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On the frequency of heavy rainfall for the Midwest of the United States

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SUMMARY

Annual maximum daily rainfall time series from 221 rain gages in the Midwest United States with a record of at least 75 years are used to study extreme rainfall from a regional perspective. The main topics of this study are: (i) seasonality of extreme rainfall; (ii) temporal stationarity and long-term persistence of annual maximum daily rainfall; (iii) frequency analyses of annual maximum daily rainfall based on extreme value theory; and (iv) clustering of heavy rainfall events and impact of climate variables on the frequency of occurrence of heavy rainfall events.

Annual maximum daily rainfall in the Midwest US exhibits a marked seasonality, with the largest frequencies concentrated in the period May–August. Non-parametric tests are used to examine the validity of the stationarity assumption in terms of both abrupt and slowly varying temporal changes. About 10% of the stations show a change-point in mean and/or variance. Increasing monotonic patterns are detected at 19 stations. Quantile regression analyses suggest that the number of stations with a significant increasing trend tends to decrease for increasing quantiles. Temporal changes in the annual maximum daily rainfall time series are also examined in terms of long-term persistence. Conclusive statements about the presence of long-term persistence in these records are, however, not possible due to the large uncertainties associated with the estimation of the Hurst exponent from a limited sample. Modeling of annual maximum daily rainfall records with the Generalized Extreme Value (GEV) distribution shows well-defined spatial patterns for the location and scale parameters but not for the shape parameter. Examination of the upper tail properties of the annual maximum daily rainfall records points to a heavy tail behavior for most of the stations considered in this study. The largest values of the 100-year annual maximum daily rainfall are found in the area between eastern Kansas, Iowa, and Missouri. Finally, we use the Poisson regression as a framework for the examination of clustering of heavy rainfall. Our results point to a clustering behavior due to temporal fluctuations in the rate of occurrence of the heavy rainfall events, which is modulated by climatic factors representing the influence of both Atlantic and Pacific Oceans.

1. Introduction

Flooding is one of the most important hazards in the United States, claiming a high toll both in terms of economic damage and fatalities (e.g., Pielke and Downton, 2000; Ashley and Ashley, 2008a,b). Over the past decades, damages from floods have been increasing in the US in general (e.g., Kunkel et al., 1999b; Pielke and Downton, 2000; Downton et al., 2005), and in the central United States (e.g., Changnon, 1999). Previous studies examined changes over time in the discharge record, finding contrasting results (e.g., Potter, 1991; Changnon and Kunkel, 1995; Changnon and Demissie, 1996; Gebert and Krug, 1996; Lins and Slack, 1999; Olsen et al., 1999; Douglas et al., 2000; Rasmussen and Perry, 2001; Schilling and Libra, 2003; Lins and Slack, 2005; Zhang and Schilling, 2006; Novotny and Stefan, 2007; Villarini et al., 2009a, in press).

Modeling results point to an acceleration of the hydrologic cycle in a warmer climate (e.g., Gleick, 1989; Voss et al., 2002; Held and Soden, 2006), with potentially large impacts on the frequency of extreme events (e.g., Voss et al., 2002; Milly et al., 2002, 2005; Christensen and Christensen, 2003). For the Midwest US, previous studies have generally suggested the presence of increasing trends in rainfall (e.g., Lettenmaier et al., 1994; Angel and Huff, 1997; Karl and Knight, 1998; Kunkel et al., 1999a, 2007; Kunkel, 2003; Peterson et al., 2008; Pryor et al., 2009). Lettenmaier et al. (1994)

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found increasing precipitation trends, in particular from September to November using monthly data. Over the Midwest US and during the period 1901–1994, Angel and Huff (1997) found an increasing trend in the number of daily precipitation events with accumulation larger than 2 in. (50.8 mm). Karl and Knight (1998) showed a widespread increase in the upper 10 percentiles of the precipitation distribution.

In this study we use observations from 221 rain gage stations with a record of at least 75 years of daily rainfall to investigate the presence of changes in heavy rainfall in the Midwest US. The main issues we address revolve around:

1. Presence of temporal nonstationarities (both in terms of abrupt and slowing varying changes) and long-term persistence in these records;
2. Frequency analyses and upper tail properties of annual maximum daily rainfall;
3. Description of the occurrence of heavy rainfall events in terms of climate indices;
4. Clustering of heavy rainfall events.

A stationary time series is a time series with probability distribution which is invariant to temporal translations (Brillinger, 2001). This definition of stationarity implies that a time series does not exhibit periodicities, abrupt and slowly varying changes (e.g., Salas, 1993). For an extensive discussion about stationarity in hydro-meteorological records, the interested reader is pointed to Matalas (1997) and Koutsoyiannis (2006). As mentioned before, several studies examined the validity of the stationarity assumption for rainfall time series in the Midwest US (e.g., Lettenmaier et al., 1994; Angel and Huff, 1997; Karl and Knight, 1998; Kunkel et al., 1999a, 2007; Kunkel, 2003; Pryor et al., 2009). The validity of the stationarity assumption is, however, assessed by only testing the record for the presence of slowly varying changes, while the presence of abrupt changes in the rainfall distribution are generally not considered. This happens despite the fact that the presence of abrupt changes could have a large impact on the results of the trend analyses (for instance, consult Villarini et al. (2009a) for a recent discussion). When change-point analysis is performed, it is mostly limited to abrupt changes in the mean, even though abrupt changes in the variance can have a large impact on the occurrence of extremes. For these reasons we examine the validity of the stationarity assumption by testing the time series of annual maximum daily rainfall for both abrupt and slowly varying changes, with change-point analysis performed to detect step changes both in the mean and variance of the rainfall distribution. The main difference between step and gradual changes is that with the former the time series remains in the same regime until another abrupt change occurs. Slowly varying changes, on the other hand, will tend to persist in the future. Non-parametric tests are employed to assess the validity of the stationarity assumption. We investigate abrupt changes in the first two moments of the distribution of annual maximum daily rainfall by means of the Pettitt test (Pettitt, 1979). The presence of slowly varying changes is examined by means of Mann-Kendall and Spearman tests (e.g., Helsel and Hirsch, 1993). In addition to these two tests, we use quantile regression (Koenker, 2005) to examine linear changes in different quantiles of the rainfall distribution.

A different way of interpreting the presence of "deterministic" trends and change-points in a time series is in terms of long-term persistence (e.g., Hurst, 1951). Analyses of long-term persistence are linked to fluctuations of climate regimes over decadal and multidecadal scales (e.g., Klemeš, 1974; Potter, 1976). Accounting for long-term persistence could better explain some of the behaviors exhibited by these time series (e.g., Potter, 1976; Koutsoyiannis, 2002, 2006; Koutsoyiannis and Montanari, 2007) and could explain the presence of statistically significant trends, even though no trends are present (e.g., Cohn and Lins, 2005; Koutsoyiannis, 2006). We therefore complement the stationarity analyses with the description of these time series in terms of long-term persistence.

The frequency analyses and upper tail properties of annual maximum daily rainfall time series are examined by means of the Generalized Extreme Value (GEV) distribution (e.g., Coles, 2001). This distribution has been widely used when dealing with hydro-meteorological extremes because of practical and theoretical considerations (e.g., Stedinger and Lu, 1995; Katz et al., 2002). The GEV distribution represents the limiting distribution of a stationary sequence obtained by taking the maxima of identically distributed and independent or weakly dependent random variables (Leadbetter, 1983). By fitting the stationary time series with the GEV distribution, we can examine regional variations in the magnitude, variability, and upper tail properties of annual maximum daily rainfall over the Midwest US.

In addition to the aforementioned analyses on the annual maximum daily time series, we also examine whether heavy rainfall events are clustered in time and whether it is possible to relate their frequency to climate indices. Clustering of events is an aspect of rainfall frequency that is often overlooked (e.g., Smith and Karr, 1983, 1985; Mailier et al., 2006; Vitolo et al., 2009). Typically, counts of heavy rainfall events are considered to be independent and follow a Poisson distribution. However, large scale weather patterns could influence the track of the storms responsible for the extreme events, resulting in clustering of heavy rainfall events. Because our study area is located at the center of the US, we use climate indices that reflect contributions from both the Atlantic and Pacific Oceans. We use a Poisson regression model to investigate the presence of clustering in the number of days exceeding different thresholds and the impact of different Atlantic and Pacific climate indices.

This paper is organized as follows. In Section 2 we describe the data and provide information about the seasonality of the extreme rainfall process in the area. In Section 3 we briefly describe the tools used in the analyses (change-point analysis, monotonic trend tests, quantile regression, fitting the data with the GEV distribution, and Poisson regression). Section 4 presents the results of our analyses, followed by Section 5 in which we summarize the main points of the paper.

2. Data

We refer to the Midwest US as the region including nine states: North and South Dakota, Nebraska, Kansas, Minnesota, Iowa, Missouri, Wisconsin, and Illinois. In this study we use rain gage measurements of daily rainfall accumulations obtained from the National Climatic Data Center (NCDC) Surface Daily Data. We limit our analyses to stations with a record of at least 75 years. Over the study region, there are 221 rain gages fulfilling this requirement (35 in Illinois, 28 in Iowa, 48 in Kansas, 25 in Minnesota, 19 in Missouri, 27 in Nebraska, 10 in North Dakota, 22 in South Dakota, and 7 in Wisconsin). These rain gages provide good coverage of the area and allow investigation of rainfall variability and nonstationarity at the regional scale (Fig. 1). Seventy out of 221 stations have a record of at least 100 years, 33 of at least 110 years, with the longest record being of 126 years (Fig. 2, bottom panel). Few stations provide measurements of rainfall during the 19th century, and most of the rain gages cover the 20th and the beginning of the 21st centuries (Fig. 2, top panel). These long time series provide valuable information about changes in heavy rainfall frequency for the Midwest US. Note that, by the different record length of the stations, the statistical estimators will have varying precision. However, a minimum

