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Changes in climate variability and seasonal rainfall extremes: a case study from San Fernando (Spain), 1821–2000

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With 9 Figures

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Summary

Small changes in the mean and standard deviation values can produce relatively large changes in the probability of extreme events. The seasonal precipitation record in San Fernando (SW Spain) for 1821–2000 is used to investigate how much the relative frequency of dry and wet seasons changes with changes in mean value and standard deviation. The percentiles P10, P25, P75 and P90 of the reference period 1961–1990 are used to define dry and wet seasons. The probability of extreme seasons as function of mean and standard deviation is analysed. The main conclusion is a non-linear relationship between changes in mean and standard deviation values and extreme seasons probability. With these threshold values, the main influence corresponds to changes in mean value. Results are discussed bearing in mind projections of General Circulation Models on future climate in southern Iberian Peninsula.

1. Introduction

Increased concentration of greenhouse gases is expected to alter the radiative balance of atmosphere, causing increases in temperature and changes in precipitation patterns and other variables. One of the most important impacts on society of future climatic changes will be changes in regional water availability. Such hydrologic changes will affect nearly every aspect of human well-being, from agricultural productivity and energy use to flood control, municipal and industrial water supply, and fish and wildlife management. The tremendous importance of water in both society and nature underscores the necessity of understanding how a change in global climate could affect regional water supplies (Chong-Yu Xu, 1999).

The primary impacts of global climate change on society results from extreme events. The focus of earlier climate model studies of global warming was mainly changes in mean climate. It has been only since the early 1990s that climate models have started to be analysed to study possible changes of future weather and extremes (Meehl et al., 2000). To investigate the consequences of climate change on the water budget in small catchments it is necessary to know the change of local precipitation. General Circulation Models (GCM) cannot provide regional climate parameters yet, because of their coarse resolution and imprecise modelling of precipitation (Bardossy and Mierlo, 2000). One of the biggest problems is determining whether extreme events have changed in observed record, and if these changes are consistent with what we may expect from an increase of greenhouse gases (Easterling et al., 2000).

There is increasing concern that one impact of global warming on the Mediterranean region of southern Europe will be changes in the precipitation regime. The region already experiences problems of water supply for agriculture and tourism, and these problems would only be exacerbated by any decrease in precipitation linked to global warming (Palutikof et al., 1999). Statistical models indicate a lengthening of dry spells over Spain under CO_2 doubling conditions (Cubasch et al., 1996). Drought originates from a deficiency of precipitation over an extended period of time, usually a season or more. Therefore, the analysis of droughts can be focused on the precipitation that occurred during a given time interval, like a year, semester, season or month (Henriques and Santos, 1999) and the drought phenomena are studied at a more convenient way using time-scale of months or seasons (Lana and Burgueño, 2000). In many regions of the world, planning agricultural and water management activities is usually done based on probabilities for monthly or seasonal rainfall. Changes in the probabilities for occurrence of monthly or seasonal rainfall amounts will influence the decisions farmers and water managers will take (Lucero, 1998).

The frequency of wet (dry) seasons increases with increasing (decreasing) mean rainfall (Yonetani and Gordon, 2001). In spite of the need to examine how the frequency of extreme events might change as the mean climate changes, attempts to quantify the nature of such relationships at local scale have been rare. Our objective is to address some practical issues regarding the relationship between changes in the mean climate and frequencies of extreme seasons. Results may be useful to test seasonal prediction analysis (Kumar and Hoerling, 2000). In a first approach to study this problem, we analyse seasonal precipitation data from San Fernando, southern Spain, a station normally used to solve homogeneity problems in the region, with one of the longest data series (Section 2). A simple statistical climate change model, based on changes in the location and scale parameters of the distribution function representing the climate variable (Katz and Brown, 1992), is proposed to analyse the variability of the data (Section 3). Afterwards, the relationship between the frequency of extreme seasons and changes in the distribution function is analysed (Section 4). Finally, in Section 5, results are discussed bearing in mind projections on southern Spain climate for the 21th century, and possible future developments in the study are outlined.

2. Data

Rainfall data analysed are from San Fernando (36°27′ N, 5°45′ W, 29,5 m above sea level), and correspond to the period 1821–2000 (Fig. 1). This series was chosen because it is the longest meteorological series in southern Spain, and San Fernando is used as reference station in homogeneity studies in the region (Almarza et al., 1996). Monthly rainfall totals were used to obtain seasonal total rainfall. The agricultural seasons of the year were considered: winter (December, January, February), spring (March, April, May), summer (June, July, August), and autumn (September, October, November). According to the WMO suggestions, the period 1961–1990 was chosen as reference period to establish general statistics and threshold values for seasonal total rainfall. Table 1 summarises the basic statistics of the seasonal series for the reference period.

As can be seen, maximum rainfall occurs in winter, and minimum in summer. Rainfall occurs predominantly between November and April, when the region is normally exposed to the influence of the Atlantic cyclones with their associated fronts. Autumn is also influenced by Mediterranean mechanisms (flows of wet air from the Mediterranean Sea, convective storms), causing higher variability than in winter. Spring is a transition season from winter to summer. The high relative variability of summer rainfall (variation coefficient around 100%) results from the irregular frequency of convective storms in this season. In general, a clear annual cycle can be appreciated.

Of particular interest here are the standardized skewness and standardized kurtosis, which can be used to determine whether the sample comes from a normal distribution. Values of these statistics outside the range of -2 to $+2$, indicate significant departures from normality. In summer and autumn, these parameters are not within the range expected for data from a normal distribution. A more definitive criterion is given by the Kolmogorov-Smirnov test (Lana and Burgueño, 2000). This test is based on the computation of the statistic

$$D = \max\{|Q_i - F_i|\}; \quad i = 1, \ldots, n$$

where Q_i is the value of the empirical distribution for the observation x_i and F_i the theoretical one to be tested, n being the number of observations. If D is equal to or less than $1.36/\sqrt{n}$ ($=0.2483$)

