Theor Appl Climatol (2018) 131:1323–1335
DOI 10.1007/s00704-017-2038-4

ORIGINAL PAPER

Evaluation of extreme temperature events in northern Spain based on process control charts

M. Villeta[1] · J. L. Valencia[1] · A. Saá[2] · A. M. Tarquis[2]

Received: 12 July 2015 / Accepted: 10 January 2017 / Published online: 2 February 2017

Abstract Extreme climate events have recently attracted the attention of a growing number of researchers because these events impose a large cost on agriculture and associated insurance planning. This study focuses on extreme temperature events and proposes a new method for their evaluation based on statistical process control tools, which are unusual in climate studies. A series of minimum and maximum daily temperatures for 12 geographical areas of a Spanish region between 1931 and 2009 were evaluated by applying statistical process control charts to statistically test whether evidence existed for an increase or a decrease of extreme temperature events. Specification limits were determined for each geographical area and used to define four types of extreme anomalies: lower and upper extremes for the minimum and maximum anomalies. A new binomial Markov extended process that considers the autocorrelation between extreme temperature events was generated for each geographical area and extreme anomaly type to establish the attribute control charts for the annual fraction of extreme days and to monitor the occurrence of annual extreme days. This method was used to assess the significance of changes and trends of extreme temperature events in the analysed region. The results demonstrate the effectiveness of an attribute control chart for evaluating extreme temperature events. For example, the evaluation of extreme maximum temperature events using the proposed statistical process control charts was consistent with the evidence of an increase in maximum temperatures during the last decades of the last century.

✉ M. Villeta
mvilleta@estad.ucm.es

[1] Facultad de Estudios Estadísticos, Universidad Complutense de Madrid (UCM), Av. Puerta de Hierro 1, E-28040 Madrid, Spain

[2] CEIGRAM (Centre for Studies and Research on Agricultural and Environmental Risk Management). E.T.S. Ing. Agrónomos, Universidad Politécnica de Madrid (UPM), Ciudad Universitaria s.n, E-28040 Madrid, Spain

1 Introduction

The sustainability of an agricultural system depends on many factors, but climate is one of the most critical (Saá et al. 2011b). The evaluation of extreme temperature events is important to the agricultural sector and associated insurance planning because extreme climate events in general, and extreme temperature episodes in particular, have high costs (Gobin 2012). Temperature observations are the primary data set used in climate variability research because they provide both temporal and spatial coverage, unlike other climate parameters (Linkosalo et al. 2009; Moratiel et al. 2011). This has led to a great deal of research on this topic in recent decades, such as the famous IPCC report (IPCC 2007).

Several methodologies have been used for studies of extreme climate events (Coles 2001; Tarquis et al. 2010; Saá et al. 2011a; Valencia et al. 2012; Gobin et al. 2013; García-Cueto et al. 2014; Fioravanti et al. 2015). For example, in the Extreme Value Theory (EVT), it is difficult to accurately estimate the parameters of the Generalized Pareto Distribution (GPD) and the Generalized Extreme Value Distribution (GEVD). Small deviations in these estimates cause major changes in the estimated values of the climate variables (Zea-Bermudez and Kotz 2010a, b; Holešovský et al. 2015). On the other hand, the analysis of extreme quantiles of interest is a simplified technique, which is not sufficient by itself for modelling the changes in the extreme values' distribution. Therefore, a search for new techniques that serve as a complementary alternative and model extreme temperature events

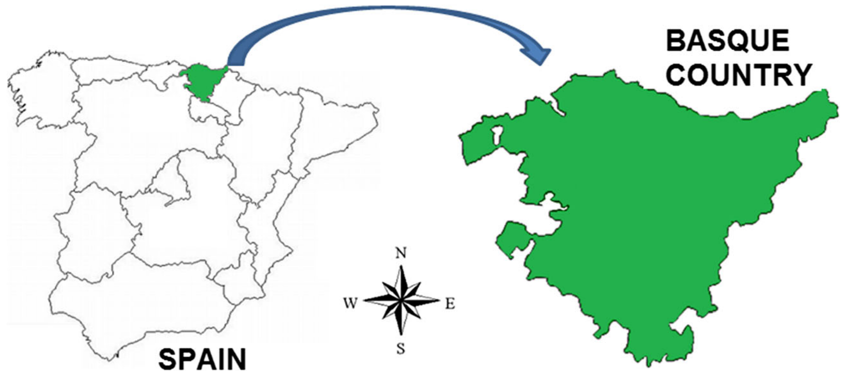

Fig. 1 Location of the Basque Country (Spain)

with greater reliability is useful, as is the methodology proposed in this study.

Statistical process control (SPC) methods, and specifically statistical process control charts (Montgomery 2013), are not commonly used in climate studies. Several authors have applied control charts of variables, mainly the cumulative sum or an exponentially weighted moving average, to detect changes in climate parameters. For example, Smadi (2006) applied cumulative sum control charts to the mean, minimum and maximum temperatures from a meteorological station in Jordan between 1923 and 2003 to detect change points in annual and seasonal temperature oscillations. Cumulative sum control charts were also employed by Smadi and Zghoul (2006) to study the occurrence of rapid changes in the total rainfall and the number of rainy days at a station in Jordan between 1922 and 2003, and they detected an abrupt change in 1957. Chirima et al. (2012) applied cumulative sum charts and exponentially weighted moving average control charts to the mean annual temperatures from a station in Zimbabwe between 1952 and 2001 and demonstrated the effectiveness of both control charts in detecting climate change. Rainfall patterns have also been analysed with cumulative sum charts, for example, by Chu et al. (2012) in southern Taiwan, who concluded that they are an effective tool to detect changes in extreme precipitation. Ramirez-Beltran and Julca (2006) used exponentially weighted moving average charts to detect climate change in the Caribbean since 1995. Other authors have demonstrated the efficiency of mean control charts for evaluating temperature variations in climate studies. For example, Ganguly and Iyer (2009) applied such process control charts to the monthly mean maximum temperatures from March to June in 1901 to 2003 for several Indian regions, and Vuĉijak et al. (2013) applied them to temperatures in Sarajevo, Bosnia and Herzegovina for 1961–1990 and 2000–2010. Vučijak et al. (Vučijak et al. 2014) recently demonstrated the applicability of control charts for individual values to detect changes in rainfall patterns based on a study of several cities in Bosnia and Herzegovina for the same period of time. However, the use of attribute control charts in studies of climate events is unusual. Cuellar (2012) applied conventional attribute control charts to the nonconforming fraction of daily temperatures observed at four meteorological

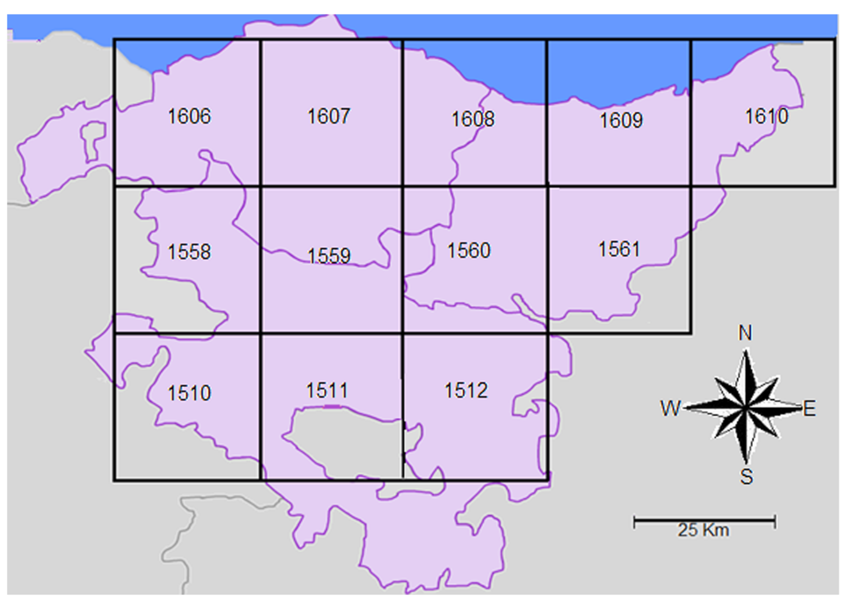

Fig. 2 The 25 km × 25 km grid over the Basque Country (Spain) that defined the 12 studied geographical areas. Each square geographical area has its own identification number

Table 1 Identification of the 12 studied geographical areas

Identification number	Geographical area
1606	Gran Bilbao
1607	Mungía
1608	Ondarroa
1609	Urola
1610	Bidasoa Donostialdea
1558	Cantábrica Alavesa
1559	Nervión
1560	Alto Deba
1561	Goierri
1510	Valles Alaveses
1511	Llanada Alavesa
1512	Montaña Alavesa

stations in central Soria, Spain, between 1931 and 2009. He concluded that the proportion of days with extreme maximum temperatures has increased since the last quarter of the last century.

