Title, English:

NON-STATIONARY FREQUENCY ANALYSIS OF HEAVY RAINFALL EVENTS IN SOUTHERN FRANCE

Title, French:

ANALYSE FREQUENTIELLE NON-STATIONNAIRE DES PLUIES EXTREMES DANS LE SUD DE LA FRANCE

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ABSTRACT (ENGLISH)

Heavy rainfall events often occur in southern French Mediterranean regions during the fall season, leading to catastrophic flood events. In the present study, a non-stationary peaks-over-threshold model with climatic covariates for these heavy rainfall events is developed. A regional sample of events exceeding the threshold of 100 mm per day is build using daily precipitation data recorded in 44 stations during the period 1958-2008. The peaks-over-threshold model combines a Poisson distribution for the occurrence and a Generalized Pareto distribution for the magnitude of the heavy rainfall events. The selected covariates are the seasonal occurrence of southern circulation patterns for the Poisson distribution parameter and monthly air temperature for the Generalized Pareto distribution scale parameter. According to the Deviance test, the non-stationary model provides a better fit to the data than a classical stationary model. Such a model incorporating climatic covariates instead of time allows re-evaluating the risk of extreme precipitation on a monthly and seasonal basis and also can be used with climate model outputs to produce future scenarios. Existing scenarios of the future changes projected for the covariates included in the model are tested to evaluate the possible future changes on extreme precipitation quantiles in the study area.

ABSTRACT (FRENCH)

Des épisodes de précipitations intenses se produisent fréquemment dans le sud de la France pendant l'automne, provoquant des inondations catastrophiques. Dans la présente étude, un modèle probabiliste non-stationnaire utilisant des covariables climatiques est développé pour ces épisodes de fortes précipitations. Un échantillon régional d'événements dépassant le seuil de 100 mm par jour est construit en utilisant les données de précipitations enregistrées dans 44 stations au cours de la période 1958-2008. Le modèle développé combine une distribution de Poisson pour l’occurrence saisonnière des épisodes et une distribution de Pareto généralisée pour leur magnitude. Les covariables utilisées dans le modèle sont i) la fréquence saisonnière du type de temps représentant un flux de composante sud à est, pour le paramètre de la distribution de Poisson et ii) la température de l'air mensuelle pour le paramètre d’échelle de la distribution Pareto généralisée. Selon le test de Déviance, le modèle non-stationnaire avec covariables fournit un meilleur ajustement aux données qu’un classique modèle stationnaire. Un tel modèle, intégrant des covariables climatiques plutôt que le temps, permet de réévaluer le risque de précipitations extrêmes sur une base mensuelle ou saisonnière et peut également être utilisé avec des sorties de modèles climatiques pour produire des scénarios futurs. Les scénarios futurs existants pour les covariables sélectionnées ont été testés afin d'évaluer les éventuels changements à venir sur les quantiles de précipitations extrêmes dans la région étudiée.

1 INTRODUCTION

The southern coastal area of France corresponding to the Cévennes region is affected by the most intense rainfall events recorded in the country. The heaviest rainfall events are occurring in the fall season, causing catastrophic flash-floods which are the main natural hazard in that region (Delrieu et al. 2005, Nuissier et al. 2008). Pujol et al. (2007a, 2007b) indicated a possible increasing trend in the intensity of extreme rainfalls in this region, in the last 50 years of records. However, there is a need to analyze the climatic factors related to the non-stationarity detected, in particular to be able to produce future scenarios (Pujol et al. 2007a, Tramblay et al. 2011). For the next century, climate models predict an amplification of precipitation extremes associated with a temperature increase in the Mediterranean basin (Alpert et al. 2002, Gibelin and Déqué 2003, IPCC, 2007, Fowler et al., 2007, Allan and Soden, 2008, Somot et al., 2008, O'Gorman and Schneider, 2009). Goubanova and Li (2007) using a general circulation model (GCM) with different scenarios predicted for the Mediterranean region during the 21st century an increase of precipitation extremes for all seasons except summer, in combination with a decrease of precipitation totals. Similarly, Gao et al. (2008) using climate change scenarios in a regional climate model (RCM) observed an increase in winter precipitation events for western and central Mediterranean regions. However, as shown by Ricard et al. (2009), even a high resolution coupled Atmosphere-Ocean RCM (Somot et al., 2008) is not able to reproduce with accuracy the extreme rainfall events in the Mediterranean region. For this reason, they recommended the combined use of statistical and dynamical downscaling methods for the analysis of future scenarios for extreme rainfall events.

The synoptic situations associated with heavy rainfall events in the Cévennes region of south France have been well documented in several studies. This has been completed through the classification of geopotential height fields during heavy rainfall events, providing a typology of the synoptic patterns generating severe rainfall (Michelangeli et al. 1995, Sanchez-Gomez et al., 2005 Joly et al. 2007, Sanchez-Gomez et al. 2008, Funatsu et al. 2009, Boudevillain et al. 2009, Garavaglia et al. 2010). In addition, several studies have provided realistic simulations of the high intensity rainfall events using mesoscale models, to better understand the physical mechanisms associated with heavy rainfall in the Cévennes region (Lebeaupin et al. 2006, Joly et al. 2007, Ducrocq et al. 2008, Nuissier et al. 2008, Ricard et al. 2009). These modelling efforts have given the opportunity to use the various greenhouse gas emission scenarios to evaluate the future changes in the occurrence and the magnitude of heavy rainfall events in the south of France. For example, Ricard et al. (2009) using future climate simulations of Arpege-Climat (2070-2099) have shown a potential increase of 16% of the synoptic situations favouring the heavy rainfall events and a possible increase of 20% of the humidity flux from the sea toward the continent. Similarly, Sanchez-Gomez et al. (2009) have tested the possibility of reproducing weather regimes in the future climates generated by different RCM. Their results indicate that the models are able to reproduce the weather regimes behaviour in terms of composite pattern, mean frequency of occurrence and persistence reasonably well.

The frequency analysis methods are widely used to relate the magnitude of extreme events (e.g. heavy rainfall, floods) to a probability of occurrence (Stedinger et al. 1993). In the context of climate change, the classical frequency analysis techniques need to be adapted, since the notions of ‘probability of exceedances’ and ‘return period’ are no longer valid in the case of non-stationarity (Khaliq et al. 2006). One way to take into account non-stationarity into frequency models is to make their parameters dependent of climatic covariates, allowing the downscaling of extremes using the simulations of large-scale circulation dynamics (Katz et al. 2002). Yet only a small number of studies have considered the use of climatic covariates, instead of time, into non-stationary models. Aissaoui-Fqayeh et al. (2009) have developed a non-stationary GEV model of annual maximum precipitation in California with the Southern Oscillation Index as a covariate. Villarini et al. (2010, 2012) also considered the use of North Atlantic Oscillation and Mediterranean Index as covariates for extreme value models of precipitation and discharge. Several recent studies have adapted in a non-stationary context the GEV model for bloc maxima (Pujol et al. 2007a, Adlouni et al. 2007) or the peak-over-threshold (POT) modelling approach (Renard et al. 2006, Laurent and Parey 2007, Pujol et al. 2007b, Sugahara et al. 2009, Kyselý et al. 2010) by making the model parameters time dependent. The main advantage of POT modelling over the bloc maxima approach is the selection of a broader range of events, depending on the threshold (Lang et al. 1999). Moreover the POT approach allows the joint characterization of the frequency and magnitude of extreme events, which is useful in a non-stationary context of climate change since it permits assessing the changes in frequency as well as in magnitude (Jacob et al. 2009). Beguería et al. (2010) in a recent study on extreme precipitation events in the North of Spain observed some difficulties for fitting non-stationary POT models to the observed data due to the fact that the model parameters were set as time dependent only. They concluded that this situation could be improved if covariates such as the North Atlantic Oscillation index or other teleconnections indices would be included in the analysis