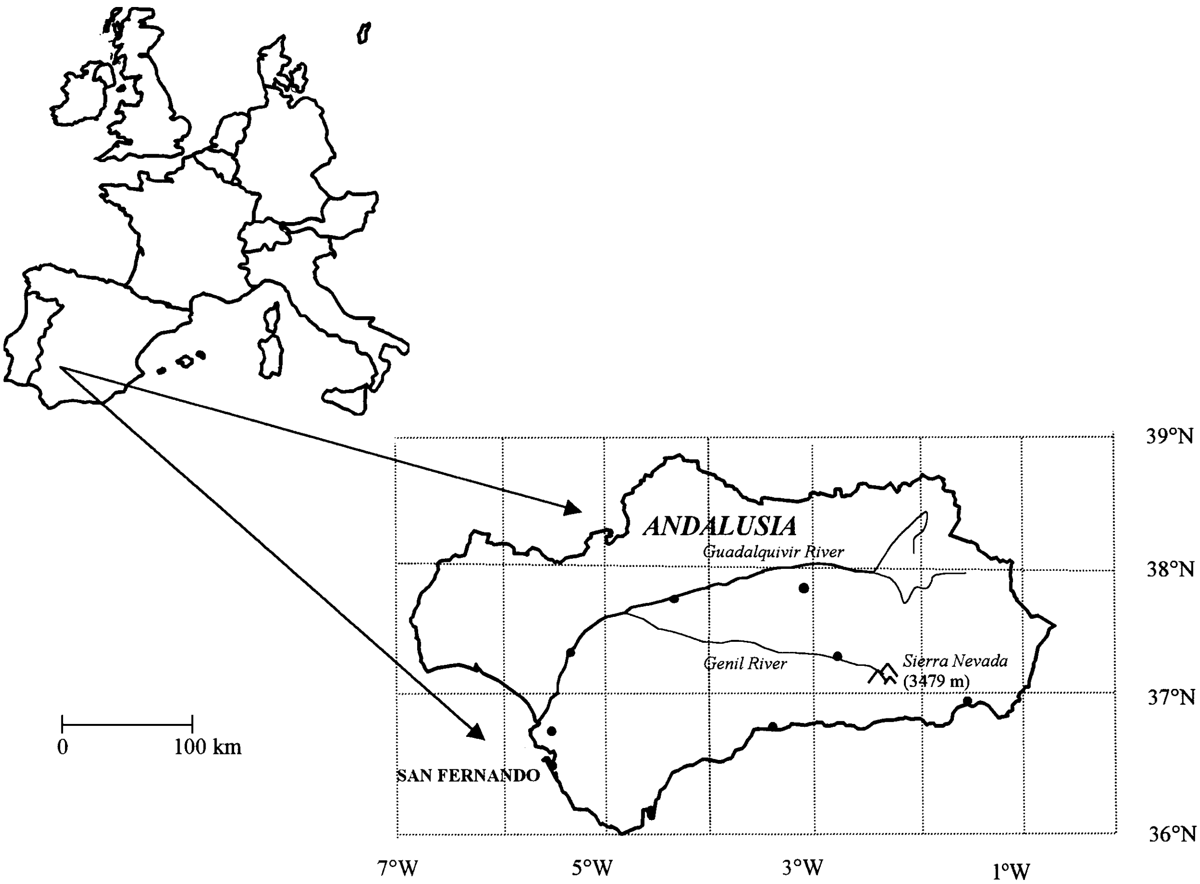

Fig. 1. Map of the study region

Table 1. Statistics of the seasonal rainfall (mm) in San Fernando during the reference period 1961–1990[1]

Parameter	Winter	Spring	Summer	Autumn
Mean	250.4	125.8	19.2	186.9
Standard dev.	116.1	53.5	18.5	119.4
P10	111.6	58.3	2.5	46.5
P25	179.3	81.5	3.4	88.1
P75	322.9	159.7	21.7	260.6
P90	390.4	197.9	47.4	306.6
Skewness	0.9325	0.5137	3.4419	2.5211
Kurtosis	0.3990	– 0.0194	2.6288	2.4762
CV (%)	46.4	42.5	96.4	63.9

[1]Pi: ith percentile, CV: coefficient of variation

the theoretical hypothesis is accepted with a confidence level of 95% (Peña Sánchez de Rivera, 1995). The hypothesis of normality is not inconsistent with the data available in winter ($D = 0.0974$), spring ($D = 0.0897$), and autumn ($D = 0.1285$). In the case of summer, given the special characteristics of this season, positively skewed distribution, the lognormal distribution function, was fitted ($D = 0.1874$).

3. Statistical model for climate change

A given climate variable X has some probability distribution with distribution function

$$F(x) = \text{Prob}\{X \leq x\}$$

possessing a location parameter μ and a scale parameter σ. In the case of F being the normal distribution, the location parameter μ is simply the mean, and the scale parameter σ is simply the standard deviation. Extreme parts of the distribution represent events in the tails of the distribution, that is, values that are far from the mean or the median value of the distribution. Climate change is envisioned to involve a combination of two different statistical operations: (i) the distribution function F is shifted, producing a change in location μ and (ii) F is rescaled, producing a change in σ (Katz and Brown, 1992). If there is a simple shift of the distribution, there will be an increase in extreme events on one end and a decrease at the other. This can occur through a change in the mean. Other aspects of the distribution may also change. For example, the standard deviation may increase, producing changes in extreme events at both ends of the frequency distribution. The mean, standard deviation, and even the symmetry of the distribution may change at the same time, consequently altering the occurrence of extremes in several different ways.

At these time scales, the probability distribution of precipitation amounts tends to be more closely approximating the normal distribution, because of the central limit theorem, which states that under fairly general conditions, the sum of independent random variables approaches normal (Lettenmaier, 1995). Other distributions, such as the lognormal or gamma distribution have often been applied. In our case, as we have seen in analysing the reference period, the normal and lognormal distributions are appropriate to model the data.

In order to analyse the long term variability of the statistical parameters, the complete series was divided into six 30 year periods (1821–1850, 1851–1880, 1881–1910, 1911–1940, 1941–1970, and 1971–2000), and the goodness of fit to a normal (lognormal for summer) distribution was tested. Main statistics of these periods (mean value, standard deviation and Kolmogorov-Smirnov test statistic) are shown in Table 2 for each season. The main result is that all the samples may be fitted by a normal distribution, except summer, where the best fit is with the lognormal distribution.

Table 2. Statistics of the different 30 year periods[1]

Period	Winter	Spring	Summer	Autumn
1821–1850				
$\bar{x}$	241.3	143.1	15.1	165.2
s	127.6	69.1	15.2	83.5
D	0.1133	0.1311	0.2197	0.1214
1851–1880				
$\bar{x}$	286.4	178.3	18.6	246.5
s	130.1	77.7	19.4	123.4
D	0.1296	0.1778	0.1636	0.2085
1881–1910				
$\bar{x}$	223.1	186.5	14.4	200.2
s	99.3	105.5	15.8	96.1
D	0.1314	0.1384	0.1209	0.1182
1911–1940				
$\bar{x}$	250.0	147.0	16.6	176.9
s	96.8	64.9	38.5	82.4
D	0.1538	0.1756	0.1231	0.0904
1941–1970				
$\bar{x}$	259.6	142.4	16.2	192.2
s	123.5	55.9	19.4	126.4
D	0.1293	0.0758	0.1989	0.1785
1971–2000				
$\bar{x}$	242.7	119.7	15.4	159.4
s	124.8	53.6	22.2	92.3
D	0.0922	0.0829	0.1523	0.1133

[1] $\bar{x}$: mean value (mm); s: standard deviation (mm); D: Kolmogorov-Smirnov statistic

Tested the normality of the different distributions, low frequency climate change in seasonal rainfall may be characterised as a shift of the distribution (change in the mean value), change in the standard deviation, or both change in mean and standard deviation. In summer, the lognormal distribution can be obtained from the normal distribution via transformation, therefore the procedure is similar. F test was done to compare variances, and t-test for difference between means to compare mean values (assuming equal or not equal variances when it was necessary). When the interval for ratio variances (difference between means) contains the value 1 (0) there is not a statistically significant difference between the standard deviation (means) of the two samples at the 95% confidence level. Results in Table 3 show statistically significant difference between the means of the 1851–1880 and 1881–1910 winters, 1821–1850 and 1851–1880 autumns, and between the standard deviations of the 1881–1910 and 1911–1940 springs, 1881–1910, 1911–1940 and 1941–1970 summers, and 1821–1850, 1851–1880 and 1911–1940 and 1941–1970 autumns. Although there are few cases to establish definitive conclusions, in general may be seen that the different ways of change explained above appear in the analysed data. The period 1851–1880 seems to be wetter in autumn and winter, a decrease of variance during 1911–1940 is detected in spring, and an increase of variance during 1941–1970 in autumn is detected. Figure 2 shows the density traces of the empirical distributions corresponding to some of these situations.