This study focuses on evaluating the occurrence of extreme temperature events as a discrete process using attribute control charts. Furthermore, because extreme temperature events exhibit autocorrelation (Mearns et al. 1984), this parameter was taken into account in the control chart to prevent a possible increase in false positives (Montgomery 2013). Conventional attribute control charts assume the independence of the observations, so this type of control chart must not be used when autocorrelation exists in the process. For this reason, several authors have attempted to model autocorrelated processes with Markov chains.

Most authors have considered the use of a binomial correlated model to obtain control charts based on the number of conforming units between a certain number of nonconforming units. Lai et al. (1998) established the basis of this type of model with charts of cumulative counts of conforming items (CCC) to detect situations in which the number of conforming units between two nonconforming units is unusually low. Lai et al. (2000) and Shepherd et al. (2007) proposed considering as a variable the number of conforming units until k nonconforming units are produced; where k is a function of the process correlation. Similarly, Shepherd et al. (2012) reduced the number of false positives by establishing additional rules for runs that conclude that the Markov chain of the process is no longer stable. Using a Markov chain with two states, Omey et al. (2008) established the distribution of the count of nonconforming units using an approximation of a normal distribution based on the limit central theorem. Weib (2009) proposed analysing discrete autocorrelated data using a binomial model AR(1). He also proposed an alternative process with binomial marginals, called the BARMA model that was based on the concept of hypergeometric thinning. Minkova and Omey (2014) generated a new binomial distribution related to an interrupted Markov chain.

In contrast, several authors have focused on determining the probability distribution of the count of nonconforming units in a process. Broadbent (1958) suggested the use of conforming and nonconforming states to model the Markov chain of a process. Bhat and Lal (1990) modelled a process with an augmented Markov chain, including the count of nonconforming units that were just produced.

Based on these previous studies and considering that the level of autocorrelation in extreme temperature events is actually quite large, the attribute control chart for the evaluation of such a process must be based on a determination of the probability distribution of the number of extreme temperature days that occurred in a year (the count of nonconforming units in the process). Furthermore, a more accurate model than that proposed by Bhat and Lal (1990) should be used because the persistence of consecutive days with extreme temperatures is actually higher than was stated in their model, as shown in the methodology section. Thus, their Markov chain model was extended to five states.

The aim of this study was to evaluate extreme temperature events using statistical process control charts and determine the probability distribution of the number of extreme days in a year using a more accurate model of this climate process with a Markov chain. To determine the efficiency of the proposed evaluation method, it was applied to a geographical region. To achieve these objectives, a procedure that combines the implementation method of attribute control charts, the autocorrelation between extreme temperature events, a new Markov binomial extended distribution, and big data processing was designed and applied to a region of northern Spain.

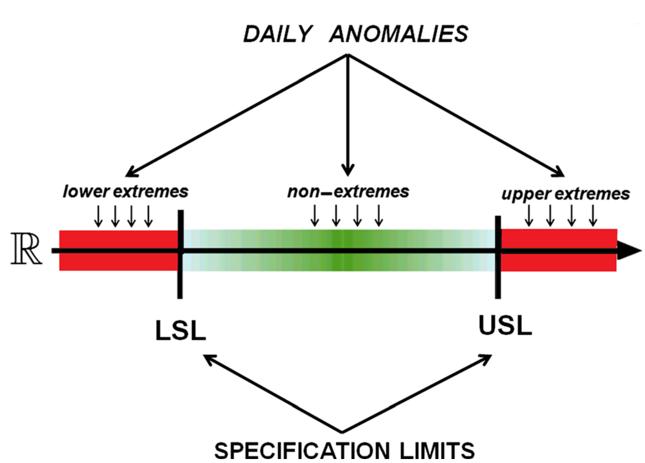

Fig. 3 Daily temperature anomalies: upper extremes and lower extremes

2 Data set and methods

The proposed methodology was applied to Basque Country, a region located in northern Spain adjacent to the Pyrenees and the Cantabrian Sea (Fig. 1). The northern part of this region is part of Green Spain, where the climate is predominantly oceanic with a constant humidity and moderate temperatures in both winter and summer. The central and southern areas in the Basque Country have a Mediterranean-continental climate but are still influenced by the oceanic climate of the north, which results in warm dry summers and cold and snowy winters. The annual average rainfall is 1200 mm, and autumn is the rainiest season.

2.1 Climate data

The climate data that was used in this study consisted of 12 complete series of daily average minimum and maximum temperatures. Each series was obtained by a kriging interpolation of a 25 km × 25 km grid by the Servicio de Desarrollos Climatológicos of the Meteorological Spanish State Agency (Sotillo et al. 2006; Luna and Almarza 2007; Luna et al. 2008; Valero et al. 2009). The series spans a period of 79 years from 1931 to 2009 and covers approximately all of Basque Country. The locations of the 12 square geographical areas are shown in Fig. 2. Table 1 identifies these geographical areas, and the associated identification numbers of the grid are in Fig. 2, which describes the region from west to east and from north to south.

2.2 Novel methodology

The procedure used to evaluate the occurrence of extreme temperature events via control charts is based on similar processes that distinguish between chance and assignable causes of variation (Shewhart 1931). Climate processes are assumed to have inherent, natural or common causes of variation (a process in statistical control), but assignable or special causes that impact the climate process occasionally occur, causing unusual levels of variability and are responsible for process shifts (an out of control process). The control charts aim to detect the occurrence of these assignable causes, so to understand the climate model of a chance or natural variable pattern, a reference time period is selected (Phase I of the control charts) and is used to estimate the variability model (an in-control process). The control chart is then established based on this model. The control chart and decision rules that are defined for the process allow the climate process of extreme temperature events to be monitored for a period of time, which is called the monitoring period (Phase II of the control charts). In the case where assignable causes for process variations of extreme events during the monitoring period are not detected, the observed variability is statistically expected to be related to the model that was determined in the reference period. If assignable causes for process shifts of extreme events are detected during the monitoring period, it is concluded that the observed variability changed with respect to the model that was determined in the reference period.

The proposed methodology is summarized as follows. First, to remove the stationarity of the daily temperature series, daily maximum and minimum temperature anomalies for each day (i) and each year (j) are defined for each of the 12 geographical areas as described in Eq. (1):

$$\mathrm{Anomal}_{\mathrm{Tmax},i,j} = \frac{\left(\mathrm{Tmax}_{i,j} - \overline{\overline{\mathrm{Tmax}_{\mathrm{i}}}}\right)}{\widetilde{\sigma}_{\mathrm{Tmax}_i}} \qquad \mathrm{Anomal}_{\mathrm{Tmin},i,j} = \frac{\left(\mathrm{Tmin}_{i,j} - \overline{\overline{\mathrm{Tmin}_i}}\right)}{\widetilde{\sigma}_{\mathrm{Tmin}_i}} \tag{1}$$

where $\mathrm{Tmax}_{i,j}$ and $\mathrm{Tmin}_{i,j}$ represent the maximum temperature and minimum temperature, respectively, for each day and each year, $\overline{\overline{\mathrm{Tmax}_i}}$ and $\overline{\overline{\mathrm{Tmin}_i}}$ represent the maximum and minimum temperature averages, respectively, for each day smoothed by the 5 previous and 5 following days, and $\widetilde{\sigma}_{\mathrm{Tmax}_i}$ $\widetilde{\sigma}_{\mathrm{Tmin}_i}$ represent the maximum temperature and minimum temperature standard deviations, respectively, for each day smoothed in the same way.

