Hydrol. Earth Syst. Sci. Discuss., 6, 2845–2892, 2009
www.hydrol-earth-syst-sci-discuss.net/6/2845/2009/

Hydrology and
Earth System
Sciences
Discussions

Effects of intersite dependence of nested catchment structures on probabilistic regional envelope curves

B. Guse[1,2], A. Castellarin[3], A. H. Thieken[1,4], and B. Merz[1]

[1]Helmholtz Centre Potsdam, GFZ German Research Centre for Geosciences, Section Hydrology, Potsdam, Germany
[2]Center for Disaster Management and Risk Reduction Technology (CEDIM), Karlsruhe, Germany
[3]Dipartimento di Ingegneria delle Strutture, dei Trasporti, delle Acque, del Rivelamento, del Territorio (DISTART), Università di Bologna, Bologna, Italy
[4]alpS – Centre for Natural Hazard and Risk Management, University of Innsbruck, Innsbruck, Austria

Received: 19 March 2009 – Accepted: 22 March 2009 – Published: 31 March 2009

Correspondence to: B. Guse (bguse@gfz-potsdam.de)

Published by Copernicus Publications on behalf of the European Geosciences Union.

Abstract

Regional flood quantile estimates are affected by intersite correlation between flood sequences observed at different discharge gauges. This study analyses the intersite dependence of nested catchment structures and investigates the possibility of improving the accuracy of regional flood quantiles, by modelling cross-correlations for pairs of nested and unnested catchments separately. Probabilistic Regional Envelope Curves are utilised to derive regional flood quantiles for 89 catchments belonging to Saxony, in the Southeast of Germany. The study area has a nested structure and a definitely stronger intersite correlation for nested pairs of catchments than for unnested ones. Probabilistic Regional Envelope Curves are constructed on the basis of flood flows observed within pooling groups of sites (regions). Their recurrence intervals are based on the number of effective sample-years of data (i.e., equivalent number of uncorrelated data). The evaluation of the effective sample-years of data required the modelling of intersite dependence, which we performed globally, using a cross-correlation formula identified for the whole study area, and by using two different cross-correlation formulas, one for nested pairs and another for unnested pairs. These two modelling approaches returned significantly different effective sample-years of data estimates, and therefore also recurrence intervals, in the majority of the cases. The differences result from various assumptions of the size and homogeneity degree of the pooling group. The reduction of the recurrence interval, when using two different cross-correlation functions, is larger for higher recurrence intervals and for a higher fraction of nested catchment within the pooling group. A separation into nested and unnested pairs of catchments gives a more realistic representation of the characteristic river network structure and improves the accuracy of the estimation of regional information content. Hence, applying two different cross-correlation functions is recommended.

1 Introduction

The estimation of flood quantiles is a major topic in hydrologic research and engineering practise. Due to the uncertainty in the estimation of high recurrence intervals in an at-site flood frequency analysis, several gauges may be pooled together in a pooling group using the principle “trading space for time” (e.g., Stedinger et al., 1993; Robson and Reed, 1999). Regional flood frequency analysis aims to improve the estimation of flood quantiles by using a larger number of flood data. A pooling group collects catchments with a similar hydrologic behaviour. In contrast to the traditional approach of fixed homogeneous regions (e.g., Acreman and Sinclair, 1986; Nathan and McMahon, 1990; Lecce, 2000; Rao and Srinivas, 2006), site-focused pooling methods (Region of Influence, RoI (e.g., Burn, 1990a; Zrinji and Burn, 1994; Cunderlik and Burn, 2002)) construct an own pooling group separately for each site of interest. Several methods and many studies of regional flood frequency analysis have been presented (e.g., Cunnane, 1988; GREHYS, 1996a, b; Robson and Reed, 1999; Merz and Blöschl, 2005; Ouarda et al., 2008). The index flood approach (e.g., Dalrymple, 1960; Stedinger and Lu, 1995; GREHYS, 1996a, b; Robson and Reed, 1999) or regression analysis (e.g., Pilgrim et al., 1982; Robson and Reed, 1999) are traditional methods. Recently, geostatistical methods have come into the focus of research (Merz and Blöschl, 2005; Skoien et al., 2006).

Pooling of flood data requires that the floods are independent and identically distributed (iid). This assumption is not valid for cross-correlated sites and, therefore, the accuracy of regional quantiles is reduced (Hosking and Wallis, 1988).

In terms of flood regionalisation, most of the studies have focused on the performance of different pooling schemes or pooling methods (e.g., Burn, 1990a; GREHYS, 1996a, b; Merz and Blöschl, 2005). Only little guidance is given on the effect of intersite correlation in estimating regional flood quantiles.

Matalas and Langbein (1962) introduced the concept of regional information content in order to determine the effect of intersite correlation within flood sequences.

The regional information content expresses the effective number of observations. In a regional flood frequency study, (Bayazit and Önöz, 2004) pointed out that quantile estimates are already affected by a relatively low intersite correlation of 0.1–0.2. Stedinger (1983) and Hosking and Wallis (1988) have shown that the influence of intersite correlation increases with higher flood quantiles and decreases for higher flood moments. These statements affirm that the influence of intersite correlation must not be ignored (e.g., Stedinger, 1983; Hosking and Wallis, 1988; Vogel et al., 2001; Castellarin et al., 2005).

The distance between two catchments is generally assumed as the main impact factor on intersite correlation resulting in different cross-correlation models. In these models, the correlation coefficient is negatively related to the distance between the catchments (Tasker and Stedinger, 1989; Troutman and Karlinger, 2003).

Castellarin et al. (2005) have developed an empirical relationship by using a Monte-Carlo simulation to reveal the reduction of the overall sample-years of data in a regional sample due to the intersite correlation, and to obtain the effective number of sample-years of data. That is the equivalent number of independent data. They determined an effective number of sample-years of data to assign an exceedance probability to a probabilistic regional envelope curve (PREC). In this method the traditional approach of a regional envelope curve is enhanced by a probabilistic statement. The method of PREC requires a pooling group, which accomplishes the homogeneity criteria of the index flood method.

In all these studies the influence of intersite correlation is considered by using the Euclidean distance between catchments centroids as the only surrogate. The effects of the structure of the river network and mutual location of catchments are generally neglected, since there is no distinction between nested and unnested catchments. In contrast, Troutman and Karlinger (2003) have shown that the correlation between the Annual Maxima Series (AMS) of gauges along the same stream, i.e. for nested catchments, is higher than for unnested conditions. They argued that the correlation effects of peak flows result from rainfall as well as from the river network.

The role of the spatial organisation of catchments, i.e. the river network structure, has been highlighted in several studies (e.g., Woods et al., 1995; Skoien et al., 2003). Comparing different regionalisation methods when deriving catchment parameters, Merz and Blöschl (2004) have recognised a slightly better performance of a kriging approach by considering upstream and downstream neighbours separately. In terms of flood regionalisation methods Skoien et al. (2006) have recently demonstrated the better performance of “Top-Kriging”, which considers the effects of nested catchments, in comparison to a traditional “Ordinary Kriging” approach, which is only based on the distances between the catchments.

The influence of intersite correlation and regional heterogeneity has been discussed by Hosking and Wallis (1988). They concluded that the regional heterogeneity affects the accuracy of regional flood frequency quantiles more significantly than intersite correlation. Madsen and Rosbjerg (1997) showed that a homogeneous region, which is delineated by a higher threshold of the heterogeneity measure, has a more scattered cloud of empirical correlation coefficients in relationship to the distance. It has recently been demonstrated by Castellarin et al. (2008) that a high cross-correlation strongly influences the H-test, because intersite correlation leads to a decrease of the H-value. A heterogeneous cross-correlated region may be evaluated as homogeneous. An empirical reduction factor is proposed in order to adjust the effect of intersite correlation (Castellarin et al., 2008).

The core idea of this study is to assess the impact on regional flood frequency analysis of different approaches to the modelling of intersite dependence. First, a global approach is considered, in which the cross-correlation formula is identified for the whole study area. The second approach derives two different cross-correlation formulas, one for nested pairs of catchments and one for unnested ones.

We emphasize the relevance of nested catchment structures on regionalisation methods by using the method of probabilistic regional envelope curves (PREC), exemplarily in Saxony/Germany. PREC is selected as regionalisation method, because the calculation of a recurrence interval is directly related to the effective sample-years of data. In this context, the method of PREC is advanced by using two different parameter sets for the cross-correlation function of nested and unnested catchments. The results of PREC are compared with a cross-correlation function using a global parameter set. In both approaches all other aspects of flood regionalisation studies such as the selection of the catchment descriptors or the pooling method are not the focus of research and are not varied. Significant factors, which influence the effect of intersite correlation on PREC, are determined. Finally, all approaches are compared for different thresholds of the heterogeneity measure.

2 Methods

2.1 Regional information content and number of effective observations

The regional information content expresses the ratio of the effective to the total sample-years of data. The core idea of the regional information content (Matalas and Langbein, 1962) is that a correlated site gives a lower degree of additional information to the site being studied than a non-correlated site. The additional information decreases for a higher intersite correlation (Hosking and Wallis, 1988). Matalas and Langbein (1962) have shown that the variance of the regional mean increases for cross-correlated sites. Furthermore, Stedinger (1983) demonstrated that the variance of the regional variance increases due to intersite correlation.

An information content of one means, that two sites are completely uncorrelated (independent), implying that the total flood sequence give additional information. The other extreme is where regional information contents close to zero indicate that there is no additional information within the time series. A lower information content leads to a lower number of effective sites (Matalas and Langbein, 1962).