Table 3. Confidence intervals (95%) for the ratio of variances (V) and difference between means (M) of different 30 year periods

Periods	Winter	Spring	Summer	Autumn
1821–1850 1851–1880	V: [0.5, 2.0] M: [– 111, 21]	V: [0.4, 1.7] M: [– 73, 3]	V: [0.3, 1.3] M: [– 12, 6]	V: [0.2, 0.9]* M: [– 136, – 27]*
1851–1880 1881–1910	V: [0.8, 3.6] M: [4, 123]*	V: [0.3, 1.1] M: [– 56, 40]	V: [0.7, 3.2] M: [– 5, 13]	V: [0.8, 3.5] M: [– 11, 103]
1881–1910 1911–1940	V: [0.5, 2.2] M: [– 33, 69]	V: [1.3, 5.5]* M: [– 6, 85]	V: [0.1, 0.4]* M: [– 18, 13]	V: [0.6, 2.9] M: [– 23, 70]
1911–1940 1941–1970	V: [0.3, 1.3] M: [– 112, 3]	V: [0.6, 2.8] M: [– 27, 36]	V: [1.8, 7.8]* M: [– 16, 16]	V: [0.2, 0.9]* M: [– 71, 40]
1941–1970 1971–2000	V: [0.5, 2.1] M: [– 47, 81]	V: [0.5, 2.3] M: [– 6, 51]	V: [0.4, 1.7] M: [– 9, 13]	V: [0.9, 3.9] M: [– 24, 90]

*: Significant difference at 95% confidence level

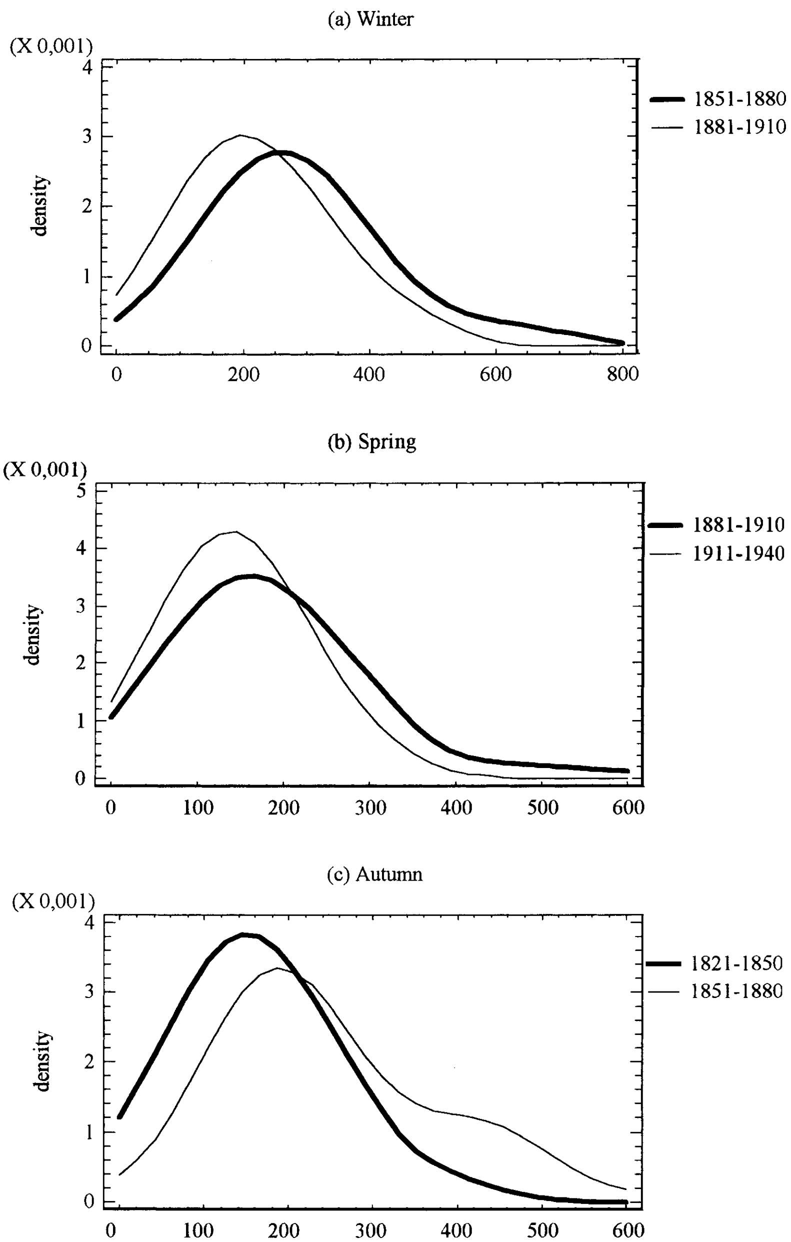

Fig. 2. Density traces of empirical data for different ways of change: (**a**) change in the mean value; (**b**) change in variance; (**c**) change in mean value and variance

Assuming the Gaussian behaviour of the seasonal total rainfall, the next step is to characterise the frequency of dry/wet seasons when the mean μ and/or the standard deviation σ change. Investigators have often used different criteria to define an extreme climate event. Drought is one of the main problems related to water supplies in southern Spain. Arranging precipitation data into deciles is an useful drought-monitoring technique. This technique requires a long climate record, but provides an accurate statistical measurement of precipitation, and requires less data and assumptions than, for instance, the Palmer Drought Severity Index (Smith et al., 1993). The criterion currently followed to characterise very dry, dry, normal, rainy, and very rainy seasons in Spain is taking into account the percentiles P10, P25, P75 and P90 (García de Pedraza and García Vega, 1989). Therefore, to establish the character of dry (wet) seasons we chose as threshold values the percentiles P10 and P25 (P75, P90) of the reference period 1961–1990 (Table 1). When seasonal total rainfall P is lower (higher) than P10, P25 (P75, P90) we characterise the season as dry (wet). The theoretical behaviour of the relative frequency f of dry/wet seasons may be estimated by the relations

$$f(P \leq P_i) = F(P_i) \qquad i = 10, 25$$

$$f(P > P_i) = 1 - F(P_i) \quad i = 75, 90$$

Using as example the percentile values corresponding to winter, the theoretical behaviour of the relative frequency of dry (wet) seasons is shown in Fig. 3, Fig. 3a showing the behaviour of the relative frequency of dry and wet seasons with changes in the mean value and constant standard deviation (116.1 mm, corresponding to the reference period), and Fig. 3b showing the behaviour with changes in standard deviation and constant mean (250.4 mm, corresponding to the reference period). Note that the frequency of extreme seasons changes nonlinearly with the change in the mean of the distribution, that is, a small change in the mean can result in a large change in the frequency of extremes (Mearns et al., 1984). On the other hand, according to Katz and Brown (1992), a change in the variance of the distribution will have a larger effect on the frequency of extremes than a change in the mean, though these events must be "enough" extremes