The reference period was fixed as 1931–1960, which corresponds to Phase I of the control charts. The reference period should extend for at least 30 years because the classical period of climate is 30 years (EEA 2008). For each of the geographical areas and considering the anomalies of the reference period, the upper specification limit (USL) and the lower specification limit (LSL) are determined by the 99 and 1 percentiles, respectively, of the distribution of the anomalies to discriminate between extreme days (upper or lower) and non-extreme days (see Fig. 3). These specification limits are used to define four types of extreme anomalies for temperature series: the lower and upper extremes for the minimum anomalies and the lower and upper extremes for the maximum anomalies (Fig. 4).

When fixing the limits of the control charts for the extreme temperature events, the number of extreme temperature days might not follow a normal distribution and such climate processes exhibit autocorrelation. Thus, to model the occurrence of extreme temperature days, a binomial Markov process was generated for each geographical area and extreme anomaly type. In general, runs of extremely high temperature days or extremely low temperature days have been observed. This implies that the probability of the occurrence of an extreme day if the last 2 days were extreme days increases relative to the probability of the occurrence of an extreme day if only the day before was extreme. Specifically, in the Spanish region of the Basque Country, this probability increases from 0.25 to 0.33, which represents an increase above 30% if the previous 2 days are considered instead of just the day before. Therefore, because important differences exist when considering the events of the previous day due to autocorrelation and also when considering the events of the days before two sequential non-extreme days, a new binomial Markov extended process with five states was generated to enlarge the model proposed by Bhat and Lal (1990). The state space is as follows:

- State 1: 000. Two non-extreme sequential days and non-extreme days in the neighbourhood of four previous days
- State 2: A00. Two non-extreme sequential days and at least one extreme day in the neighbourhood of 4 previous days
- State 3: 10. An extreme day and a non-extreme day in the last two sequential days
- State 4: 01. A non-extreme day and an extreme day in the last two sequential days
- State 5: 11. Two extreme days in the last two sequential days

in contrast to the state space proposed by Bhat and Lal (1990): 0, 1, which model only considers the probability of occurring extreme day or not extreme day just conditioned by what happened the previous day.

The transition matrix, M, that corresponds to the new binomial Markov extended process with five states is represented by Eq. (2). The stationary probabilities for each state may be found from the transition matrix M (see Eq. (3)).

$$\mathbf{M}=\begin{array}{c} \\ \mathbf{000} \\ \mathbf{A00} \\ \mathbf{10} \\ \mathbf{01} \\ \mathbf{11} \end{array}\begin{array}{c} \begin{array}{ccccc} \mathbf{000} & \mathbf{A00} & \mathbf{10} & \mathbf{01} & \mathbf{11} \end{array} \\ \begin{pmatrix} 1-p_{000} & 0 & 0 & p_{000} & 0 \\ k(1-p_{A00}) & (1-k)(1-p_{A00}) & 0 & p_{A00} & 0 \\ 0 & 1-p_{10} & 0 & p_{10} & 0 \\ 0 & 0 & 1-p_{01} & 0 & p_{01} \\ 0 & 0 & 1-p_{11} & 0 & p_{11} \end{pmatrix} \end{array} \quad where\ k=\frac{(1-p_{A00})^3 p_{A00}}{1-(1-p_{A00})^4} \qquad (2)$$

$$\Pr(X_0 = \text{state } j) = \pi_j \qquad (3)$$

To obtain the probability distribution of the number of extreme days, the transition matrix M must be expanded to the cumulative number of extreme days. An augmented Markov chain P (a square matrix of dimension 1830) was created, where the cumulative number of extreme days is noted in brackets (see Eq. (4)).

$$P=\begin{array}{c|cccccccccccc} & 000(0) & A00(0) & 10(0) & 01(0) & 11(0) & 000(1) & A00(1) & 10(1) & 01(1) & 11(1) & \dots & 11(365) \\ \hline 000(0) & 1-p_{000} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & p_{000} & 0 & \dots & 0 \\ A00(0) & k(1-p_{A00}) & (1-k)(1-p_{A00}) & 0 & 0 & 0 & 0 & 0 & 0 & p_{A00} & 0 & \dots & 0 \\ 10(0) & 0 & 1-p_{10} & 0 & 0 & 0 & 0 & 0 & 0 & p_{10} & 0 & \dots & 0 \\ 01(0) & 0 & 0 & 1-p_{01} & 0 & 0 & 0 & 0 & 0 & 0 & p_{01} & \dots & 0 \\ 11(0) & 0 & 0 & 1-p_{11} & 0 & 0 & 0 & 0 & 0 & 0 & p_{11} & \dots & 0 \\ 000(1) & 0 & 0 & 0 & 0 & 0 & 1-p_{000} & 0 & 0 & 0 & 0 & \dots & 0 \\ A00(1) & 0 & 0 & 0 & 0 & 0 & k(1-p_{A00}) & (1-k)(1-p_{A00}) & 0 & 0 & 0 & \dots & 0 \\ 10(1) & 0 & 0 & 0 & 0 & 0 & 0 & 1-p_{10} & 0 & 0 & 0 & \dots & 0 \\ 01(1) & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1-p_{01} & 0 & 0 & \dots & 0 \\ 11(1) & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1-p_{11} & 0 & 0 & \dots & 0 \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ 11(365) & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \dots & 1 \end{array} \qquad (4)$$

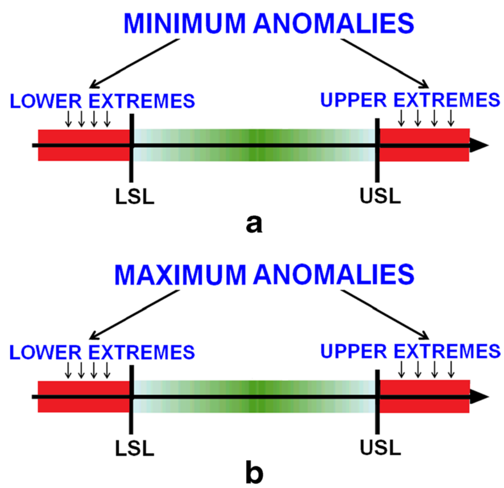

Fig. 4 Extreme temperature anomalies: **a** lower extremes and upper extremes for minimum anomalies and **b** lower extremes and upper extremes for maximum anomalies

The augmented Markov chain P must then be raised to the power of 365, and the first 5 rows of the matrix $P^{(365)}$ must be selected by considering columns from 1 to 5, from 6 to 10, ... and from 1826 to 1830, to determine the probabilities of obtaining r extreme days in a year. These probabilities are presented in Eq. (5):

$$\Pr(\text{number of extremes} = r) = \sum_{i=1}^{5}\left(\sum_{j=1}^{5} P^{(365)}(i, 5r+j)\right) \times \pi_i \quad (5)$$

The limits of the control chart for the annual proportion of extreme days can then be obtained based on the probability distribution found in Eq. (5). The limits of probability $\alpha/2 = 0.00135$ were established to fix the control limits to be equivalent to the usual 3-sigma Shewhart control limits under the hypothesis of a normal distribution (Montgomery 2013). The 0.00135 probability limits can be established by using Eq. (5) with Eq. (6):

$$\begin{array}{l}\Pr(\text{number of extremes} > \text{UCL}) = 0.00135 \quad \text{and} \\ \Pr(\text{number of extremes} < \text{LCL}) = 0.00135\end{array} \quad (6)$$

where UCL is the upper control limit and LCL is the lower control limit. These control limits provide a novel fraction nonconforming control chart that is associated with the new binomial Markov extended process.

