

Chapter 3

Analysis of Temporal Variability of Droughts in Southern Paraguay and Northern Argentina (1961–2011)

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Abstract The study presents an analysis of droughts using monthly rainfall data, from January 1961 to December 2011, from 11 rain gauges located in Paraguay and Northern Argentina. The characterization of the drought events used the standardized precipitation index (SPI) applied at different time scales (3, 6, and 12 consecutive months). The temporal variability of the droughts in the study period was analyzed in terms of changes in their frequency—regardless of the severity, has the frequency of droughts increased or decreased?—and in their severity—are we experiencing more severe droughts or not? The results achieved, despite proving the suitability of the approaches applied, did not reveal any trend towards an increase or a decrease either in the frequency of the droughts or in their severity in the studied area.

Keywords Drought • Standardized precipitation index (SPI) • Kernel occurrence rate estimator (KORE) • Drought occurrence rate • Drought severity

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Introduction

Droughts are generally associated with the persistence of low rainfall, soil moisture and water availability relative to the normal levels in a designated area. Although there is no universally accepted definition for drought, Tallaksen and Van Lanen (2004) defines it as “a sustained and regionally extensive occurrence of below average natural water availability”. Unlike other extreme events, like floods and earthquakes, droughts remain a less visible natural risk, whose impacts are not systematically recorded. Droughts are among the most complex and least understood natural hazards, affecting more people than any other one. They are also recurrent hazards particularly in areas with pronounced natural climate temporal variability, as those under analysis.

The objective of the present study was to quantify the yearly drought occurrence rates in the northern Argentina and in Paraguay, using a new approach, the Kernel occurrence rate estimation method coupled with bootstrap confidence band and the standardized precipitation index, SPI, for drought recognition.

Some authors have studied drought occurrences in several countries. Recently, for Japan, Lee et al. (2012) have analyzed the spatiotemporal characteristics of drought occurrences over Japan for the period from 1902 to 2009 using an effective drought index (EDI). With hierarchical cluster analysis applied to drought characteristic data (such as duration, severity and onset and end dates) available at 50 observational stations, drought regions were identified and drought occurrences analyzed.

Using future climate scenarios, Sheffield and Wood (2008) analyzed changes in drought occurrence using soil moisture data. According to the same authors for the future projections, the models showed decreases in soil moisture globally for all scenarios with a corresponding doubling of the spatial extent of severe soil moisture deficits and frequency of short-term (4–6-month duration) droughts from the mid-20th to the end of the 21st centuries. Long-term droughts become three times more common. Regionally, the Mediterranean, west African, central Asian and central American regions show large increases most notably for long-term frequencies as do mid-latitude North American regions but with larger variation between scenarios.

For Argentina some related studies have also been pursued, namely the work of Capriolo and Scarpati (2012). Given the soil water balance obtained by the evapotranspiration formula of Penman–Monteith, soil water deficit and surplus were considered as triggers of extreme hydrologic events. The authors considered annual threshold values of 200 mm of soil water deficit and 300 mm of soil water surplus for drought and flood recognition, respectively. Using the Mann–Kendall statistical test the results have shown significance trends at level 0.1 for drought and for two periods, one of 20 years (1991–2010) and the other of 10 years (2001–2010). Ravelo (2000), have analyzed droughts for the period 1931–1999 in the plains region of Argentina. Meteorological drought indices were used in a time and space analysis to establish drought intensity, frequency, probability distribution and levels of probability for the occurrence of given drought intensities. More extensively Barrucand et al. (2007) studied the frequency and spatial distribution of droughts in different regions of Argentina during the 20th century. The behavior of the mean

monthly atmospheric circulation associated with dry conditions in the Pampas during the second half of the century was analyzed.

Within the study area, Paraguay is particularly affected by droughts. The potential impacts of such hazards on the economy of the country can be significant, especially taking into account that Paraguay is the sixth largest producer of soybean in the world (Masuda and Goldsmith 2009a, b). As a consequence of one of the most severe drought periods, from November 2008 to March 2009, the Gross Domestic Product (GDP) fell by 4.2 % in the first trimester of 2009, and the yield of soybean suffered a reduction of 30 %. In Argentina, the impact event was worst.