On the basis of the regional information content, Castellarin et al. (2005) and Castellarin (2007) estimated the exceedance probability of a regional envelope curve. The effective sample-years of data, hereafter also referred to as effective observations, were calculated by reducing the total sample-years of the AMS of all gauges (Castellarin, 2007). In this context, a regional cross-correlation function (Eq. 1), proposed by Tasker and Stedinger (1989), was applied, which is based on the distances between catchment centroids, the correlation coefficients between the AMS and the length of overlapping time series (Castellarin, 2007). In order to consider the nested catchment structure, Troutman and Karlinger (2003) recommend the use of catchment centroids for calculating the distance. In the optimisation process the parameters λ_1 and λ_2 of the cross-correlation function were fitted according to Eq. (1). The parameters were weighted by the length of the time series as proposed by Stedinger (1983).

$$\rho_{i,j} = \exp\left(-\frac{\lambda_1 d_{i,j}}{1+\lambda_2 d_{i,j}}\right) \qquad (1)$$

d=Distance between catchment centroids, ρ=Correlation coefficient by Pearson, λ_1, λ_2=parameters, i, j=Index denoting pairs of Catchments.

The overall effective sample-years of data n_{eff} was provided by an empirical relationship derived by Castellarin et al. (2005) and Castellarin (2007) in Monte-Carlo simulations for all years N with discharge measurements (Eq. 2). In a first step, all years n_1 with only one observation were considered separately, because these samples are certainly not affected by intersite correlation. The remaining years N_{sub} $(N-n_1)$ were further separated in subsets s, which include the same gauges L_s. Each subset contains a specific number of years l_s. The effective number of observations was calculated for each subset separately. In the last step, the number of effective observations was calculated by summing up the effective samples for all years. The effective observations represent the number of independent observations within a pooling group (Castellarin, 2007).

$$n_{\mathrm{eff}} = n_1 + \sum_{s=1}^{N_{\mathrm{sub}}} n_{\mathrm{eff},s} = n_1 + \sum_{s=1}^{N_{\mathrm{sub}}} \frac{L_s l_s}{1+\left[\overline{\rho^{\beta}}\right]_{L_s}(L_s-1)} \text{ with } \beta := 1.4\frac{(L_s l_s)^{0.176}}{\left[\overline{(1-\rho)^{0.376}}\right]_{L_s}} \qquad (2)$$

2.2 Probabilistic regional envelope curves (PREC)

The calculation of the number of effective sample-years of data is a fundamental step towards estimating the exceedance probability of a regional envelope curve. The method of a probabilistic regional envelope curve (PREC) is based on two assumptions. Firstly, the index flood hypothesis requires that all gauges of a region are homogeneous. And secondly, there is a relationship of the index flood μ_X to the drainage area (A) (Eq. 3). Following these principles, the index flood scales with the drainage area and depends alone on the drainage area (Castellarin, 2007).

$$\mu_X = a * \mathrm{A}^{b+1} \tag{3}$$

a=intercept of REC, b=slope of REC.

The regional envelope curve was derived in two steps. First, the slope b was estimated by a regression analysis of the index flood relating to the drainage area (Fig. 1). The second step is a parallel upshift of this regression up to the intercept a, at which the regional envelope curve (REC) bounds all floods of record (Castellarin et al., 2005). In this study PREC was applied for all regions with at least four sites.

The core idea of PREC is an assignment of an exceedance probability to that particular data pair of unit flood of record and its drainage area, which determines the intercept of REC. That is the exceedance probability of the largest standardised annual maximum peak flow observed in the region.

Therefore the plotting position of the maximum unit flood of record was used, which was determined by the number of effective observations n_{eff} and the formula of Hazen (Eq. 4). The recurrence interval T is identical for all gauges and valid in the range of the catchment size (Castellarin, 2007).

$$T = 2 * n_{\mathrm{eff}} \tag{4}$$

2.3 Pooling scheme

In order to determine the influence of intersite correlation and of nested catchment structures on the number of effective observations and the recurrence interval of PREC, it is essential to provide homogeneous regions of sites. Several pooling groups were constructed in a preliminary study (Guse et al., 2008). (1) At the beginning, useful predictor variables were selected. (2) Next, behavioural subsets of two or three predictor variables were determined. (3) Each subset is used to derive a pooling group using the RoI approach. (4) Finally, the pooling groups were checked for homogeneity.

The Region of Influence (RoI) approach (Burn, 1990b) identifies a specific pooling group of sites (region in the widest sense) for each site of interest. In this way, hydrologically similar gauges were selected for each gauge. The rationale behind this approach is that the specific hydrologic conditions of the site of interest are considered. Instead of the geographical distance, a predictor space is formed by the catchment descriptors of a selected subset. A central point is the determination of the size of a RoI, which is derived by a threshold in the Euclidean space in this study. All gauges, which were closer to the site of interest in the predictor space than a specific threshold, were assigned to the Region of Influence. Similarity was evaluated by the Euclidean distance of each site to the site of interest in this predictor space (Zrinji and Burn, 1994). In this study, three different thresholds for the similarity measure (0.5, 1 and 2) were assessed. The different thresholds reflect the trade-off between the size and the regional homogeneity of a pooling group (Castellarin et al., 2001).

2.3.1 Homogeneity test

A homogeneity test is directly included in the RoI approach. The heterogeneity measure (H-test) (Hosking and Wallis, 1993) compares the regional heterogeneity of a pooling group in terms of the variability of L-moment ratios with simulated synthetic time series obtained by a Monte-Carlo simulation. The H_1-test focuses on the sample variability of the L-coefficient of variation (L-CV). Hosking and Wallis (1993) mentioned that a very low value of their heterogeneity measure ($H<-2$) indicates a high intersite correlation. Since synthetic time series used in the test deemed to be independent by definition, intersite correlation introduces some bias in the H-test results.

In this study, each RoI with $H_1<2$ was used to form a pooling group and to derive a PREC. Consequently, the number of PREC realisations was identical with the number of homogeneous RoIs. It is common practise to use this threshold (Lettenmaier et al., 1987; Castellarin et al., 2001; Castellarin et al., 2007). All regions below two are seen as homogeneous ($H<1$) or possibly heterogeneous ($H<2$), which means that a review of the region is not required or optional, respectively (Robson and Reed, 1999).

2.4 Application and interpretation of different cross-correlation functions

In this study, the number of effective observations was calculated using two different approaches with separately optimised parameter sets for the cross-correlation function (Eq. 1). In a first approach, the effective observations were calculated by using one cross-correlation function for the whole study area (termed: $\mathrm{EFFOBS}_{\mathrm{GLOBAL}}$). Next, different cross-correlation functions for nested and unnested catchments were applied (termed: $\mathrm{EFFOBS}_{\mathrm{NESTED}}$).

As mentioned before, the number of effective observations was calculated separately for each year, because the length of the time series varied between the gauges. In each year only sites with discharge measurements were used. The parameter set for nested structures was used for all pairs of catchments, which are in an upstream-downstream relationship. Otherwise, the unnested parameter set was employed. In order to compare both approaches, the number of effective observations was calculated for the same pooling groups.

2.4.1 Information content

To compare both approaches, the information content, i.e. the fraction of the effective observations to the total observations OBS, was calculated (termed: $\mathrm{IC}_{\mathrm{NESTED}}$ and

IC_{GLOBAL} in Eqs. 5, 6).

$$IC_{\mathrm{NESTED}}=\frac{\mathrm{EFFOBS}_{\mathrm{NESTED}}}{\mathrm{OBS}}*100 \tag{5}$$

$$IC_{\mathrm{GLOBAL}}=\frac{\mathrm{EFFOBS}_{\mathrm{GLOBAL}}}{\mathrm{OBS}}*100 \tag{6}$$

2.4.2 Effective observations

In a next step, $\mathrm{EFFOBS}_{\mathrm{NESTED}}$ and $\mathrm{EFFOBS}_{\mathrm{GLOBAL}}$ were compared using $\mathrm{EFFOBS}_{\mathrm{GLOBAL}}$ as reference. Therefore, the ratio R_{NESTED} (Eq. 7) was calculated, which reveals the difference between the number of effective observations using a global parameter set and different parameters for nested and unnested catchment structures. This method enables an interpretation of the influence of the different parameter sets on the effective observations.

$$R_{\mathrm{NESTED}}=\frac{\mathrm{EFFOBS}_{\mathrm{NESTED}}-\mathrm{EFFOBS}_{\mathrm{GLOBAL}}}{\mathrm{EFFOBS}_{\mathrm{GLOBAL}}}*100 \tag{7}$$

2.4.3 Recurrence interval of PREC

Furthermore, the study focuses on the recurrence interval T of PREC, which, according to Eq. (4), is twice as high as the number of effective observations. Consequently, the ratio R_{NESTED} is identical when using the recurrence interval instead of the effective observations (Eq. 8).

$$R_{\mathrm{NESTED}}=\frac{T_{\mathrm{NESTED}}-T_{\mathrm{GLOBAL}}}{T_{\mathrm{GLOBAL}}}*100 \tag{8}$$

2.4.4 Degree of nesting

Next, the effect of the nested structure on T was emphasized by calculating a degree of nesting D_{NESTED} (Eq. 9). All pairs of catchments P_{ALL} within a pooling group were checked to see if their catchments were nested or unnested. The degree of nesting is defined as the ratio between nested catchment relations P_{NESTED} and P_{ALL}.