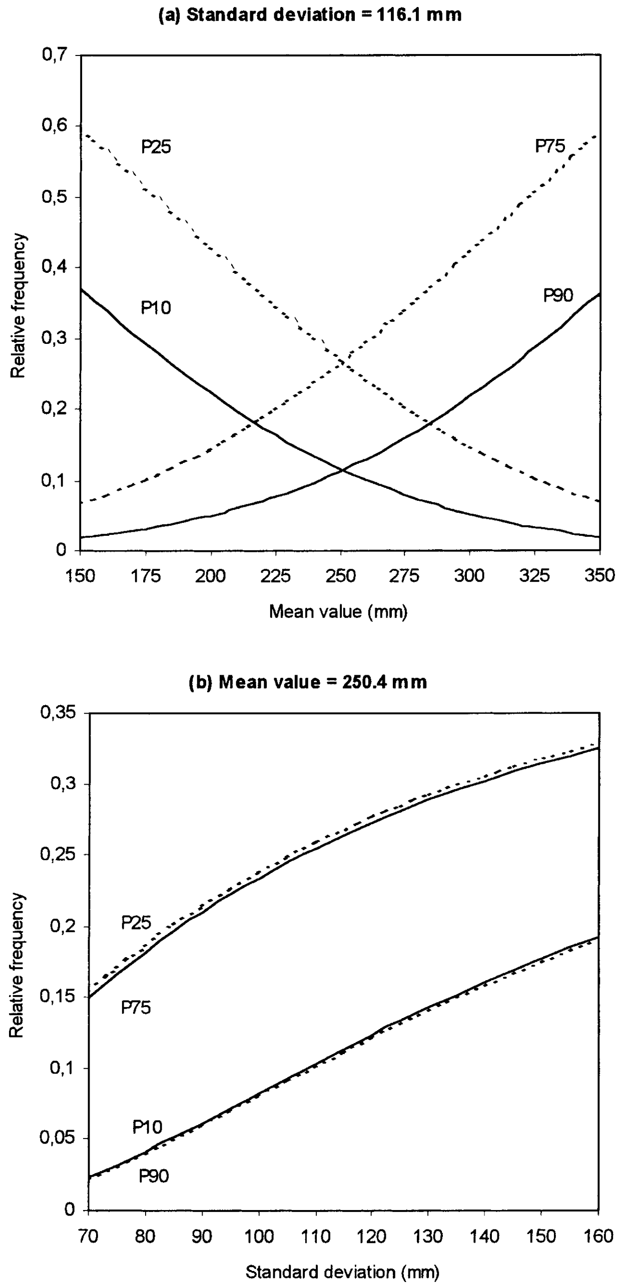

Fig. 3. Theoretical estimations of relative frequency of extreme winters, considering the percentiles P10, P25, P75, P90 of the reference period as threshold values. (**a**) Standard deviation constant; (**b**) Mean value constant

(i.e. more than one standard deviation from the mean). In Fig. 3 the range of mean and standard deviation values was chosen bearing in mind the changes detected in the data. In general, the threshold values given by the percentiles P10 and P90 are approximately one standard deviation from the mean, and therefore the changes in extreme frequency are similar in order of magnitude to those provoked by changes in mean value, although the variation in the last ones is greater. Therefore, with the threshold values chosen, the main impact comes from changes in mean value, more than in the standard deviation. In general terms, frequency of dry (wet) seasons decreases (increases) when the mean value increases, and it increases when the standard deviation increases. Therefore, when the mean value decreases and standard deviation does not change, the frequency of dry seasons must increase, and the frequency of wet seasons must decrease. Thus, for instance, in the case of 1851–1880 and 1881–1910 winters, there was a significant change in mean value, from 286.4 mm to 223.1 mm. The relative frequency of dry seasons increased from 0.03 to 0.13 using the percentile P10 as threshold value, and from 0.20 to 0.40 using P25. On the other hand, the relative frequency of wet seasons decreased from 0.37 to 0.17 using the percentile P75 and from 0.17 to 0.10 using P90.

4. Frequency of extreme seasons

The six not overlapping 30 year periods compared above are few cases to calibrate the suitability of the theoretical estimations. In order to establish a comparison between theoretical and empirical frequencies, the complete series was divided into 150 series, the first one being 1821–1850, the second one 1822–1851, until the last 30 year series 1971–2000. For each series the mean value, standard deviation and relative frequency of dry and wet seasons (according the reference period percentiles) were calculated. Empirical estimates of the probability of extreme precipitation are calculated as relative frequency of events below/above a given threshold. Despite the problems of running means in time series analysis, in this work we are not interested to investigate the time evolution of the series, but the relationship between mean, standard deviation values, and frequencies of extreme seasons. We simply use this technique to construct a large empirical sample. Results are shown in Figs. 4 to 7. Mean and standard deviation values are expressed as percentage with respect to the reference period values. In winter (Fig. 4), a similar behaviour of running mean and standard deviation, is observed with variations of the order of 40% with respect to the reference period, and with higher values of the standard deviation (higher dispersion of the data) corresponding to the periods with high mean value. The frequency of dry winters seems to follow an opposite trend to mean and standard deviation values, and the frequency of wet winters behaves in a similar way, reflecting the result of changes in mean value, but not in standard deviation (Table 3). In spring (Fig. 5), mean value and standard deviation show a behaviour very similar, with very high standard deviation (around 100%) corresponding to the time interval 1866–1895. This is caused by the very high data of 1881, 531.1 mm. The frequency of dry springs is very similar for the two threshold values, reflecting the fact that the reference period 1961–1990 is one of the drier periods in the complete series. In general, the evolution of the frequency of dry and wet springs seems to reflect the influence of the mean value shifts. In summer (Fig. 6), again very high values of the standard deviation (around 120%) are observed in 1915–1944, corresponding to the high summer rainfall (206.9 mm) in 1930. The frequency of dry summers is very similar for the two threshold values, because of the slight differences between P10 (2.5 mm) and P25 (3.4 mm). Finally, in autumn (Fig. 7) variations in mean value and standard deviation are 40% of the reference period values, with similar behaviour of the frequency of dry autumns for the two threshold values (indicating the dry character of the reference period, similar to spring), and an increase of the frequency of dry and wet autumns from 1940, reflecting the influence of changes both in standard deviation and mean value.