The decision rules that were used to determine whether the extreme temperature events changed during the monitoring period (1961–2009, which corresponds to Phase II of the control charts) compared to the reference period (1931–1960) based on the control charts established for the annual fraction of extreme days are as follows:

- Test 1: One point outside of the control limits
- Test 2: Run up of length 10
- Test 3: Run down of length 10
- Test 4: Run of 20 consecutive points on one side of the centre line

Only 3 types of runs were selected (test 2 to test 4) because the probability α of false positives increases as more runs are applied (Montgomery 2013).

Finally, the occurrence of annual extreme days over the monitoring period in each geographical area for each type of extreme temperature event was monitored with its assigned fraction nonconforming control chart and the established decision rules.

Table 2 Upper Control Limits (UCL) established for the control charts of the annual fraction of extreme temperature days for each of the 4 extreme event types in the 12 analysed geographical areas

Geographical area	Upper Control Limits (UCL)			
	Minimum anom. lower extremes	Minimum anom. upper extremes	Maximum anom. lower extremes	Maximum anom. upper extremes
Gran Bilbao	0.049	0.041	0.055	0.055
Mungía	0.047	0.044	0.052	0.049
Ondarroa	0.047	0.047	0.055	0.047
Urola	0.055	0.041	0.055	0.044
Bidasoa Donostialdea	0.055	0.047	0.052	0.055
Cantábrica Alavesa	0.052	0.044	0.060	0.052
Nervión	0.049	0.044	0.060	0.049
Alto Deba	0.044	0.047	0.055	0.047
Goierri	0.055	0.047	0.052	0.047
Valles Alaveses	0.049	0.041	0.055	0.055
Llanada Alavesa	0.049	0.041	0.058	0.047
Montaña Alavesa	0.049	0.044	0.058	0.049

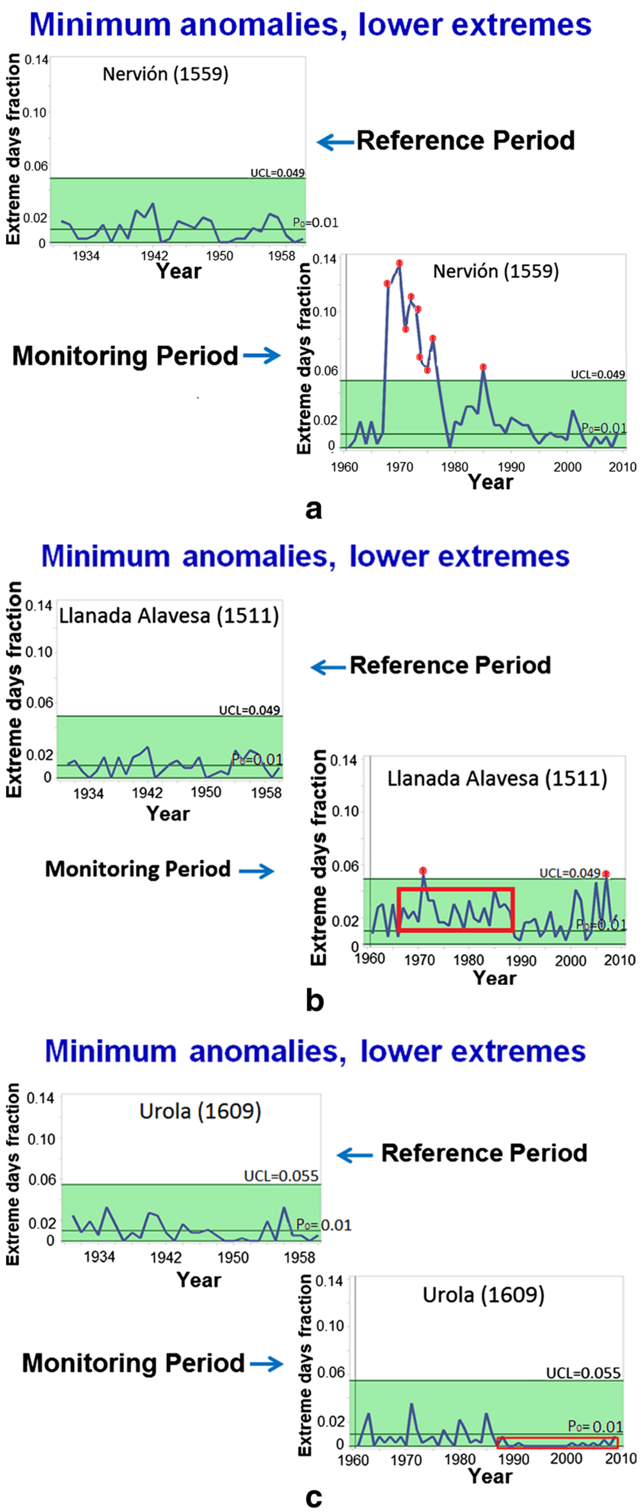

Fig. 5 Control charts for the annual fraction of extreme days that correspond to the lower extreme events of minimum temperatures, which distinguish between the graph for the reference period (1931–1960) and the graph for the monitoring period (1961–2009). **a** Control chart for the Nervión geographical area, **b** control chart for the Llanada Alavesa geographical area, **c** control chart for the Urola geographical area

The data series of the daily average minimum and maximum temperatures from 1931 to 2009 for the 12 geographical areas in the Basque Country (Fig. 2) were analysed with the proposed methodology using SAS® software (SAS® 2011).

3 Results and discussion

Four attribute control charts were obtained using the proposed methodology for each geographical area: a control chart for the lower extreme temperature events and a control chart for the upper extreme temperature events from the data series of the daily minimum anomalies and a control chart for the lower extreme temperature events and a control chart for the upper extreme temperature events from the data series of the daily maximum anomalies in the area. The UCL limits established for these control charts are shown in Table 2. The LCL limits and the centre lines p_0 have the same values (0.010 and 0, respectively) in all of the control charts for the selected region, so these values are not shown in Table 2.

The description of the results and the discussion are focused on a statistical analysis of the lower extreme temperature events of the minimum anomalies or the extremely low minimum temperatures because they are of greatest interest to the agricultural sector in this region. Figure 5 shows 3 of the 12 control charts obtained for the annual fraction of extreme low minimum temperature days, which distinguish between the reference period and the monitoring period. This figure illustrates some of the various situations that can occur when the method of evaluating extreme temperature events based on process control charts is applied to climate processes. The 3 control charts obtained from the reference period show the natural variability of the annual fraction of extreme days between 1931 and 1960, displaying such a process in the statistical control state. Furthermore, the control charts in the 3 areas detect changes during the 1961–2009 monitoring period because some of the tests that are associated with the decision rules of change that were considered for the evaluation of the extreme event processes (tests 1 to 4) occurred. The changes detected are not always the same. For example, the control chart shown in Fig. 5a, which corresponds to the Nervión geographical area (number 1559 in Fig. 2), shows evidence of an increase in extreme temperature events over the monitoring period (1961–2009); 9 points are out of control (test 1) in the first half of the monitoring period compared to the reference period (1931–1960), which appears to be under statistical control. From the aspect of statistical significance, the probability that a point corresponding to the monitoring period exceeds the upper limit of the control chart, conditional on an occurrence of events of extreme temperature that keep on the climate reference period model, is 0.00135 (see Eq. (6)), therefore, the observation of a point that exceeds the limits of the control chart allows the conclusion that the variability of the process of occurrence of annual extreme days has changed with regard to the reference period model in a statistically