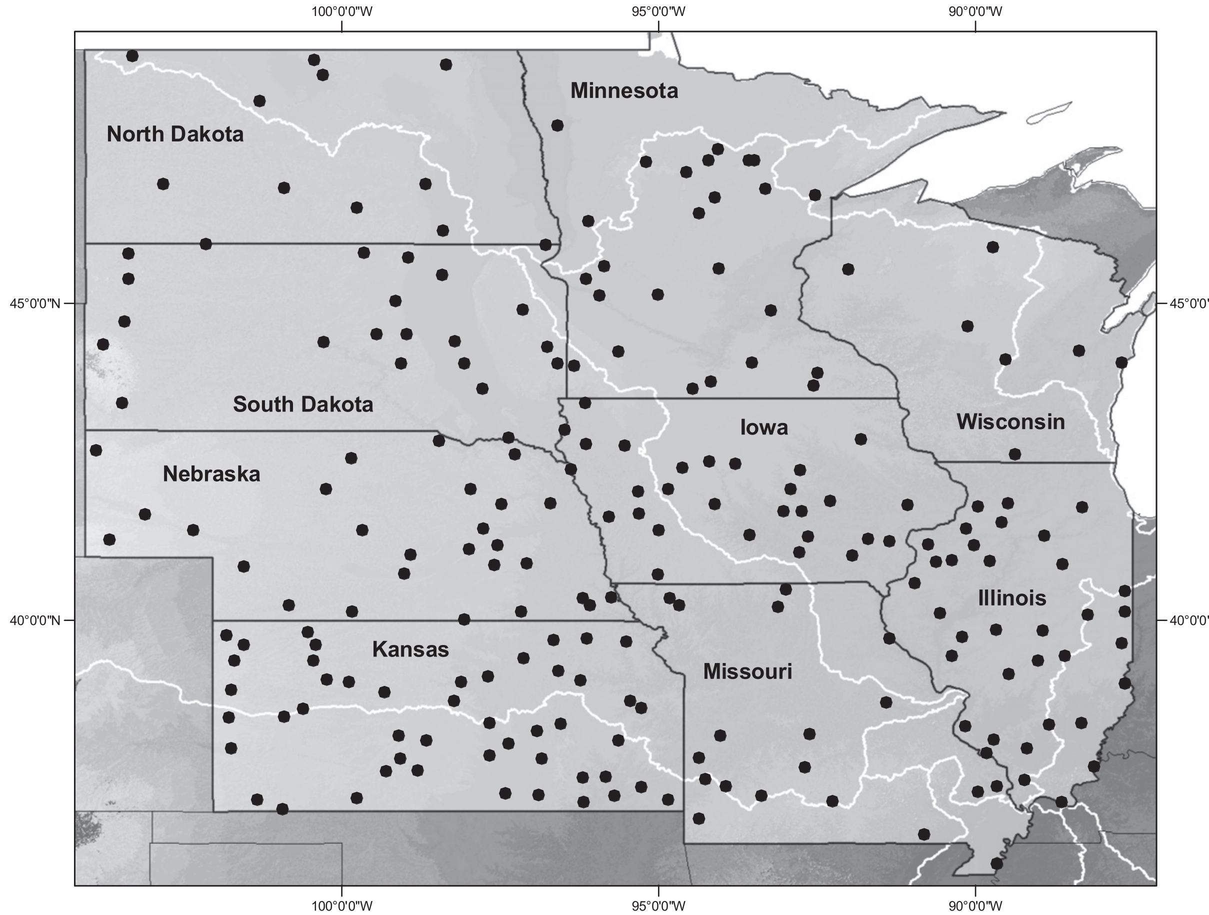

Fig. 1. Map showing the location of the 221 rain gages with a record of at least 75 years included in this study.

precision is enforced by the requirement of having at least 75 years of data in the record.

The climatology of heavy rainfall over this area exhibits a marked peak during the late spring to summer seasons (from May to August). During this period, organized convective systems are often responsible for heavy rainfall events (e.g., Diehl and Potter, 1987; McAnelly and Cotton, 1989; Olsen et al., 1999; Zhang et al., 2001; Schumacher and Johnson, 2006; Wang and Chen, 2009; Villarini et al., in press). A small percentage of annual maximum daily rainfall occurs during the winter months and early spring (Fig. 3). During April, we find a widespread increase in frequency of annual maximum rain events over the domain. This increase becomes more apparent in May, a month in which approximately 20% of the annual maximum daily rainfall occurs over the western part of the region. With the exception of Illinois and Missouri, we have the highest frequencies in June, with values ranging from 20% to 30%. After peaking in June, the months of July, August, and September experience a decrease in frequency, with the areas of higher frequency moving eastward. The percentage of annual daily maxima decreases from October to December. These results are consistent with Villarini et al. (in press), who found a similar seasonality in annual maximum flood peak time series.

Seasonal distribution of annual maximum daily rainfall are generally unimodal, with mode between June and July (Fig. 4) and small variability from station to station. Several rain gages in Illinois and Missouri do not exhibit the marked seasonal peak as the other stations. These stations are in the southeastern part of the states and exhibit anomalously uniform distributions throughout the year (Fig. 3).

3. Methodology

In this section we provide an overview of the tools used to perform change-point and trend analyses, analyses of long-term persistence, and Poisson regression. We also present a discussion of the Generalized Extreme Value (GEV) distribution used to model annual maximum daily rainfall.

3.1. Change-point, trend analyses, and quantile regression

Change-point analysis provides a tool to check for the presence of abrupt changes in the distribution of the variable under study. These abrupt changes could be due to climatic changes (e.g., Karl and Knight, 1998; Hare and Mantua, 2000; Alley et al., 2003; Mauget, 2003; Swanson and Tsonis, 2009) as well as other anthropogenic effects (e.g., gage relocation, changes in the measuring procedure; Potter, 1979; Groisman and Legates, 1995; Peterson et al., 1998). Change-point tests generally focus on the first and second moments of the distribution of the variable of interest. Several approaches have been proposed to check for the presence of change-points in the mean of the data (e.g., Potter, 1981; Buishand, 1984; Lombard, 1987; Perreault et al., 2000; Lund and Reeves, 2002; Reeves et al., 2007; Wang et al., 2007; Aksoy et al., 2008; Beaulieu et al., 2009). In this study we use the Pettitt test (Pettitt, 1979), which was successfully used in previous studies (e.g., Bárdossy and Caspary, 1990; Caspary, 1995; Tomozeiu et al., 2005; Villarini et al., 2009a, in press; Villarini and Smith, 2010). It is a non-parametric test based on a version of the Mann–Whitney statistic and allows testing whether two samples come from the same population. This test detects change-points

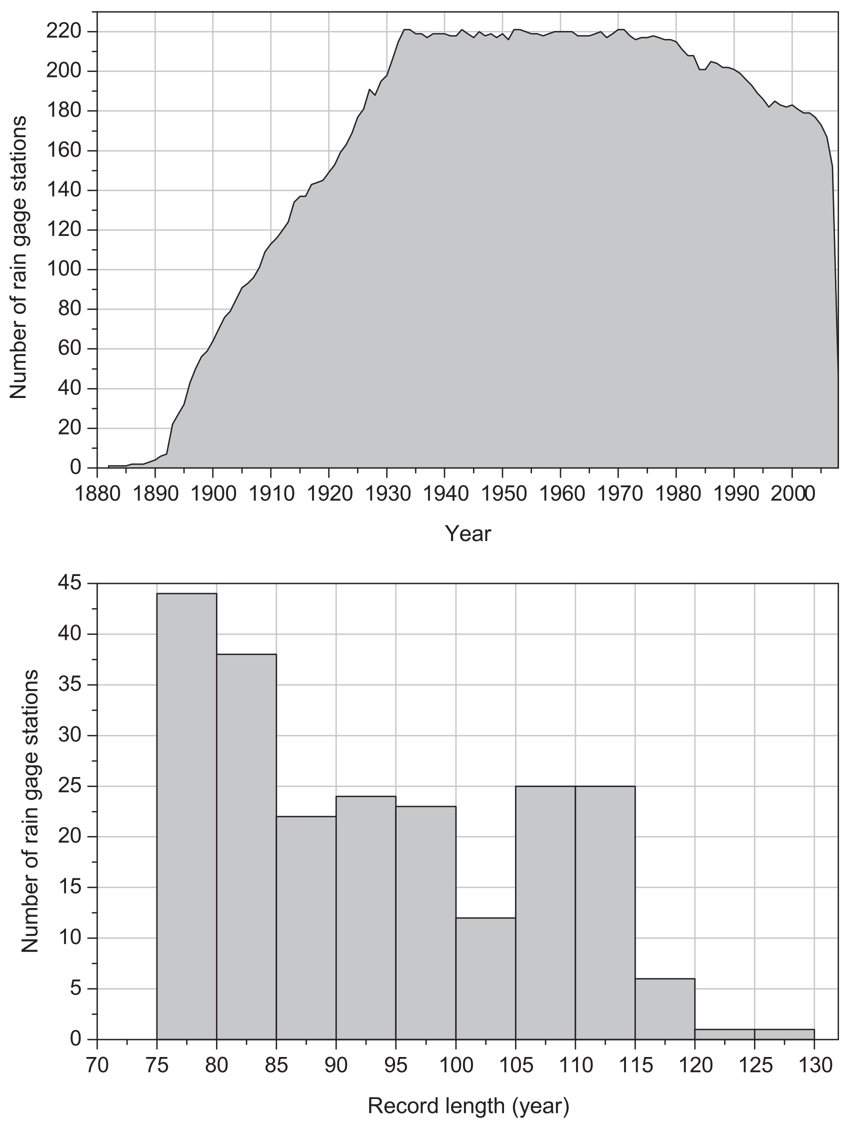

Fig. 2. Top panel: time series of the number of rain gages available in a given year (out of 221). Bottom panel: histogram with the record length for the 221 rain gages.

in mean at an unknown point in time. The main advantages of this test are that it is less sensitive to outliers and skewed distributions, and the test significance can be computed (see Pettitt, 1979). In this study we assume that there is no more than one change-point. Even though multiple change-points could be present, we make this assumption to avoid segmenting the time series into multiple subseries, affecting our capability to perform meaningful trend analysis.

Most applications of change-point tests have been designed to detect abrupt changes in the mean of the distribution, and only few can detect changes in the variance (e.g., Perreault et al., 2000). It is, however, important to test the data for changes in variance, since increasing or decreasing variance significantly affects the distribution of extremes (e.g., Katz and Brown, 1992; Meehl et al., 2000; Ferro et al., 2005). In addition to testing the data for abrupt changes in the mean, we investigate the presence of change-points in variance by using the Pettitt test on the squared residuals (similar to what suggested by Pegram (2000); Section 9.2.3) computed with respect to the local polynomial regression line (loess function Cleveland (1979) with a span of 0.75). We have selected a 5% significance level for the change-point analyses.

The presence of slowly varying monotonic patterns (we will refer to them simply as monotonic trends), which are often related to human-induced climate changes, are investigated by means of two of the most widely used tests, Mann-Kendall and Spearman tests (e.g., Mann, 1945; Kendall, 1975; Helsel and Hirsch, 1993; McCuen, 2003; Kundzewicz and Robson, 2004). These tests, like the Pettitt test, are non-parametric, making them more robust against outliers and departures from normality. Both of these tests have a similar power (see Yue et al. (2002) for an extensive comparison). Because these tests are widely used in studies of this kind, we refer the interested reader to Helsel and Hirsch (1993) (and references therein) for details. We test the data for monotonic patterns even though we acknowledge that it is possible that other patterns could be present in the data (e.g., Hall and Tajvidi, 2000; Ramesh and Davison, 2002; Mudelsee et al., 2003; Villarini et al., 2009b, 2010a). We set a 5% significance level for both Mann-Kendall and Spearman tests.

The presence of change-points can have a significant impact on the results of the monotonic trend analyses (see Villarini et al. (2009a) for a recent discussion). For this reason, we follow the approach in Villarini et al. (2009a) and first perform change-point analysis; if no statistically significant change-point in mean is detected, we perform monotonic trend analysis on the entire record. If a change-point in mean is detected, we split the record into two subseries (before and after the change-point) and perform monotonic trend analysis on each subseries separately.