Since the effective observations were calculated separately for each year, the nested catchment structure was also estimated separately for each year. Ultimately, the mean degree of nesting for the n years was calculated for each RoI.

$$D_{\mathrm{NESTED}}=\frac{\sum\limits_{y=1}^{n}\frac{P_{\mathrm{NESTED}_y}}{P_{\mathrm{ALL}_y}}}{n} \tag{9}$$

2.4.5 Regional heterogeneity

Finally, the influence of the degree of heterogeneity on the intersite correlation was analysed, because regional heterogeneity and intersite correlation affect the estimation of flood quantiles. In order to consider the influence of the threshold of the heterogeneity measure, the same procedure described above was repeated for a higher (H<1) and lower (H<4) threshold. According to the classification of Hosking and Wallis (1997) a threshold of H<1 means that possibly homogeneous regions (H<2) are excluded (Table 2). By increasing the threshold to 4, also slightly heterogeneous regions are included.

3 Study area

The study area is the federal state of Saxony, in the Southeast of Germany, which is characterised by high-elevated parts in the Southwest (*Erzgebirge*) and lower elevation in the northern parts (Fig. 2). The Elbe is the largest river with a catchment size

Title Page
Abstract Introduction
Conclusions References
Tables Figures
◀| |▶
◀ ▶
Back Close
Full Screen / Esc
Printer-friendly Version
Interactive Discussion

of 52 000 km^2 at gauge Dresden. There are six large catchments in Saxony (Weisse Elster, Mulde, Elbe tributaries, Schwarze Elster, Spree and Lausitzer Neisse, from west to east) (Fig. 2).

Only gauges were used, which (1) had a time series of more than 30 years, (2) were not strongly influenced by mining activities, (3) had a catchment size larger than 10 km^2, and (4) were not located directly downstream of a dam. Furthermore, gauges were omitted, whose catchments were mostly outside of Saxony. Ultimately, 89 gauges were considered. For all gauges, the Annual Maxima Series (AMS) and the highest observed discharge, the flood of record (FOR), were derived from the data.

Climatic, geomorphologic, geologic and land-use data were used to derive catchment descriptors as basis for pooling catchments into homogeneous regions. Precipitation data was provided by the German Weather Service (DWD). Precipitation indices were estimated by using 453 stations in and around Saxony, which have a time length of at least 30 years and endured at least up to 2002. Owing to the severe wide-spread flood occurred in 2002, in particular along the Elbe and Mulde, it is useful to include this year in the data set. Precipitation time series shorter than thirty years were additionally added to derive the maximum daily precipitation and the five-day precipitation sum, if the flood of record of the downstream gauge occurred during the period of the precipitation time series. Therefore, 23 stations were additionally added, because the maximum precipitation occurred on the same date as the flood of record at the downstream gauge. All precipitation indices were interpolated by ordinary kriging.

Mean elevation, mean slope and catchment centroids were derived from digital elevation models. In Saxony a grid size of 25 meters was used, whereas the SRTM DEM with a grid size of 90 meters was resampled to a grid size of 25 m for the areas outside of Saxony. Furthermore, landscape parameters derived from the digital landscape model ATKIS (BKG GeoDataCentre, 2005) and hydrogeological parameters derived from the hydrogeological map (HÜK 200) by the Saxon State Agency of Environment and Geology were applied.

3.1 Selection of catchment descriptors

Thirteen catchment descriptors were selected (Table 1). The standardised catchment descriptors (mean=0, standard deviation=1) were combined to create all possible subsets of one, two and three catchment descriptors. Among all subsets, only these subsets of catchment descriptors were selected, which correlated to the index flood (mean of AMS) using a correlation coefficient of 0.6 as threshold for all sites. The index flood was selected, because the validity of the index flood hypothesis is a fundamental assumption of PREC. Next, all subsets with three catchment descriptors were checked on redundancy compared with the selected subsets of two catchment descriptors. Only the subsets were maintained, which led to a larger proportion of explained variance (higher correlation coefficient). All subsets were checked on multicollinearity by the Variance Inflation Factor (VIF) (Hirsch et al., 1992) and removed if VIF was larger than five. Ultimately, this led to 10 subsets (Table 2). These 10 subsets were used to construct a Region of Influence (RoI) and to derive a probabilistic regional envelope curve.

4 Results

4.1 Intersite correlation in the study area

Figure 3 illustrates the variability of empirical correlation coefficients for pairs of annual flood sequences in the study area. The heterogeneity of the correlation pattern becomes apparent when comparing empirical correlation coefficients higher than 0.8 (e.g., Mulde gauges, sites 34–60 in Fig. 3) and also very low correlation coefficients (e.g. Mulde vs. Spree gauges (sites 71–83)). The gauges of the Mulde catchment and the western tributaries to the Elbe River originating in the *Erzgebirge* are characterised by large empirical correlation coefficients also beyond catchment boundaries. Generally, the correlation coefficients of neighbouring catchments are larger than comparable coefficients across the catchment boundaries.

This correlation pattern demonstrates that AMS of neighbouring catchments are more correlated. In this context, this study examines the effect of nested catchment relationships on PREC results.

4.2 Nested catchment structure

The pairs of nested catchments are illustrated in Fig. 4. Among the 3916 possible pairs of catchments, there are 179 nested (5%) and 3737 unnested ones. Since the gauges are arranged by their geographical location, nested pairs of catchments are mainly arranged near the diagonal. Most of the gauges have a few nested catchment relationships. Nested catchment structures are especially located in the Mulde catchment. All tributaries of the Mulde catchments originating in Erzgebirge are related to the two most downstream gauges (sites 34–35, see Fig. 2) explaining the large number of nested pairs of these catchments (see Fig. 4).

4.3 Cross-correlation functions

The relationship of the correlation coefficient to the distance of the catchment centroids for all pairs of sites shows that the correlation coefficients vary between −0.25 and 1 (Fig. 5). As expected, the correlation decreases with increasing distance. Due to the structure of the river network in Saxony, all distances between the centroids of nested catchments are lower than 50 km, whereas unnested catchment relationships reach up to a distance of more than 200 km.

The cross-correlation function strongly decreases up to a distance of about 50 km between the catchment centroids. The slope of the function decreases slightly for larger distances. This distance coincides with the study of Merz and Blöschl (2003). They assumed that all those catchments are close to each other, whose centroids have a distance less than 50 km. These catchments are frequently affected by the same event, resulting in a relatively large correlation between their flood sequences.

The differentiation in nested and unnested catchments shows a remarkable difference in terms of average cross-correlation. As expected, the cross-correlation function for nested catchments yields higher correlations than the function for unnested conditions. The difference between them is up to 0.2. In a distance of 40 km there is a correlation coefficient of 0.7 for nested catchments and only 0.5 for unnested catchments (Fig. 5).

Troutman and Karlinger (2003) pointed out the following correlation: the higher the scattering in the correlation-distance plot, the lower the influence of the distances between catchment centroids owing to the higher influence of physiographic factors. The scattering in Fig. 5 illustrates that the distance is not the unique relevant explanatory variable. However, the distance has a high explanatory power for this study area.

The different parameter sets for the cross-correlation function (Eq. 1) are given in Table 3. The parameters for the global and unnested cases are similar, whereas the parameters for the nested catchments are different. Consequently, it is expected that no large differences will arise by using the parameters for unnested relationships instead of the global parameter set. In contrast, larger effects will occur by using nested parameters.

4.3.1 Theoretical example

In order to demonstrate the effect of different parameter sets of the cross-correlation function on the number of effective observations, a theoretical example is given, which demonstrates all steps of the calculation procedure. The effective observations for one year were derived for hypothetical regions with two and ten sites. A distance of 50 km between all centroids of the catchments and the cross-correlation function parameters of Table 3 were assumed leading to a correlation of 0.49 (global), 0.69 (nested) and 0.48 (unnested), respectively (Table 4). Comparing the effective sites, the difference of the nested to the global and the unnested case are relatively low for two sites (1.63 and 1.62 vs. 1.43). For 10 catchments, however, the numbers of effective sites for the global and unnested cases are significantly higher than for nested conditions (4.32 and 4.42 vs. 2.74). Keeping in mind that, according to Eq. (4), the recurrence interval of

PREC is twice as high as the effective observations, the effect of a differentiation in nested and unnested catchments is already apparent in this example of only one year.

4.4 Region of influence

The Region of Influence approach was applied for each of the 89 gauges separately, using the ten behavioural subsets of catchment descriptors and the three different thresholds in the Euclidean space. Ultimately, 670 pooling groups, accomplishing the homogeneity criteria ($H_1 < 2$), were available with on average 14 sites within a RoI.

4.5 Influence of intersite correlation on information content

The number of effective observations was calculated for all 670 pooling groups with the global parameter set ($\mathrm{EFFOBS}_{\mathrm{GLOBAL}}$) for the cross-correlation function as well as with the separate parameter sets for nested and unnested catchment structures ($\mathrm{EFFOBS}_{\mathrm{NESTED}}$). In order to consider the influence of intersite correlation on the total observation data of all gauges within a pooling group, the effective number of observations was compared with the total number of observations.

It is apparent that the number of effective observations is lower than the total observations (Fig. 6a). Figure 6b illustrates that the information contents $\mathrm{IC}_{\mathrm{NESTED}}$ and $\mathrm{IC}_{\mathrm{GLOBAL}}$ decreases with increasing number of total observations. Whereas the information content is about half of the total observations for data sets with 300 values, it decreases to only 20% in the case of more than 2000 observations.

These results show how the information content decreases when an additional site is added. The larger the sample-years of data, the lower the additional gain of information by adding one site to the pooling group. Furthermore, the additional gain of information is slightly lower for nested catchments.

4.6 Recurrence interval

Whereas a comparison of the effective sample-years of data to the total sample-years of data already illustrates the effect of intersite correlation on the information content, the recurrence interval T of PREC shows this effect more clearly, because T is directly related to flood quantile estimates, according to Eq. (4).