Impact assessment of a specific drought requires knowing its causes and the spatial and temporal distribution of the rainfall anomalies. Grimm et al. (2000) and Grimm (2004), analyzed the influence of El Niño Southern Oscillation (ENSO) warm (El Niño) and cold (La Niña) phases in the rainfall patterns of southeastern region of South America, providing a comprehensive view of the anomalies of rainfall and atmospheric circulation associated with both ocean–atmosphere phase events. The La Niña phase coincides with a reduction of rainfall in northern Argentina, southern Brazil and southeastern Paraguay. Fraisse et al. (2008) analyzed soybean yields in Paraguay and rainfall amounts during different phases of crop phenological development, finding significant rainfall reductions during La Niña phases. Podestá et al. (2002) also demonstrated the influence of ENSO phases on agriculture in central and eastern Argentina.

To assess the drought occurrence in the region and to understand the historical and recent climatic variability, it is worthwhile to study the long-term time series of rainfall regarding their nonhomogeneous climatic and hydrological conditions. The present study was based on 51 years of rainfall data, from 1961 to 2011, in 11 rain gauges distributed over the study area (Argentina and in Paraguay). The yearly drought occurrence rates were quantified using a new approach, the Kernel occurrence rate estimation (KORE) method coupled with bootstrap confidence band. To recognize the drought occurrences the standardized precipitation index (SPI), developed McKee et al. (1993), was applied. This index was designed to quantify the precipitation deficit at multiple time scales, which reflect the impact of droughts on the different types of reservoirs of fresh water at the watershed level. Indeed, soil moisture conditions respond to precipitation anomalies on a relatively short scale, while streamflow, reservoir storage and groundwater reflect the longer-term precipitation anomalies.

The perception of the meaning of drought and of its impacts varies significantly (Vogt and Somma 2000) as, in fact, drought does not have a precise and universally accepted definition. According to Rossi (2003), most of drought definitions refer to one or more components of the hydrological cycle, and to the impacts of the water shortages on ecosystems or on specific water users, according to the respective branch of science or activity (agriculture, socioeconomics, health, etc.). Nevertheless, it should be stated that there is a consensus regarding the following different types of drought: meteorological, agricultural, hydrological and the socio-economic (Wilhite and Glantz 1985). Such types of drought can also be defined in straight connection with the SPI index.

Meteorological drought, also termed climatological drought, is caused by a precipitation deficit over an extended period of time. This deficit may be accumulated and expressed relative to a climate norm and to the duration of the dry period (Lloyd-Hughes 2002). The SPI is linked to this drought type when calculated at 1–3 months' time scale (Hayes et al. 1999).

The water soil deficiency is usually connected to agricultural drought and is caused by a deficit of fresh water relative to evapotranspiration losses. A drought exists when the water availability at the root-zone is insufficient to sustain crops and pasture between precipitation events (Tate and Gustard 2000). For agricultural drought Sims et al. (2002), reported a strong relationship between SPI over short time scales (3–6 months) and temporal variations of soil moisture.

A hydrological drought results directly from reduced precipitation, which originates reduced surface runoff and, indirectly, from reduced groundwater discharge to the river channel. Key indicators are reduced river flows and low water levels in lakes and reservoirs. According to Lloyd-Hughes (2002), hydrological droughts are the most visible and important in terms of human perception. The SPI at 12 month time scale is considered a hydrological drought index, having been tested for monitoring surface water resources, e.g., river flows and water levels in lakes (Szalai and Szinell 2000; Hayes et al. 1999).

At longer time scales of the SPI (24 or 36 months), droughts last longer, but are less frequent. They are used to monitor the impact of droughts on aquifers, which are systems that respond more slowly to changing conditions (Changnon and Easterling 1989).

In the applications carried out the time scales considered were 3, 6 and 12 months (SPI3, SPI6 and SPI12, respectively).

Study Region and Rainfall Data

The study region spreads from the southern half of Paraguay to the contiguous Northeastern states of Argentina, namely the states of Formosa, Chaco, Corrientes, and Misiones. The data consists of 11 series of monthly rainfall, from January 1961 to December 2011 (50 years), from rain gauges distributed on that region. Figure 3.1 shows the study region, along with the location of the rain gauges. The rain gauges were spatially grouped as further justified in [Sect. Changes in Drought Occurrence Rate](#).