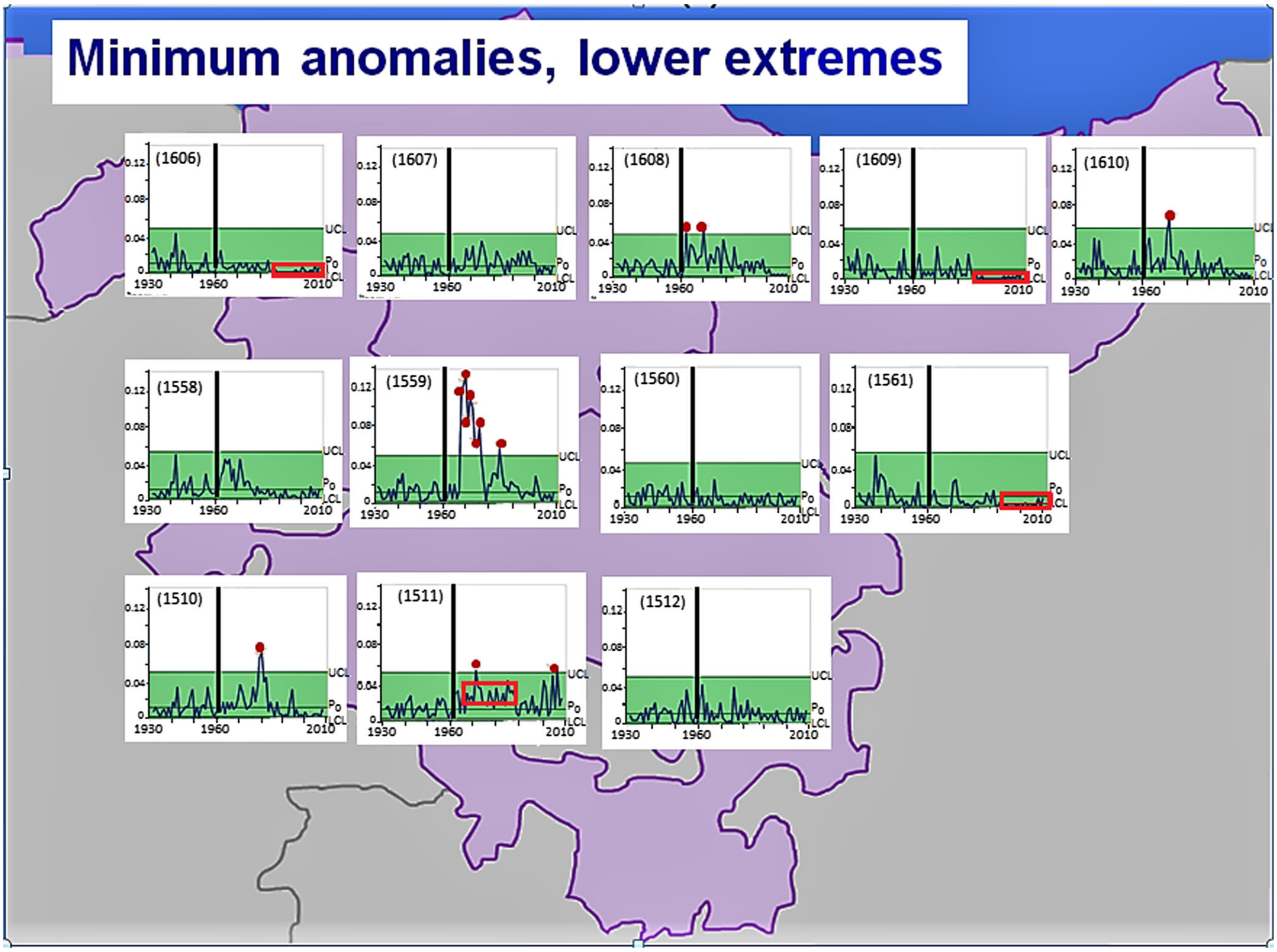

Fig. 6 Control charts for the Basque Country (Spain) of the annual fraction of extreme days that correspond to the lower extreme events of minimum temperatures, which distinguish between the graph for the reference period (1931–1960) and the graph for the monitoring period (1961–2009)

significant manner. Because 9 points in Fig. 5a exceeded the upper control limit, an increase in lower extreme temperature events of the minimum anomalies in the Nervión area could be said to have occurred with a significance level <0.0001 in the first half of the monitoring period. The analysis of the temperature data of Llanada Alavesa (number 1511) resulted in the control chart shown in Fig. 5b, in which the evidence of an increase in lower extreme minimum anomalies in the first half of the monitoring period was reinforced by the presence of runs of 20 consecutive points above the centre line (test 4, represented by a red box). The probability of the occurrence of a point above the centre line of the control chart can be obtained from the matrix $P^{(365)}$ that corresponds to the temperature data of Llanada Alavesa, using Eq. (5) with $r \geq 4$. The value of that probability is 0.4336; therefore, the probability of the occurrence with a run of length 22, as observed in Fig. 5b, assuming the reference period model is $(0.4336)^{22} < 0.0001$. Thus, evidence for an increase in the lower extreme minimum anomalies in the first half of the monitoring period was obtained at a significance level <0.0001. However, in the control chart for Urola (number 1609), which is shown in Fig. 5c, runs of 20 consecutive points below the centre line (test 4, depicted by a red box) indicate a decrease in the annual fraction of extreme days during the second half of the monitoring period. In this case, the occurrence of a run of 23 consecutive points below the centre line of the control chart indicates a decrease in the annual fraction of extreme days at a significance level of $(0.5715)^{23} < 0.0001$.

In contrast, the control charts could show no evidence of a change in the proportion of annual extreme days over the monitoring period compared to the expected values from the reference period. This was the case for the areas of Mungía (1607), Cantábrica Alavesa (1558), Alto-Deba (1560) and Montaña Alavesa (1512), as is shown in Fig. 6. This figure shows the control charts that were obtained for the 12 areas, in which vertical lines separate the reference period from the monitoring period. None of the decision rule identifiers of change in the model of extreme temperature events (test 1 to test 4) were present during the monitoring period in these 4 areas. This indicates that in Mungía, Cantábrica Alavesa, Alto