A comparison of T_{GLOBAL} and T_{NESTED} points out that the recurrence interval is higher in most cases when using a global cross-correlation function (Fig. 7). The range of the ratio R_{NESTED} is between −15 and 3% (Fig. 8). In other words, the recurrence interval is up to 15% lower when using separate parameter sets for nested and unnested conditions. The difference increases with increasing recurrence interval (Fig. 7), but it becomes apparent that the ratio R_{NESTED} does not show a decrease relating to the recurrence interval (Fig. 8).

The results are coloured differently in Fig. 8 according to the degree of heterogeneity. The RoI with a larger degree of heterogeneity ($1<\mathrm{H}_1<2$) have a larger T, because a larger degree of heterogeneity leads to more sites within the pooling group and therefore to a larger recurrence interval.

4.7 Degree of nesting

The estimation of T_{GLOBAL} varies from T_{NESTED} only in different parameter sets for the cross-correlation function. Therefore, it is interesting to relate the ratio R_{NESTED} to the degree of nesting D_{NESTED} (Eq. 9), i.e. the relative number of nested catchments within a pooling group. R_{NESTED} decreases with a higher degree of nesting (Fig. 9). Up to a degree of nesting of 0.4, R_{NESTED} decreases. Above 0.4, there is no further decrease of R_{NESTED}.

Positive values of R_{NESTED} are observed for a degree of nesting lower than 0.2, and therefore, for pooling groups without or with only a couple of nested catchments. A closer look at the calculation procedure indicates that the correlation is lower if only the unnested catchments were used in comparison to all catchments (global). The lower correlation between unnested catchments in comparison to the global correlation function therefore leads to a higher recurrence interval.

The differentiation in two ranges of the heterogeneity measure illustrates that the degree of nesting for $1<H_1<2$ is lower. For a given degree of nesting, the ratio R_{NESTED} is larger for $H_1<1$ than for $1<H_1<2$.

4.8 Influence of regional heterogeneity

Intersite correlation and regional heterogeneity influence regional flood quantile estimates. In considering the heterogeneity measure of Hosking and Wallis (1993), there is a direct link of regional heterogeneity to intersite correlation. The variability of L-CV, checked in the H_1-test, increases with increasing intersite correlation, since the H_1-test assumes uncorrelated sites for the reference simulation (Hosking and Wallis, 1988; Castellarin et al., 2008).

The relationship of the intersite correlation to the regional heterogeneity is revealed in relating the mean correlation coefficient of a pooling group, weighted by the length of the time series, to the heterogeneity measure. As expected, the heterogeneity measure increases with decreasing mean of empirical cross-correlation values (Fig. 10). For a correlation coefficient larger than 0.6, the heterogeneity measure is mostly lower than the threshold of 2. In contrast, for a lower correlation coefficient the heterogeneity measure is above the threshold of $H_1=2$ in most of the cases.

Hosking and Wallis (1988) inferred that an H_1-value<-2 affirms the existence of intersite correlation within the pooling group. In this study the results of the H_1-test are higher than -2 except for four pooling groups (see Fig. 11). However, there are several H_1-values close to -2, indicating the presence of intersite correlation and an effect on the heterogeneity measure.

Next, the degree of nesting was related to the heterogeneity measure. Figure 11 illustrates that the H-value decreases with a higher degree of nesting (correlation coefficient: -0.49). The heterogeneity measure is negative in most of the cases for a degree of nesting higher than 0.6. Therefore the degree of nesting affects the results of the

H-test (Fig. 11). This empirical evidence supports the numerical results of Castellarin et al. (2008) on the impact of cross-correlation on the heterogeneity measure defined by Hosking and Wallis (1993).

4.9 Different thresholds of the heterogeneity measure

In order to investigate the effect of regional heterogeneity on intersite correlation and, in particular, on the recurrence interval of PREC, the threshold of the heterogeneity measure was varied. The procedure for $H_1<2$ was repeated for $H_1<1$ and $H_1<4$, respectively. Only gauges were considered with at least ten homogeneous pooling groups within the equidistant intervals.

Figure 12 shows that R_{NESTED} decreases with the degree of nesting for all three thresholds of the heterogeneity measure. The number of pooling groups increases for a higher threshold (Table 5), because of the weakening of the homogeneity criteria. There are more realisations for $H_1<4$, especially for a degree of nesting lower than 0.2. Figure 11 already demonstrated that there is a negative relationship between the degree of nesting and the heterogeneity measure. Consequently, a higher threshold of the heterogeneity measure leads to a larger number of pooling groups with a low degree of nesting. This explains the larger number of PREC realisations with a low degree of nesting for $H_1<4$. Keeping in mind that only a couple of sites are nested in this study area (see Fig. 4), the additional sites are not in an upstream-downstream relationship in the majority of the cases.

The comparison of the three thresholds of the heterogeneity measure shows that R_{NESTED} has generally smaller values for a higher threshold. For a degree of nesting of 0.15–0.25, the ratio is about 5% lower for $H_1<4$ in comparison to $H_1<1$. Figure 12 shows that a degree of nesting higher than 0.15 leads to a mean of R_{NESTED} with a maximum value of −5%. For this reason, different cross-correlation functions are recommended for nested and unnested catchments. In this study, there is a relevant influence for a degree of nesting larger than 0.15.

The comparison of the ratio R_{NESTED} with T_{GLOBAL} points out that R_{NESTED} decreases

Title Page
Abstract | Introduction
Conclusions | References
Tables | Figures
◀◀ | ▶▶
◀ | ▶
Back | Close
Full Screen / Esc
Printer-friendly Version
Interactive Discussion

for all three thresholds of the heterogeneity measure (Fig. 13). Therefore the interpretations for $H_1<2$ are still valid for a smaller ($H_1<1$) and larger threshold ($H_1<4$). Regional heterogeneity affects the results, however, it does not influence the general statements.

It is counterintuitive that the ratio R_{NESTED} decreases for higher thresholds of the heterogeneity measure for recurrence intervals from 400 to 800 years. A closer look to the previous results could explain this unexpected behaviour. As mentioned above, the increase of the threshold from two to four leads to an inclusion of several pooling groups with a lower degree of nesting (see Fig. 12). A lower degree of nesting results in a more positive R_{NESTED} (see Fig. 9). Consequently, also the mean of R_{NESTED} increases for a higher threshold. Additionally, it is necessary to consider the increase of sample size for a higher threshold (Table 6). These constraints avoid a clear statement regarding the differences in the recurrence interval between global and nested cross-correlations on the threshold of the heterogeneity measure.

5 Discussion

The NRC (1988) recommended the consideration of three principles for hydrometeorological methods. These principles were: (1) “trading space for time”, (2) more structure in the methods and (3) a detailed consideration of the extremes. Stedinger et al. (1993) related these principles to flood regionalisation studies. The method of PREC directly contains the first and third principle by using a pooling group to estimate a high flood quantile. In this study the second principle was highlighted by introducing the nested structure of catchments in the cross-correlation function and, therefore, in the estimation of the recurrence interval of PREC.

Skoien et al. (2006) mentioned two types of hydrological parameters. First, there are parameters, which are continuous in space, such as rainfall. Second, there are parameters, which are characterised by the river network. Troutman and Karlinger (2003) have emphasized that both rainfall (as the most relevant example for a continuous-in-space-parameter) and a river network system were responsible for correlation effects.

The effect of the river network was emphasized here by the distinction in nested and unnested catchments.

By using separate cross-correlation functions for nested and unnested catchment pairs, a more detailed consideration of the spatial correlation structure was realised. It was possible to improve the description of the intersite correlation for pairs of nested catchments. This leads to a lower number of effective observations and, therefore, to lower recurrence intervals. This indicates that the observations of nested catchments have a lower information content, which was highlighted by a theoretical example as well as with a real data set. The result is comprehensive, because of the direct relationship of upstream and downstream gauges.

The decrease in the regional information content with increasing sample-years of data (see Fig. 6b) coincide with the statement of Hosking and Wallis (1988) that high flood quantiles are stronger affected by intersite correlation. They explained this result with the spreading of extreme floods across wide areas.

High floods occurring at one gauge are naturally also observed at a downstream gauge. Whereas widespread floods occur at neighbouring gauges across catchment boundaries, local floods might be observed only along the river itself. It becomes apparent that large-scale precipitation events lead to larger intersite correlation between gauges than local convective rainfalls. The relevance of separate cross-correlation functions for nested and unnested catchments therefore depends on the prevailing flood regime and the spatial extent of floods. In regions, which are mainly influenced by long precipitation events, floods may occur in the whole region independently of catchment structure. And in this case, the gauges might be correlated beyond catchment boundaries (Merz and Blöschl, 2003). It is assumed that especially extreme floods across wide areas lead to a large correlation between catchments (Hosking and Wallis, 1988). Similar process control and seasonality of the largest floods explains the large correlation coefficient (Troutman and Karlinger, 2003). In this case, only limited or no differences between the correlation relationships within and across catchment boundaries are expected. A complementary situation is given for flood regimes that are dominated by local convective precipitation events with small spatial extent, which occur in Saxony mainly in summer (Petrow et al., 2007). A local precipitation event might evoke a flash flood along the river. Then, only a few catchments, in particular nested catchments, are affected by the same flash flood and, low correlation relationships across catchment boundaries are expected.