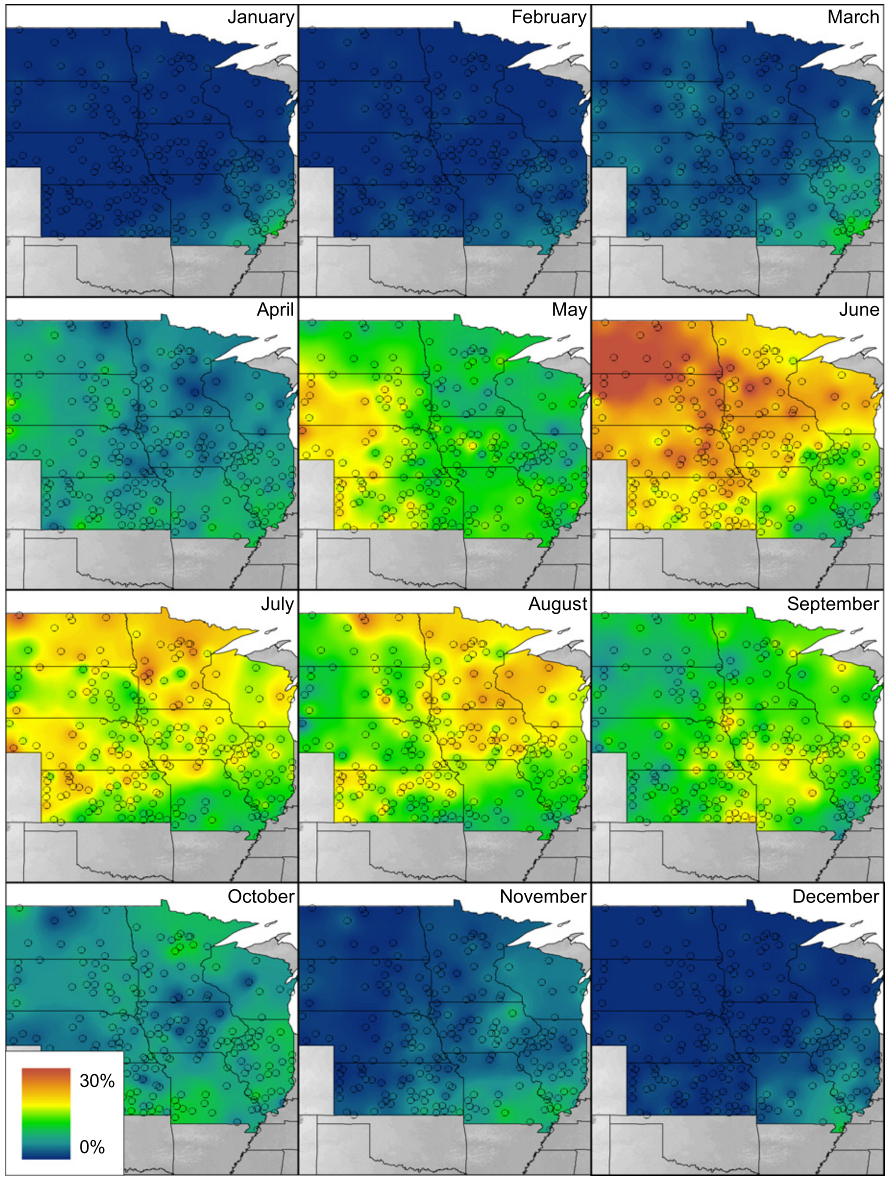

Fig. 3. Maps showing the frequency of the annual maximum daily rainfall for each month of the year. The empty circles indicate the location of the rain gages. Spatial interpolation is performed by means of inverse distance weighted method.

Mann-Kendall and Spearman tests provide information about the presence of monotonic trends in the central part of the distribution. It is also useful to check for the presence of trends in other parts of the distribution. Examining the width of the conditional distribution by focusing on the high and low quantiles provides uncertainty information. We use quantile regression to investigate the presence of a linearly increasing or decreasing trend for different quantiles of the rainfall distribution. Quantile regression was introduced by Koenker and Basset (1978) and has been widely used in fields ranging from economics to ecology. We provide a brief overview of quantile regression and point the interested reader to Koenker (2005) for an extensive discussion about model fitting, applications, and references.

We start by comparing the linear regression where the parameters have been estimated with the ordinary least square method (OLS) with respect to the median regression (quantile $\tau = 0.5$). While in OLS we minimize the sum of the squared errors, in median regression we minimize the sum of the absolute errors. This can be generalized to any other quantile τ, by computing the slope and intercept for different quantiles through the minimization of an asymmetrically weighted sum of absolute errors. In this way, we obtain information about the presence of linear trends for other levels of the distribution of the data. We compute the significance of the slope by means of bootstrap and set a significance level α of 5%. All the calculations are performed in `R` (R Development Core Team, 2008) using the freely available `quantreg` package (Koenker, 2009).

3.2. Long-term persistence

Decadal to multidecadal oscillations in climate regimes can result in apparent trends and change-points in stationary time series (e.g., Potter, 1976; Cohn and Lins, 2005; Koutsoyiannis, 2006). In addition to examining change-points and trends in rainfall series, we also test the data for the presence of long-term persistence.

The presence of long-term persistence is studied by estimating the Hurst exponent H (Hurst, 1951). Values of H range from 0 to 1, where a value of 0.5 indicates lack of long-term persistence, while

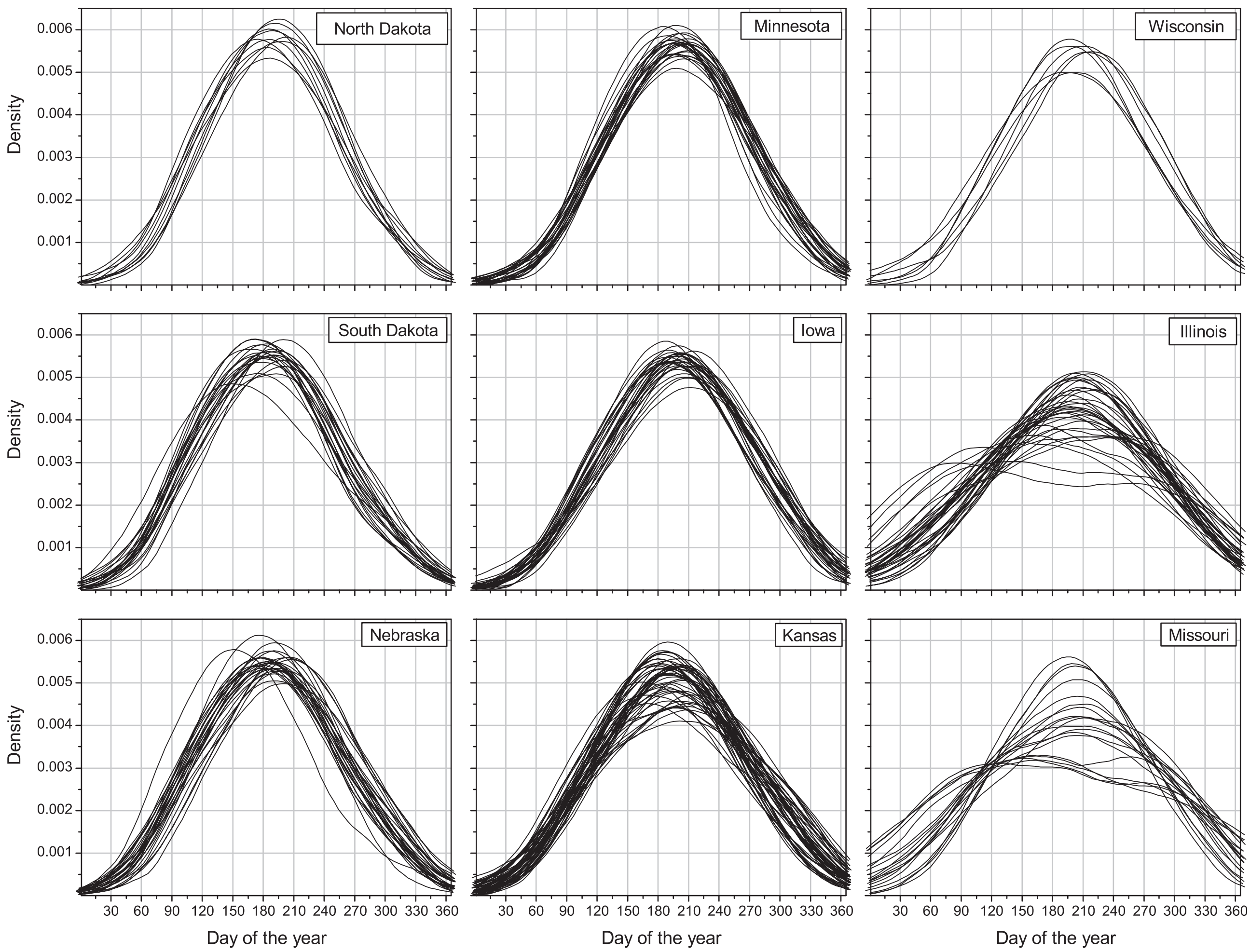

Fig. 4. Plots of the seasonal distributions of annual maximum daily rainfall. Each line represents a station.

values larger than 0.5 indicate the presence of long-term persistence. Several estimators of the Hurst exponent have been proposed, such as aggregated variance method, differenced variance method, rescaled range statistic (R/S) method, and the Whittle method (e.g., Taqqu et al., 1995; Montanari et al., 1999; Kantelhardt, 2008; Rea et al., 2009; consult Serinaldi (2010) for a recent comparison among estimators). In this study we use one of the most widely used estimators, the aggregated variance method:

$$Var(\overline{X}_N) \sim cN^{2H-2} \tag{1}$$

where N is the sample size, c is a positive constant, and $\overline{X}_N$ is the sample mean.

Because the estimates of H are affected by large uncertainties due to the limited sample size (e.g., Maraun et al., 2004; Koutsoyiannis and Montanari, 2007; Rea et al., 2009; Villarini et al., 2009a), we use a bootstrap approach to test whether the values of the Hurst exponent are different from 0.5 from a statistical standpoint (Villarini et al., 2009a). In this case, the null hypothesis H_0 is $H = 0.5$ (lack of long-term persistence), while the alternative hypothesis H_a is that H is different from 0.5. By resampling the time series with replacement we destroy the memory of the series, obtaining the bootstrap distribution of the Hurst exponent under the null hypothesis (e.g., Efron and Tibshirani, 1997). We resample the series M times (M is taken to be 8000, in agreement with the suggestion by Efron (1990)) and for each new series we compute H. Using the M values of H obtained from the resampling procedure, we can build the empirical distribution of H from which we can compute the p-value associated with the estimate of H from the original time series. This approach is used to test the hypothesis that H is different from 0.5. We use a two-tailed test and we set a 5% significance level.