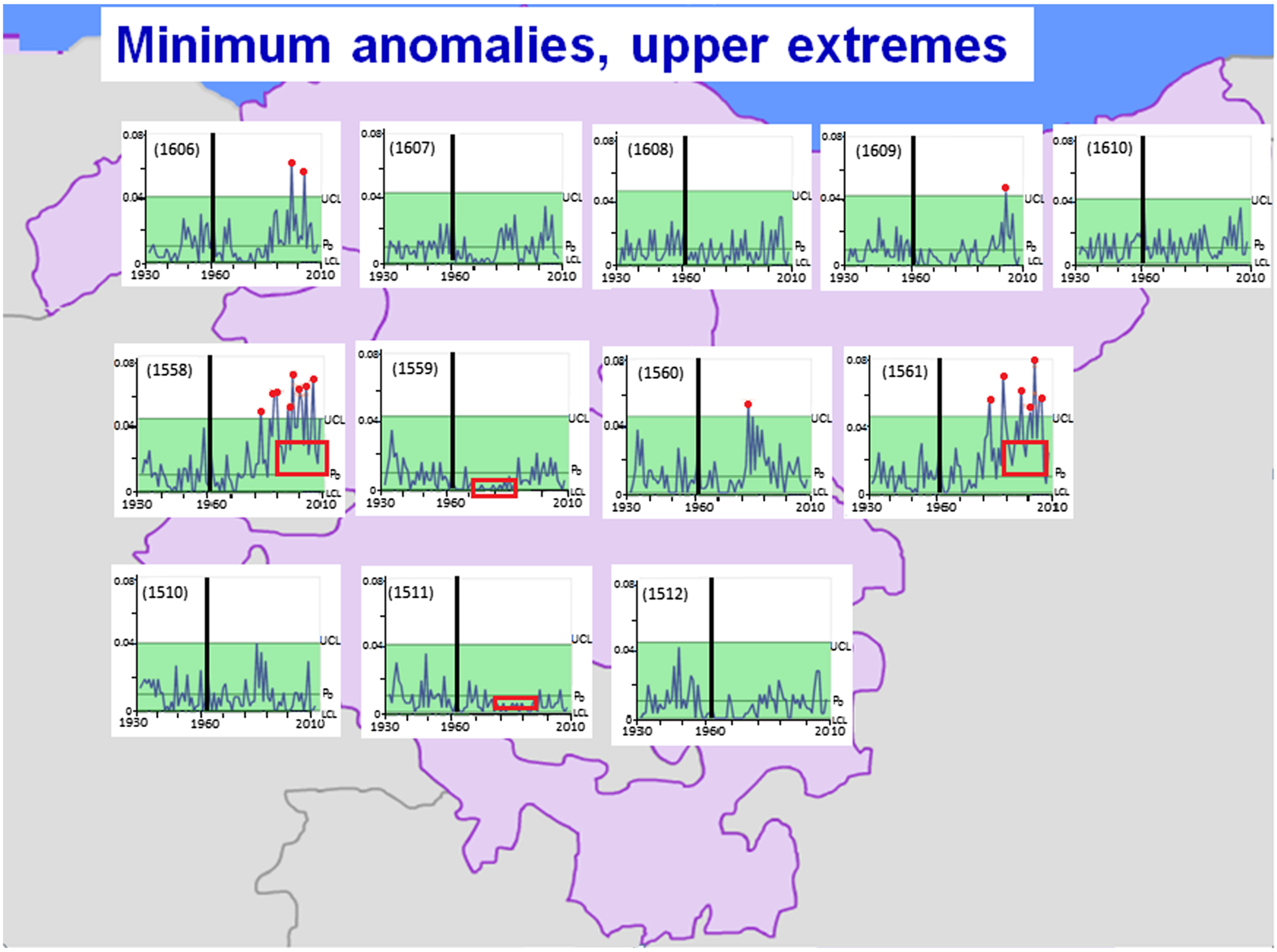

Fig. 7 Control charts for the Basque Country (Spain) of the annual fraction of extreme days that correspond to the upper extreme events of minimum temperatures, which distinguish between the graph for the reference period (1931–1960) and the graph for the monitoring period (1961–2009)

Deba and Montaña Alavesa, the annual fraction of lower extreme days with minimum anomalies remained stable during the entire study period of 1931–2009. That is, the variability of these extreme events was only due to natural or chance causes, and during the second period (1961–2009), this variability is as statistically expected from the pattern observed during the previous period (1931–1960).

An analysis of the control charts for the entire region (Fig. 6) shows that a general behaviour for the lower extreme temperature events of the minimum anomalies over the monitoring period was not observed. Five areas showed an increase in the proportion of annual extreme days during the second period, including Ondarroa (1608), Bidasoa Donostialdea (1610), Nervión (1559), Valles Alaveses (1510) and Llanada Alavesa (1511), and 3 areas showed a decrease, including Gran Bilbao (1606), Urola (1609) and Goierri (1561). The remaining 4 areas, Mungía (1607), Cantábrica Alavesa (1558), Alto Deba (1560) and Montaña Alavesa (1512), did not show any statistically significant changes in the proportion of extreme temperature events. However, when an increase or decrease in the fraction of extreme days was observed, the time intervals in which such changes were detected were similar in the different areas. In the 5 areas that exhibited an increase, the increases mainly occurred between 1961 and 1980, except for Llanada Alavesa (1511), for which an increase signal was detected at the end of the monitoring period. Furthermore, in the 3 areas that showed a decrease, the decreases all occurred between 1980 and 2009. This global behaviour is consistent with the accepted evolution of temperature in Europe, which includes a slight decrease of temperatures in 1960–1980 and a temperature increase at the end of the last century (IPCC 2007).

The control charts obtained for the upper extreme temperature events of the minimum anomalies (i.e., the extremely high minimum temperatures) are summarized in Fig. 7. The results show that, as with the lower extreme temperature events of the minimum anomalies, no general behaviour of the upper extreme temperature events of the minimum anomalies during the monitoring period (1961–2009) compared to the reference period (1931–1960) in the 12 geographical areas

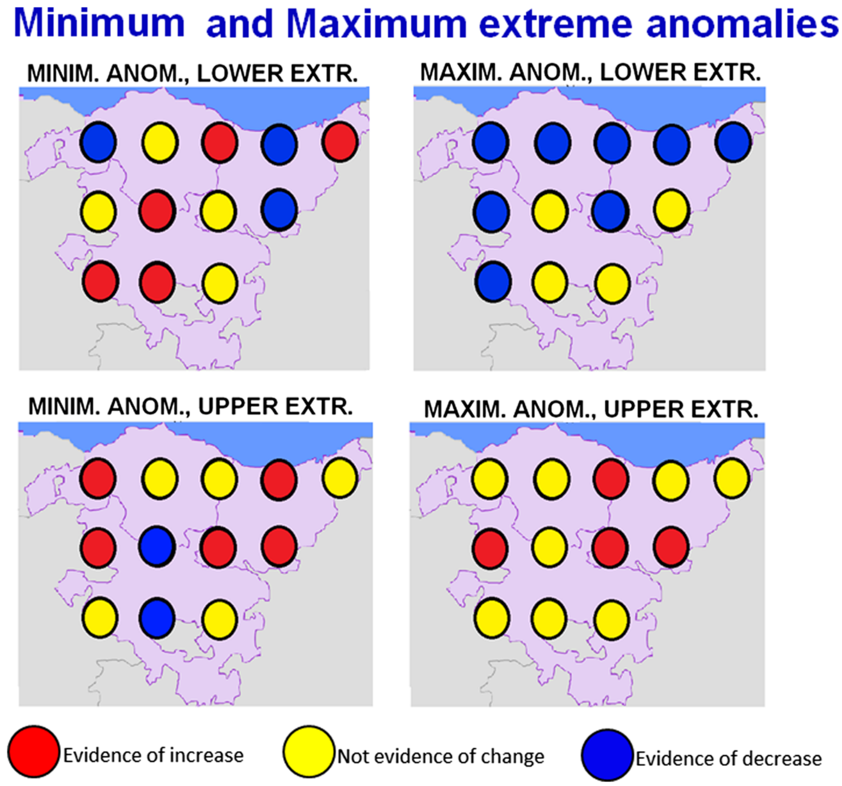

Fig. 8 Evaluation of extreme temperature events for the Basque Country based on the control charts that were established for the annual fraction of extreme days for the four types of extreme events: lower extreme temperature events of the minimum anomalies, upper extreme temperature events of the minimum anomalies, lower extreme temperature events of the maximum anomalies and upper extreme temperature events of the maximum anomalies

was apparent. Five areas showed an increase in the proportion of annual extreme days during the second period, including Gran Bilbao (1606), Urola (1609), Cantábrica Alavesa (1558), Alto Deba (1560) and Goierri (1561), and 2 areas showed a decrease: Nervión (1559) and Llanada Alavesa (1511). The remaining 5 areas did not show any changes in the model of occurrence of extreme temperature events, including Mungía (1607), Ondarroa (1608) and Bidasoa Donostialdea (1610) in the north and Valles Alaveses (1510) and Montaña Alavesa (1512) in the south. However, when a type of change in the fraction of extreme days was detected, the time interval for which the change was observed were similar in all of the affected geographic areas. The increases in the 5 areas occurred mainly during the second half of the monitoring period, and the decreases in the 2 areas occurred during the 2 middle decades of the monitoring period. An analysis of the upper extreme temperature events of the minimum anomalies has also been carried out by other researchers, such as García-Cueto et al. (2014). That group analysed 4 weather stations in Baja California, Mexico, between 1950 and 2010, finding an increase of such extremes for most stations. Their result was consistent with the present research, in which most areas that showed a change in the upper extreme of the minimum temperature in the monitoring period showed that change in the same direction.