In this study area of Saxony, local (e.g., in 1927, 1957) as well as regional widespread (e.g. in 1954, 1958, 2002) floods have occurred in the past (e.g., Pohl, 2004; Petrow et al., 2007). The rivers of the Erzgebirge, specifically the headwaters of the Mulde and in particular the western tributaries of the Elbe, were affected by flash floods (e.g., Ulbrich et al., 2003). Flash floods occurred in Saxony mostly in July and August. These floods are the highest unit floods in the study area. Due to the fast catchment response in the *Erzgebirge*, downstream gauges are directly affected. In this context, it is necessary to mention that the western tributaries of the Elbe are relatively small tributaries with only up to three gauges, whereas there are lots of nested relationships among the gauges of the Mulde catchment (see Fig. 4).

Since no gauges located at the River Elbe, the largest river in the study area, are included, the differences between the catchment sizes of nested relationships are not too large. This aspect is especially important for this study area, since most of the largest floods occurred in the western tributaries of River Elbe. These rivers flow into the Elbe upstream of the gauge Dresden. Because of these relatively small catchments ($<170\,\mathrm{km}^2$) in comparison to the gauge Dresden ($52\,000\,\mathrm{km}^2$), it is not expected that the mean discharge at gauge Dresden is significantly influenced only by a local flood in one of the western tributaries.

In the study area, there are only 5% of pairs of nested catchments. The effect of a distinction in nested and unnested cross-correlation functions might be even larger in regions with a larger number of nested catchment relationships.

6 Conclusions

This study addresses the effects of nested catchment structures on the cross-correlation between flood sequences. This is a very important aspect of regional flood frequency analysis, since a correct representation of the intersite dependence is fundamental for quantifying the regional information content of a pooling group of sites. The study considers the modelling of intersite dependence in the context of estimation of the return period associated to a Probabilistic Regional Envelope Curve (PREC), for which the identification of the effective observation is a key step.

The regional information content is defined as the ratio between the effective sample-years of data (i.e., equivalent number of independent observations) and the overall sample-years of data in the regional sample. For a rather large study area in Germany it is shown that the regional information content decreases with an increase in the overall sample-years of data. Consequently, a correct representation of correlation structure is especially relevant for large groups of sites.

The analysis points out that the intersite correlation for nested pairs of catchments is significantly larger than the dependence for unnested pairs, suggesting separate cross-correlation functions for nested and unnested pairs of catchments. A separation in nested and unnested pairs of catchments, while modelling the intersite dependence, represents an innovation and a refinement of the existing approach.

The study adopts a cross-correlation formula whose parameters are identified for the whole study area (traditional approach) or differentiated between nested and unnested pairs (proposed approach). The main outcomes can be summarised as follows:

1. the differentiation in cross-correlation functions for nested and unnested pairs of catchment enables one to improve the estimates of the number of effective observations;

2. in most of the cases, the number of effective observations and, therefore, the recurrence interval of PREC are significantly reduced by modelling the intersite dependence for pairs of nested and unnested catchments separately;

3. the reduction of the estimated recurrence interval increases with higher recurrence intervals, or, evidently, with higher degree of nesting in the pooling group of sites;

4. The results of the analysis are valid for different degrees of heterogeneity of the pooling group of sites. Defining the heterogeneity degree as proposed by Hosking and Wallis (1993) in terms of H_1 values, the study shows that the same considerations that are valid for possibly heterogeneous pooling groups of sites ($1<H_1<2$) still hold for acceptably homogeneous ($H_1<1$) and heterogeneous ($2<H_1<4$) groups.

Because of the effect of nested catchment structures on the recurrence interval of PREC, it is recommended that different cross-correlation functions for nested and unnested catchments in PREC studies should be applied. The study has pointed out that the effect of nested structure becomes relevant for regions, in which the number of nested pairs of catchments is larger than 15% of the total number of pairs. The discussion of flood generation processes highlighted that particular catchments are affected, whose flood characteristics controlled by local precipitation events. Separate cross-correlation functions reflect the characteristic catchment structure and lead to more structure in the estimation of flood quantiles.

Acknowledgements. This work is part of the Center for Disaster Management and Risk Reduction Technology (CEDIM) (www.cedim.de), a joint venture between the Helmholtz Centre Potsdam – GFZ German Research Centre for Geosciences, the Technical University of Karlsruhe (TH) and the Forschungszentrum Karlsruhe. We thank CEDIM and the GFZ for the financial support. A. Castellarin acknowledges the Italian Ministry of Education for the grant no. 2007HBTS85_003.

We thank the State Agency of Environment and Geology of the Free State of Saxony for the permission to use the discharge data and the hydrogeological map (HÜK 200) (http://www.umwelt.sachsen.de/umwelt/geologie/7703.htm, 5 February 2007). Furthermore, we thank the State Agency of Flood Prevention and Water Management of Saxony-Anhalt and the State Agency for Environment of Thuringia for additional discharge data. We also thank the Potsdam Institute for

Climate Impact Research (PIK) and the German Weather Service (DWD) for the precipitation data. Furthermore, we thank the Federal Agency for Cartography and Geodesy of Germany (BKG) for the ATKIS-Basis-DLM and the digital elevation model for Saxony. The SRTM Digital Terrain Model was downloaded from (http://srtm.csi.cgiar.org/SELECTION/inputCoord.asp, 19 May 2008).

References

Acreman, M. C. and Sinclair, C. D.: Classification of drainage basins according to their physical characteristics: an application for flood frequency analysis in Scotland, J. Hydrol., 84(3), 365–380, 1986.

Bayazit, M. and Önöz, B.: Sampling variances of regional flood quantiles affected by intersite correlation, J. Hydrol., 291(1–2), 42–51, 2004.

BKG Geodatenzentrum (Federal Agency for Cartography and Geodesy – GeoDataCentre): Digital Landscape Model ATKIS Basis DLM, Frankfurt/Main, 2005.

Burn, D. H.: An appraisal of the "region of influence" approach to flood frequency analysis, Hydrolog. Sci. J., 35(2), 149–165, 1990a.

Burn, D. H.: Evaluation of Regional Flood Frequency Analysis with a Region of Influence Approach, Water Resour. Res., 26(10), 2257–2265, 1990b.

Castellarin, A.: Probabilistic envelope curves for design flood estimation at ungauged sites, Water Resour. Res., 43(4), W04406, doi:10.1029/2005WR004384, 2007.

Castellarin, A., Burn, D. H., and Brath, A.: Assessing the effectiveness of hydrological similarity measures for flood frequency analysis, J. Hydrol., 241(3), 270–285, 2001.

Castellarin, A., Burn, D. H. and Brath, A.: Homogeneity testing: How homogeneous do heterogeneous cross-correlated regions seem?, J. Hydrol., 360(1–4), 67–76, 2008.

Castellarin, A., Vogel, R. M., and Matalas, N. C.: Probabilistic behaviour of a regional envelope curve, Water Resour. Res., 41, W06018, doi:10.1029/2004WR003042, 2005.

Castellarin, A., Vogel, R. M., and Matalas, N. C.: Multivariate probabilistic regional envelopes of extreme floods, J. Hydrol., 336(3–4), 376–390, 2007.

Cunderlik, J. M. and Burn, D. H.: The use of flood regime information in regional flood frequency analysis, Hydrolog. Sci. J., 47(1), 77–92, 2002.

Cunnane, C.: Methods and Merits of Regional Flood Frequency Analysis, J. Hydrol., 100(1–3), 269–290, 1988.

Dalrymple, T.: Flood frequency analyses, U.S. Geol. Surv. Water Supply Pap., 1543-A, 1960.

GREHYS: Inter-comparison of regional flood frequency procedures for Canadian rivers, J. Hydrol., 186(1–4), 85–103, 1996a.

GREHYS: Presentation and review of some methods for regional flood frequency analysis, J. Hydrol., 186(1–4), 63–84, 1996b.

Guse, B., Thieken, A. H., Castellarin, A., and Merz, B.: Deriving probabilistic regional envelope curves with different pooling groups, J. Hydrol., in review, (available upon request), 2008.

Hirsch, R. M., Helsel, D. R., Cohn, T. A., and Gilroy, E. J.: Statistical analysis of hydrological data, in: Handbook of Hydrology, edited by: Maidment, D. A., McGraw-Hill, New York, 17.1–17.55, 1992.

Hosking, J. R. M. and Wallis, J. R.: The effect of intersite dependence on regional flood frequency analysis, Water Resour. Res., 24(4), 588–600, 1988.

Hosking, J. R. M. and Wallis, J. R.: Some statistics useful in regional frequency analysis, J. Hydrol., 29(2), 271–281, 1993.

Hosking, J. R. M. and Wallis, J. R.: Regional frequency analysis: an approach based on L-moments, Cambridge University Press, Cambridge/UK, 1997.

Lecce, S. A.: Spatial variations in the timing of annual floods in the southeastern United States, J. Hydrol., 235(3–4), 151–169, 2000.

Lettenmaier, D. P., Wallis, J. R., and Wood, E. F.: Effect of Regional Heterogeneity on Flood Frequency Estimation, Water Resour. Res., 23(2), 313–323, 1987.

Madsen, H. and Rosbjerg, D.: Generalized least squares and empirical Bayes estimation in regional partial duration series index-flood modelling, Water Resour. Res., 33(4), 771–781, 1997.

Matalas, N. C. and Langbein, W. B.: Information content of the mean, J. Geophys. Res., 67(9), 3441–3448, 1962.

Merz, R. and Blöschl, G.: A process typology of regional floods, Water Resour. Res., 39(12), 1340, doi:10.1029/2002WR001952, 2003.

Merz, R. and Blöschl, G.: Regionalisation of catchment model parameters, J. Hydrol., 287(1–4), 95–123, 2004.

Merz, R. and Blöschl, G.: Flood frequency regionalisation-spatial proximity vs. catchment attributes, J. Hydrol., 302(1–4), 283–306, 2005.