The goal of this study is to develop a non-stationary POT model including climatic covariates, for the extreme rainfall events occurring in southern France. In a preliminary study (Tramblay et al. 2011) several climatic covariates have been tested to be included in such a model for the same region. Among all the variables tested, the frequency of synoptic patterns, air temperature, sea level pressure and moisture flux from the Mediterranean Sea were found to improve the model. The selected covariates in the present paper are the frequency of southern-type circulation patterns and air temperature, those for which future scenarios are readably available, in order to make future projections. This non-stationary approach is taking advantage of the extensive research conducted on the physical mechanisms such as the synoptic patterns associated with heavy rainfall and the development of reliable future climate projections. The paper is organized as follow; in section 2 the non-stationary modelling approach is presented, in section 3 the datasets and the regional sample of events are detailed, and finally in section 4 the results are discussed.

2 NON-STATIONARY FREQUENCY ANALYSIS

2.1 Peaks-Over-Threshold modelling

In the POT approach, the samples are not collected monthly or annually but include all the values of the variable that exceed a specific threshold. The POT approach is not limited to only one event per year. The choice of the threshold value is critical since meeting the independence condition between the exceedances is a prerequisite for frequency analysis. This represents the main difficulty in the POT modelling approach and various sampling rules have been established (Lang et al. 1999, Beguería 2005, Beguería et al. 2010). Relying on asymptotic convergence results in Extreme Value Theory, the occurrence times of threshold exceedances follows a Poisson process and the magnitude of exceedances a Generalized Pareto (GP) distribution (Madsen et al. 1997, Önöz and Bayazit 2001), which could be adapted for the non-stationary context (Kyselŷ et al. 2010, Beguería et al. 2010).

The estimation of the model parameters for the stationary and the non stationary Poisson distribution in the present study is performed with the Maximum Likelihood Estimation (MLE) method. The MLE approach is general and flexible, and can be easily extended to encompass regression relationships between data and other explanatory variables (Coles

2001). In the present study, the GP distribution parameters are estimated with the Generalized Maximum Likelihood (GML) method. The GML method is based on the same principle as the ML method with an additional constraint on the shape parameter κ of the GP distribution, to eliminate potentially invalid values (El Adlouni et al. 2007). A prior distribution of κ adapted to hydro-meteorological data was introduced by Martins and Stedinger (2000). The prior for κ has a Beta distribution (with shape parameters α=3 and ß=6) with a mode at -0.1 and the shape parameter values are limited to the interval [-0.5, +0.5].

The n occurrences for a given year follow a Poisson distribution, whose probability distribution function (pdf) is given by:

$$F(n) = \exp^{-\lambda} \frac{\lambda^n}{n!} \qquad (1)$$

The parameter λ corresponds to both the mean number of exceedances per year and the variance (Önöz and Bayazit, 2001) and can be estimated from the sample mean. The Poisson assumption implies that the occurrences are independent. In the stationary case, λ is constant. In a non-stationary context, the intensity of the Poisson process could vary in time and be related to a covariate x_1:

$$\lambda(t) = \exp(a_1 x_1 + b_1) \qquad (2)$$

The a_1 and b_1 parameters are constants and are estimated with the ML method.

The GP distribution is fitted to the peak magnitudes (the threshold exceedances). The GP distribution has the cumulative distribution function:

$$F(q) = 1 - \left(1 - \kappa \frac{q - q_0}{\alpha}\right)^{-1/\kappa} \qquad \kappa \neq 0 \tag{3}$$

$$F(q) = 1 - \exp\left(-\frac{q - q_0}{\alpha}\right) \qquad \kappa = 0$$

Where α is the scale parameter, κ the shape parameter and q_0 the threshold level. The threshold level is determined a priori, only the scale and shape parameters of the GP need to be estimated from the sample.

A non-stationarity feature can be incorporated in the GP distribution, usually in the scale parameter (Coles 2001, Khaliq et al. 2006). The non-stationarity can also be incorporated into the shape parameter but it is not a common practice as the estimation of the shape parameter is difficult, even more when considering covariates (Coles 2001, Renard et al. 2006, Pujol et al. 2007b). Nevertheless, in recent case study Kyselŷ et al. (2010) have shown that making both the shape and scale parameters time dependent was not improving their POT model for temperature. In the present paper, only a dependency on the scale parameter is considered:

$$\alpha(t) = \exp(a_2 x_2 + b_2) \tag{4}$$

Where x_2 is a covariate, a_2 and b_2 constants estimated with the GML method.

In addition, Sugahara et al. (2009) or Kyselŷ et al. (2010) warn about the use of a fixed threshold value for the whole observation period in the presence of a trend in the event magnitudes. This would violate the asymptotic property of the Poisson model, leading to an artificially increased frequency of exceedances towards the beginning or the end of the period.

This indicates the importance of conducting an analysis prior to frequency modelling to detect the possible trends.

Finally, using the parameters of the Poisson and GP distributions and inverting Eq. 1, it is possible to derive the q_p event that is the event which has a p probability of non exceedances each year:

$$q_p = q_0 + \frac{\alpha}{\kappa}\left[(\lambda T)^{\kappa} - 1\right] \qquad \kappa \neq 0 \tag{5}$$

$$q_T = q_0 + \alpha(\ln \lambda T) \qquad \kappa = 0$$

In the stationary case, a unique q_p quantile is computed using the parameter values. For the non-stationary case, the q_p quantile is a function of the covariates used for the Poisson and GP model parameters. As the covariates considered are time-dependent, in the non-stationary case the q_p quantiles are also time dependent. The uncertainties on quantile estimates can be evaluated with a parametric bootstrap (Kyselý 2010).

