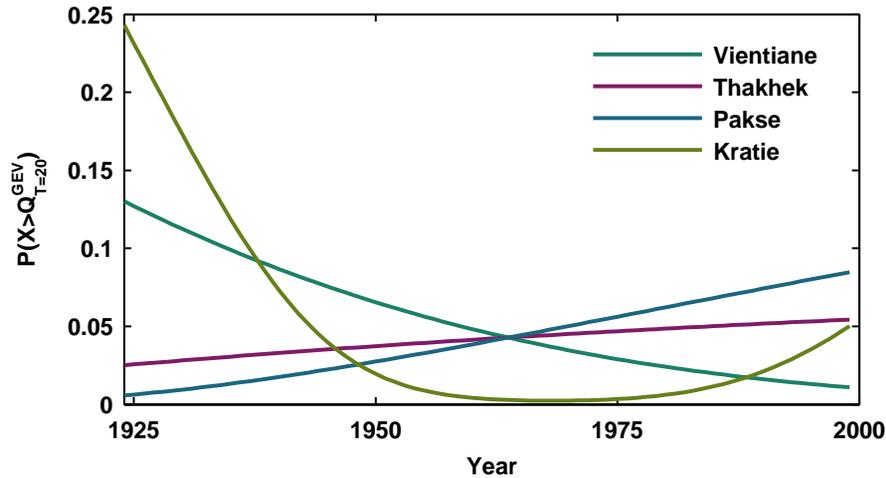


Fig. 5. Probability (computed with NSGEV) of exceeding the 20-year flood estimated by the stationary GEV in Vientiane, Thakhek, Pakse and Kratie.

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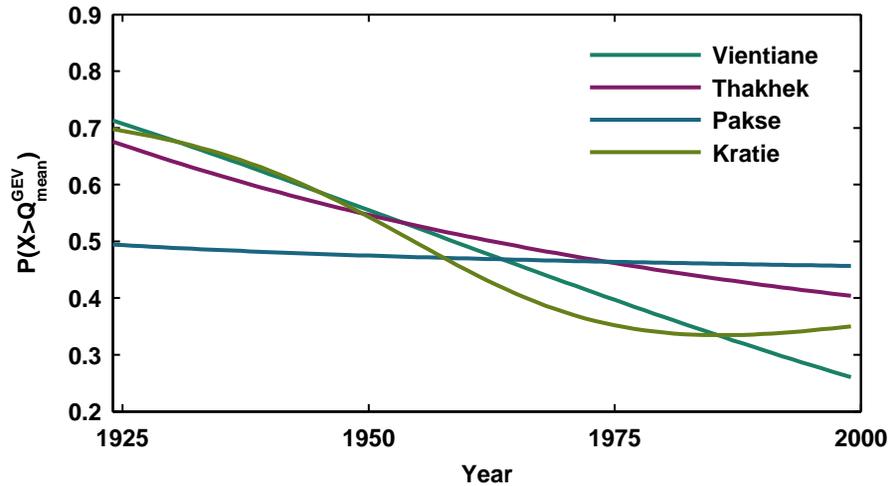


Fig. 6. Same as in Fig. 5, but for the probability of exceeding the expected value.

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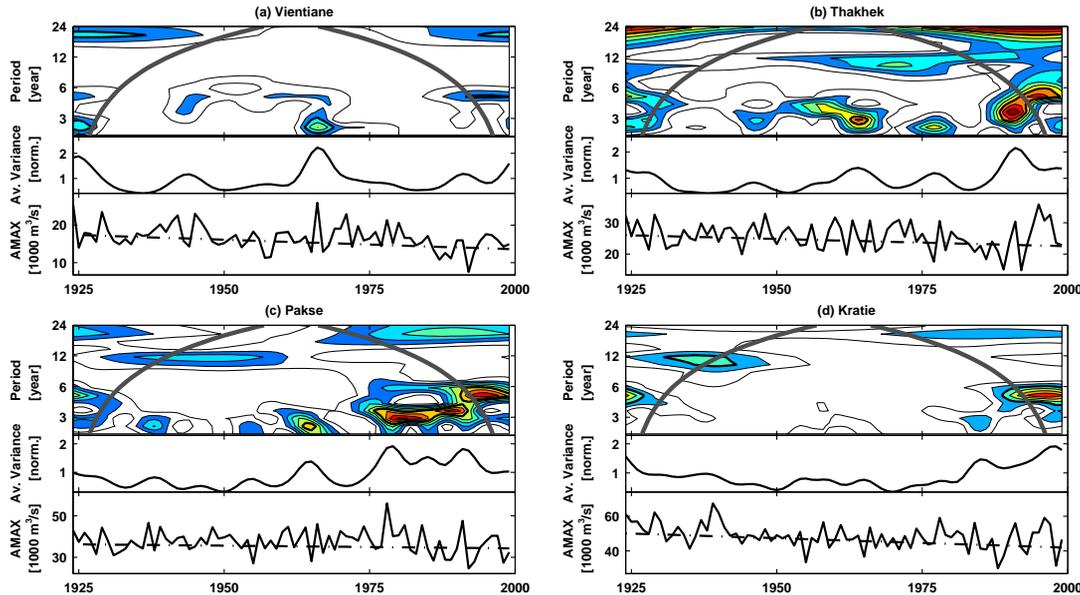


Fig. 7. Top: wavelet power spectrum of AMAX for Vientiane **(a)**, Thakhek **(b)**, Pakse **(c)** and Kratie **(d)**. Colder colors correspond to smaller wavelet coefficients and warmer colors to greater wavelet coefficients. Middle: Average variance (normalized) over the scale domain. Bottom: AMAX magnitude and μ (location parameter) of the NSGEV.

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