If evidence of a change in both the lower and upper extreme temperature events of minimum anomalies in an area is present, the changes are opposite. The graphs on the left side of Fig. 8, which correspond to extreme temperature events of the minimum anomalies, show this characteristic. This result suggests that no evidence exists for the variation in the amplitude of the extreme events of minimum temperatures.

Figure 8 summarizes the evaluation of the four types of extreme temperature events in Basque Country based on the proposed control charts. The graphs on the right side of Fig. 8 show the results for the lower extremes (top) and for the upper extremes (bottom) of the maximum temperature anomalies. The lower extremes of the maximum anomalies show a decrease in the proportion of annual extreme days during the second period with respect to the expected values from the previous period in 8 areas mainly in the northwest part of the region. The remaining 4 areas did not show any changes. Most of the control charts did not show evidence of changes in the upper extreme temperature events of the maximum anomalies, and only 4 areas showed increases. This result is consistent with the noted increase in the maximum temperatures in Europe during the last decades of the last century (IPCC 2007). The increase observed in the number of upper extreme days of the maximum temperatures (especially at the end of the monitoring period) is in line with the results obtained by Ramos et al. (2011) for 23 weather stations from Portugal that were analysed for the period between 1941 and 2006. Furthermore, Fioravanti et al. (2015) analysed 12 indices of extreme temperatures from 50 meteorological stations in Italy during the period 1961 to 2011. They also found that the distribution of extreme days with higher maximum temperatures had increased during the last period, mostly in summer. These results also show that when evidence of changes in both the lower and upper extreme anomalies was present, and occurred in 3 areas, the changes were opposite. Therefore, no evidence exists for a variation in the amplitude of extreme events of maximum temperatures.

The application of the proposed method of evaluating extreme temperature events based on process control charts for the Spanish Basque Country region offers interesting information for the agriculture sector and associated insurance planning in some areas. The lower extreme temperature events of the minimum anomalies are of special interest because an important wine industry exists in the southern part of the study region. In this context, it is important to note that the increase in the proportion of extreme days in the area of Rioja Alavesa could affect the vineyards, creating an imbalance in the ripening grapes with respect to sugar and acidity content (Odó and Ramos 2012). In the same areas south of the analysed region, quite a lot of sugar beets are also produced, and their production can be damaged by an increase in extreme days with lower night temperatures (Jones et al. 2003). For wheat, which is the other product with a high volume of cultivated land in the three southern areas of the Basque Country, no evidence of change was observed in the upper extremes of the maximum temperatures, allowing the conclusion that, from a climatic point of view, it is still advisable to grow wheat in that zone (Tao et al. 2015).

The great variability of meteorological phenomena makes it difficult to detect statistically significant changes in temperature patterns. The proposed approach is interesting for climate studies because it considers the autocorrelation between extreme temperature events, as well as a new Markov binomial extended distribution to model the occurrence of extreme temperature events more accurately. By considering this probability distribution, the approach introduces a novel fraction nonconforming control chart. Therefore, the proposed monitoring of the extreme temperature events based on such process control charts allows the reliable determination of whether the variability observed in extreme temperatures is as statistically expected or is different from that of the reference period model. As a result, this easily implemented novel approach will be useful for finding geographical regions where climate change is more critical.

4 Conclusions

This paper proposed a novel approach for the evaluation of extreme temperature events based on attribute process control charts, which was applied to a daily maximum and minimum temperature series from the Basque Country of northern Spain. The analytical results led to the following conclusions, which are based on the control charts for each of the 12 geographical areas and four types of extreme temperature events:

(1) Evidence exists for an increase in the proportion of annual days of extremely low minimum temperatures during the monitoring period compared to the expected values for the reference period in 5 areas. These increases were mainly observed during the first half of the monitoring period. Evidence also exists for a decrease in this proportion in 3 areas during the last two decades of the monitoring period, and no evidence of change was found in the remaining 4 areas.

(2) The control charts obtained for the upper extreme events of the minimum temperatures indicate that an increase in the proportion of annual extreme minimum temperature days occurred during the monitoring period with respect to the expected values for the reference period in 5 areas, and these increases were mainly detected during the second half of the monitoring period. Evidence was also found for a decrease in this proportion in 2 areas, and the other 5 areas remained stable during the entire study period.

(3) For the upper extreme events of maximum temperatures, evidence for an increase in the proportion of annual extreme days over the monitoring period was detected in 4 areas, while evidence for a decrease in the lower extreme events of maximum temperatures was observed in 8 areas. For both types of extreme events, no evidence of change was found in the remaining areas. Therefore, the evaluation of extreme maximum temperature events using the proposed attribute control charts was consistent with the evidence for an increase in the maximum temperature over the last decades of the last century.

(4) If evidence of changes in both upper and lower extreme events of the minimum and maximum temperatures was found, the changes were opposite. This behaviour suggests that no evidence exists for a change in the amplitude of extreme events for either the minimum or maximum temperatures.

(5) In Rioja Alavesa (in the southern part of the study region), the increase in the proportion of annual days of extremely low minimum temperatures over the monitoring period could affect vineyards with a consequent loss of wine quality and could affect sugar beets as well. Moreover, because no evidence of change was detected in the upper extremes of the maximum temperatures, wheat production is still recommended for that area.

The novel approach is of interest to climate studies because it considers, among other contributions, the autocorrelation between extreme temperature events, which is always present in such climate processes, and a new Markov binomial extended distribution to more accurately model the occurrence of extreme temperature events. Further research on the selection of the specification limits is required to study the effect of the number of extreme events collected in a data series of daily temperatures on the proposed control charts. An increase in the number of extreme observations would allow a higher precision to be achieved when obtaining the transition matrix of the Markov process of the occurrence of extreme temperature days. Future research will focus on the trade-off between the number of observed extreme events and the consideration of each extreme event. In this regard, it would be greatly beneficial if the scientific community could reach a consensus on a universal definition of a day with an extreme temperature anomaly. The next step in future research will be the development of evaluation procedures based on other types of control charts and a comparison with the approach proposed in this study to optimize the efficiency of monitoring the occurrence of extreme temperature events.

Acknowledgements The authors wish to thank the Spanish Meteorology Agency (AEMET, Spain) for their contribution to this research and for sharing the temperature data analysed. Funding was provided by the Spanish Ministry of the Economy and Competitiveness through project no. MTM2013-46374-P, project no. MTM2016-78227-C2-1-P, project no. CGL2014-58322-R and project no CICYT PCIN-2014-080 and is greatly appreciated.

References

Bhat UN, Lal R (1990) Atribute control charts for Markov dependent production processes. IIE Trans 22:181–188

Broadbent SR (1958) The inspection of a Markov process. J R Stat Soc Ser B 20:111–119

Chirima J, Chinofunga PT, Zvobgo RJ, Mufandaedza J, Dambaza M (2012) Application of statistical control charts to climate change detection in Masvingo city, Zimbabwe. J Environ Res Develop 7: 780–786

Chu H-J, Pan T-Y, Liou J-J (2012) Change point detection of long-duration extreme precipitation and the effect on hydrologic design: a case study of south Taiwan. Stoch Environ Res Risk Assess 26: 1123–1130. doi:10.1007/s00477-012-0566-0

Coles S (2001) An introduction to statistical modeling of extreme values. Springer Series in Statistics, London

Cuellar J (2012) Aplicación del control estadístico de procesos a las temperaturas diarias máximas y mínimas del centro de la provincia de Soria. Universidad Complutense de Madrid, Degree Project

EEA-JRC-WHO (2008) EEA Report N° 4/2008 Impacts of Europe's changing climate – 2008 indicator based assessment. European Environment Agency, European Commission, WHO Office for Europe, Copenhagen

Fioravanti G, Piervitali E, Desiato F (2015) Recent changes of temperature extremes over Italy: an index-based analysis. Theor Appl Climatol. doi:10.1007/s00704-014-1362-1

Ganguly ND, Iyer KN (2009) Long-term variations of surface air temperature during summer in India. Int J Climatol 29:735–746. doi:10.1002/joc.1748