2.2 Climatic covariates

The selection of the covariates is based on a previous study (Tramblay et al. 2011) where several potential covariates to be included in a non-stationary POT model have been identified. The seasonal occurrence of southern synoptic patterns for the parameter of the Poisson distribution and the monthly air temperature for the scale of the GP distribution are selected since future scenarios for these covariates have been proposed by Gibelin and Déqué (2003), Somot et al. (2008) and Ricard et al. (2009). The mean monthly air temperature is computed from NCEP/NCAR reanalysis data (Kalnay et al. 1996). The frequency of the synoptic patterns are obtained from the EDF-2006 classification of the synoptic patterns associated with rainfall events over France developed by Paquet et al. (2006) and Garavaglia et al. (2010). This classification is based on the geopotential height fields at 700 and 1000 hPa pressure levels for rainy days over France (Garavaglia et al. 2010). The resulting weather patterns (WP) provide a picture of the diversity of synoptic situations associated with rainfall over France (Paquet et al. 2006, Garavaglia et al. 2010). Figure 1 shows the averaged geopotential height at 1000hpa for the 8 patterns (Garavaglia et al. 2010). WP2 (Steady Oceanic), WP1 (Atlantic Wave) and WP3 (South-West Circulation) correspond to west oceanic circulations. WP7 (Central Depression) and WP4 (South Circulation) correspond to Mediterranean circulations that usually brings heavy rains to south-eastern France. WP6 (East Return) also correspond to a Mediterranean circulation, but rain is generally limited to the Italian border and Eastern Pyrenees. WP5 (North East) is a continental circulation, and finally WP8 shows an undefined circulation, associated with non-rainy days.

2.2 Comparison between stationary and non-stationary models

Let M_0 and M_1 be respectively the stationary and the non-stationary models for the Poisson of the GP distributions. Table 1 shows the distribution parameters for the two cases. The Poisson process can be considered stationary (model $Pois_0$) or with a log-linear dependency of the λ parameter with a covariate x_1 (model $Pois_1$). Similarly, the GP distribution can be stationary with fixed scale and shape parameters (model GP_0) or with a log-linear dependency on the scale parameter (α) with a covariate x_2 (GP_1). The deviance test based on the log-likelihood difference is chosen to compare the nested models. Let M_0 and M_1 be two models such has $M_0 \subset M_1$. The method of the deviance test is to compare the validity of the model M_1 against the model M_0, based on the deviance statistic (Adlouni et al. 2007, Coles 2001):

$$D = 2\left\{l_n^*(M_1) - l_n^*(M_0)\right\} \qquad (6)$$

Where $l_n^*(M)$ is the maximized log-likelihood function of the model M computed on n observations. Large values of D indicate that the model M_1 is more adequate at representing the data than the model M_0. The D-statistic is distributed according to a chi-square distribution, with υ degrees of freedom, where υ is the difference between the number of parameters of the M_1 and M_0 models. Therefore, a formal statistical test can be performed to assess the difference between M_1 and M_0.

3 REGIONAL SAMPLING OF HEAVY RAINFALL EVENTS

Daily rainfall from 44 Météo-France rain gauges in the South of the Cévennes-Vivarais region were used, with daily rainfall between 1958 and 2008 and less than 2% missing data. The stations are covering the area from the Mediterranean Sea to the foothills of the Cévennes mountainous area, in the French departments of Hérault, Gard and Ardèche (Fig.2). The selected stations fall within a homogeneous region with regards to extreme rainfall events, as shown in the regionalization proposed by Pujol et al. (2007a).

The heavy rainfall events, defined in the present study as daily rainfall exceeding a threshold during the fall season, have been extracted for each station of the database. Using this set of events extracted from each individual station, a regional sampling / de-clustering type-of approach has been considered in order to avoid spatial and temporal correlations between the heavy rainfall events. This sampling approach was chosen since the validity of the frequency analysis results could be questioned if the observations are dependent (Khaliq et al. 2006). In addition, the construction of a regional sample of independent heavy rainfall events based on a large number of events allows a robust estimation of the regional distribution parameters (Mora et al. 2005). Therefore, to build the regional sample without temporal or spatial redundancy between the events the two following rules have been adopted:

- To avoid temporal redundancy, a minimum of two days between two consecutive rainfall events has been respected, to retain only one occurrence per event. This is particularly important for the most important events during which the threshold could be exceeded for several consecutive days.

- To remove spatial redundancy, for the events occurring in several stations the same day, only the maximum of the threshold exceedances for that day was selected. This rule avoids to include several time the same event in the regional sample in the cases of events with a large spatial extension.

3.1 Threshold selection

There are tools to check the validity of threshold values for the POT model: if the threshold is too low, it violates the asymptotic basis of the model, leading to bias, and if the threshold is to high, it generates too few excesses, leading to high variance (Coles 2001, Katz et al. 2002). For the GP distribution, the mean excess plot represents the average of threshold exceedances for different thresholds values (Coles 2001, Beguería et al. 2010). Another method requires fitting data to the GP distribution several times, each time using a different threshold. The stability in the parameter estimates can then be checked (Coles 2001, Katz et al. 2002). For the Poisson distribution, the suitability of the Poisson assumption can be tested with the dispersion index (DI) statistic, the ratio between the variance and the average number of exceedances per year (Cunnane 1979, Beguería 2005).

In this study, a range of different thresholds values have been tested to build the regional sample. The mean excess plot does not always help to discriminate an appropriate threshold: in the present case, the plot is roughly linear from 20 mm to 200 mm (Fig. 3). This approach can be rather subjective and difficult to apply when working on many different series. A discussion on automatic threshold selection methods can be found in Deidda and Puglia (2006). The plots of the GP scale and shape parameters obtained with different threshold values suggests that thresholds between 90 mm and 120 mm are suitable. A daily threshold of 100mm, exceeded in average once a year in the stations of the study area, is chosen from expert knowledge as it is often used to define heavy rainfall events in the West Mediterranean area (Martin-Vide et al., 2008). In an impact study in the same region, Boissier and Vinet (2009) have identified this value of 100 mm as a critical threshold that could trigger fatalities. It also respects the Poisson assumption, according to the DI statistic with a p-value of 0.184 indicating no significant difference in the mean and variance at the 5% level.

3.2 Regional homogeneity tests

Two regional homogeneity tests are considered to test whether the heavy rainfall distributions at the different stations constituting the regional sample could be assumed to be drawn from the same probability distribution:

- The Hosking and Wallis (1993) heterogeneity statistic, measuring the sample variability of the L-moments CV ratios and comparing it to the variation that would be expected in a homogeneous region. The HW statistic is computed with Monte-Carlo simulations of homogeneous regions with samples drawn from a four parameter kappa distribution (Hosking and Wallis 1993, Viglione et al. 2007).

- The Anderson Darling regional test is the generalization of the classical Anderson-Darling goodness of fit test (Scholz and Stephens 1987, Viglione et al. 2007). It is testing the hypothesis that *k* independent samples belong to the same population without specifying their common distribution function. The test is based on the comparison between local and regional empirical distribution functions and the AD statistic is obtained via bootstrap (Viglione et al. 2007).

The two statistics are computed from the regional sample of heavy rainfall events exceeding 100 mm and indicate an homogeneous region, with *AD*= 66.07 and *HW*=0.32 with the critical values of the two tests at the 5% level being respectively 69,99 for the AD test and 3.09 for the HW test). The two tests also report a homogeneous region at the 1% significance level. It must be noted that these procedures are devised for stationary data; they have been adapted by Cunderlik and Ouarda (2006) or Hanel et al. (2009) to the non-stationary case.