The next step in the analysis is to test if the Gaussian model (lognormal for summer) is convenient to analyse the frequency of extreme seasons. The methodology followed was to construct distributions with the mean and standard deviation values estimated by the values corresponding to each one of the 150 empirical series, and to calculate the relative frequency of dry and wet seasons from these theoretical distributions. These frequencies were compared with the empirical values shown in Figs. 4 to 7. Afterwards, the correlation coefficients between empirical and theoretical frequencies were calculated. Results are summarised in Table 4. All the coefficients were significant at the 95% confidence level. For winter, spring

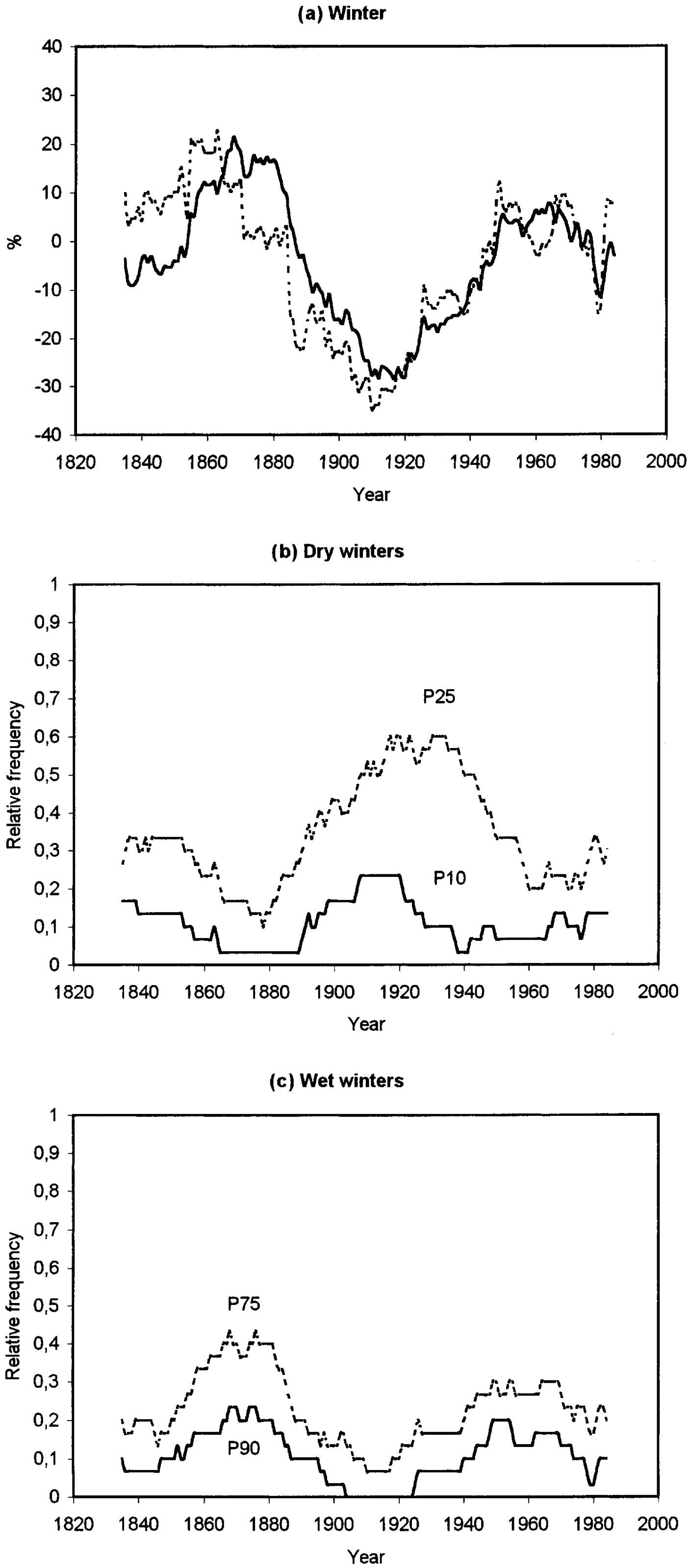

Fig. 4. (**a**) 30 year moving average of the mean (continuous line) and standard deviation (dashed line) for winter; (**b**) Relative frequency of dry winters; (**c**) Relative frequency of wet winters

and autumn, the results corresponding to P10 were worst, basically because of the slight positive skewness of the data and the symmetry of the Gaussian model. In summer, the goodness of the fit to a lognormal distribution allows to obtain the best estimation for this percentile.