The rainfall data from Paraguay and Argentina comes from the National Meteorological Services of both countries. In the case of Paraguay, the institution is the Direction of Meteorology and Hydrology of the National Directorate of Civil Aeronautical (DINAC—Spanish acronym, www.meteorologia.gov.py) and in Argentina is the National Weather Service (www.smn.gov.ar) that depends on the Defense Ministry of Argentina.

The measurement of the rainfall is accomplished at stations equipped with standard pluviometers (Hellman type) and in some cases with automatic weather stations, in both cases following the World Meteorological Organization, WMO,

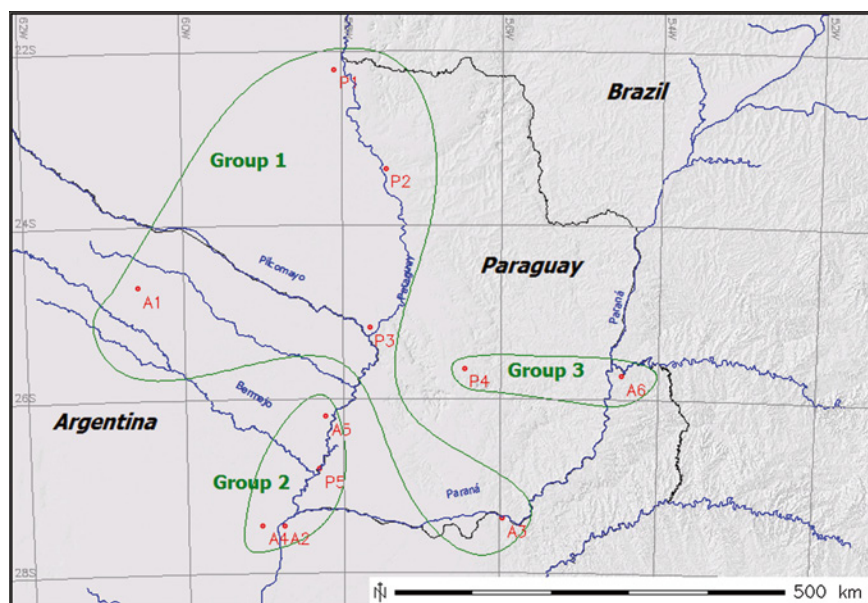


Fig. 3.1 Map of the study area. Location and grouping of the 11 rain gauges

Table 3.1 Name and location of the 11 rain gauges; mean annual rainfall (MAR); standard deviation of the annual rainfall (SDAR)

Sample code	Country	Location	Latitude	Longitude	MAR (mm)	SDAR (mm)
A1	Argentina	Las lomas	-60.58	-24.7	911	189
A2		Corrientes	-58.77	-27.45	1,436	341
A3		Posadas	-55.97	-27.37	1,758	361
A4		Resistencia	-59.05	-27.45	1,379	317
A5		Formosa	-58.23	-26.2	1,413	276
A6		Iguazu	-54.47	-25.73	1,843	276
P1	Paraguay	Pto. Casado	-58.09	-22.21	1,245	250
P2		Concepcion	-57.45	-23.35	1,356	268
P3		Asuncion	-57.66	-25.18	1,392	299
P4		Villarica	-56.46	-25.65	1,668	327
P5		Pilar	-58.31	-26.8	1,397	297

standards and normative. The data, which is subjected to quality control (QC) is processed in the climatology department of both meteorological services. Normally the quality control search for integrity of daily data and missing data. Another QC applied is the verification of the rainfall occurrence between near meteorological stations, which represent the coherence with the meteorological system that produce the rainfall. The information of both meteorological services is available for research and exchangeability between national intuitions.

