Theor. Appl. Climatol. (2008) 93: 107–115
DOI 10.1007/s00704-007-0341-1
Printed in The Netherlands

Theoretical and Applied Climatology

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Robust trend estimation of observed German precipitation

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With 4 Figures

Received 15 September 2006; Accepted 22 June 2007; Published online 12 October 2007

Summary

Trends in climate time series are habitually estimated on the basis of the least-squares method. This estimator is optimal if the residuals follow the Gaussian distribution. Unfortunately, only a small number of observed climate time series fulfil this assumption. This work introduces a robust method for trend analyses of non-Gaussian climate variables. Robust trend analyses as well as probability assessments of extreme events (Trömel and Schönwiese 2006) represent an application of the generalized time series decomposition technique. Trömel (2005) and Trömel and Schönwiese (2005) applied this decomposition technique to monthly precipitation sums from a German station network of 132 time series covering 1901–2000 in order to achieve a statistical modeling of the time series. The time series under consideration can be interpreted as a realization of a Gumbel-distributed random variable with time-dependent scale and location parameter. More precisely, each observed value can be seen as one possible realization of the estimated probability density function (PDF) with the location and the scale parameter of the respective time step. Consequently, the expected value of the Gumbel-distributed random variable can be estimated for every time step of the observation period and the statistical modeling represents an alternative approach to estimate trends in observational precipitation time series. The method is robust with respect to observed high precipitation values. The influence of relatively high precipitation sums is not larger than justified from a statistical point of view and changes in all parameters (here location and scale parameter) of the distribution can be taken into account. Monte-Carlo-simulations demonstrate the smaller mean squared error of the trend estimator using the statistical modeling. The least-squares estimator often shows a positive bias, while the method introduced provides robust monthly trend estimates taken into account the statistical characteristics of precipitation.

1. Introduction

One important task of statistical climatology is the description of climate variability. Observed climate time series represent a reliable basis for statistical analyses. The most simple and broadly used model in trend analyses is the interpretation of the time series as a superposition of a linear trend and Gaussian noise, i.e., the deterministic part is restricted to a trend and the residuals should follow the Gaussian distribution. However, this model is insufficient to achieve a complete description of most of the observed time series. So, Grieser et al. (2002) consider temperature time series as a superposition of trends, annual cycle, episodic components, extreme events and noise. Actually, the residuals can not be distinguished from the realization of a Gaussian-distributed random variable. In that case the expectation at a given time is determined easily as the sum of the detected analytical functions. The so-called distance function used to fit the analytical function is the quadratic function and

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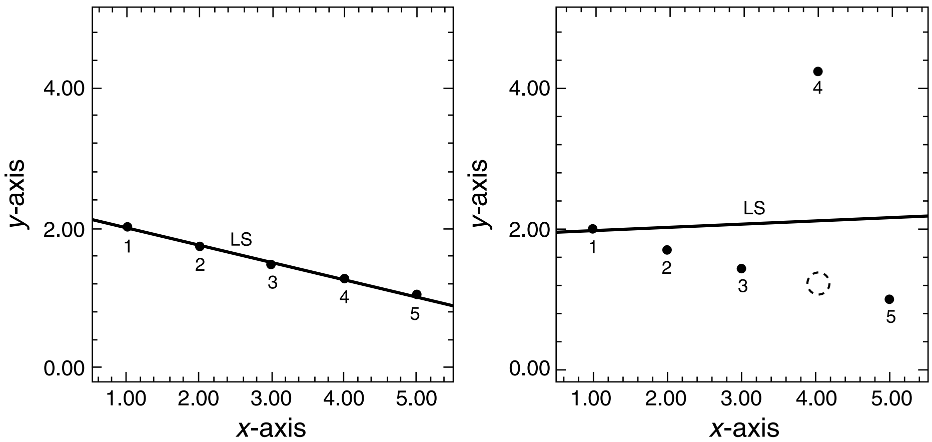

Fig. 1. Original data with five points and their least-squares regression line (left) and the same data, but with one oulier in the y-direction (right, from Rousseeuw and Leroy 1987)

the associated method including the minimization rule of quadratic deviations from fitted functions is the least-squares method itself. The estimator becomes a maximum likelihood estimator if the residuals can not be distinguished from the realization of a Gaussian random variable. Obviously, under the assumption of Gaussian-distributed residuals, the influence of a single point increases very fast with increasing distance from the mean value. The expected probability of occurrence is very small, so high relevance is attributed to their occurrence. Figure 1 illustrates the sensitivity of the least-squares method i.e., linear regression to relatively high values. On the left-hand side, all values are in line with a negative linear trend. On the right-hand side, it is just one single value turning the negative into a positive signed trend. The influence of a single value is unlimited, i.e., the larger the value considered in Fig. 1 the larger the amplitude of the estimated trend.