3.3. Extreme value distribution

Statistical modeling of the annual maximum daily rainfall is performed using the Generalized Extreme Value distribution (among others, see Coles (2001) for a detailed discussion). Let us consider the random variable X, which represents the annual maximum daily rainfall. For stations without statistically significant change-points in mean and variance, and monotonic trends, we can write the cumulative distribution function of the GEV as follows:

$$F(x|\mu,\sigma,\xi) = \exp\left\{-\left[1+\xi\left(\frac{x-\mu}{\sigma}\right)\right]^{-1/\xi}\right\} \tag{2}$$

where $\mu \in (-\infty,+\infty)$ is the location parameter (in mm) and is related to the magnitude of the record, $\sigma > 0$ is the scale parameter (in mm) and is related to the record variability, and $\xi \in (-\infty,+\infty)$ is the shape parameter, which provides information about the heaviness of the tail of the distribution (the larger the value of ξ, the heavier the tail, the more likely extreme events are to occur; e.g. Malamud, 2004; Resnick, 2006; ElAdlouni et al., 2008). The GEV distribution combines the Weibull, Frechet, and Gumbel distributions. If $\xi > 0$ the distribution is unbounded above and belongs to the Frechet distribution. For $\xi < 0$, the distribution is bounded above with an upper bound of $\mu - \sigma/\xi$ and represents the Weibull distribution. The Gumbel distribution is the special case for $\xi \to 0$ and corresponds to the case of unbounded, "light" upper tails.

We assess the quality of the fit using three goodness-of-fit tests (Kolmogorov–Smirnov, Anderson–Darling, and Cramer–von Mises; e.g., Laio, 2004; Kottegoda and Rosso, 2008; Serinaldi, 2009). Because the parameters of the GEV distribution are estimated from the data, we use a Monte Carlo approach to compute the critical values of the test statistics, under the null hypothesis that the data come from the GEV distribution. We set a significance level to 5%.

We estimate the parameters of the GEV distribution by means of maximum likelihood estimation (consult Hosking (1990), Martins and Stedinger (2000), Coles (2001), Morrison and Smith (2002) among others for a discussion about other estimation techniques). For each of the stationary stations, we examine spatial distribution of the parameters of the GEV distribution to highlight their regional variability. In particular, we examine the shape parameter, since it provides information about the tail thickness and, consequently, about how likely extreme events are to occur.

Another commonly used approach for the study of extreme events is the so-called Peaks-Over-Threshold (POT) method, based on the Generalized Pareto distribution (e.g., Coles, 2001). In this approach one considers the datapoints in the record lying above a threshold chosen by the user. Note that both the GEV and the POT approaches require an assumption of temporal stationarity in the data. Ad-hoc approaches can be devised, but this requires a careful analysis of the non-stationarity features in the data (e.g., Coles, 2001). The POT analysis is in our case substantially more complex due to the intra-annual (seasonal) variability. This requires to specify a time-dependent, seasonally varying threshold and the results may be sensitive to this choice. Hence, we focus on the GEV approach, for which we check the stationarity assumption in the annual daily maxima.

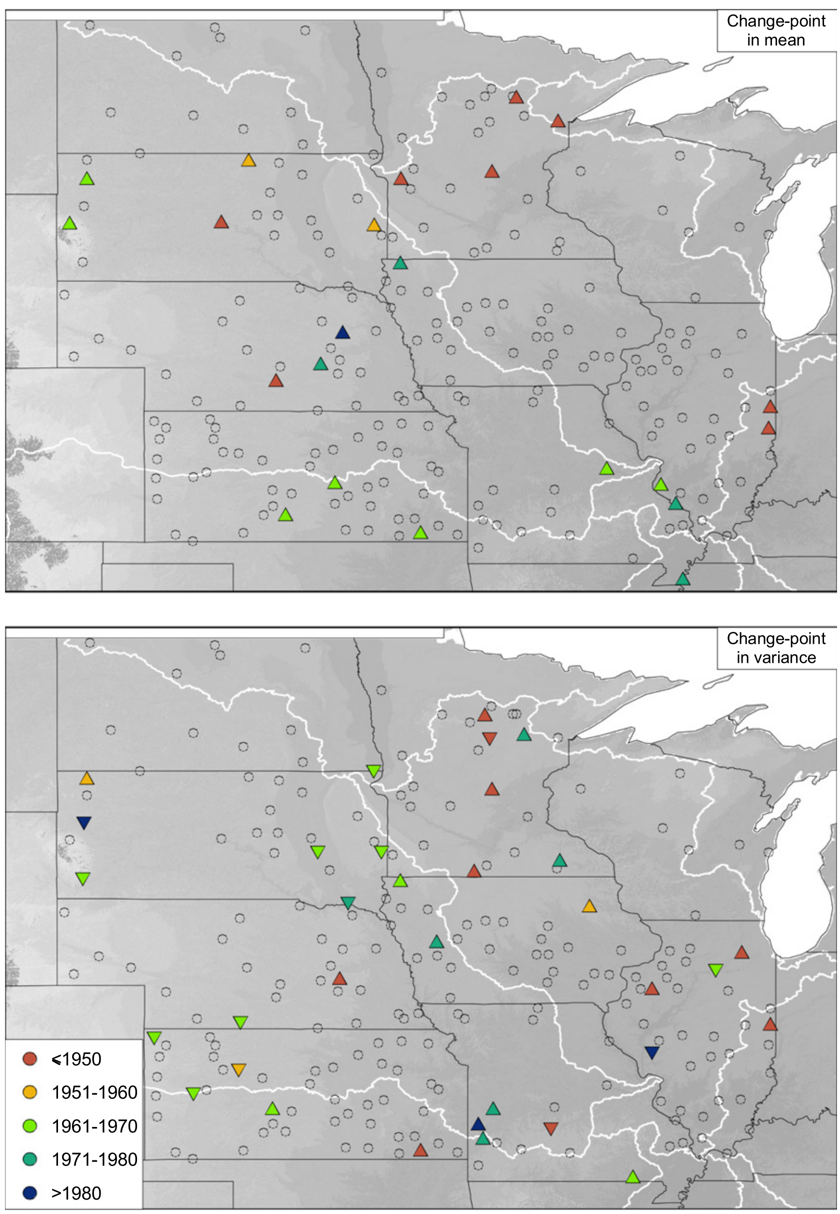

Fig. 5. Maps with the location of the stations with a change-point in mean (top panel) and variance (bottom panel) significant at the 5% level. The pointing-down (pointing-up) triangles indicate a decrease (an increase) in mean or variance after the change-point, while the empty circles a lack of statistically significant change-point. These results are based on the Pettitt test.

3.4. Poisson regression

We examine clustering of heavy rainfall events from the perspective of Poisson models. Homogeneous Poisson point processes provide a frame of reference for interpreting occurrences as "not clustered" (Karr, 1991; see also Smith and Karr, 1985; Mailier et al., 2006; Vitolo et al., 2009). Such processes arise naturally under the assumptions of stationarity and independence of the events. Counts of event occurrences from a Poisson process over a specified time interval (a year, for example) have a Poisson distribution. This distribution is characterized by equality of variance and mean (equidispersion). Overdispersion is said to occur in observed count data when the variance is larger than the mean. Overdispersion indicates violation of either (or both) the assumptions of independence and stationarity underlying the Poisson processes. In this case we speak of clustering (in a broad sense), following Smith and Karr (1983), Mailier et al. (2006), and Vitolo et al. (2009).

In this study, we want to evaluate whether clustering characterizes the number of days with rainfall accumulations larger than 25 mm. To evaluate whether the assumption that the data follows a Poisson distribution is valid, we compute the dispersion coefficient (defined as the ratio between variance and mean): deviation from unity indicates that the assumption of Poisson distribution is incorrect.

Poisson regression is then used as modeling framework to examine the number of days with heavy rainfall. Poisson regression is a form of generalized linear model (GLM) suitable for count data (e.g., McCullagh and Nelder, 1989; Dobson, 2001). Let us define N_i as the count data for the year i. We say that N_i has a conditional Poisson distribution with rate of occurrence Λ_i, given that:

$$P(N_i = k|\Lambda_i) = \frac{e^{-\Lambda_i}\Lambda_i^k}{k!} \quad [k = 0, 1, 2, \ldots] \tag{3}$$

where Λ_i is a non-negative random variable.

In a Poisson regression model, the parameter Λ_i can be modeled as a linear function h of predictors $x_{1i}, x_{2i}, \ldots, x_{ni}$:

$$\Lambda_i = \exp[\beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_n x_{ni}] \tag{4}$$

where β_j is the coefficient for jth predictor, to be estimated by e.g. maximum likelihood. For the predictors $x_{1i}, \ldots, x_{ni}$ we use yearly time series of several climatic indices. Please note that the original climatic indices which we use (NAO, AMO, SOI and PDO, see below

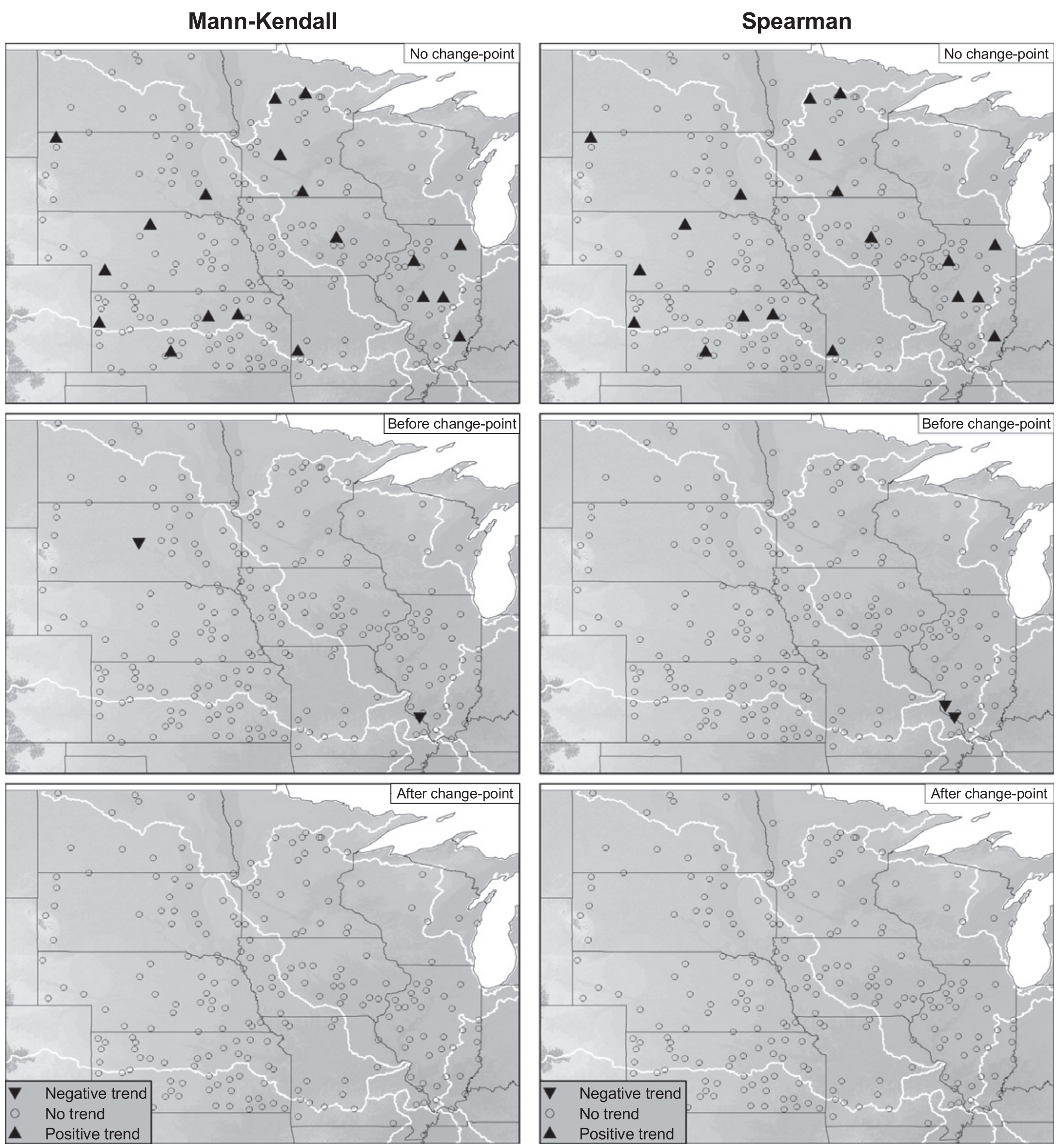

Fig. 6. Maps with the results of Mann-Kendall (left panels) and Spearman (right panels) tests for the series without change-point in mean (top panel), and with change-point in mean (middle and bottom panels). The test is significant at the 5% level.