4 RESULTS

4.1 Analysis of heavy rainfall events

With the regional sampling approach described above, the sample of heavy rainfall events includes 168 events, ranging from 100 mm to 543 mm, the largest event occurred in September 2002 and is documented in several studies (Delrieu et al. 2005, Lebeaupin et al. 2006, Nuissier et al. 2008). Figure 4 shows the temporal distribution of the events. A slight increase in the number of the most extreme rainfall events can be observed after 1980. The first event to exceed 300 mm occurred on November 7th 1982, with a daily rainfall of 315 mm. Only five events exceeding 300 mm of rainfall have been observed between 1982 and

2008, none prior 1982. This finding suggests an increase in the heaviest rainfall events, in terms of magnitude, for the recent past. However, the non-parametric Mann-Kendall (Mann 1945) trend detection test was applied to the regional sample and no significant trend was detected in the event magnitudes, at the 5% or 10% significance levels. Similarly, no significant trend was detected in the number of occurrences per year during this period.

The frequency of occurrence of heavy rainfall events for each weather patterns of the EDF-2006 classification is shown in Figure 5. It can be seen that most of the heavy rainfall events (82%) occurs during WP4 (South Circulation) and WP7 (Central Depression). WP4 accounts for 113 (67%) of the events recorded and WP7 for 25 events (15%). These two patterns represent a southerly low level flow, which is the typical synoptic situation associated with high intensity precipitation events described in previous studies (Sanchez-Gomez and Terray 2005, Joly et al. 2007, Nuissier et al. 2008). This indicates that the EDF-2006 classification is able to discriminate adequately the synoptic situations associated with heavy rainfall in the south of France. Figure 6 shows the empirical cumulative distribution plot for the events associated with WP4, WP7 and the other Weather Patterns. The events associated with WP7 have a slightly higher median, 149 mm, than the median of the events associated with WP4, 136.5 mm. The median of the events associated with the other Weather Patterns (WP1, WP2, WP3, WP5 and WP6) is 145 mm. The non-parametric Kolmogorov-Smirnov (Darling 1957), test for the equality of probability distributions can be used to compare two samples, by computing the maximum difference between the two empirical cumulative distribution functions. Results indicate that at a 5% significant level, the null hypothesis cannot be rejected, therefore the events associated with the different Weather Patterns are assumed to belong to the same distribution.

There is a positive correlation (at the 5% level) between the number of events during the fall season with the frequency of WP4 (with a Spearman correlation coefficient ρ = 0.62) and also with the frequency of WP7 (ρ = 0.5). Increased frequencies of WP4 and WP7 appear to be associated with an increased number of heavy rainfall events. Figure 7 shows the annual number of rainfall events exceeding 100 mm together with the frequency of WP4 in fall, indicating a decrease from 1958 to 1980, followed by an increase during the period 1980 to 2008. A significant correlation (at the 5% significance level) is also found between the magnitude of the events and the monthly mean air temperature (ρ = 0.17), indicating higher intensity of heavy rainfall events during warmer months. Although the correlation is significant, the relationship is highly scattered (Fig.8). As shown on Figure 8, it is the variability in the magnitude of the events that is increasing with higher monthly air temperature.

4.2 A non-stationary POT model for heavy rainfall events

The goal of the present study is to develop a frequency model able to produce future scenarios of the heavy rainfall event distribution; consequently there is a need to include in the model covariates that could be retrieved from GCM or RCM outputs. For this reason, time should not be considered as a valid predictor since there is no evidence that the trends observed in the past would be the same in future climate. However, the use of climatic covariates to produce future predictions is based on the hypothesis that the relationships between heavy rainfall and large-scale fields are unchanged from the present to the future climates (Ricard et al. 2009, Driouech et al. 2010).

The frequency of WP4 (fWP4) is selected as a covariate for the Poisson distribution and provides a significant deviance score of D=14.31 when compared to a stationary model (the critical value is D=3.84). For the scale parameter of the GP distribution, the monthly air temperature (TEMP) is selected as a covariate. Any event during the same month would then be associated with the same value of the covariate. The deviance test result, with D = 5.8, also indicates an improvement by comparison to a stationary model without covariate information. In the case of a stationary POT model, the seasonal occurrences of heavy rainfall events are modelled with a Poisson distribution with λ_s = 0.035 and the magnitudes with a GP distribution with α_s = 54.07 and κ_s = 0.06. For the non-stationary case, the distribution parameters λ_{ns} and α_{ns} can be computed as functions of the covariates to calibrate the parameters a_i and b_i in these functions. The obtained fitted relationships are:

$$\lambda_{ns}(fWP4) = \exp(0.29\, fWP4 - 3.36) \qquad (7)$$

$$\alpha_{ns}(TEMP) = \exp(0.05 TEMP + 3.12) \qquad (8)$$

The value of the shape parameter for the non-stationary GP distribution with the covariate TEMP is similar to the value obtained for the stationary model, with κ_{ns} = 0.055. With this type of frequency model, it is possible to compute quantiles corresponding to different probability of exceedances as a function of the time-dependent covariates. The risk of heavy precipitation events can then be assessed on a seasonal basis for the occurrence, and on a monthly basis for the magnitude of the events. Figure 9 show the 24-hour rainfall quantiles corresponding to a non-exceedance probability of 0.98 and 0.99 (equivalent to return periods of 50 and 100 years in the stationary case) computed with the stationary model, and with the non-stationary model. A great range of variability can be seen in the quantiles values computed with the non-stationary model, exceeding 200 mm some years, indicating the effects of taking into account the non-stationarity of climate when computing these probabilities of exceedance commonly used for engineering design such as bridges, highway or flood protection works. The 95% confidence interval limits of the stationary model are not including all the non-stationary point estimates (9% of the non-stationary estimates are outside the 95% confidence intervals limits of the stationary model for p=0.98, 5% for p=0.99), indicating that the non-stationary quantiles are in several cases significantly different than the stationary ones.

4.3 Projections in future climate

Some recent studies provided simulations of future climatic covariates using the different IPCC scenarios (IPCC, 2007). The results of Gibelin and Déqué (2003), Somot et al. (2008) and Ricard et al. (2009) indicate a possible increase by +16% of the synoptic situations favouring heavy rainfall events, associated with and increase of SST and air temperature ranging from +2° to +3.5°C. These projections were calculated with the reference period 1960-2002 and the future climate simulations for 2070-2099, with the IPCC emission scenario A2. As an example of application of the non-stationary model developed, with these projections for the next century it is possible to compute quantiles for the projection period 2070-2099. In Figure 10 are shown the quantiles corresponding to the probabilities of exceedances ranging from 0.1 to 0.99, using a stationary model or two non stationary models considering the hypothesis of an increase by 16% of the frequency of WP4 with an increase by 2°C or 3.5°C in the mean air temperature in fall. By comparison with figure 9, in this case the non-stationary curves refer to an average increase of the frequency of WP4 and air temperature for the period 2070-2099 compared to the reference period 1960-2002. If seasonal projections of the WP4 patterns in the period 2070-2099 were available, it could be possible to assess the year-to-year variability around the average non-stationary curve, similarly to what is shown in Figure 9.