One simple step towards robust trends is the elimination of extreme values before trend analyses are performed. A similar approach is presented by Huber (1981). The main idea of Huber-k estimators is to prevent the quadratic influence of values more deviant than k units from the mean value.

Huber-k estimators are less sensitive to extreme values. However, they do not take advantage from knowledge of the PDF of the residuals. The distribution of monthly precipitation time series is not Gaussian. The tails are more pronounced and a greater number of relatively high deviations can be expected. Contrary to the Gaussian distribution, observed precipitation distributions are skewed to the left. Furthermore, the traditional Gaussian model is not suitable to describe observed changes in the variance of precipitation time series. Therefore, another statistical model should be applied for description of precipitation time series. Even though skewed distributions are already broadly used in analyses of observational precipitation data (IPCC 2001), no time series decomposition technique on the basis of such a distribution, analogous to the Gaussian approach introduced by Grieser et al. (2002), has been carried out before. Consistently with the maximum likelihood principle the negative logarithm of the PDF defines the distance function to be minimized. Consequently, the distance function affords the free choice of the distribution the decomposition procedure is based on. Additionally, the distance function allows for time-dependent parameters in any case. Actually, the generalized time series decomposition technique (Trömel and Schönwiese 2005) optionally interprets climate time series as a realization of a Gaussian- or Gumbel-distributed random variable with time-dependent location and scale parameter, respectively, or time series are interpreted as a realization of a Weibull-distributed random variable with time-dependent scale and shape parameter. Application of the decomposition technique to monthly precipitation sums from a German station network of 132 time series provides a complete analytical description of the time series on the basis of the Gumbel distribution. The corresponding distance function ρ of the Gumbel distribution is

$$\rho(x,t) = \ln(b(t)) + \exp\left(-\frac{x-a(t)}{b(t)}\right) + \frac{x-a(t)}{b(t)} \tag{1}$$

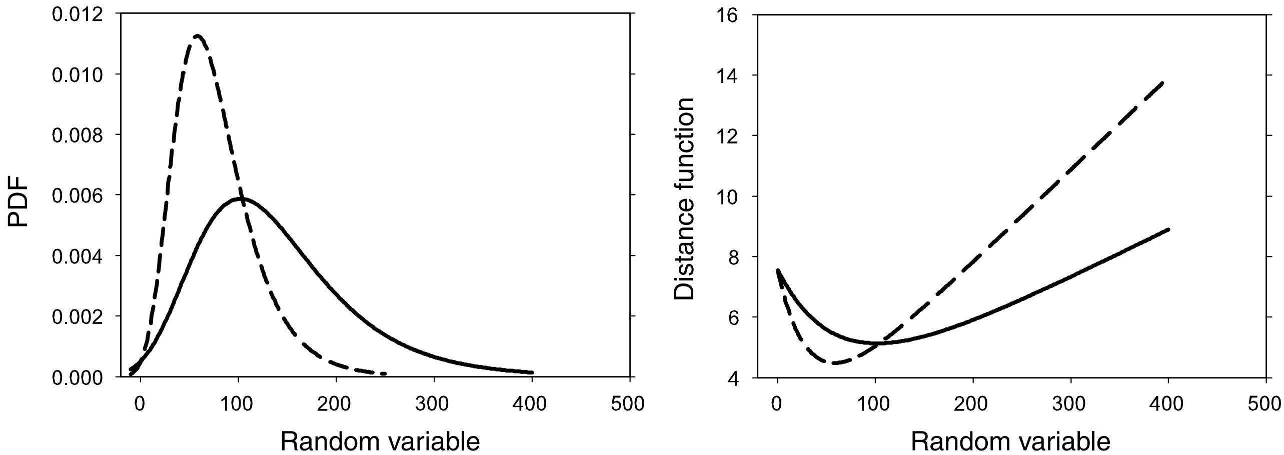

Fig. 2. The PDFs (left) of the Gumbel distribution with two different scale and location parameters and the respective distance functions (right)

with the location parameter $a(t)$ and the scale parameter $b(t)$. So, the basis functions are now used to describe the scale and the location parameter of the Gumbel distribution. Different kinds of trend (linear, progressive and degressive), constant or significantly changing annual cycle and episodic components are allowed. Figure 2 shows on the left-hand side the PDF of the Gumbel distribution for two different location and scale parameters. On the right-hand side the respective distance functions can be seen. The tails are more prominent and consequently, if we take a look at the distance functions, the influence increases less rapidly than in the quadratic case. We observe an almost linear increase for large distances (see also Eq. (1)). Furthermore, one value in a given distance from the location estimator has more weight the smaller the scale parameter. In this way, structured components can be detected in different parameters and estimators of different parameters compete with each other.