for details) are defined on monthly timescales. However, we derive time series of yearly values by considering averages over suitable periods, following an established approach (see e.g. Vitolo et al., 2009). For clarity, please note that our response variable N_i, to be modeled in Eq. (3) is a time series of counts and that exactly one such series corresponds to each of the stations. The regression model in Eqs. (3) and (4) is therefore independently fitted to each station (that is, independently to each time series of yearly counts). Hence,

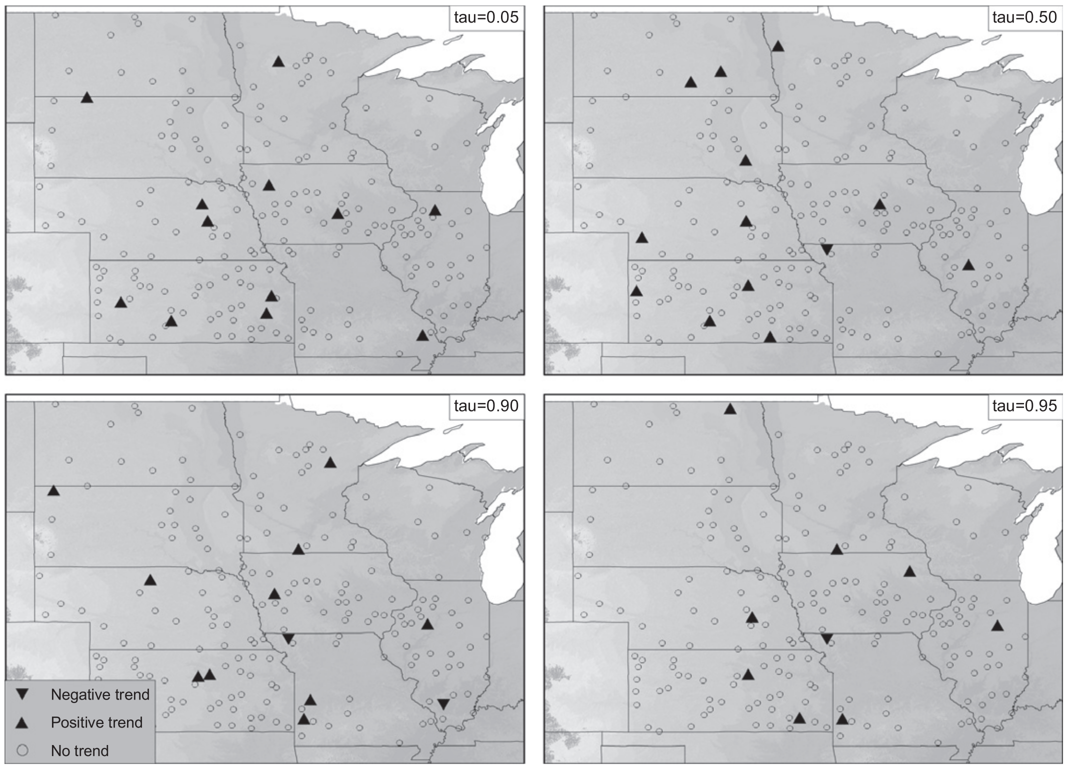

Fig. 7. Maps with the results of the linear regression for four different quantiles (τ = 0.05, τ = 0.50, τ = 0.90, τ = 0.95) by means of quantile regression The results are significant at the 5% level.

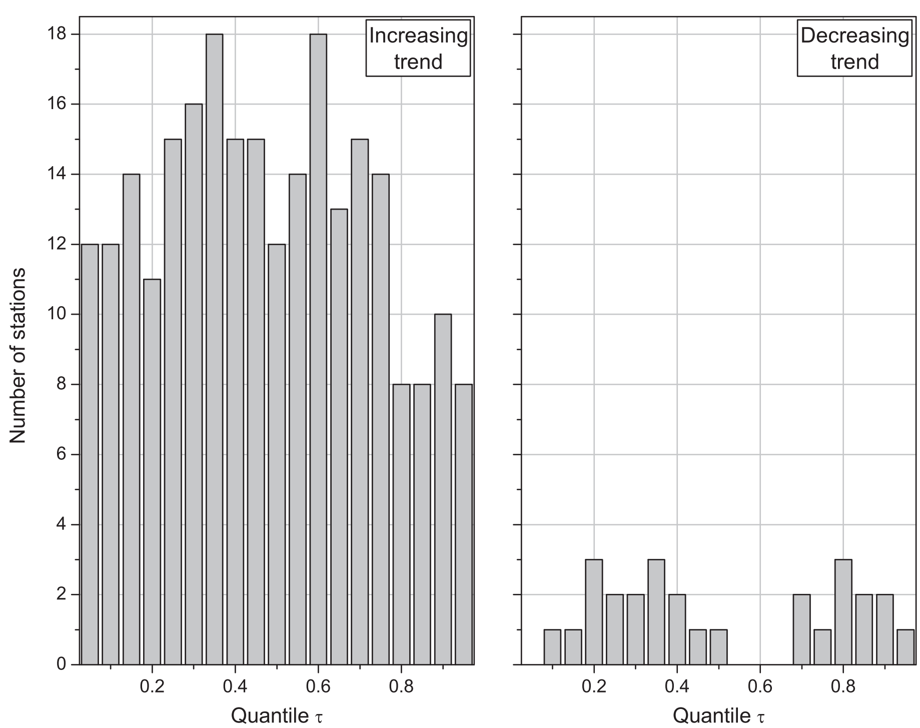

Fig. 8. Plot of the number of stations with a statistically significant (at the 5% significance level) increasing (left panel) and decreasing (right panel) trends for different quantiles τ. The results are based on quantile regression.

one set of fitted regression parameters $\beta_1, \ldots, \beta_n$ is obtained for each station. Our analysis aims at discussing climatic effects by also taking into account the spatial variability of these estimated parameters as a function of the station.

In this study we consider four different climate-related covariates that have been linked to rainfall variability over the central US (e.g., Bunkers et al., 1996; Ting and Wang, 1997; Bates et al., 2001; Barlow et al., 2001; Enfield et al., 2001; Mauget, 2003; Higgins et al., 2007; Hu and Huang, 2009; Coleman and Budikova, 2010; Meng and Quiring, 2010). In particular, we use the North Atlantic Oscillation (NAO; Hurrell, 1995; Hurrell and Van Loon, 1997; Jones et al., 1997), the Atlantic Multidecadal Oscillation (AMO; Kerr, 2000; Enfield et al., 2001), the Southern Oscillation Index (SOI; Trenberth, 1984; Ropelewski and Jones, 1987), and the Pacific Decadal Oscillation (PDO; Mantua et al., 1997; Hare and Mantua, 2000) The time series of these predictors were downloaded from the Global Climate Observing System (GCOS) Working Group on Surface Pressure (WG-SP) website (www.esrl.noaa.gov/psd/gcos_wgsp/Timeseries/). With the exception of NAO, we average these climatic indexes over the period May–September since this is the period in which most of the heavy rainfall events are concentrated (Figs. 3 and 4). We average the NAO index over the months of May and June since this is the period (together with boreal winter) during which the signal-to-noise ratio is the largest (e.g., Elsner et al., 2001; Villarini et al., 2010b). For each rain gage, we investigate the dependence of the rate of occurrence parameter on the four predictors by selecting the model with the lowest value of the Akaike Information Criterion (AIC; Akaike, 1974), in agreement with the parsimony principle and to avoid model overfitting. We have considered 16 possible models: a model with constant Λ, and 15 models in which Λ is a linear function of all the possible combinations of these four covariates. All these calculations are performed in `R` (R Development Core Team, 2008) using the freely available `gamlss` package (Stasinopoulos et al., 2007).

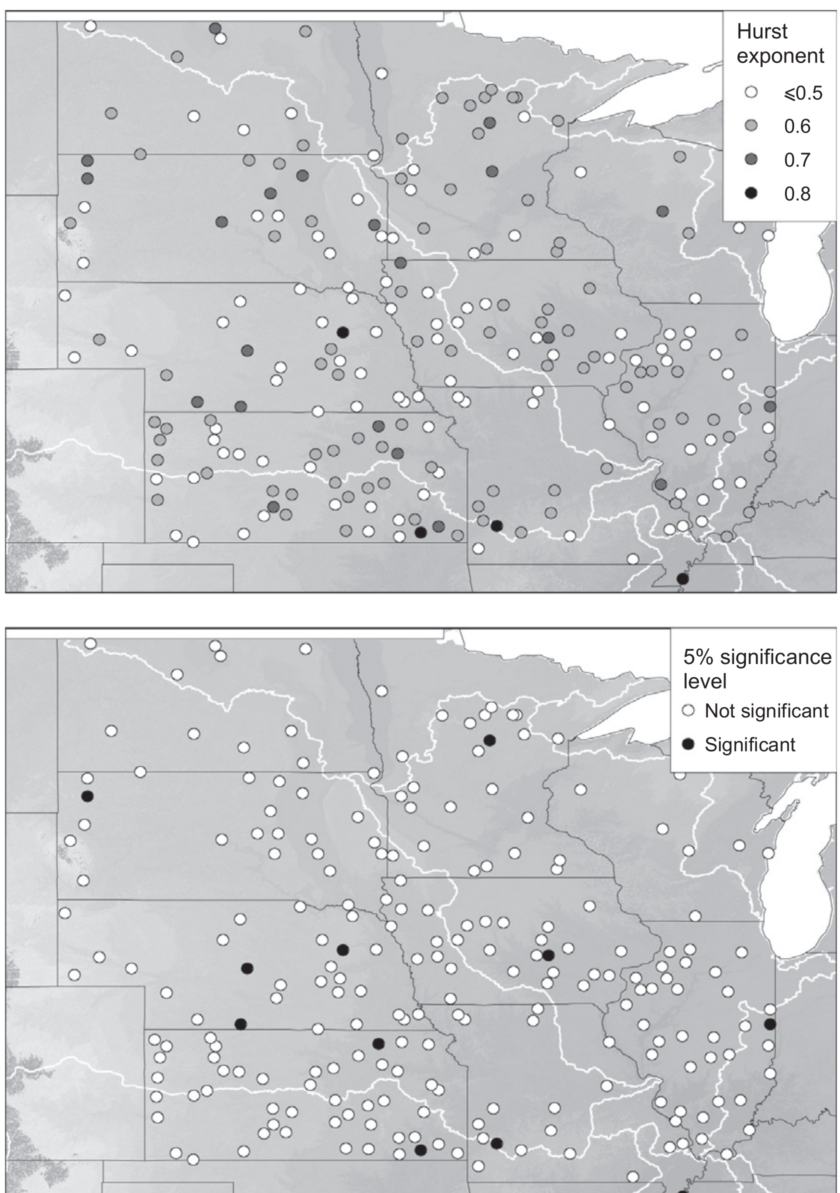

Fig. 9. Maps with the values of the Hurst exponent *H* (top panel) and with the stations for which *H* is significantly different from 0.5 at the 5% confidence level (bottom panel). The significance of the Hurst exponent is computed by means of bootstrap.