The quantiles obtained using the three different models are different as seen in Figure 10. On average, the quantiles obtained with a non-stationary model, considering the hypotheses of an increase of the frequency of WP4 by 16% with a +2°C increase in the air temperature, are 9% higher than the quantiles obtained with a stationary model. If the same non-stationary model is used to compute the quantiles with the hypothesis of an air temperature increase by +3.5°C, the obtained quantiles would be in average 16% higher than the quantiles of the stationary model. However, the 95% confidence intervals limits for the stationary model in Figure 10 indicate that the projected changes are not significant (at the 5% level); the projected quantile values remain within the confidence interval of the stationary quantiles estimates. It must be noted that here we do not refer to the scenario uncertainties but only to the statistical inherent uncertainties of the developed model. Overall, the statistical uncertainty is high and this might be caused by the small sample size and the high inter-annual variability of precipitation extremes in Mediterranean regions.

6 SUMMARY AND CONCLUSIONS

In the present study a non-stationary POT model incorporating climatic covariates has been developed for the heavy rainfall events occurring in the French Mediterranean Region. The non-stationary model proposed a better fit to the observed data than a classical stationary POT model, according to the Deviance statistical test. The main conclusion that could be drawn from the present study is that accounting for the non-stationarity signal in the frequency analysis of heavy rainfall events with climatic covariates can help understand the relationships between extreme events and other climatic parameters. The model developed includes explanatory covariates in order to possibly re-assess the risk of extreme precipitation on a monthly or seasonal basis. The non-stationary POT model includes as covariates the seasonal occurrence of southern circulation patterns (WP4 in the EDF-2006 classification) for the

Poisson distribution parameter and monthly air temperature for the GP distribution scale parameter. The proposed model provides an improvement by comparison to a non-stationary model with time as a covariate, since the use of climatic covariates allows taking into account the non-linear climatic fluctuations.

The main advantage of using a non-stationary model with climatic covariates instead of time-dependent distribution parameters is the possibility to produce scenarios of future evolution for the heavy rainfall events. However, the use of climatic covariates to produce future predictions is based on the stationary hypothesis implying that the relationships observed in the past between heavy rainfall and large-scale fields, such as synoptic patterns or air temperature, remain unchanged in the future climate. Various scenarios are available, providing different hypothetical future climates from climate models. A first example of application of the non-stationary model developed using available scenarios has been presented in the present paper. Although since many climatic simulation are becoming available, there is a need to conduct further studies to test different scenarios and model outputs, in order to better evaluate the range of uncertainties.

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TABLES

Table 1: Model parameters for the stationary and non-stationary cases (x_i is a covariate, *a* and *b* constants to be estimated)

Model parameters:	Occurrence (Poisson distribution)	Magnitude (Generalized Pareto distribution)
Stationary model (M_0)	λ	α,κ
Non-stationary model (M_1)	$\lambda(t)=exp(ax+b)$	$\alpha(t)= \kappa / exp(ax+b)$

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Figure 1: EDF-2006 synoptic circulation patterns classification (from Garavaglia et al., 2010)