García-Cueto OR, Cavazos MT, de Grau P, Santillán-Soto N (2014) Analysis and modeling of extreme temperatures in several cities in northwestern Mexico under climate change conditions. Theor Appl Climatol 116:211–225. doi:10.1007/s00704-013-0933-x

Gobin A (2012) Impact of heat and drought stress on arable crop production in Belgium. Nat Hazards Earth Syst Sci 12:1911–1922. doi:10.5194/nhess-12-1911-2012

Gobin A, Tarquis AM, Dalezios NR (2013) Weather-related hazards and risks in agriculture: preface. Nat Hazards Earth Syst Sci 13:2599–2603. doi:10.5194/nhess-13-2599-2013

Holešovský J, Fusek M, Michálek J (2015) Modelling of precipitation extremes using parametric and nonparametric methods with automated threshold selection. International Journal of Mathematics and Computers in Simulation 9:94–102

IPCC (2007) Climate Change, Synthesis Report Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, Geneva

Jones PD, Lister DH, Jaggard KW, Pidgeon JD (2003) Future climate impact on the productivity of sugar beet (*Beta vulgaris* L.) in Europe. Clim Chang 58:93–108. doi:10.1023/A:1023420102432

Lai CD, Govindaraju K, Xie M (1998) Effects on correlation on fraction nonconforming statistical process control procedures. J Appl Stat 25:535–543. doi:10.1080/02664769823007

Lai CD, Xie M, Govindaraju K (2000) Study of a Markov model for a high-quality dependent process. J Appl Stat 27:461–473. doi:10.1080/02664760050003641

Linkosalo T, Häkkinen R, Terhivuo J, Tuomenvirta H, Hari P (2009) The time series of flowering and leaf bud burst of boreal trees (1846-2005) support the direct temperature observations of climate warming. Agricu For Meteorol 149:453–461. doi:10.1016/j.agrformet.2008.09.006

Luna MY, Almarza C (2007) Interpolation of 1961–2002 daily climatic data in Spain. In: Szalai S, Bihari Z, Szentimrey T, Lakatos M (eds) Proc Conf spat interpolation Climatol Meteorol. COST action 719 the use of geographic information Systems in Climatology and Meteorology. Office for Official Publications of the European Communities, Luxembourg, pp 189–196

Luna MY, Morata A, Martín ML, Santos-Muñoz D, De la Cruz J (2008) Validación de la base de datos reticular de la AEMet. Temperatura diaria máxima y mínima. In: Sigró J, Brunet M, Aguilar E (eds) Cambio Climático General y sus Impactos, Serie A N°, vol 6. Asociación Española de Climatología (AEC), Tarragona, pp 173–182

Mearns LO, Katz RW, Schneider SH (1984) Extreme high-temperature events: changes in their probabilities with changes in mean temperature. J Climate Appl Meteor 23:1601–1613

Minkova LD, Omey E (2014) A new Markov binomial distribution. Comm Stat Theor Meth 43:2674–2688. doi:10.1080/03610926.2012.681538

Montgomery DC (2013) Statistical quality control: a modern introduction, 7th edn. Wiley, Hoboken

Moratiel R, Snyder RL, Durán JM, Tarquis AM (2011) Trends in climatic variables and future reference evapotranspiration in Duero Valley (Spain). Nat Hazards Earth Syst Sci 11:1795–1805. doi:10.5194/nhess-11-1795-2011

Odó J, Ramos MC (2012) Grape harvest and yield responses to inter-annual changes in temperature and precipitation in an area of north-East Spain with a Mediterranean climate. Int J Biometeorol 56:853–864. doi:10.1007/s00484-011-0489-3

Omey E, Santos J, Van Gulck S (2008) A Markov-binomial distribution. Appl Anal Discrete Math 2:38–50. doi:10.2298/AADM0801038O

Ramirez-Beltran ND, Julca O (2006) Detection of a local climate change. In: 18th Conference on Climate Variability and Change, at the 86th American Meteorological Society Annual Meeting

Ramos AM, Trigo RM, Santo FE (2011) Evolution of extreme temperatures over Portugal: recent changes and future scenarios. Clim Res 48:177–192. doi:10.3354/cr00934

Saá A, García R, Díaz MC, Burgaz F, Tarquis AM (2011a) Analysis of hail damages and temperature series for peninsular Spain. Nat Hazards Earth Syst Sci 11:3415–3422. doi:10.5194/nhess-11-3415-2011

Saá A, García R, Díaz MC, Burgaz F, Tarquis AM (2011b) Influence of climate change on damages to fruit trees produced by frost temperatures at Spanish semiarid region of Murcia. In: Degenovine KM (ed) Semi-Arid Environments: Agriculture. Engineering and Technology, Nova Science Publisher, Water Supply & Vegetation. Environmental Science, pp 131–144

SAS® (Statistical Analysis System) software (2011) version 9.3 for Windows. SAS Institute Inc., Cary

Shepherd DK, Champ CW, Rigdon SE, Fuller HT (2007) Attribute charts for monitoring a dependent process. Qual Reliab Enging Int 23:341–365. doi:10.1002/qre.793

Shepherd DK, Rigdon SE, Champ CW (2012) Using runs rules to monitor an attribute chart for a Markov process. Qual Technol Quantit Manag 9:383–406

Shewhart WA (1931) Economic control of quality of manufactured product. D. Van Nostrand Company, Inc., Toronto

Smadi MM (2006) Observed abrupt changes in minimum and maximum temperatures in Jordan in the 20th century. Am J Environ Sci 2:114–120

Smadi MM, Zghoul A (2006) A sudden change in rainfall characteristics in Amman, Jordan during the mid 1950s. Am J Environm Sci 2:84–91

Sotillo MG, Martín ML, Valero EF, Luna MY (2006) Validation of a homogeneous 41-year (1961–2001) winter precipitation hind casted dataset over the Iberian Peninsula: assessment of the regional improvement of global reanalysis. Clim Dyn 27:627–645. doi:10.1007/s00382-006-0155-3

Tao F, Zhang Z, Zhang S, Röter RP (2015) Heat stress impacts on wheat growth and yield were reduced in the Huang-Huai-Hai Plai of China in the past three decades. Europ J Agronomy 71:44–52. doi:10.1016/j.eja.2015.08.003

Tarquis AM, Gobin A, Semenov MA (2010) Agriculture in a changing climate: Preface. Clim Res 44:1–2

Valencia JL, Tarquis AM, Saa-Requejo A, Gascó JM (2012) Change of extreme rainfall indexes at Ebro River Basin. Nat Hazards Earth Syst Sci 12:2127–2137. doi:10.5194/nhess-12-2127-2012

Valero F, Martín ML, Sotillo MG, Morata A, Luna MY (2009) Characterization of the autumn Iberian precipitation from long-term datasets: comparison between observed and hindcasted data. Int J Climatol 29:527–541. doi:10.1002/joc.1726

Vučijak B, Kupusović T, Midžić-Kurtagić S, Ċerić A (2013) Climate change assessment using statistical process control methods. In: Climate-Smart Technologies. Springer, Berlin Heildelberg, pp 113–125

Vučijak B, Kupusović T, Midžić-Kurtagić S, Silajdžić I, Ćerić A (2014) Evaluation of the climate change effects to the precipitation patterns in the selected Bosnia and Herzegovina cities. Thermal Sci 18:787–798. doi:10.2298/TSCI1403787V

Weib C (2009) Monitoring correlated processes with binomial marginals. J Appl Stat 36:399–414. doi:10.1080/02664760802468803

Zea-Bermudez P, Kotz S (2010a) Parameter estimation of the generalized Pareto distribution—Part I. J Stat Plan Infer 140:1353–1373. doi:10.1016/j.jspi.2008.11.019

Zea-Bermudez P, Kotz S (2010b) Parameter estimation of the generalized Pareto distribution—Part II. J Stat Plan Infer 140:1374–1388. doi:10.1016/j.jspi.2008.11.02