One drawback in its application to time series analysis of observed precipitation sums is the unbounded lower tail of the Gumbel distribution. A fitted Gumbel distribution often provides a non-zero probability for negative precipitation sums (see again Fig. 2, left). However, the maximum likelihood principle chooses the distribution parameters that maximize the probability of the whole data set and the terminal residual analysis of the generalized time series decomposition technique confirms the complete description of the time series as a realization of a Gumbel-distributed random variable. Unfortunately, the Gumbel model is not sufficient for all monthly precipitation time series. Already within the European precipitation regime an annual cycle or long-term trends in the shape of the distribution are observed. A statistical modeling based on the Weibull distribution represents an adequate description in these cases (see again Trömel and Schönwiese 2005). The Weibull distribution owns three parameters, namely the location, the scale and the shape parameter. Not until arid or semi-arid precipitation regimes are considered the method fails. A sufficient amount of rain is required each month in order to estimate a PDF for every time step of the observation period.

In Sect. 2 of this paper the definitions of the expected value of a Gumbel-distributed random variable and a Weibull-distributed random variable are given. These equations can be used to perform trend analyses. In Sect. 3 some results of an application to a German station network of 132 precipitation time series are presented. A subsequent presentation of results of performed Monte-Carlo simulations underlines the advantages of the trend estimator introduced and quantifies the mean squared error of both, the least-squares estimator and the estimator based on the statistical modeling of the time series.

2. Method

The expected value $\mu(t)$ at time t of a Gumbel-distributed random variable is defined as

$$\mu(t) = a(t) + \gamma b(t) \tag{2}$$

(Rinne 1997) with Eulers constant $\gamma = 0.57722$, indicating that changes in the location $a(t)$ and the scale parameter $b(t)$ reveal changes in the mean value. So, if the decomposition procedure succeeds, the full analytical description of monthly precipitation series provides the expected value for every time step of the observation period. This result can be used to take into account the skewness of the distribution and changes in different parameters to estimate trends in the expectation.

Addressing $L = N/12$ years of monthly climate time series, the trend of a Gumbel-distributed climate variable in a specific month $j = 1, \ldots, 12$ can be defined as

$$\Delta\mu_j = a(T_{Lj}) + \gamma b(T_{Lj}) - a(T_{1j}) - \gamma b(T_{1j}) \quad (3)$$

where the new time variable T_{ij} with subscripts $i = 1, \ldots, L$ and $j = 1, \ldots, 12$ denotes the j-th month in the i-th year of the observation period.

The expectation $\mu(t)$ at time t of a Weibull-distributed random variable with constant location parameter $a_W = 0$ mm, time-dependent scale parameter $b_W(t)$, and shape parameter $c_W(t)$ is defined as

$$\mu(t) = b_W(t)\Gamma\left(1 + \frac{1}{c_W(t)}\right) \quad (4)$$

(Rinne 1997) with the Gamma-function

$$\Gamma(z) = \int_0^\infty t^{z-1} e^{-t} dt. \quad (5)$$

Analogous to Eq. (3) the trend in a specific month $j = 1, \ldots, 12$ of a Weibull-distributed climate variable can be defined as

$$\Delta\mu_j = b_W(T_{Lj})\Gamma\left(1 + \frac{1}{c_W(T_{Lj})}\right) - b_W(T_{1j})\Gamma\left(1 + \frac{1}{c_W(T_{1j})}\right). \quad (6)$$

This approach robustifies trend estimation on three different perspectives: One step towards robust trend estimates is the a priori elimination of unexpected values. Grieser et al. (2002) defined extreme events as unlikely extreme values which did not happen by chance. After the separation of structured components they found a small number of these extreme events which may let the residuum differ from Gaussian noise. In this work the definition of extreme events is applied analogously to the Gumbel model. So, extreme events with respect to the Gumbel model are extracted and do not influence the trend estimation.