Nathan, R. J. and McMahon, T. A.: Identification of homogeneous regions for the purposes of regionalization, J. Hydrol., 121(1–4), 217–238, 1990.

National Research Council (NRC): Estimating Probabilities of Extreme Floods, Methods and Recommended Research, National Academy Press, Washington D.C., 1988.

Ouarda, T. B. M. J., Bâ, K. M., Diaz-Delgado, C., Cârsteanu, A., Chokmani, K., Gingras, H., Quentin, E., Trujillo, E., and Bobée, B.: Intercomparison of regional flood frequency estimation methods at ungauged sites for a Mexican case study, J. Hydrol., 348(1–2), 40–58, 2008.

Petrow, T., Merz, B., Lindenschmidt, K. E., and Thieken, A.: Aspects of seasonality and flood generating circulation patterns in a mountainous catchment in south-eastern Germany, Hydrol. Earth Syst. Sc., 11(4), 1455–1468, 2007.

Pilgrim, D. H., Cordery, I., and Baron, B. C.: Effects of catchment size on runoff relationships, J. Hydrol., 58(3–4), 205–221, 1982.

Pohl, R.: Historische Hochwasser aus dem Erzgebirge, Wasserbauliche Mitteilungen, Heft 28, Fakultät Bauingenieurwesen, Institut für Wasserbau und Technische Hydromechanik, Technische Universität Dresden, Dresden, 2004.

Rao, R. and Srinivas, V. V.: Regionalization of watersheds by hybrid-cluster analysis, J. Hydrol., 318(1–4), 37–56, 2006.

Robson, A. and Reed, D.: Flood Estimation Handbook 3: Statistical procedures of flood frequency estimation, Institute of Hydrology, Wallingford/Oxfordshire/UK, 338 pp., 1999.

Skoien, J. O., Blöschl, G., and Western, A.: Characteristic space scales and timescales in hydrology, Water Resour. Res., 39(10), 1304, doi:10.1029/2002WR001736, 2003.

Skoien, J. O., Merz, R., and Blöschl, G.: Top-kriging – geostatistics on stream networks, Hydrol. Earth Syst. Sc., 10(2), 277–287, 2006.

Stedinger, J. R.: Estimating a Regional Flood Frequency Distribution, Water Resour. Res., 19(2), 503–510, 1983.

Stedinger, J. R. and Lu, L.: Appraisal of regional and index flood quantile estimators, Stoch. Hydrol. Hydraul., 9(1), 49–75, 1995.

Stedinger, J. R., Vogel, R. M., and Foufoula-Georgiou, E.: Frequency Analysis of extreme events, in: Handbook of Hydrology, edited by: Maidment, D. A., McGraw-Hill, New-York, 18.1–18.66, 1993.

Tasker, G. D. and Stedinger, J. R.: An operational GLS model for hydrologic regression, J. Hydrol., 111(1–4), 361–375, 1989.

Troutman, B. M. and Karlinger, M. R.: Regional flood probabilities, Water Resour. Res., 39(4), 1095, doi:10.1029/2001WR001140, 2003.

Ulbrich, U., Brücher, T., Fink, A. H., Leckebusch, G. C., Krüger, A.. and Pinto, J. G.: The central European floods of August 2002: part 1 – Rainfall periods and flood development, Weather, 58, 371–377, 2003.

Vogel, R. M., Zafirakou-Koulouris, A., and Matalas, N. C.: Frequency of record-breaking floods in the United States, Water Resour. Res., 37(6), 1723–1731, 2001.

Woods, R., Sivapalan, M., and Duncan, M.: Investigating the representative elementary area concept: an approach based on field data, Hydrol. Process., 9(3), 291–312, 1995.

Zrinji, Z. and Burn, D. H.: Flood frequency analysis for ungauged sites using a region of influence approach, J. Hydrol., 153(1–4), 1–21, 1994.

Table 1. List of catchment descriptors.

Abbreviation	Catchment descriptors
MAP	Mean annual precipitation [mm]
MAXDAY	Maximum daily precipitation [mm]
P50	Annual frequency of precipitation higher than 50 mm/d [%]
MAX5DAY	Maximum precipitation in five days [mm]
PAMS	Mean of the Annual Maximum Series of daily precipitation [mm]
ELEV	Mean elevation of the catchment [m]
SLOPE	Mean slope of the catchment [%]
RANGE_NORM	Range of catchment elevation, normalised with the catchment size [$10^{-3}m^{-1}$]
ARABLE	Fraction of arable land coverage [%]
URBAN	Fraction of urban land coverage [%]
MINING	Fraction of mining activities [%]
BEDROCK	Fraction of bedrock areas [%]
KF_LOW	Fraction of low permeability areas [%]

Table 2. Subsets of catchment descriptors (CD) and the correlation coefficient (COR) to the index flood of the annual maxima series of all gauges.

CD1	CD2	CD3	COR
MAX5DAY	ELEV	RANGE_NORM	0.69
MAP	MAX5DAY	RANGE_NORM	0.69
MAX5DAY	RANGE_NORM		0.68
ELEV	RANGE_NORM		0.63
MAX5DAY	ELEV		0.62
MAP	MAX5DAY		0.62
MAP	RANGE_NORM		0.62
PAMS	RANGE_NORM		0.62
MAX5DAY	ARABLE		0.60
RANGE_NORM	BEDROCK		0.60

Table 3. Parameters (λ_1, λ_2) of the cross-correlation function by Tasker and Stedinger (1989) and available sample size (n) for different catchment structures.

	Global	Nested	Unnested
λ_1	0.021	0.012	0.023
λ_2	0.009	0.012	0.011
n	3916	179	3737

Table 4. Theoretical example of the calculation of effective sites for a distance of 50 km and one year (Eq. 2).

	Global	Nested	Unnested	Global	Nested	Unnested
Correlation	0.49	0.69	0.48	0.49	0.69	0.48
Number of Sites	2	2	2	10	10	10
Beta	2.04	2.44	2.02	2.71	3.25	2.69
Information content	0.81	0.72	0.81	0.43	0.27	0.44
Effective sites	1.62	1.43	1.63	4.32	2.74	4.42

Table 5. Number of homogeneous regions for three different thresholds of the heterogeneity measure in equidistant intervals of the degree of nesting.

Degree of nesting	H1<1	H1<2	H1<4
0–0.05	124	191	285
0.05–0.10	48	100	172
0.10–0.15	37	54	149
0.15–0.20	63	75	122
0.20–0.25	53	58	78
0.25–0.30	38	42	58
0.30–0.35	25	30	44
0.35–0.40	32	33	40
0.40–0.45	27	28	30
0.45–0.50	24	24	24
0.50–0.55	7	7	8
0.55–0.60	4	4	6
0.60–0.65	3	4	5
0.65–0.70	6	6	6
0.70–0.75	2	2	2
0.75–0.80	8	9	9
0.80–0.85	1	1	1
0.85–0.90	0	0	0
0.90–0.95	2	2	2
0.95–1.00	0	0	2

Table 6. Number of homogeneous regions for three different thresholds of the heterogeneity measure in equidistant intervals of the recurrence interval for a global cross-correlation function.

Recurrence interval (global)	H1<1	H1<2	H1<4
0–200	31	36	38
200–400	189	230	281
400–600	163	213	311
600–800	67	115	190
800–1000	49	63	129
1000–1200	5	13	89
1200–1400	0	0	5

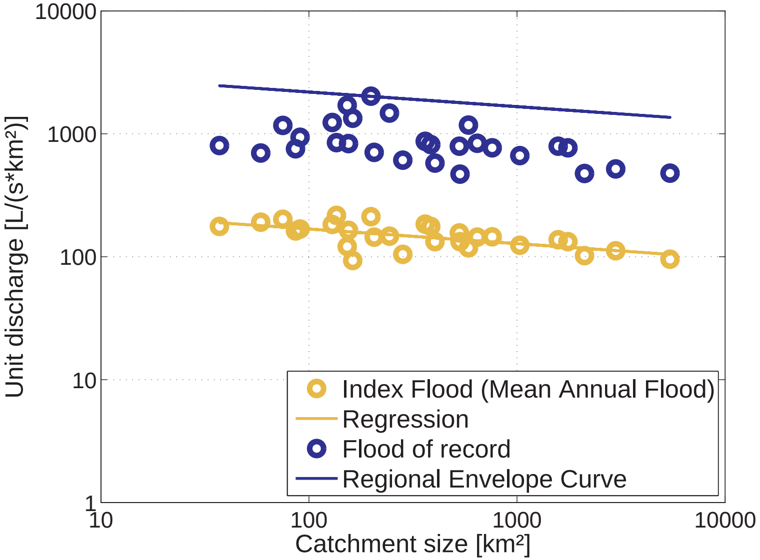

Fig. 1. Example of a probabilistic regional envelope curve (PREC).