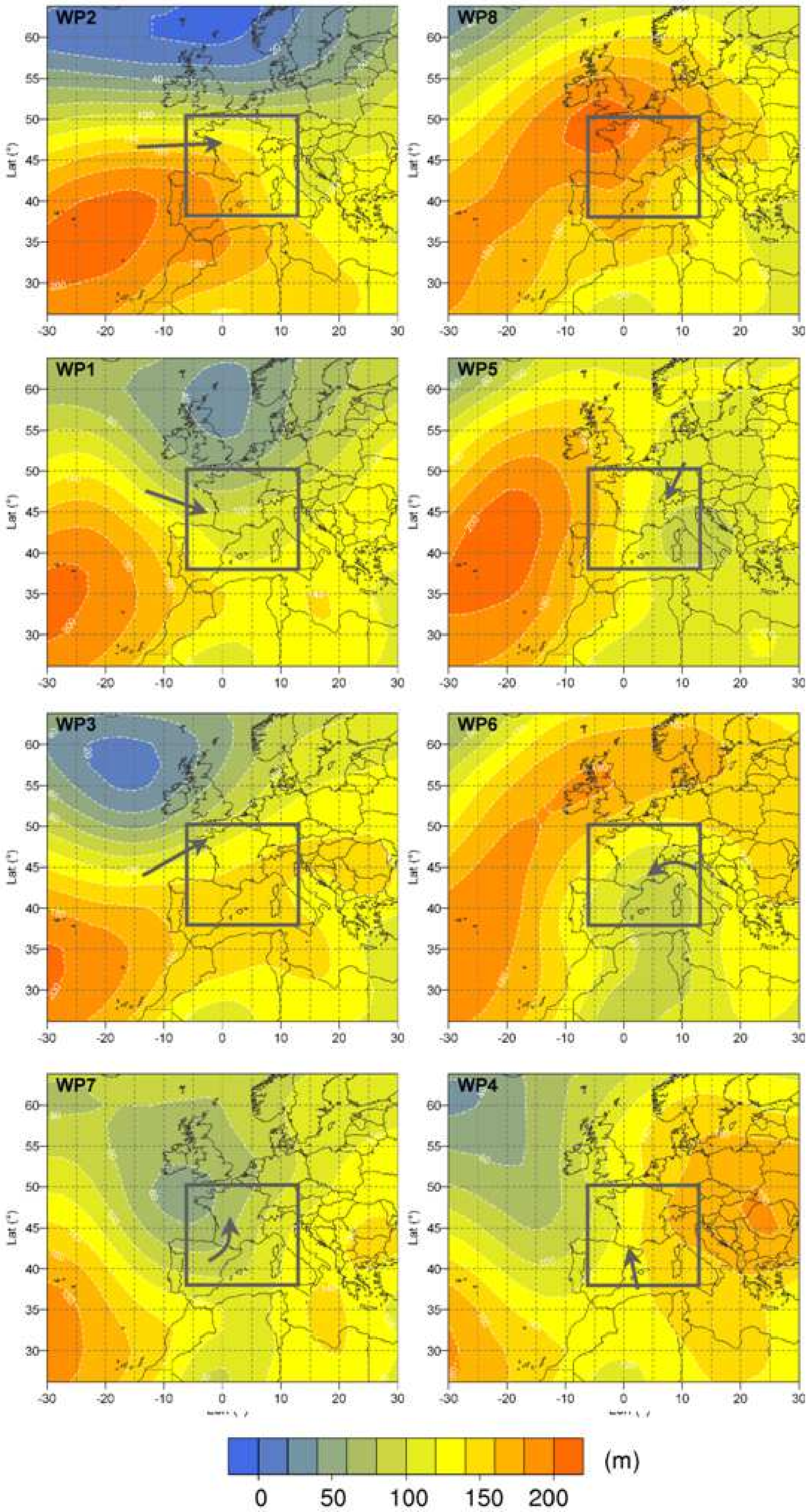

Figure 2: Location of the 44 meteorological stations

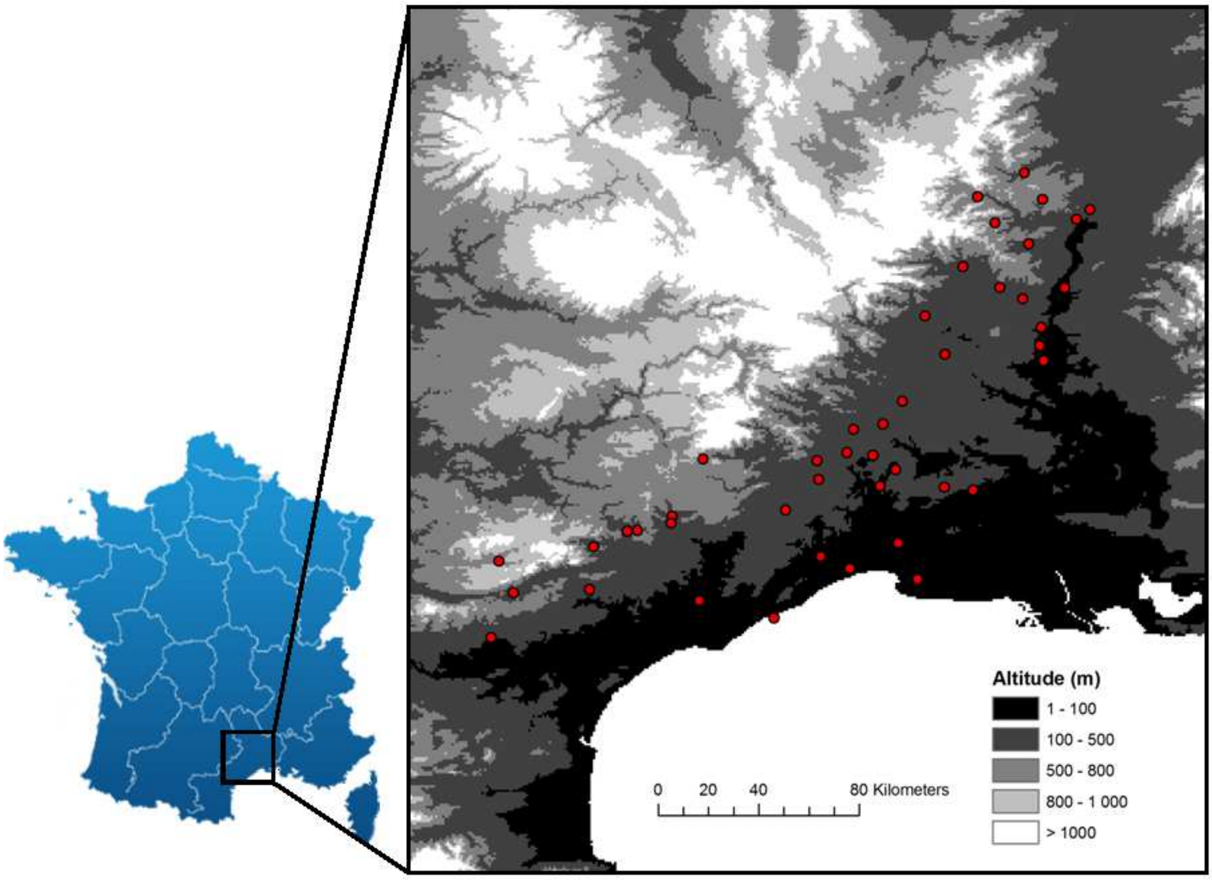

Figure 3: Mean excess plot (left) and sensitivity of the GP scale and shape parameters (right) to different threshold values