4. Results

4.1. Stationarity and long-term persistence

In this section we discuss the stationarity assumption by examining both change-points in mean and variance, as well as monotonic trends. As a preliminary step, we have checked the validity of the independence assumption, since its violation could result in the detection of a statistically significant trend, even if no trend was present (e.g., Cox and Stuart, 1955; Cohn and Lins, 2005). For each station we check whether the lag-one autocorrelation was significantly different from zero. In only eight out of 221 stations we found that the lag-one autocorrelation was significantly different from zero at the 5% level. Even though different methods have been proposed and developed to account for temporal dependencies in the records (e.g., Kulkarni and von Storch, 1995; Yue and Wang, 2004), we do not implement them in this study due to the limited impact they have on our results (see later in the section).

We start the assessment of the validity of the stationarity assumption by testing the annual maximum daily rainfall time series for the presence of abrupt changes in the first two moments of the rainfall distribution using the Pettitt test (Fig. 5). We have 22 stations with a statistically significant change-point in mean and 33 in variance (Fig. 5). Each of the 22 stations with a change-point

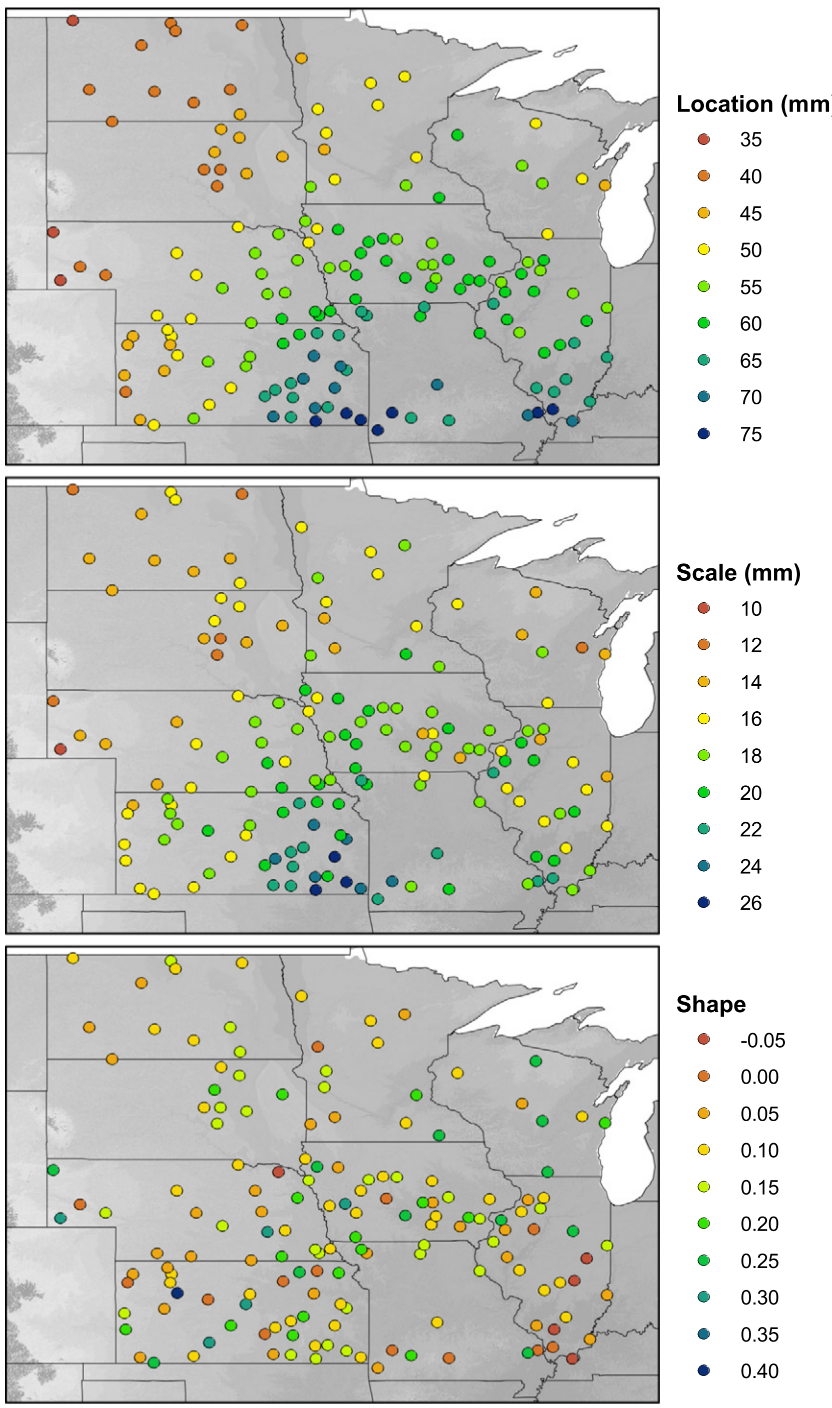

Fig. 10. Maps of the parameters of the GEV distribution for the series without change-points and monotonic trends.

in mean have a larger mean after the change-point. For the change-point in variance, 19 stations show an increase and 14 a decrease after the change-point. For three cases we observe a change-point both in mean and variance. The change-points in mean tend to occur earlier in the record in the northern part of the domain, and later moving southward. For the change-point in variance, there is no clear spatial pattern.

For the annual maximum peak discharge data over this area, (Villarini et al., in press) related observed change-points to anthropogenic effects (e.g., construction of dams, changes in land use/land cover and agricultural practice). For the rainfall series, we examined the metadata associated with these stations and found that in several instances the year of the change-point is close to the year in which the rain gage was relocated (e.g., placed at higher elevation and/or placed at a different site; e.g., Potter, 1979, 1981; Easterling and Peterson, 1995; Groisman and Legates, 1995; Changnon and Kunkel, 2006; Daly et al., 2007; Allard et al., 2009). For some of the stations, however, it is possible that the change-points are linked to changes in the rainfall regime (e.g., Karl and Knight, 1998).

We test the records for monotonic trends using both Mann-Kendall (Fig. 6, left panels) and Spearman (Fig. 6, right panels) tests. Out of the 199 stations without a statistically significant change-point in mean, we detected a statistically significant increasing monotonic trend in 19 of them and no decreasing trends (Fig. 6, left-top panel). These increases are not restricted to a specific area, but are distributed over the entire study domain. For the stations with a change-point in mean, only two of them show a statistically significant decreasing trend before the change-point. No station exhibits statistically significant trends after the change-point. These conclusions are supported by the results of the Spearman test (Fig. 6, right panels). The only difference is for the subseries before the change-point in mean (Fig. 6, middle panels). In this case, decreasing trends are detected by both tests at only one of the two stations. The use of more than one test as in this case can provide valuable information about the robustness of our results.

We have performed quantile regression on the time series of the stations that do not exhibit a statistically significant change-point in mean. With these analyses we can investigate the presence of linear trends for different quantiles. We focus our attention on the 0.05, 0.50 (median regression), 0.90, and 0.95 quantiles (Fig. 7). The picture does not change significantly for the quantile regression results with respect to the results of Mann-Kendall and Spearman tests (Fig. 6). Even in this case, we observe a tendency towards increasing trends. For the 0.05 quantile, 12 stations have a statistically significant increasing trend. For the median, 12 stations have a statistically significant increasing and one a decreasing trend. For the largest quantiles, we have a slightly smaller number of increasing trends. The number of stations with a statistically significant increasing trend tends to decrease for increasing quantile value (Fig. 8). On the other hand, the number of stations with a statistically significant decreasing trend tends to be small, independently of the quantile.

In addition to describing these time series in terms of deterministic abrupt and slowly varying changes, we also consider long-term persistence, which can result in apparent trends or change-points in time series that are actually stationary. For each station we have computed the Hurst exponent H using the aggregated variance method and summarized the results in Fig. 9 (top panel). Approximately 40% of the stations have a Hurst exponent smaller than or equal to 0.5, suggesting that the time series do not exhibit long-term persistence. On the other hand, for almost 60% of the stations the estimated Hurst coefficient is consistent with long-term persistence. Estimation of the Hurst exponent, however, is affected by large sampling uncertainties that should be quantified and accounted for in order to assess the significance of these results. To evaluate the statistical significance of our findings, we have used