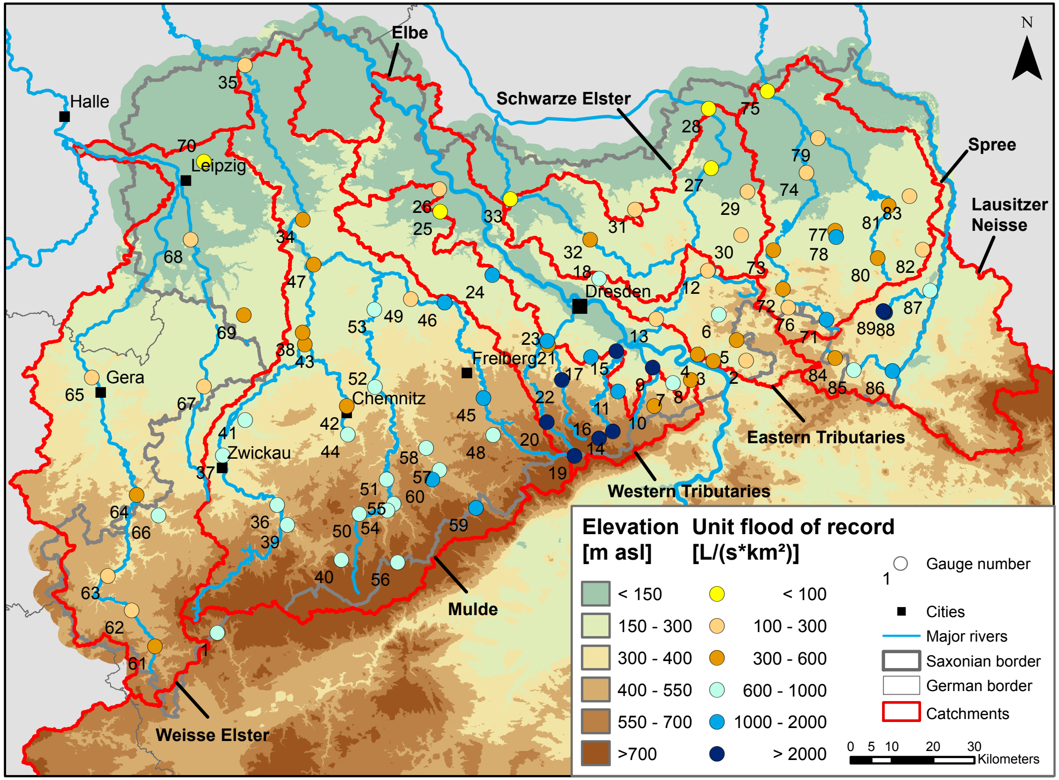

Fig. 2. Elevation and large catchments in Saxony, Germany. The catchments were extended until the last available gauge. Available discharge gauges were numbered consecutively according to their geographical location. The gauges are coloured by the unit flood of record.

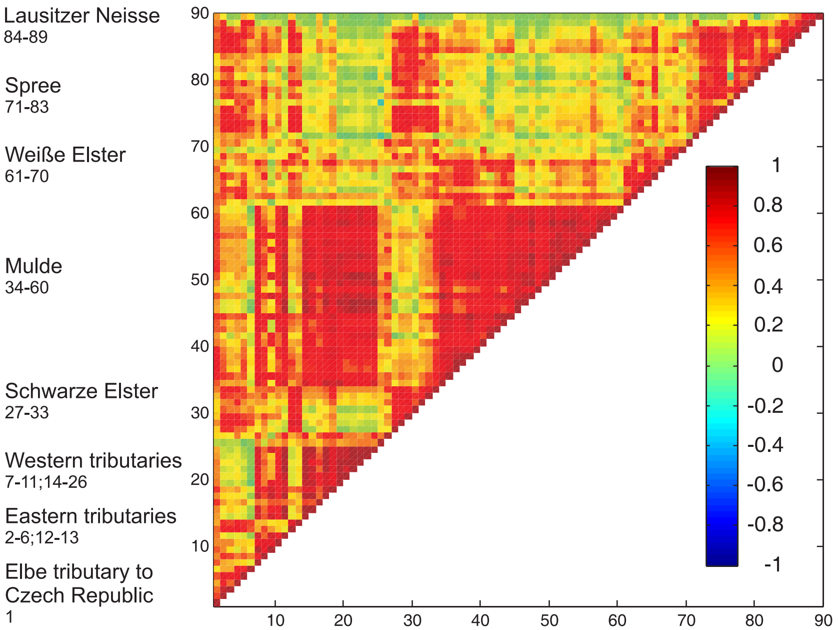

Fig. 3. Matrix of cross-correlations between the AMS of Saxonian gauges.

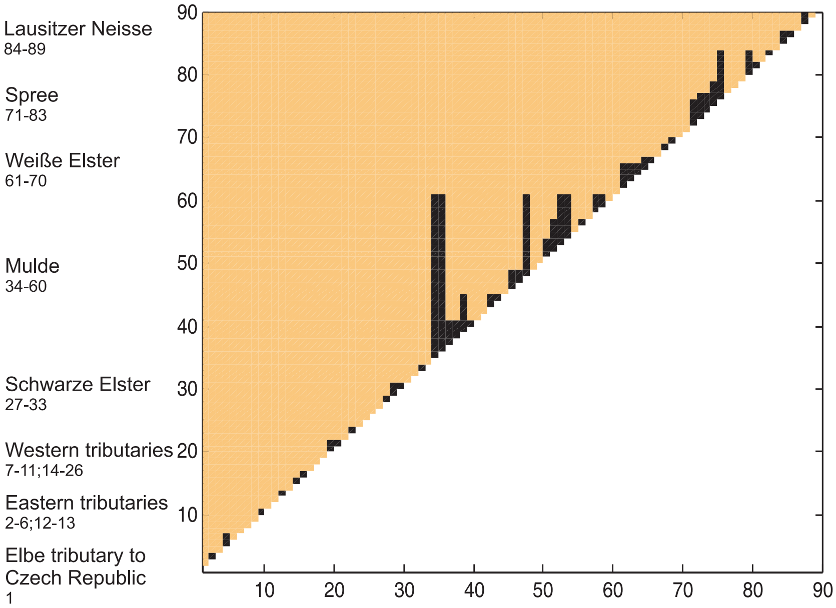

Fig. 4. Differentiation in nested (black) and unnested (orange) pairs of catchments.

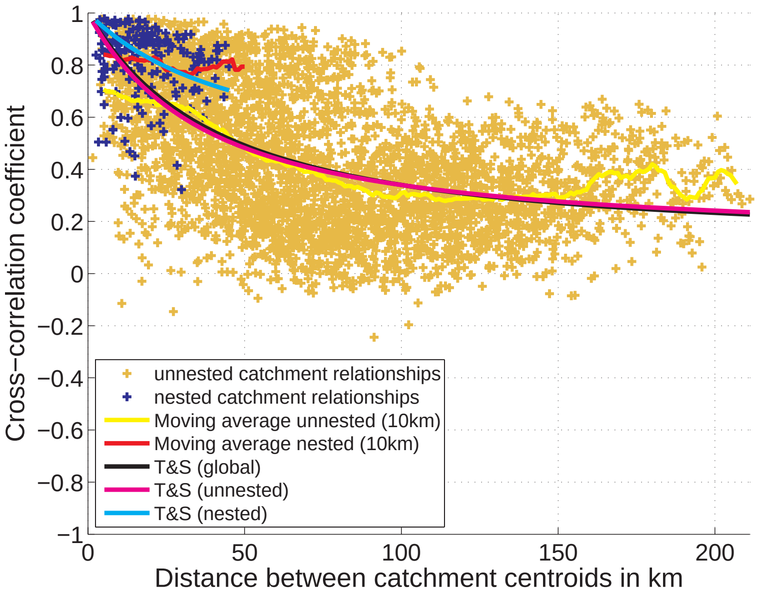

Fig. 5. Cross-correlation functions using different parameter sets for global, unnested and nested catchment structures (T&S: crosscorrelation function by Tasker and Stedinger (1989)).

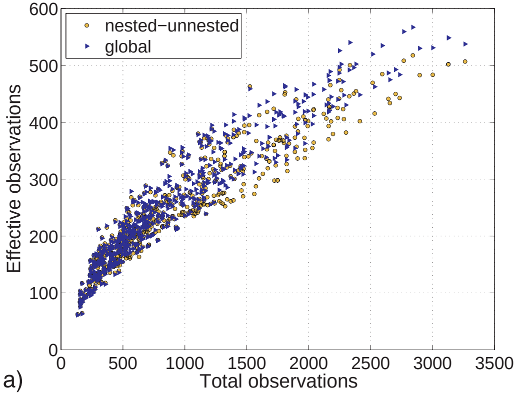

Fig. 6. Effective number of observations **(a)** and Information content [%] **(b)** in relationship to the total observations within the pooling groups for a global cross-correlation function and separate cross-correlation functions for nested and unnested catchments.

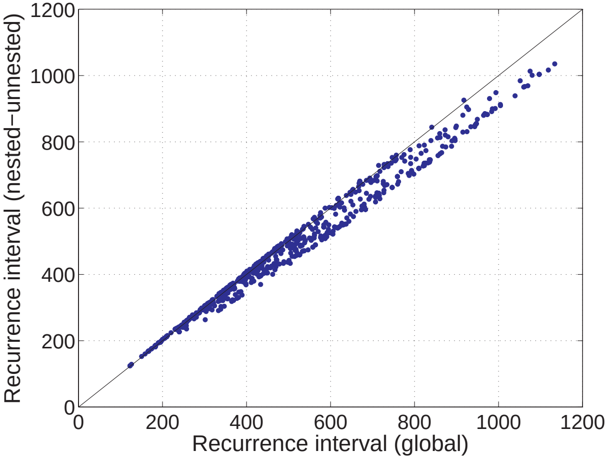

Fig. 7. Difference in recurrence interval between different cross-correlation functions (nested vs. global) (H1<2).