The specific rainfall records utilized in this study are identified in Table 3.1 which includes, for each rain gauge, some statistical characteristics of the annual

Table 3.2 Mean monthly rainfall at the 11 rain gauges

Sample code	Mean monthly rainfall (mm)											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
A1	127	117	139	90	52	20	13	16	31	62	115	128
A2	171	152	163	180	88	61	43	49	75	141	167	146
A3	159	152	142	162	127	130	98	100	142	209	164	173
A4	169	154	166	174	81	57	37	44	69	128	159	140
A5	169	142	148	155	99	66	48	48	86	135	164	155
A6	169	142	148	155	99	66	48	48	86	135	164	155
P1	141	128	126	107	83	54	32	40	57	128	169	178
P2	159	139	133	127	120	59	40	44	71	127	176	161
P3	147	134	128	157	115	71	49	58	84	134	162	153
P4	174	139	148	160	142	114	72	89	115	178	180	157
P5	165	142	151	173	84	58	53	44	80	157	155	135

rainfall series—the mean (MAR) and the standard deviation (SDAR)—as well as its geographic coordinates. Table 3.2 shows the corresponding mean monthly rainfalls. The rain gauge of A1—Las lomas will be adopted along the text to exemplify some of the intermediate results. Due to space constraints, only the more relevant results from this study are summarized for the all rain gauges.

SPI and Drought Occurrences

The analysis of the temporal variability of droughts in the study region was assessed via the standardized precipitation index (SPI), one of the most popular and common drought indexes (Santos et al. 2010; Vicente-Serrano 2006).

The SPI, originally developed by McKee et al. (1993), remaps the rainfall records into a standardized probability distribution function so that an index of zero indicates the median rainfall amount, while a negative index stands for drought conditions and a positive one, for wet conditions, Santos et al. (2011). A comprehensive description of the calculation and of the advantages of the SPI index can be found in Edwards and McKee (1997), Guttman (1998, 1999), Hayes et al. (1999), Lloyd-Hughes and Saunders (2002) and Santos and Portela (2010).

As summarized by Santos et al. (2010), there are several advantages to the SPI, namely (1) its flexibility, as it can be applied at various time scales; (2) there is less complexity involved in its implementation, relative to other drought indices; (3) it is adaptable to other hydroclimatic variables besides precipitation, Santos et al. (2010); and (4) its suitability for spatial analysis, allowing comparison between sites in a given region as it is a normalized index.

Though originally the computation of the SPI index utilized a Gamma distribution function applied to the monthly rainfall series, for SPI1, and to cumulative rainfall series, for the other time scales (McKee et al. 1993), several authors tested different distributions based on different time scales and concluded that, compared

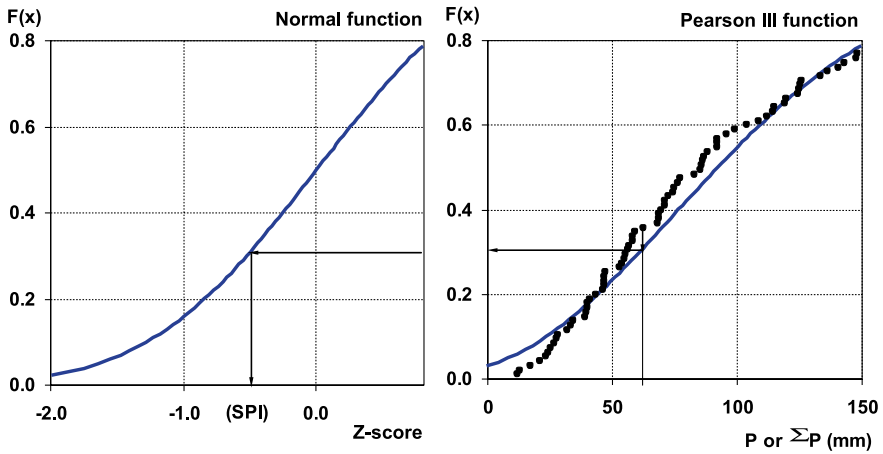


Fig. 3.2 Schematic representation of the SPI calculation procedure (reproduced from Santos et al. 2013)

with the Gama distribution, the Pearson type III distribution ensured the best fit due to its higher flexibility given by its three parameters (Guttman 1999; Ntale and Gan 2003; Vicente-Serrano 2006). The Pearson III probability distribution function is given by:

$$f(x) = \frac{1}{\alpha \Gamma(\beta)} \left(\frac{x - \gamma}{\alpha} \right)^{\beta-1} \exp \left(-\frac{x - \gamma}{\alpha} \right) \quad (3.1)$$

where γ , α , and β are the location, scale, and shape parameters, respectively. The parameters of the previous distribution should be estimated using the L-moments method.