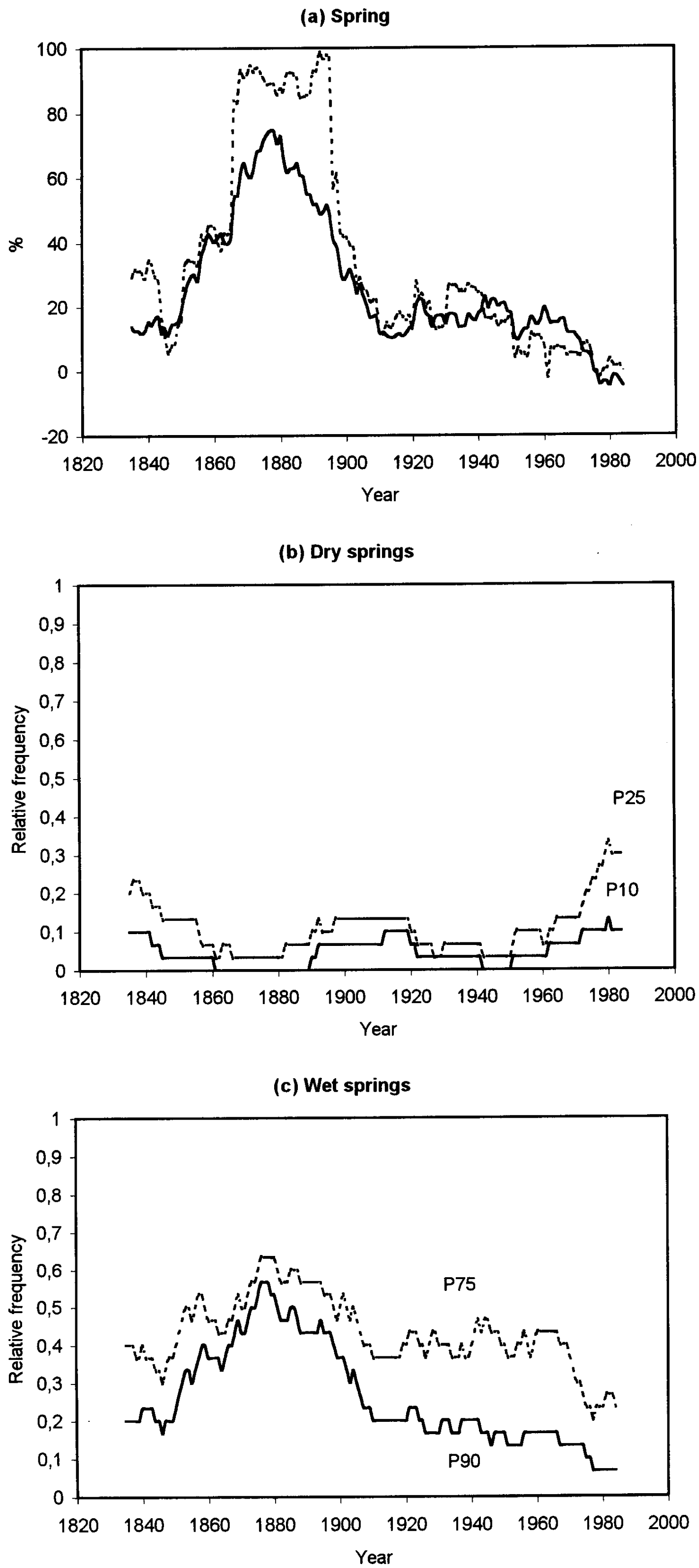

Fig. 5. As Fig. 4 for spring

In winter the best correlation corresponds to the percentile P25, and in spring and autumn to the percentile P90. The statistical significance correlation between the theoretical and empirical frequencies is difficult to estimate, since the level of autocorrelation in both time series has to be very

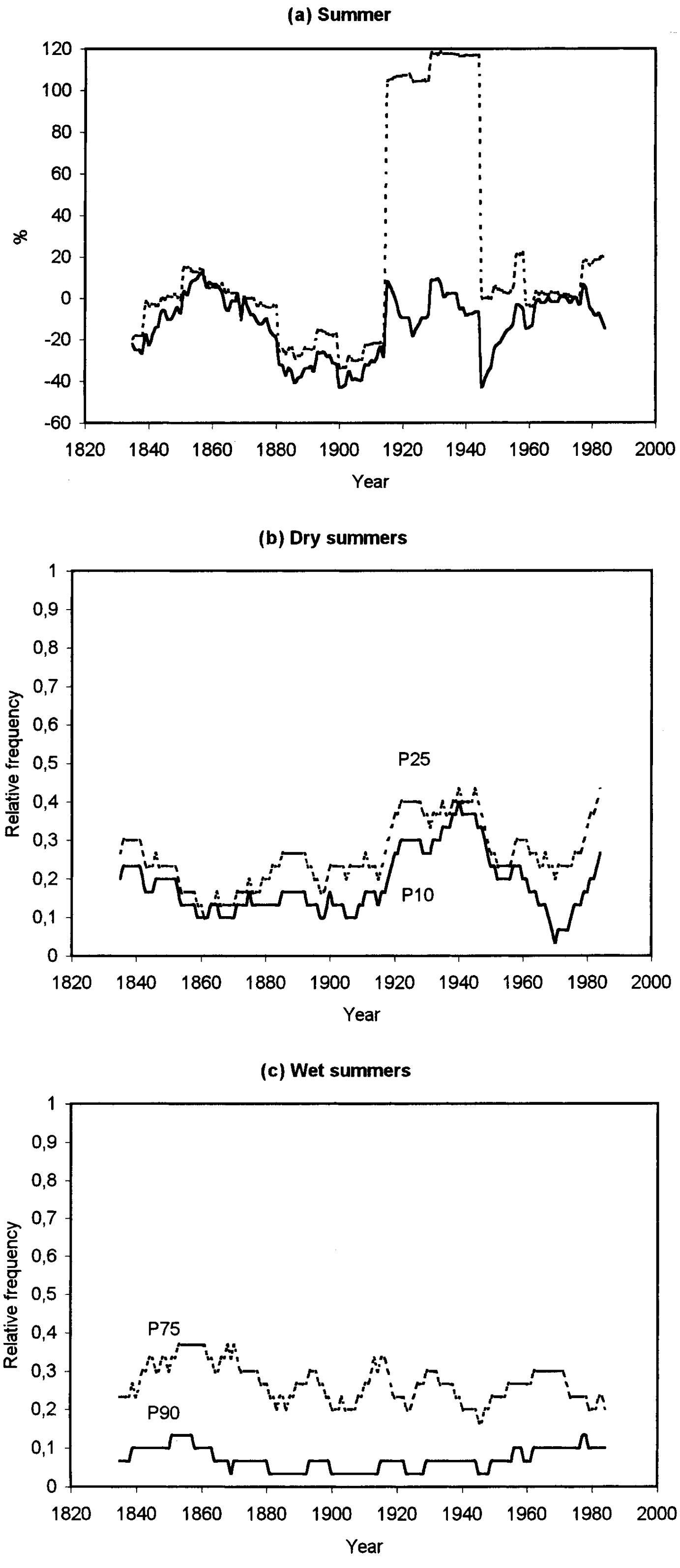

Fig. 6. As Fig. 4 for summer

large. Therefore, to compare model and empirical data, at least from a qualitative point of view, Fig. 8 shows 1:1 diagrams of some selected cases. So, although empirical frequencies for P75 in winter (Fig. 8b) seems to be correctly modelled, in the case of the percentile P25 (Fig. 8a) the theoretical