Secondly, the fit of an adequate PDF by comparing Gumbel, Weibull, and the Gaussian distribution is a further contribution to robustification of trend estimates. Under Gaussian assumptions with constant variance, the quadratic function is used to fit the linear trend, for example. Now, the use of the distance function which can be justified from a statistical point of view ensures proper weighting of the observed values in order to estimate structured components in the distribution parameters. Relatively high values get less influence in the Gumbel or Weibull case, because their occurrence is not as likely as in the Gaussian case.

Thirdly, significant structured components are fitted to the whole time series instead to the sub-series of single calendar months. The least-squares estimator only takes into account $N/12$ monthly values in order to estimate the trend of a specific month during an observation period of $N/12$ years. Contrary, the method introduced estimates the trend in each month on the basis of all N monthly precipitation sums. Consequently, estimated trends in different months are less sensitive to single values. Seasonal differences concerning the sign and the magnitude of the trend are given by long-term changes in the annual cycle of the distribution parameters and further several significant changes in the parameters. Unreasonable changes in the trend estimates between adjacent calendar months caused by single relatively high precipitation sums are avoided.

3. Application to observed German precipitation

In this section the application of the generalized decomposition technique to estimate changes in the expected value of precipitation time series, that is ordinary trends, is discussed. Figure 3 shows trend estimates for January (left chart) provided by the method introduced in this paper compared to the results of linear trend estimates on the basis of the ordinary least-squares method (right chart). Obviously, in January both estimators provide similar spatial structures. We observe positive trends in the western and the southern part of Germany and negative trends

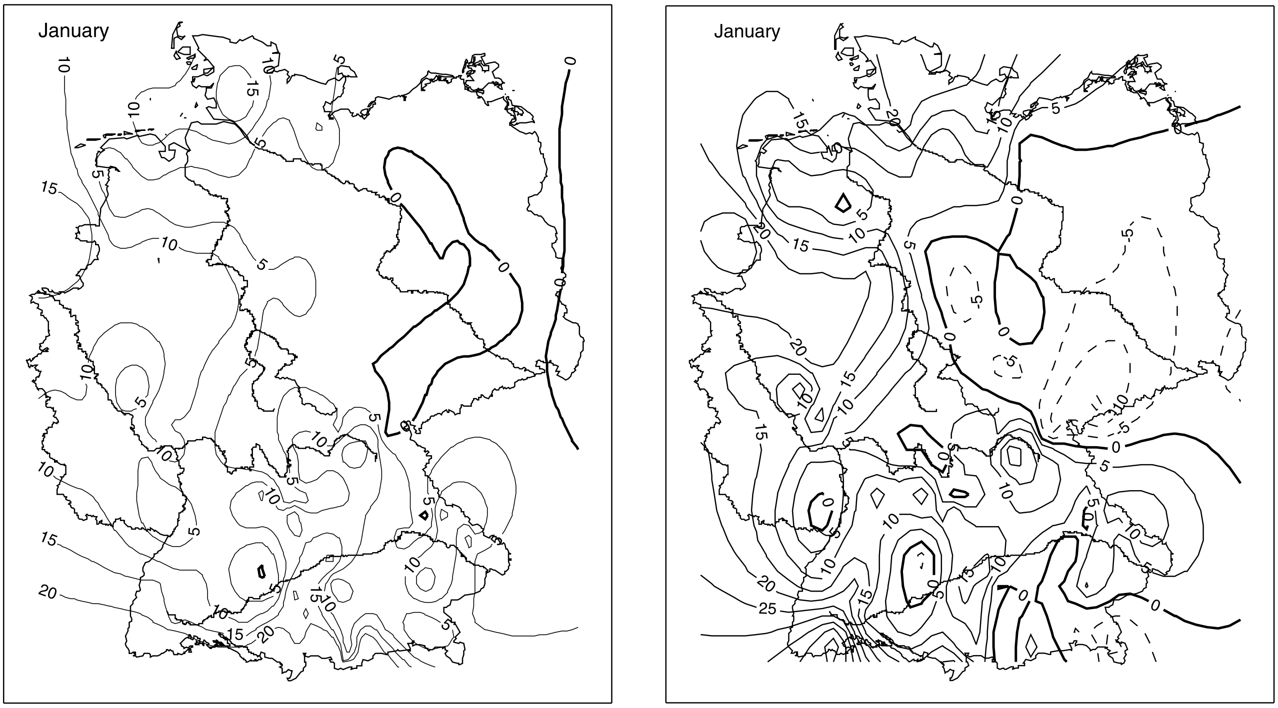

Fig. 3. Precipitation trends in mm in the expected value during 1901–2000 for Germany, January, estimated on the basis of the statistical modeling (left) compared to the linear trend estimates using Gaussian assumptions (right)

or nearly unchanged expectations in the eastern part of Germany. But the least-squares estimator provides higher trend amounts. Consequently, these results confirm that application of the least-squares estimator to non-Gaussian precipitation time series often implies a positive bias. Gaussian assumptions may generate or amplify a trend. While a stationary Gumbel distribution