The value of SPI assigned to each rainfall is the z-standard normal associated to the probability of non-exceedance of that rainfall, according to the Pearson type III distribution, as represented in Fig. 3.2.

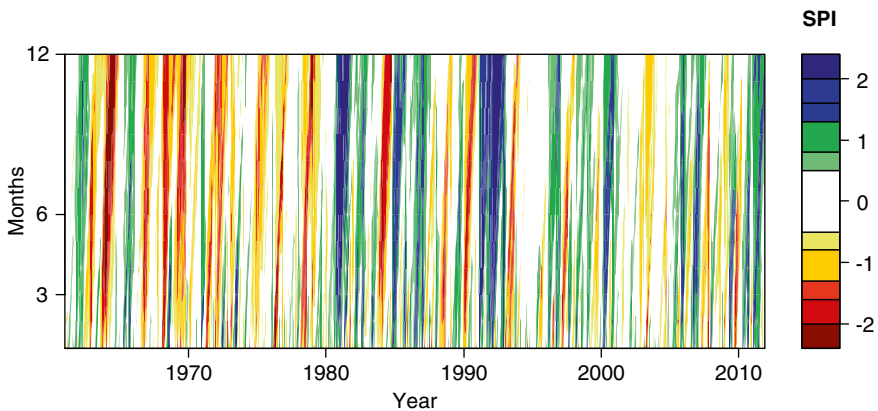
The relationship among the SPI values, the probabilities of non-exceedance and the drought categories are shown in Table 3.3.

The SPI calculated at 1 month, SPI1, is the normalized monthly rainfall and essentially conveys meteorological drought identification. At the 3–6-month time scales it may be taken as an agricultural drought index, and at 6–12-month time scales it constitutes a hydrological drought index, useful for monitoring surface water resources, as previously specified.

Figure 3.3, exemplifies how the evolution of the SPI index for increasing time scales can be synthetically represented. The figure (concept taken from <http://joewheatley.net/visualizing-drought/>), which illustrated the SPI at the time scales from 1 to 12 months at rain gauge A1—Las lomas, in Northern Argentina, clearly shows a pronounced recurrence of dry periods in the 1960s and 1970s

Table 3.3 Drought categories given by the SPI, after Agnew (2000)

Probability	SPI	Drought category
0.05	>1.65	Extremely wet
0.10	>1.28	Severely wet
0.20	>0.84	Moderately wet
0.60	>−0.84 and <0.84	Normal
0.20	<−0.84	Moderate drought
0.10	<−1.28	Severe drought
0.05	<−1.65	Extreme drought

**Fig. 3.3** SPI at rain gauge A1—Las lomas at several time scales

(yellow/brown colors especially marked in the higher time scales of SPI), followed by a wetter period (green/blue colors) in the 1980s and early 1990s. Figure 3.3 also shows that as the SPI time scale increases towards the 12 months the number of drought events decreases, because the droughts at longer time scales tend to be longer. Thus, the number of droughts of longer duration increased with longer SPI time scales.

To study the spatial and temporal variability of different types of droughts in Paraguay and in the Northeastern states of Argentina, the SPI was used at three time scales: 3 (SPI3), 6 (SPI6) and 12 (SPI12) months, mainly to be focused on agricultural and hydrological drought monitoring, in respect to two of the most important South American resources.

Figure 3.4, included in the next page, shows the time series of SPI3, SPI6, and SPI12 at rain gauge A1—Las lomas along with the threshold at -1.28 , which is used to identify severe droughts (see Table 3.3). The red tick marks along the time axis indicate the months with droughts. The figure clearly shows the higher occurrence of drought events in the first decades of the study period, as already suggested by Fig. 3.3 for the same rain gauge.