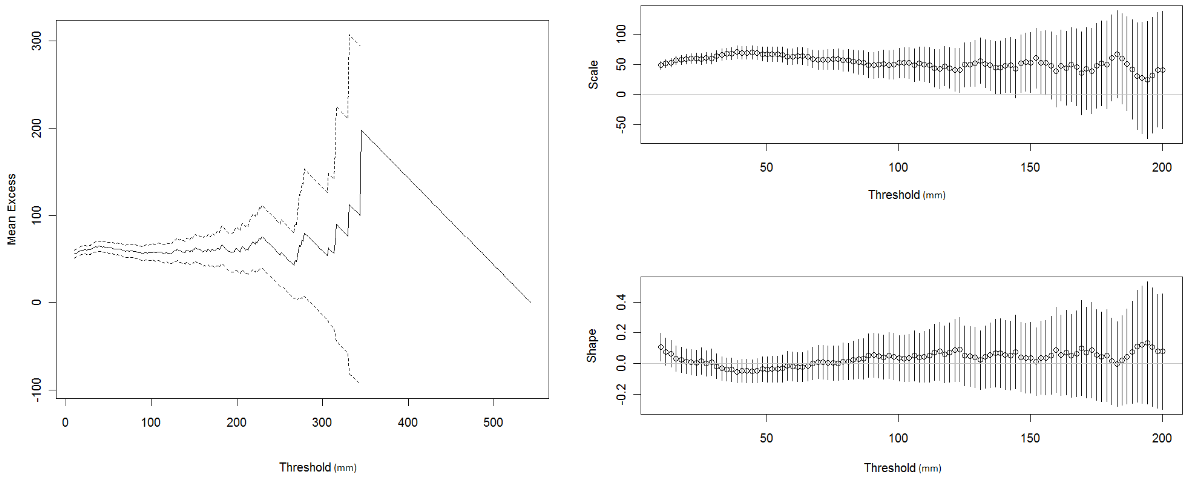

Figure 4: Heavy rainfall events exceeding 100m in fall between 1958 and 2008

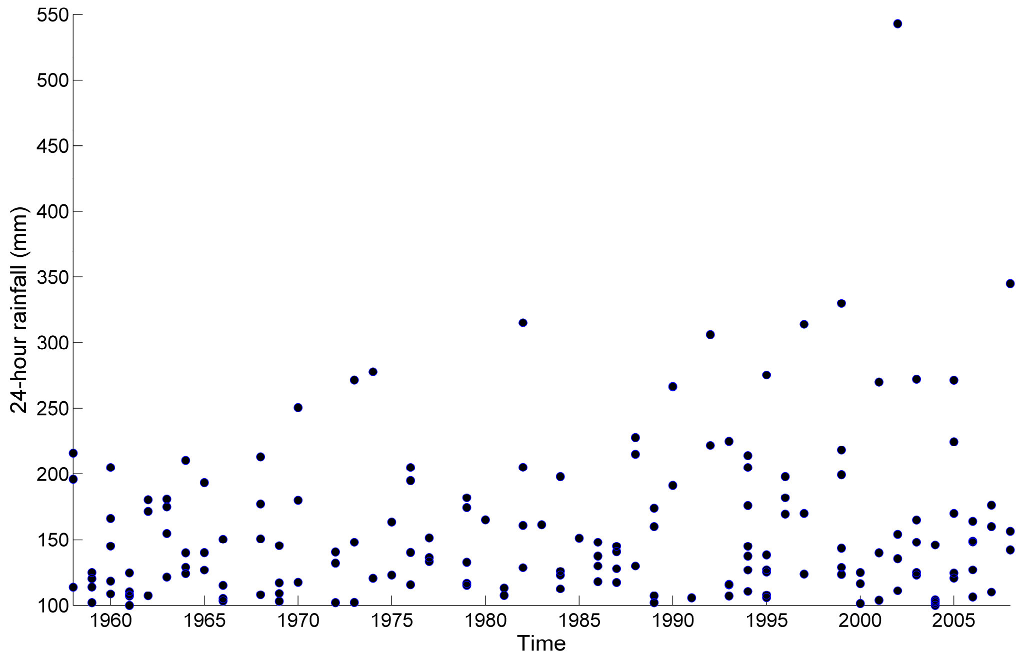

Figure 5: Frequency of heavy rainfall event for each of the weather patterns from the EDF-2006 classification

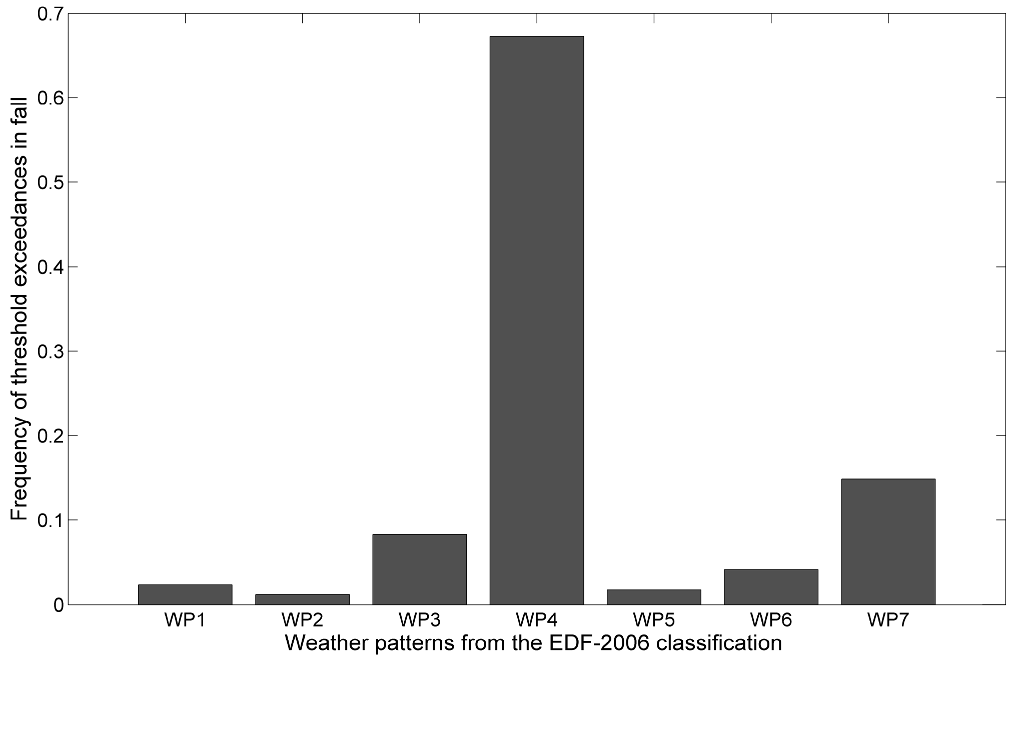

Figure 6: Cumulative empirical probability plot of the heavy rainfall events associated with WP4, WP7 and the remaining Weather Types (WP1, WP2, WP3, WP5, and WP6)

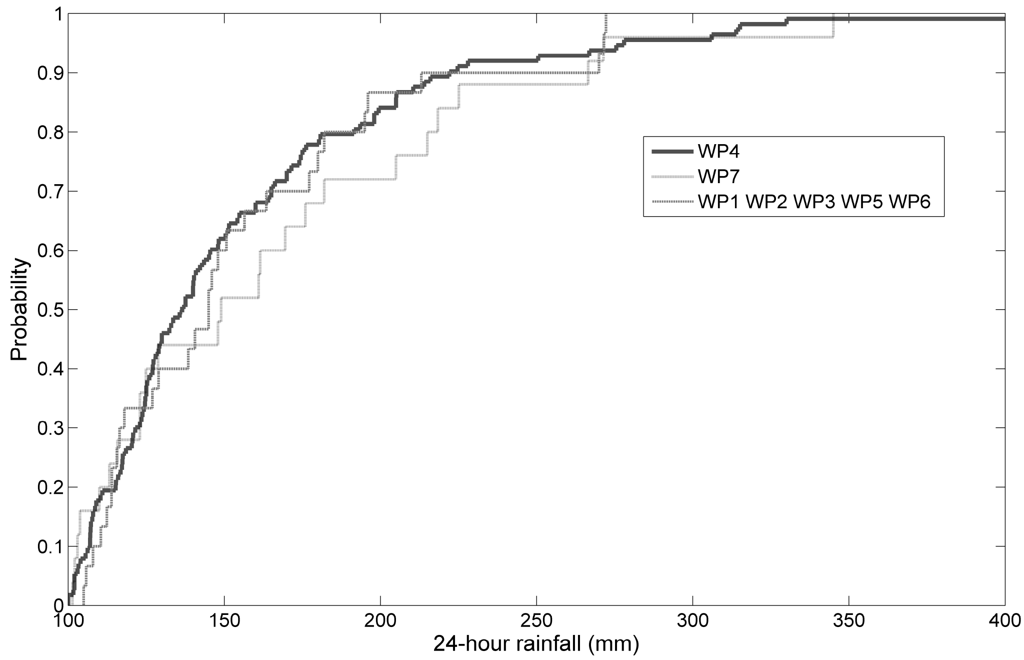

Figure 7: Relationship between the occurrence of rainfall events exceeding 100mm and the frequency of WP4 in fall