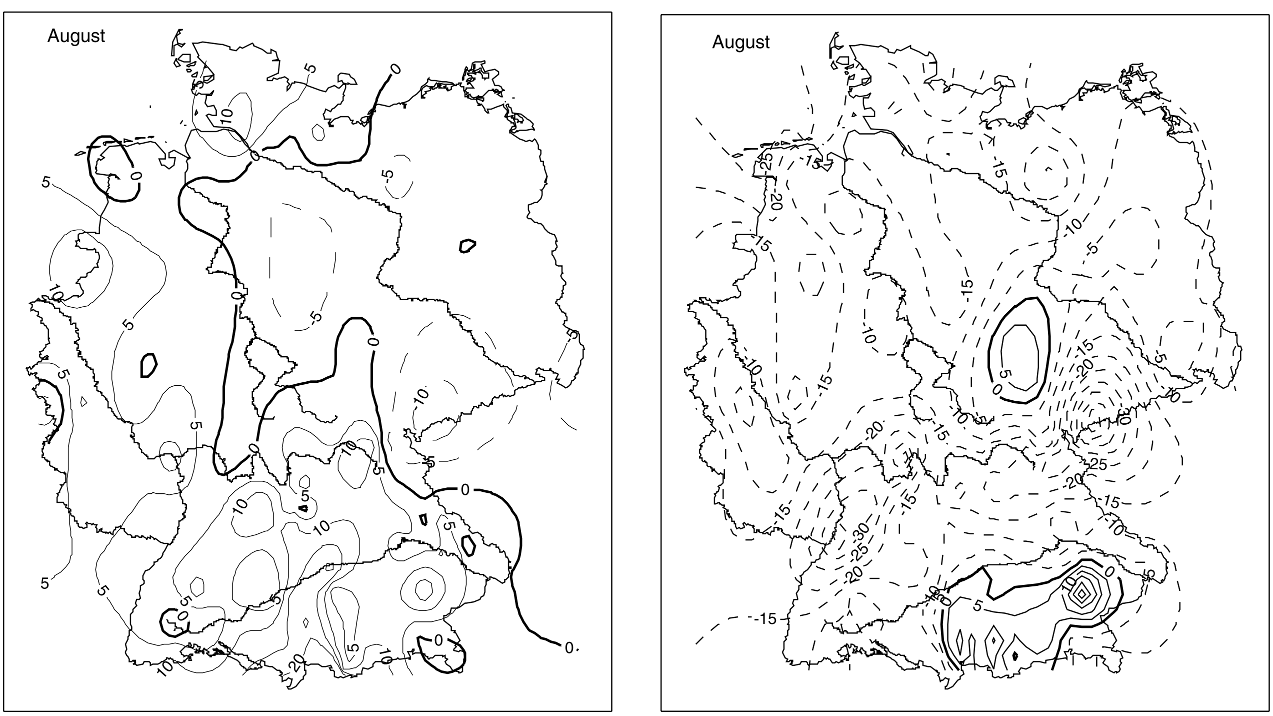

Fig. 4. Same as in Fig. 3 but for August

could still explain the occurrence of some relatively high values, Gaussian assumptions may already cause a shift of the distribution in order to explain their occurrence. Figure 4 shows again both trend maps but for August. Now, the differences are more conspicuous. The least-squares estimator assumes negative trends in the greatest part of Germany. Compared to January, the negative trends in the eastern part of Germany are now more pronounced, even if the Gumbel model is used. However, the trend map provided by the method introduced still shows positive trends in the south. No significant change in the sign of the trend is detected within the statistical modeling of the whole time series. The least-squares estimator is applied to 12 sub-time series separately in order to yield the trend for every single month. This approach is less robust and provides unreasonable differences between the trends of the single months. Within the method introduced large unreasonable differences in trend estimates are condemned as untrustworthy from a meteorological point of view. The reader should also compare monthly trend maps of subsequent calendar months on the basis of the Gumbel model (see Trömel 2005, for the other trend maps of the year) with trend maps estimated on the basis of the least-squares method (Rapp and Schönwiese 1996).