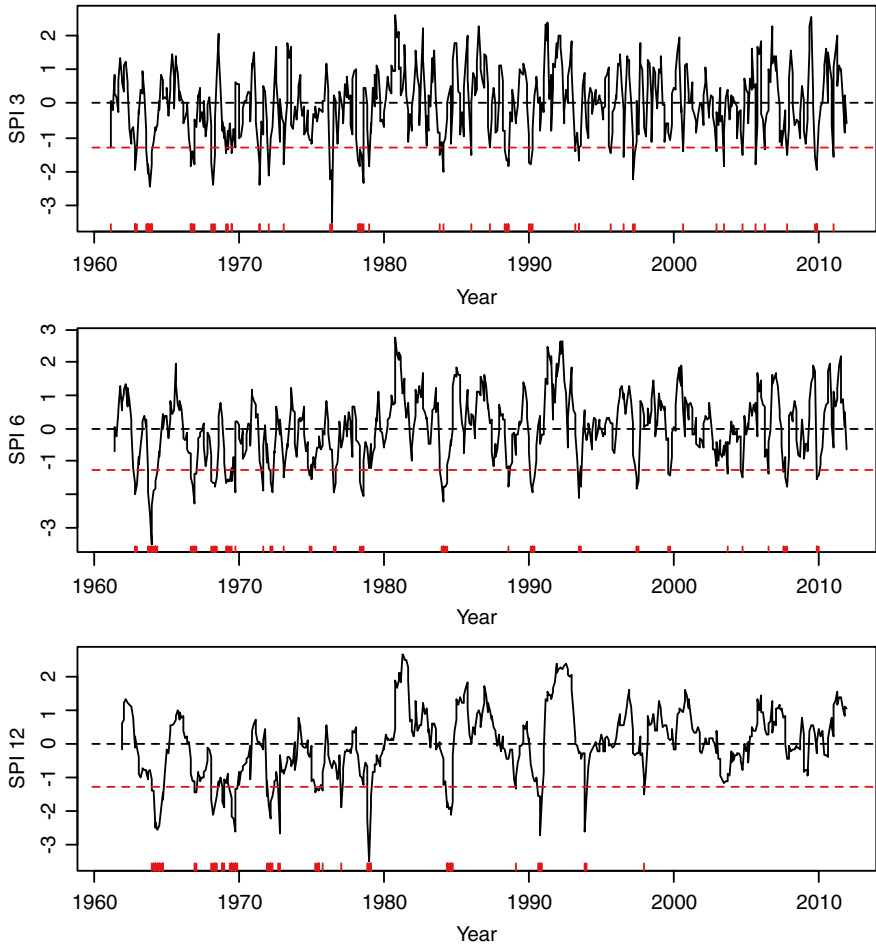


Fig. 3.4 SPI3 (*top*), SPI6 (*middle*) and SPI12 (*bottom*) at rain gauge A1—Las Lomitas (Northern Argentina). The *red tick marks* indicate the occurrence of droughts (attributed to the last month of the interval), as the SPI drops below -1.28

Temporal Variability of Droughts

Changes in Drought Occurrence Rate

Analysis of changes in temporal occurrence attempt to answer the question: regardless of the severity of the drought, that is to say, of the rainfall deficit, has the occurrence of droughts increased or decreased? Hence the analyzed variable is not related to the SPI themselves but to the temporal distribution of the occurrence of droughts.

To address the previous question, a kernel occurrence rate estimator, KORE (Mudelsee et al. 2003; Silva et al. 2012), may be applied to a historical series of

drought occurrences with the aim of estimating how the mean number of drought months per year, λ , changes over time, that is, to characterize $\lambda(t)$. This technique may be formulated as:

$$\hat{\lambda}(t) = h^{-1} \sum_{i=1}^m K \left(\frac{t - T_i}{h} \right) \quad (3.2)$$

where K is the kernel function and h is the bandwidth. The following Gaussian kernel was used (Mudelsee et al. 2004, 2006):

$$K(y) = \frac{1}{\sqrt{2\pi}} \exp \left(-\frac{y^2}{2} \right) \quad (3)$$

To reduce the boundary bias near the extremes of the time interval, pseudo data was generated outside of the observation interval, before estimating $\lambda(t)$. For that purpose a straightforward method of reflection was used to generate pseudo data, covering the amplitude of three times the bandwidth h before and after the limits of the time interval (Mudelsee et al. 2004). The bandwidth was obtained using Silverman's 'rule of thumb', Silverman (1986, p. 48). Its values range from 1.387 to 7.513 years.

Other authors, such as Girardin and Mudelsee (2008), have also used the Kernel estimator for studying the occurrence rate of extreme events, namely the fire years in Canadian boreal forests. The results obtained from their approach, and using the same Kernel approach used herein, suggested that by the horizon 2061–2100, the median number of large forest fires per year could increase by 39 % (ECHAM4 B2 scenario run) to 61 % (A2 scenario run) when compared with the 1901–1940 and 1781–1820 reference periods used in the study. The same results if considering the full 1999–2100 horizon.