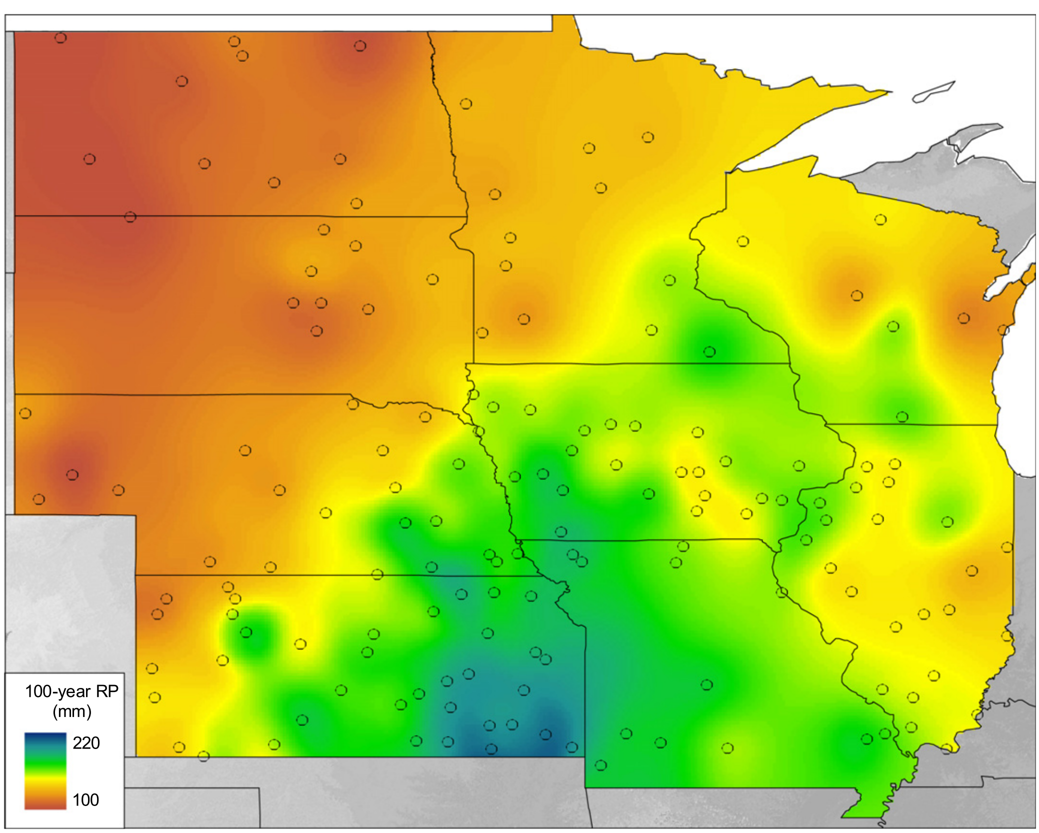

Fig. 11. Map with the 100-year return period rainfall based on the GEV modeling in Fig. 10. Spatial interpolation is performed by means of inverse distance weighted method.

a bootstrap approach (Fig. 9; bottom panel), testing the null hypothesis that the Hurst exponent H is equal to 0.5. Once we account for the estimation uncertainties, there is enough statistical evidence against the null hypothesis in only 11 out of 221 stations. To complicate the matter, it is also possible that for these 11 stations the observed long-term persistence could be related to rain gage relocation (e.g., Potter, 1979; Rust et al., 2008). These results highlight the difficulty of making conclusive statements about the presence of long-term persistence in hydro-meteorological time series due to the limited sample sizes.

4.2. Extreme value distribution

After examining the validity of the stationarity assumption, we present results from modeling of the annual maximum daily rainfall time series for stations that do not exhibit statistically significant change-points and monotonic trends. We use the Kolmogorov–Smirnov, Anderson–Darling, and Cramer–von Mises tests to assess the quality of the GEV fit, and compute their p-values using a Monte Carlo approach. The results of these tests indicate that we cannot reject the null hypothesis (samples generated from the GEV

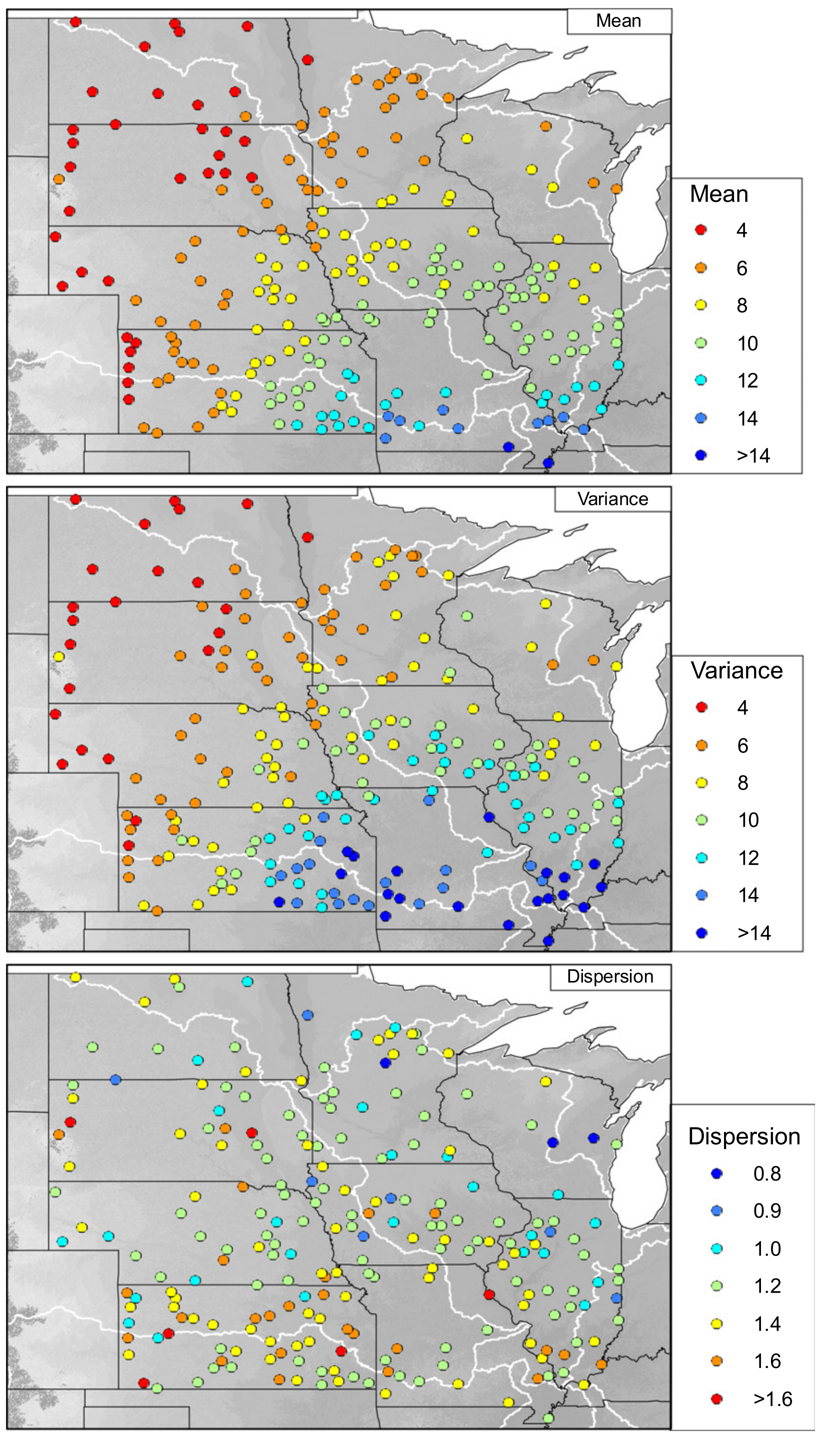

Fig. 12. Map with the mean (top panel), variance (middle panel), and dispersion coefficient (bottom panel) of the number of days exceeding daily rainfall accumulations of 25 mm. The dispersion coefficient (units are 1/year) is defined as the ratio of the variance and the mean.

distribution) at the 5% significance level for all of the rain gages, justifying the use of this distribution.

We have summarized our results in Fig. 10, with the spatial distribution of the location (top panel), scale (middle panel), and shape (bottom panel) parameters. The map of the location parameter shows an organized pattern, with increasing values from the northwestern to the southeastern part of the domain, mirroring the climatology of rainfall over the Midwest United States. For estimates of the scale parameter, we can see a similar spatial pattern as for the location parameter. For the shape parameter, there is not a clear spatial pattern. Approximately 90% of the stations have a shape parameter larger than zero, indicating that the rainfall process in this area exhibits heavy tail behavior. Over this region, Villarini et al. (in press) found that estimates of the shape parameter for annual maximum peak discharge time series are generally larger than zero as well.

Given the parameters of the GEV distribution, we can compute the 100-year return period rainfall over this area by computing the annual maximum daily rainfall value with a probability of non-exceedance of 0.99. Despite the fact that our records are "long" compared to those employed in other studies, this approach is preferable to the one in which we estimate the high quantiles directly from a limited sample (e.g., Stedinger et al., 1993). As shown in Fig. 11, we have a marked northwest–southeast gradient, similar to what we found for the location and scale parameters (Fig. 10). In Illinois, however, even though the location parameter was higher than in other areas, the 100-year return period maximum daily rainfall is smaller than the surrounding regions due to the values of the scale parameter and the lighter tail of the distribution. This analysis highlights the gradient in extreme rainfall, with the largest values concentrated in the eastern portion of Kansas, Missouri and Iowa.

4.3. Poisson regression

The Poisson regression model is the framework we have used to examine clustering of heavy rainfall events, and the link between their frequency of occurrence and climate variables. The mean and variance in number of days with rainfall accumulations larger than 25 mm (Fig. 12) exhibit a rather well organized spatial pattern, and similar to what shown in Fig. 10 (top two panels). The mean decreases from northwest to southeast, with values smaller than 4 days per year in South Dakota increasing to values larger than 14 days per year in southern Missouri and Illinois. The variance exhibits a similar spatial pattern. The coefficient of dispersion (ratio between the variance and the mean) is greater than 1 in the