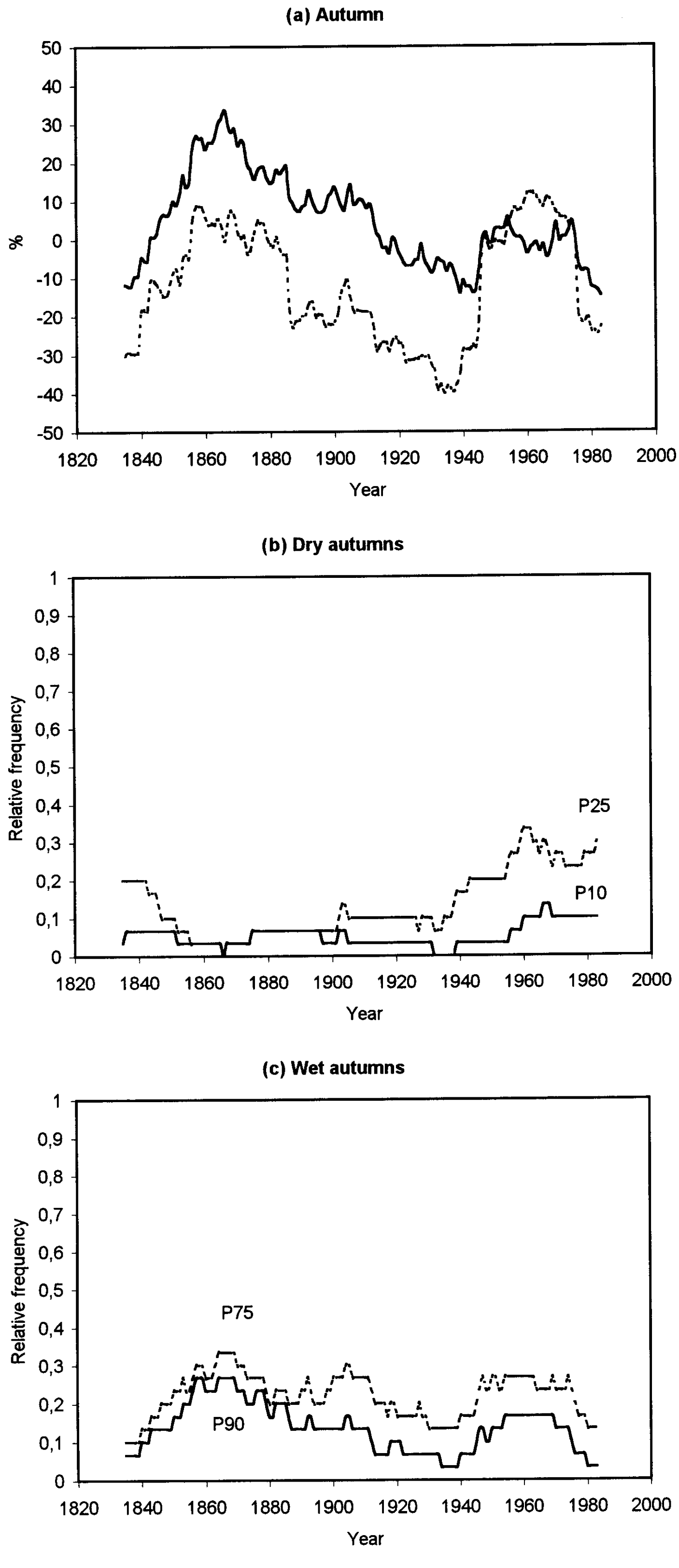

Fig. 7. As Fig. 4 for autumn

frequencies slightly underestimate the empirical data. Similar results are obtained for spring and autumn with the percentile P25 (Fig. 8c, 8e). In relation to the wet seasons, percentile P75 (Fig. 8d, 8f), theoretical results for spring and autumn slightly overestimate empirical data.

Table 4. Correlation coefficients between empirical and theoretical frequencies of extreme seasons

Percentile	Winter	Spring	Summer	Autumn
P10	0.81	0.70	0.81	0.66
P25	0.94	0.83	0.73	0.95
P75	0.90	0.94	0.76	0.89
P90	0.91	0.98	0.74	0.98

In general, theoretical estimations reproduce reasonably good empirical frequencies.

5. Discussion

There are some problems in applying this methodology. First, the reference period 1961–1990 may be not appropriate to establish reliable threshold values to analyse the frequency of extreme seasons, particularly in spring (Fig. 5), when the period 1961–1990 was one of the driest in the total period. However, this period has been used as reference period to accomplish the WMO suggestions, and to maintain the coherence in the study, because it does not present problems in other seasons, as winter. The period 1961–1990 was compared with the 30 years periods from Table 2. The results show that there are no significant differences at the 95% confidence level between mean and standard deviation of 1961–1990 and the other periods for winter. Significant differences were found between mean and standard deviation of the reference period and 1851–1880, 1881–1910 springs, and between the variances of the reference period and 1911–1940 for summer and autumn. Therefore, although slight over-or underestimation may be yielded by the choice of the threshold values, it seems convenient to maintain this reference period. In addition, future projections on climate change, as we will see below, use this period as reference period and express climate changes as percentages of this period values.

Another problem is the choice of the theoretical distribution function to fit the data. Slight departures from normality may yield doubts about the inferences on the frequency of extreme seasons. This is particularly important when the distribution is positively skewed, and the analysis is focused on the P10 percentile (correlations between empirical and theoretical estimations lower than for the other threshold values, Table 4). For variables which are not normally distributed, but better represented by a gamma distribution, the sensitivity to changes in mean and/or variance may be tested analysing the variations in the shape and scale parameters (Groisman et al., 1999). Mean and variance depend on both the shape and scale parameters of the gamma distribution, and it is possible to change those parameters in a way that adjusts the mean while holding the variance constant (Meehl et al., 2000). The extension of the analysis to variables with non normal distributions will be the object of a future work.

Although we have seen that changes in the variance are also detected in data, these changes have less impact on the frequency of extreme seasons, such as they have been defined, using the percentiles P10, P25, P75 and P90 (Fig. 3). Therefore, in the following, we focus on changes in mean value.

Following the criterium given by Wigley (1985), the change in the mean value may be expressed as a multiple of standard deviation of the reference period. Thus, the change C was calculated

$$C = \frac{\overline{X} - \overline{X}_{ref}}{s_{ref}}$$

where $\overline{X}_{ref}$ and s_{ref} are, respectively, the mean value and the standard deviation of the reference period 1961–1990. Based on assumed distribution and constant standard deviation, the sensitivity of the frequency of extreme seasons to changes in the mean is defined as

$$S_i = \frac{F(P_i)}{F^*(P_i)} \quad i = 10, 25$$

$$S_i = \frac{1 - F(P_i)}{1 - F^*(P_i)} \quad i = 75, 90$$

where $F(P_i)$ is the cumulative distribution function corresponding to the new mean value distribution and the percentile P_i, and $F^*(P_i)$ is the cumulative distribution function corresponding to the reference period.

Figure 9 shows the behaviour of this variable for the threshold values P25 and P75, where the symmetry of the curves is due to the symmetry of the normal distribution. The graph is valid for any season, provided that data may be fitted by a normal distribution. Positive (negative) changes