Regarding the use of drought indices, Christie et al. (2011) finds for the Andes Cordillera, that severe and extreme drought events reveal unprecedented increments on the respective occurrence rates during the last century when compared with the previous six centuries. For that purpose the previous authors considered the Palmer Drought Severity Index (PDSI) to account with regional moisture and the same advanced statistical tool as in the present study, the Kernel estimation method, to analyze the occurrence rates of droughts.

Figure 3.5 summarizes the application of the KORE estimator to the SPI at rain gauge A2—Las Lomitas. The analysis focused on the occurrence of severe droughts, that is, the occurrence of SPI values lower than -1.28 . To account for the uncertainty of the KORE estimates, a point wise 90 % confidence band was constructed around $\lambda(t)$, by means of a bootstrap simulations (Cowling et al. 1996, Mudelsee 2011), according to the methodology described in Silva et al. (2012). The Kernel occurrence rate estimation method coupled with bootstrap confidence band construction was first introduced into the analysis of climate extremes, by Mudelsee et al. (2003); with detailed description given by Mudelsee et al. (2004).

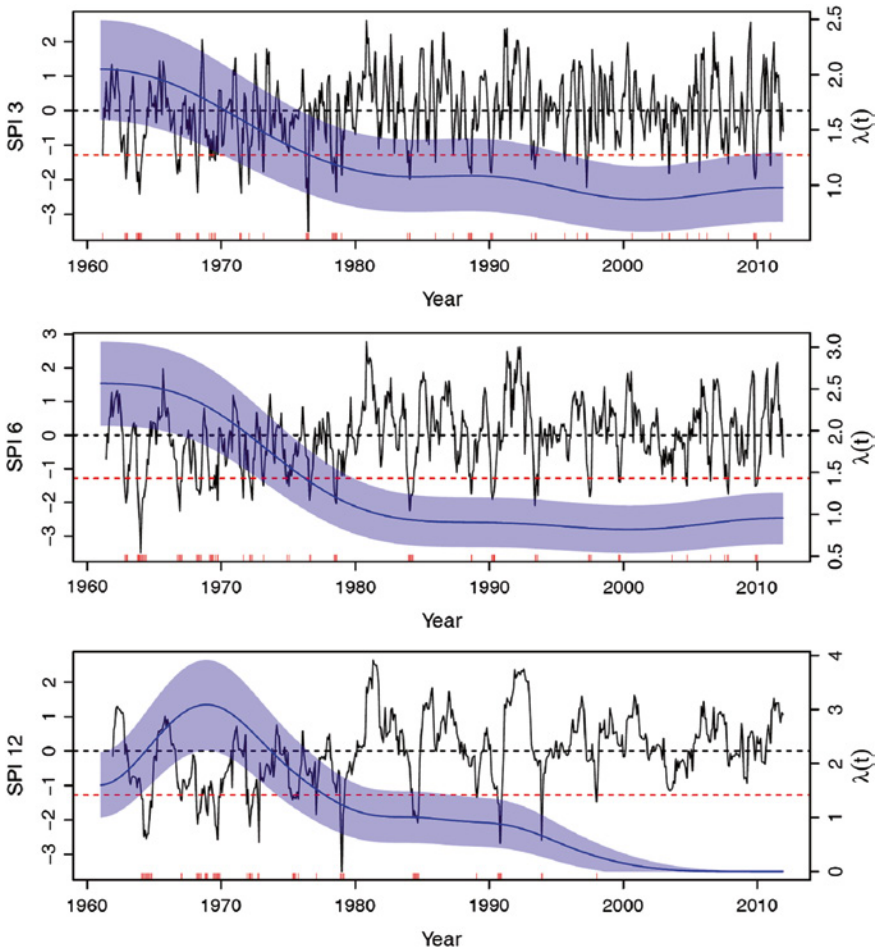


Fig. 3.5 SPI3, 6 and 12 at rain gauge A1—Las lomas (*left axis*); occurrence of droughts (*red tick marks* along the time axis), and time-dependent occurrence rate of droughts, $\lambda(t)$, and corresponding 90 % bootstrap confidence intervals

Figure 3.5 shows, that, for all the studied SPIs (3, 6 and 12) the occurrence rate of drought months in A1—Las lomas is lower in recent years than it was in the past. The width of the confidence bands attest to the significance of the changes in the observed occurrence rate.