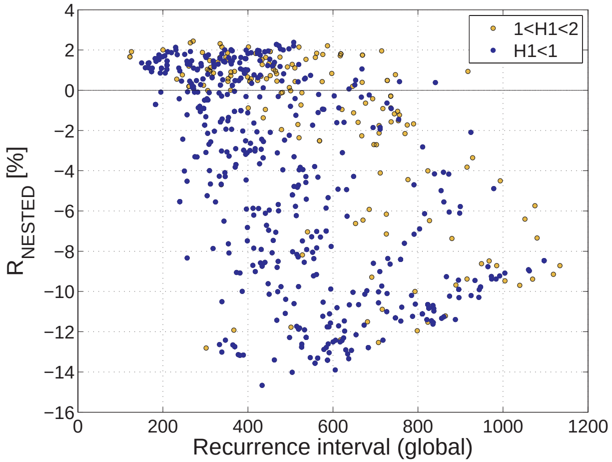

Fig. 8. Ratio of recurrence interval related to the recurrence interval estimated by a global cross-correlation function, separated in two classes of the heterogeneity measure.

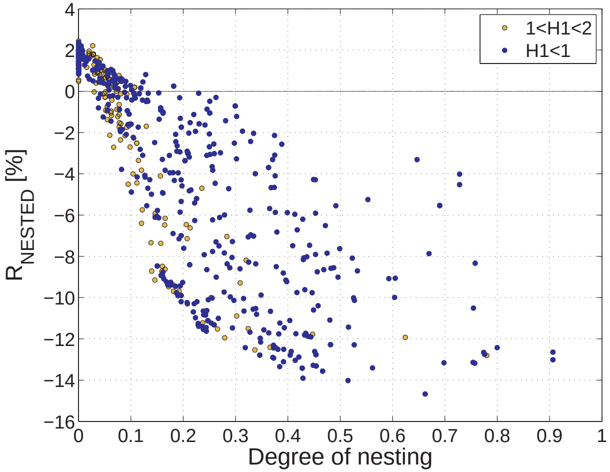

Fig. 9. Ratio of recurrence interval related to the degree of nesting, separated in two classes of the heterogeneity measure.

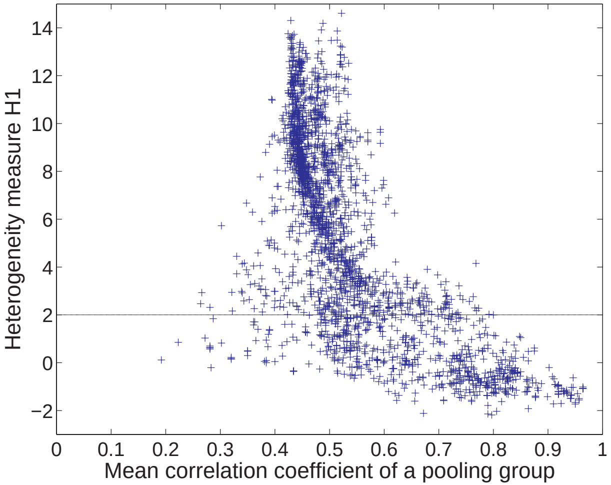

Fig. 10. Heterogeneity measure of a region versus the mean correlation coefficient.

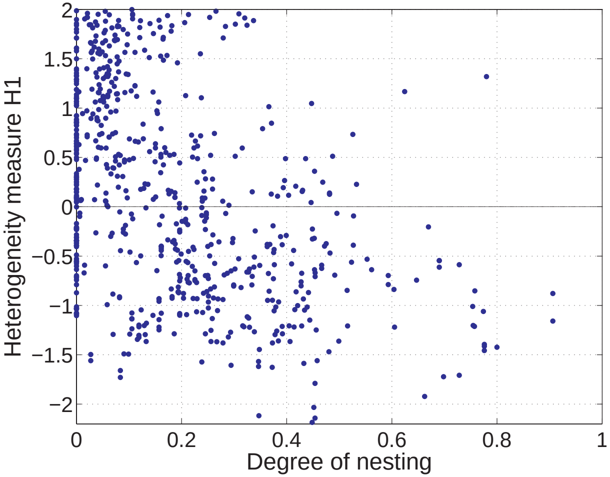

Fig. 11. Heterogeneity measure of a region versus its degree of nesting.

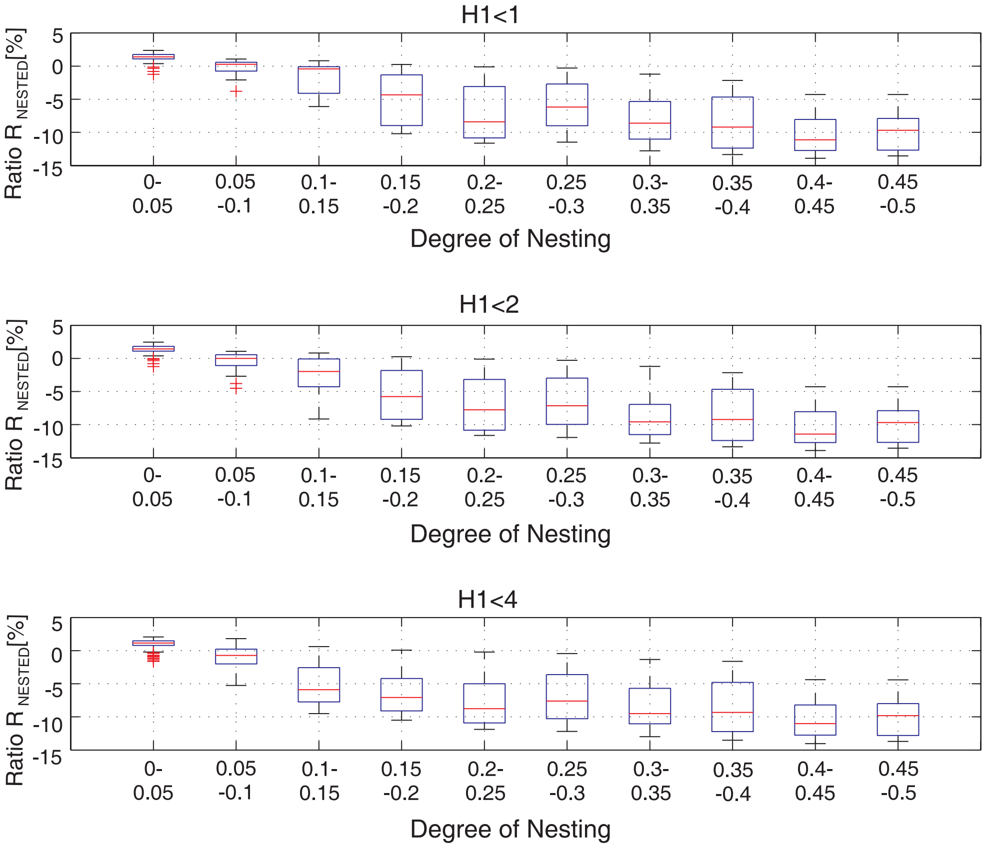

Fig. 12. Relative reduction of effective observations (and recurrence intervals) when considering different cross-correlation functions for nested and unnested catchment related to the degree of nesting for different thresholds of the heterogeneity measure.

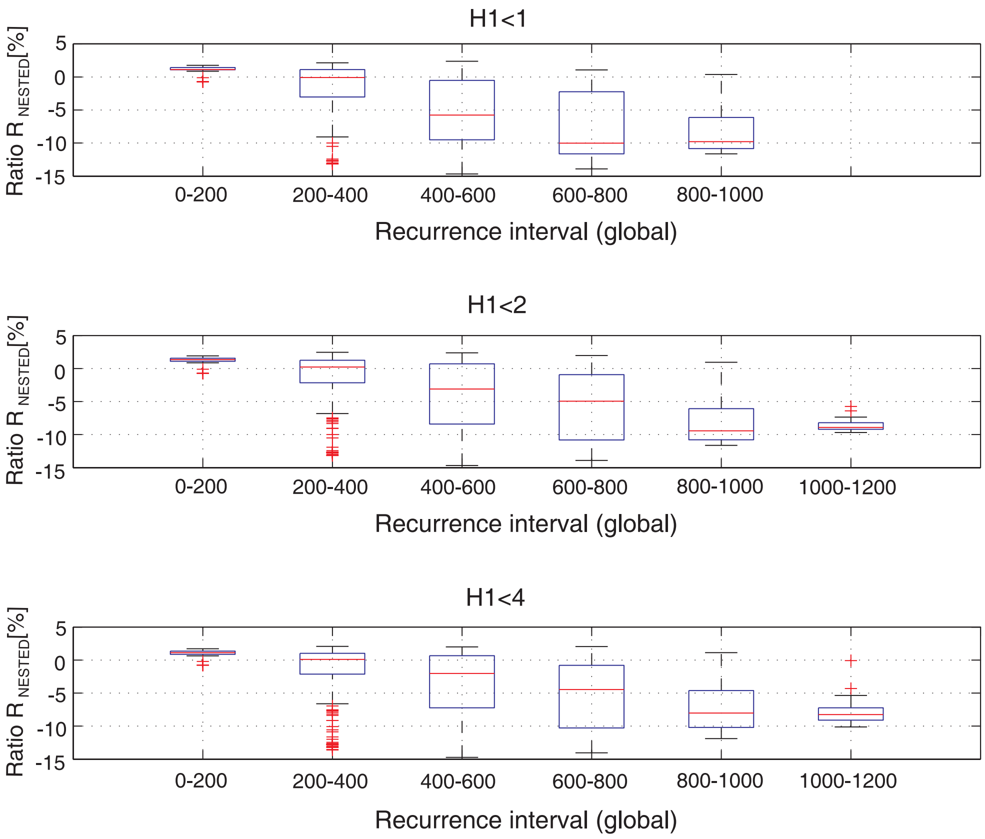

Fig. 13. Relative reduction of effective observations (and recurrence intervals) when considering different cross-correlation functions for nested and unnested catchment related to the recurrence interval estimated by a global cross-correlation function for different thresholds of the heterogeneity measure.