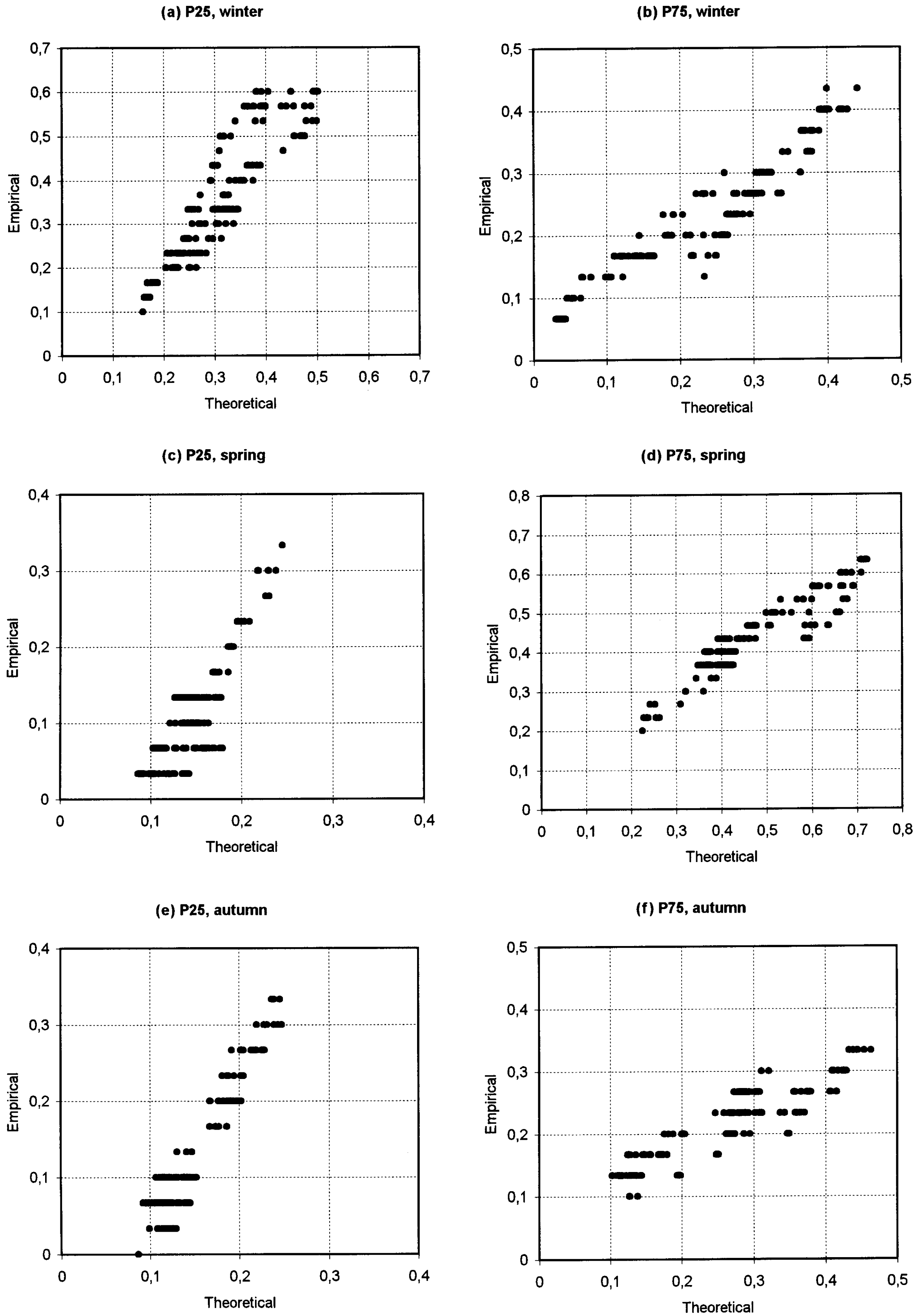

Fig. 8. Comparison between empirical and theoretical estimation of relative frequencies of extreme seasons

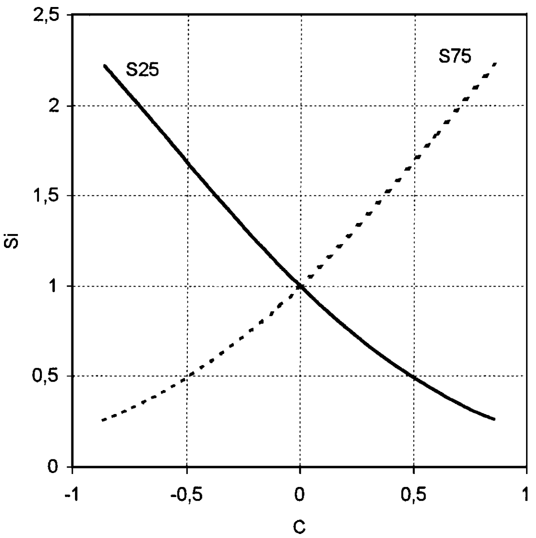

Fig. 9. Sensitivity of the frequency of extreme seasons (threshold values P25 and P75) as function of changes in the mean value

C indicate an increase (decrease) mean value. Changes are lower than 1 standard deviation, indicating that small changes in the mean can produce relatively large changes in the frequency of extreme seasons. Although these are idealised calculations, they do serve to emphasize the importance of extremes and provide a conceptual framework for estimating the impacts of future climate change. In this sense, changes hypothesised in the mean seasonal rainfall from different GCM experiments (Cubasch et al., 2000) indicated that global precipitation increases on the order of 5% within the next 100 years in a "business-as-usual" scenario. On the regional scale, the effects are more drastic. According to these experiments, precipitation increases during the winter season, but decreases during summer in southern Europe. The changes in future for southern Spain for 30 year periods obtained by Hulme and Sheard (1999), are summarised in Table 5. These authors express changes as percentages of the reference period 1961–1990 means. In this sense, note that projected changes are lower than changes detected in data (Figs. 4 to 7). Table 5 shows these figures, the new mean value, and the magnitude of the change such as it has been defined here. In the case of summer, a season with scarce or null rainfall, except dispersed and torrential rains, results indicate less torrential rain events. In any case, decrease in summer rainfall from 19.2 mm in the reference period to 13.2 mm in the period 2061–2090 does not seem very significant. However, changes in winter, spring and autumn may be important because rainfall occurs predominantly in these seasons. In this sense, note that the magnitude of changes in spring and autumn is higher than in winter. So, in 2031–2060, the change in winter is $+0.17$ while changes in spring and autumn are, respectively, -0.24 and -0.23. The sensitivity of extreme seasons (except summer) S25 and S75, corresponding to these changes is shown in Table 6. Results indicate that the frequency of dry springs and autumns is multiplied by a factor 1.36 in 2031–2060, and 1.48 and 1.47 in 2061–2090. If these dry events occurred around 25% of the years in the reference period, this result implies that they will occur in around 30% of the years in future.

Of particular interest are the results corresponding to winter. An increase in precipitation might increase water supplies, but, if associated with increased rainfall intensity, might lead to enhanced erosion rates and soil loss (Palutikof et al., 1999). In fact, GCM results suggest that the simulated changes in means are associated with and mainly effected by a shift towards more frequent heavy precipitation events (Groisman et al., 1999; Frei and Schär, 2001). Therefore, an increase in winter rainfall and decrease in spring and autumn rainfall may have important impacts

Table 5. Changes in precipitation for southern Europe from GCM experiments (Hulme and Sheard, 1999)

	2001–2030			2031–2060			2061–2090		
	%	Mean (mm)	C	%	Mean (mm)	C	%	Mean (mm)	C
Winter	0	250.4	0	+8	270.4	+0.17	+12	280.4	+0.26
Spring	0	125.8	0	−10	113.2	−0.24	−13	109.4	−0.31
Summer	−15	16.32	−0.16	−25	14.4	−0.26	−31	13.2	−0.32
Autumn	0	186.9	0	−15	158.9	−0.23	−19	151.4	−0.30

Table 6. Sensitivity of extreme seasons under assumed mean changes in Table 5

	2031–2060		2061–2090	
	S25	S75	S25	S75
Winter	0.80	1.22	0.71	1.34
Spring	1.36	0.73	1.48	0.66
Autumn	1.36	0.73	1.47	0.67

on land use and water supplies, accelerating desertification process. Unfortunately, seasonal total rainfall is not a variable suitable to analyse this problem. The direct analysis of extremes and the study of theoretical extreme distributions using daily data, will allow to refine this study and obtain a better understanding of the related physical mechanisms.

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