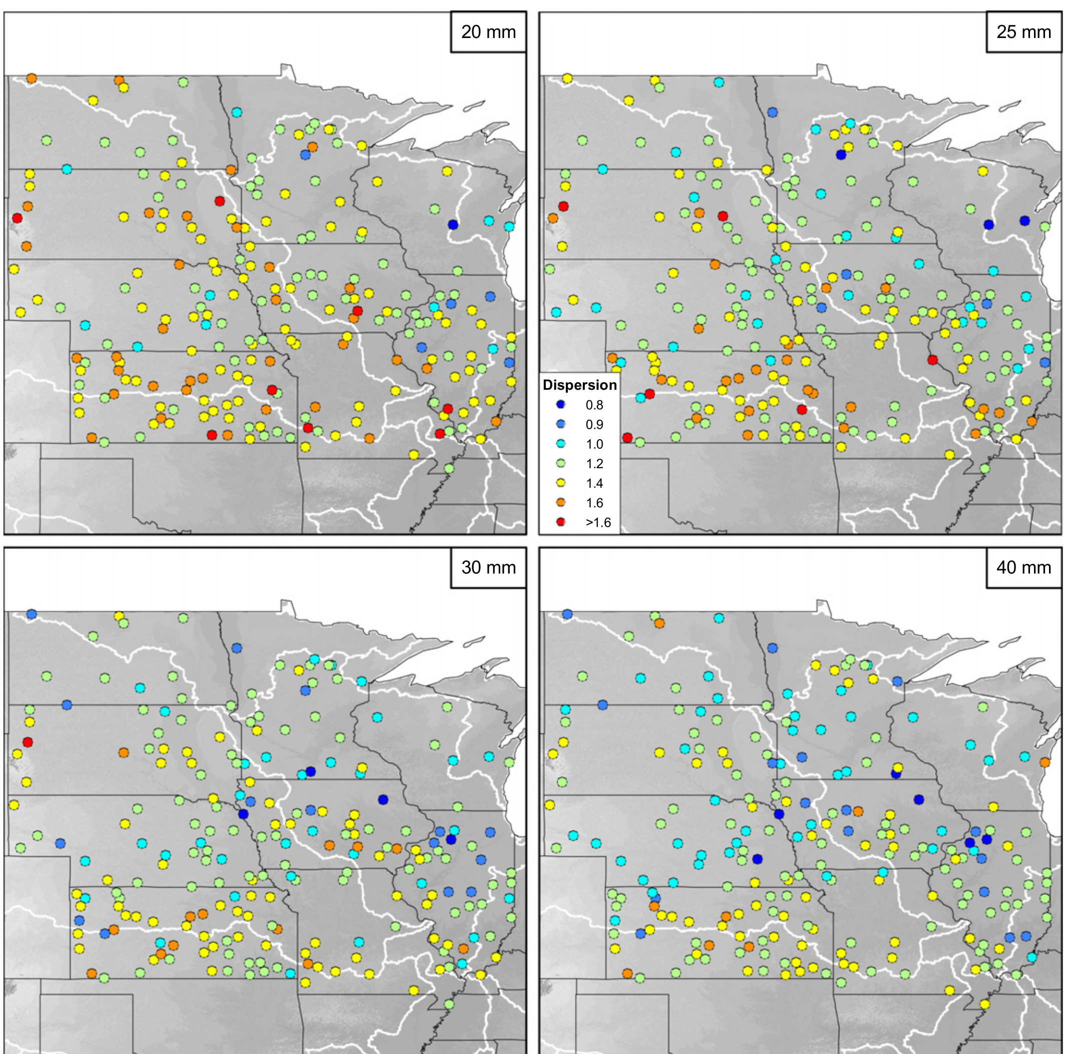

Fig. 13. Map with the dispersion coefficient for the number of days exceeding daily rainfall accumulations of 20 mm (top left panel), 25 mm (top right panel), 30 mm (lower left panel), and 40 mm (lower right panel). The dispersion coefficient is defined as the ratio of the variance and the mean.

vast majority of the cases. These results suggest that clustering may play a role in heavy rainfall occurrences. To better understand the effects of the selected threshold on the results of the dispersion coefficient, we have computed it for three additional thresholds (20 mm, 30 mm, and 40 mm) and summarized the results in Fig. 13. The dispersion coefficient tends to increase with decreasing threshold. Over most of the domain, however, the data exhibit overdispersion independently of the selected threshold.

The Poisson regression model (Eqs. (3) and (4)) is used to examine clustering of heavy rainfall counts (days exceeding 25 mm and 50 mm) in terms of time-varying climate indices. These analyses allow us to assess specific modes of climate variability as sources of overdispersion in heavy rainfall counts. For 147 out of 221 stations at least one of the four climate indices is a significant covariate (figure not shown), with the western part of the domain exhibiting the largest frequency. In the western portion of the domain, most of the covariates are significant (Fig. 14). NAO tends to be a significant predictor for most of the stations in the southwestern part of the domain (Fig. 14). There are no pronounced pattern in location of stations with significant dependence on AMO, SOI, and PDO. If we set a threshold of 50 mm, the results are the same as those presented in Fig. 14 for a 25-mm threshold, suggesting that the patterns observed in these figures are not very sensitive to the selected threshold.

The presence of statistically significant climatic effects indicates that the overdispersion in the data may be caused by nonstationarity due to a time-varying rate. In other words, the modulation of the rate of occurrence parameter Λ by the climatic factors, expressed in Eq. (4), induces periods of enhanced and reduced activity. This corresponds to a larger interannual variability than would be expected from a totally random (Poisson) process. This does not rule out the presence of statistical dependence between the events. More sophisticated statistical models must be used to investigate this.

5. Conclusions

In this study we have analyzed the annual maximum daily rainfall time series from 221 rain gages with a record of at least 75 years over the Midwest United States (North and South Dakota, Nebraska, Kansas, Minnesota, Iowa, Missouri, Wisconsin, and Illinois). The results of this study can be summarized as follows.

1. Our study indicates significant temporal inhomogeinities in the heavy rainfall records, the strongest being related to seasonality and to the influence of large-scale climatic factors. These temporal features are organized in a clear spatial pattern (namely, a north-west to south-east spatial gradient), which is coherent

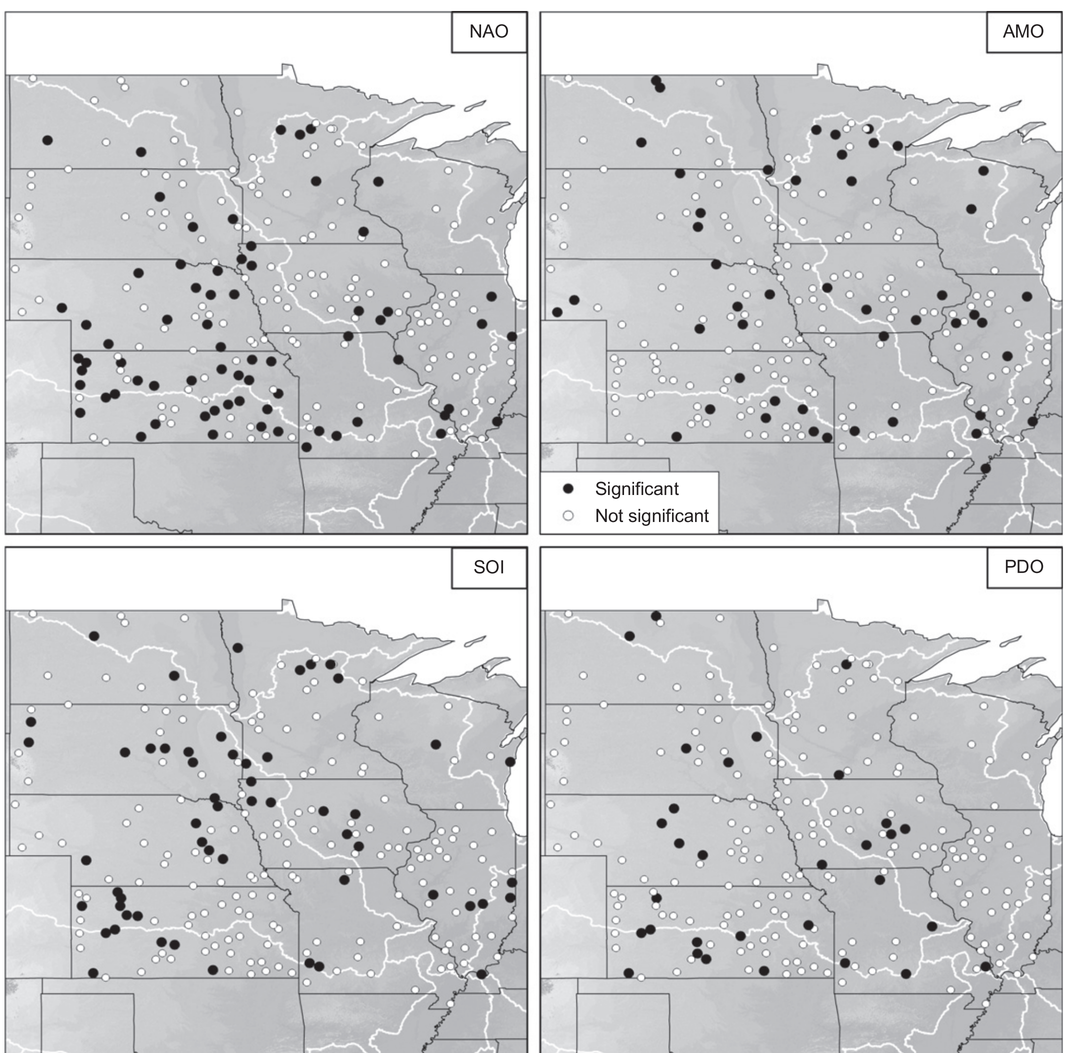

Fig. 14. Map showing the stations for which NAO (top left panel), AMO (top right panel), SOI (lower left panel), and PDO (lower right panel) are significant covariates in the Poisson regression model.

from the physical viewpoint. Non-stationarities and long-term persistence appear to be less spatially consistent.

2. Annual maximum daily rainfall occurrence exhibits a marked seasonality within the study domain, with the largest frequencies between May and August. The seasonal distribution is unimodal, with the exception of few stations in the southeastern part of the domain.
3. Approximately 10% of the stations exhibit a change-point in mean and variance. By examining the metadata associated with these stations, it is possible to relate some of the change-points to rain gage relocation. For other stations, however, abrupt changes are potentially linked to changes in rainfall regime.
4. The results of the monotonic trend analysis based on Mann-Kendall and Spearman tests show a slight tendency towards an increase in annual maximum daily rainfall over time. The results of the quantile regression suggest that these changes over time are less significant for higher quantiles.
5. Long-term persistence analyses show that for approximately 60% of the stations, the estimated Hurst coefficient H is larger than 0.5. However, once the uncertainties associated with the estimation of the Hurst exponent are accounted for by means of bootstrap, there is statistical evidence to support long-term persistence for only 11 stations. Our study highlights the difficulties in making conclusive statements about the presence of long-term persistence in hydro-meteorological time series due to the limited sample sizes. Future studies should examine the sensitivity of these findings to different estimators of the Hurst coefficient.
6. We modeled the time series of the stations with no statistically significant change-points or monotonic trends with the Generalized Extreme Value distribution. We found that the location and scale parameters exhibit a pronounced increasing gradient from the northwestern to southeastern part of the study region. The shape parameter did not exhibit a marked spatial pattern. The shape parameter is larger than zero for almost 90% of the stations, pointing to a heavy tail behavior of these time series. A map of the 100-year return period annual maximum daily rainfall shows that the largest rainfall values are concentrated in the area between eastern Kansas, Iowa, and Missouri.
7. We used a Poisson regression model to examine clustering of heavy rainfall, and the relation between their frequency of occurrence and climate indices. The mean and variance of the yearly number of days exceeding a 25-mm threshold tend to increase from the north-west to the south-east regions of our domain. This pattern is similar to the one exhibited by the location and scale parameters of the GEV distribution. The number of days with rainfall accumulations larger than 25 mm exhibit overdispersion in most of the cases. Similar conclusions could be drawn for different thresholds (20 mm, 30 mm, and 40 mm). Four climate indices reflecting the influences of both Atlantic and Pacific Oceans (NAO, AMO, SOI, and PDO) were found to be significant predictors in modeling the frequency of heavy rainfall events (defined as days exceeding a 25-mm and 50-mm thresholds). These are strong indications of clustering behavior due to temporal fluctuations in the rate of arrival of the events, which is modulated by climatic factors. The possibility of statistical dependence in the data (on top of the climate-induced modulation) is not ruled out and is the subject of on-going research.
8. One issue that should be object of future studies is the transferability of these results to other areas of the world. Among several outstanding questions, statements about the presence of increasing or decreasing trends are important to assess the impact of human-induced climate warming: can we detect an anthropogenic climate change signal in heavy rainfall in other parts of the world? Moreover, since the Midwest US is a relatively flat region, it would be particularly interesting to compare our results against others from areas characterized by different topography (e.g., marked orography). Additionally, given the large impact of events from the tail of the distribution, future analyses should focus on the upper tail properties of the heavy rainfall time series and examine whether the heavy tail behavior exhibited by these stations is a common feature across different regions.

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