3.1 Monte Carlo simulations

In the following, the results of Monte-Carlo simulations should clarify whether the more extensive statistical modeling really provides the more reliable trend estimates. In particular, these simulations quantify the mean squared errors of both estimators.

For the German station network the residual analysis of the generalized time series decomposition technique approves the complete description of the time series as a realization of a Gumbel-distributed random variable. Consequently, the least-squares estimator is applied to artificial generated Gumbel-distributed time series in order to evaluate the trend estimates on the basis of the least-squares method on the one hand and the trend estimates on the basis of the statistical modeling on the other hand. Generated random time series with a priori defined changes in the expected value are used to compare the given trends with the least-squares estimates. In this way a possible systematic bias associated with the application of the least-squares method to observed non-Gaussian precipitation time series can be identified.

Eight different experiments, i.e., positive and negative changes in the expectation caused by changes in the location and the scale parameter of the distribution, are performed. Trend amplitudes are set to be in the magnitude of monthly trends in precipitation time series in millimetre per year observed in the 20th century in Germany. The experiments only consider linear trends.

In the first step 100 Gumbel-distributed random time series with a sample size of $N = 1000$ values are generated for each experiment, respectively. Table 1 shows for each experiment the predefined change in the expected value $\Delta\mu$, caused by linear changes in the location parameter Δa and the scale parameter Δb, in comparison to the mean value $\overline{\Delta\mu_{KQ}}$ of all 100 least-squares estimates of the trend, determined by linear regression, as well as the standard deviation of these trends $\sigma_{\Delta\mu}$, the maximum $\Delta\mu^{+}_{KQ}$ and

Table 1. Trends of 100 generated Gumbel-distributed time series of sample size $N = 1000$. The predefined linear trends $\Delta\mu$ are caused by linear changes in the location parameter Δa with simultaneous changes in the scale parameter Δb or constant scale parameter b. Real changes in the expected value $\Delta\mu$ are compared to the mean value of least-squares estimates $\overline{\Delta\mu_{KQ}}$. Furthermore, the standard deviation $\sigma_{\Delta\mu}$ as well as he maximum and the minimum $(\Delta\mu^{+}_{KQ}\ bzw\cdot\ \Delta\mu^{-}_{KQ})$ of the trend estimates are given

	$\Delta a = 15$, $b = 50$	$\Delta a = 15$, $b = 20$	$\Delta a = 8$, $b = 40$	$\Delta a = 0$, $b = 40$	$\Delta a = 8$, $b = 40 + \Delta 8$	$\Delta a = -15$, $b = 50$	$\Delta a = -8$, $b = 40 - \Delta 8$	$\Delta a = 0$, $b = 40 + \Delta 10$
$\Delta\mu$	15	15	8	0	12.6	−15	−12.6	5.77
$\overline{\Delta\mu_{KQ}}$	15.49	15.20	8.39	0.39	13.05	−14.51	−12.27	6.22
$\sigma_{\Delta\mu}$	6.97	2.79	5.57	5.57	6.16	6.70	5.02	6.31
$\Delta\mu^{-}_{KQ}$	0.78	9.31	−3.38	−11.38	ß.08	−29.22	−22.83	−7.06
$\Delta\mu^{+}_{KQ}$	33.44	22.38	22.75	14.75	28.23	3.44	1.27	21.81

Table 2. Same as Table 1, but the sample size of the random time series is $N = 100$

	$\Delta a = 15$, $b = 50$	$\Delta a = 15$, $b = 20$	$\Delta a = 8$, $b = 40$	$\Delta a = 0$, $b = 40$	$\Delta a = 8$, $b = 40 + \Delta 8$	$\Delta a = -15$, $b = 50$	$\Delta a = -8$, $b = 40 - \Delta 8$	$\Delta a = 0$, $b = 40 + \Delta 10$
$\Delta\mu$	15	15	8	0	12.6	−15	−12.6	5.77
$\overline{\Delta\mu_{KQ}}$	12.85	14.14	6.28	−1.72	10.78	−17.15	−14.21	3.90
$\sigma_{\Delta\mu}$	23.82	9.53	19.06	19.06	20.91	23.82	17.31	21.39
$\Delta\mu^-_{KQ}$	−43.84	−8.54	−39.07	−47.07	−38.96	−73.84	−55.18	−49.93
$\Delta\mu^+_{KQ}$	59.52	32.81	43.62	35.62	51.44	29.52	22.13	46.37