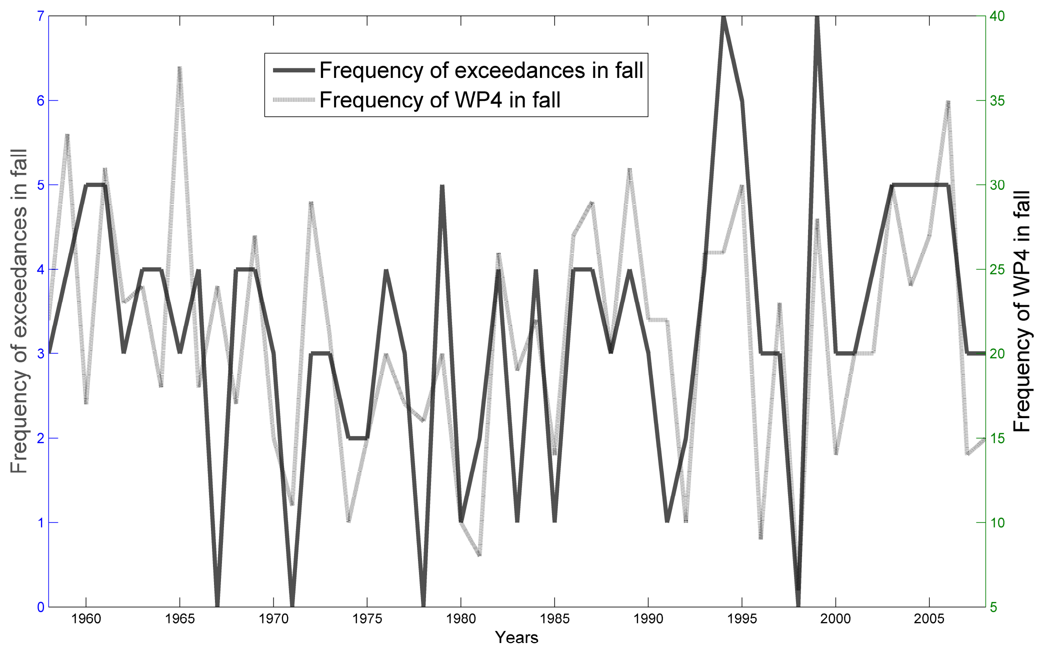

Figure 8: Relationship between the magnitude of rainfall events exceeding 100mm and mean monthly air temperature

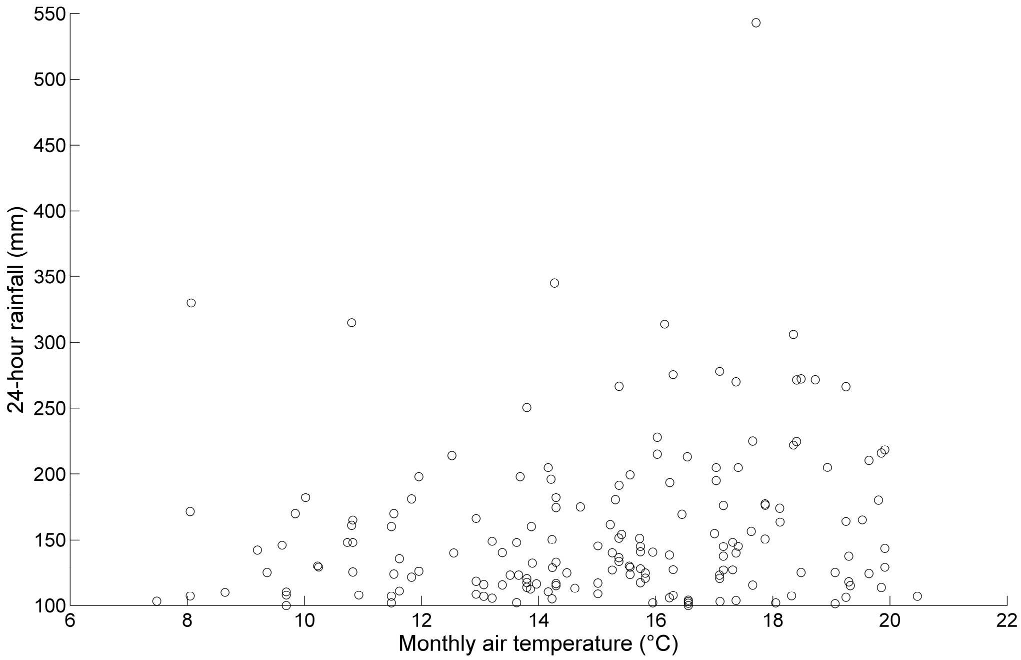

Figure 9: Extreme rainfall quantiles computed with the stationary and non stationary models for the probabilities of non-exceedance 0.98 and 0.99 with their 95% confidence intervals (CI_{NS} stands for the confidence intervals of the non-stationary quantiles, CI_S for the confidence intervals of the stationary quantiles)

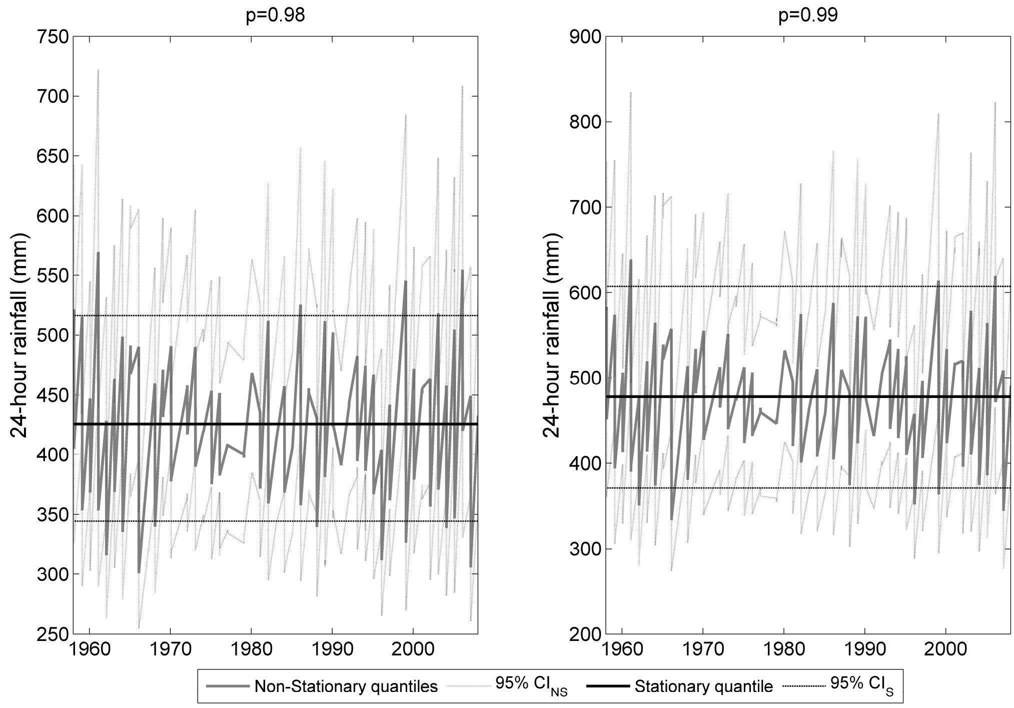

Figure 10: Quantiles corresponding to probabilities of exceedances from 0.1 to 0.99, obtained with a stationary POT model or with two non-stationary POT models, considering the hypotheses of an increase by +16% of the frequency of WP4 associated with an increase in air temperature by 2°C or 3.5°C. The thin black line represents the 95% confidence intervals for the stationary model.