the minimum $\Delta\mu^-_{KQ}$ of all the trend estimates. Evidently, Table 1 shows only minor differences in the mean value $\overline{\Delta\mu_{KQ}}$ and a priori defined trend amplitudes $\Delta\mu$. However, we observe a positive bias and the bias increases with magnitude of the scale parameter. One possible explanation is that relatively high values are getting more weight than justified from a statistical point of view. The standard deviations $\sigma_{\Delta\mu}$ are considerably high. Depending on the occurrence of the relatively high values in the Gumbel-distributed random time series, the least-squares estimator varies in the first experiment with linear increment in the location parameter $\Delta a = 15$ and constant scale parameter $b = 50$ between 0.78 and 33.44. Furthermore, this range also increases with the value of the scale parameter. It is worth mentioning that the least-squares method sometimes provides negative trend estimates if we keep the predefined expected value constant ($\Delta a = 0$, $b = 40$). Even though in case of an increase of the expected value ($\Delta a = 8$, $b = 40$), negative trend estimates occur.

The sample size plays a major role for the mean squared error of the estimator, defined as the sum of the squared bias $(\overline{\Delta\mu_{KQ}} - \Delta\mu)^2$ and the variance $(\sigma_{\Delta\mu})^2$. So, all experiments are performed again with the sample size $N = 100$. Table 2 shows the results analogous to Table 1. We now observe a negative bias in all experiments. Furthermore, the absolute value of the bias is significantly higher compared to the experiments with sample size $N = 1000$. Generally, the standard deviation or variance of the trend estimator is higher in case of smaller sample size. The experiment with a linear increase of 15 units in the location parameter and unvaried scale parameter provides trend amplitudes between −43.83 and 59.52.

The least-squares estimator provides large mean squared errors in estimated precipitation trends. However, it is interesting to see the mean squared error of the trend estimator using the distance function of the Gumbel distribution ρ_G. Smaller mean squared errors are anticipated using the adequate distance function. The experiments presented in Tables 1 and 2 are performed again and the distance function of the Gumbel distribution is used now. Statistical trend tests are not applied in order to retain comparability. Using Gaussian assumptions an F-test (Storch and Zwiers 1999) proves the significance of a regression relationship, but a modification of the test statistic is necessary for non-Gaussian residuals (Schrader and Hettmansperger 1980). Tables 3 and 4 show again for all experiments the mean value of the trend estimates $\overline{\Delta\mu_G}$, the standard deviation $\sigma_{\Delta\mu_G}$, the minimum $\Delta\mu^-_G$ and

Table 3. With the distance function of the Gumbel distribution (index G instead of KQ) estimated trends of 100 generated Gumbel-distributed time series of sample size $N = 1000$. The experiments and notation are the same as in Tables 1 and 2

	$\Delta a = 15$, $b = 50$	$\Delta a = 15$, $b = 20$	$\Delta a = 8$, $b = 40$	$\Delta a = 0$, $b = 40$	$\Delta a = 8$, $b = 40 + \Delta 8$	$\Delta a = -15$, $b = 50$	$\Delta a = -8$, $b = 40 - \Delta 8$	$\Delta a = 0$, $b = 40 + \Delta 10$
$\Delta\mu$	15	15	8	0	12.6	−15	−12.6	5.77
$\overline{\Delta\mu_G}$	15.56	15.20	8.5	0.47	13.27	−14.25	−12.23	6.21
$\sigma_{\Delta\mu_G}$	7.14	2.87	5.76	5.67	5.91	7.01	4.1	5.90
$\Delta\mu^-_{KQ}$	0.66	9.18	−3.57	−11.82	1.22	−29.20	−22.70	−6.24
$\Delta\mu^+_{KQ}$	32.22	21.87	25.08	13.73	27.50	1.60	−0.04	20.33

Table 4. Same as Table 3, but the sample size of the random time series is $N = 100$

	$\Delta a = 15$, $b = 50$	$\Delta a = 15$, $b = 20$	$\Delta a = 8$, $b = 40$	$\Delta a = 0$, $b = 40$	$\Delta a = 8$, $b = 40 + \Delta 8$	$\Delta a = -15$, $b = 50$	$\Delta a = -8$, $b = 40 - \Delta 8$	$\Delta a = 0$, $b = 40 + \Delta 10$
$\Delta\mu$	15	15	8	0	12.6	−15	−12.6	5.77
$\overline{\Delta\mu_G}$	11.18	13.43	5.06	−2.88	9.39	−18.24	−14.95	2.57
$\sigma_{\Delta\mu_G}$	23.48	9.40	18.71	18.72	20.48	23.54	16.88	20.91
$\Delta\mu_{KQ}^-$	−44.70	−9.49	−40.28	−47.66	−40.38	−74.08	−55.58	−48.27
$\Delta\mu_{KQ}^+$	57.51	31.81	41.37	33.73	49.43	28.16	19.56	43.13

maximum $\Delta\mu_G^+$ arising in 100 generated time series, respectively. Again experiments are performed using the sample sizes $N = 1000$ and $N = 100$. Obviously, application of the adequate distance function is not definitely associated with a smaller mean squared error of the trend estimator. It is interesting to see that not the distance function ρ but the sample size N is the most important factor to achieve reliable estimators for trends of precipitation time series. Generally, consistency is a property of the maximum likelihood estimator. A possible explanation for similar mean squared errors may be the significance of the trends, which was not considered in the Monte-Carlo simulations. The additional differences between the F-test and the modified F-test would complicate the comparison of the two trend estimators.

However, the use of the adequate distance function is necessary in order to retain a complete analytical description of observed precipitation. In this way, monthly trends can be estimated on the basis of the whole sample size. Separate analyses of sub-time series containing only one 12th of the whole sample size are no longer necessary.

4. Conclusions

This paper introduces an alternative approach to estimate trends in observed precipitation time series. In the special case of 132 time series of monthly precipitation totals 1901–2000 from German stations, the interpretation as a realization of a Gumbel-distributed random variable with time-dependent location parameter and time-dependent scale parameter reveals a complete analytical description of the time series. The deterministic part contains the annual cycle and its changes concerning amplitude and phase shifts, trends (linear, progressive and degressive) and low frequency variations. These structured components are detected in the location and the scale parameter of the Gumbel distribution, which describes the statistical part of the series. On the basis of the achieved complete description of the time series, the difference between the expectation in a special month in the last year and the first year of the observation period can be defined as the trend in the considered month.

In winter, both trend maps, on the basis of the least-squares estimator and on the basis of the Gumbel model, show the same spatial distribution of detected trends but the amplitudes are smaller in the latter case. In summer, the differences are more pronounced. While the least-squares estimator shows negative trends in the overwhelming majority of stations, the time series decomposition technique does not detect negative trends in the southern part of Germany. A shift of the distribution to higher values describes the observational time series in the southern part of Germany in winter and in summer.

Enhanced robustness of the trend estimates based on the time series decomposition technique is achieved from three different perspectives: (1) the elimination of unexpected values, (2) the fit of an adequate PDF, and (3) the fit of a structure to whole time series but not only single calendar months.

Monte-Carlo simulations underline the smaller mean squared error associated with an increase of the sample size. It is surprising, that the least-squares estimator does not seem to be inferior to the estimator of the Gumbel model if the bias and the variance are compared for the same sample size. Smaller errors were anticipated using the adequate distance function, because the distance function of the Gumbel distribution takes the skewed distribution of precipitation time series as well as the more prominent tails into account. The possibility to take into account changes in different parameters of the distribution speaks also in the favour of the more extensive statistical modeling because observed precipitation time series often show changes in the variance as well as in the shape of the distribution. A possible explanation for similar mean squared errors using the same sample size may be the significance of the trends, which was not considered in the Monte-Carlo simulations. The additional differences between the F-test, used for the least-squares estimator, and the modified F-test, used within the generalized time series decomposition technique, and further several possible tests like the Mann–Kendall statistic (Schönwiese 2006) would derange the comparison of the two trend estimators considered.

Definitely, the least-squares method provides less robust estimates and generates greater differences in the trends of various months. These unreasonable changes in trend amplitudes of adjacent calendar months are untrustworthy from a meteorological point of view. Within the method applied significant detected changes in the annual cycle of the distribution parameters may generate different trends in various months. However, these seasonal variations are not caused by single relatively high values.

To summarise, the method introduced provides robust monthly trend estimates of observed precipitation time series taken into account the characteristics of the climate variable and constrains the influence of single high values.

Acknowledgement

We gratefully acknowledge that this work was supported by the Federal German Minister of Education and Research (BMBF) under grant No. 01 LD 0032 within the context of the German Climate Research Programme (DEKLIM, http://www.deklim.de).

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