Similar figures were obtained for all 11 historical monthly rainfall series but are not shown due to space constraints. Significant changes in occurrence rate of severe drought months were detected at all the studied sites. However, those changes were not homogeneous in space: in some samples there is a visible increase in the occurrence rates of the droughts towards the present, while other samples show a decrease in the same temporal direction.

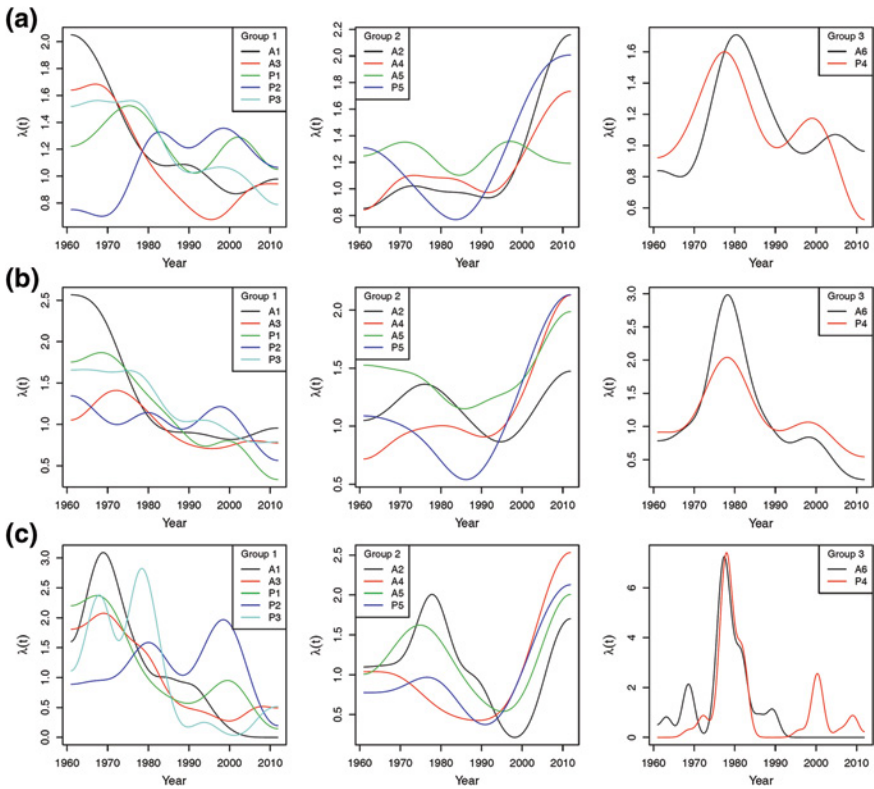


Fig. 3.6 Time-dependents occurrence rate of drought months at the 11 rain gauges, organized into the three groups of Fig. 3.1, according to the similarity of the exhibited frequency changes. Results at **a** 3, **b** 6 and **c** 12-months' time scales

By analyzing the previous results, three groups of rain gauges were identified where the temporal evolution of the KORE estimates behave similarly, at least for most of the time scales of SPI. Except for the rain gauge of A3—Posadas of group 1, the areas that encompass the rain gauges of the three groups do not overlap, and are spatially apart, as represented in Fig. 3.1.

Figure 3.6 shows the KORE estimates (without the bootstrap confidence bands) for all the studied samples, grouped by similarity in the behavior of the frequency changes over time.

The results of Fig. 3.6 show that, generally, the sites in group 1 have seen a recent decrease in the occurrence of severe drought months, while the sites belonging to group 2 have seen a recent increase in all of the studied time scales. The figure shows that the rain gauges of group 3 have verified a clustering of drought months at the end of the 1970s.

It should be mentioned that the behavior detected for group 1 is in agreement with the one reported by Barrucand et al. (2007) and Penalba and Vargas (2001) that find a reduction in the number of dry cases during the second half of the 20th century. In their study the drought index was calculated as the percentage of

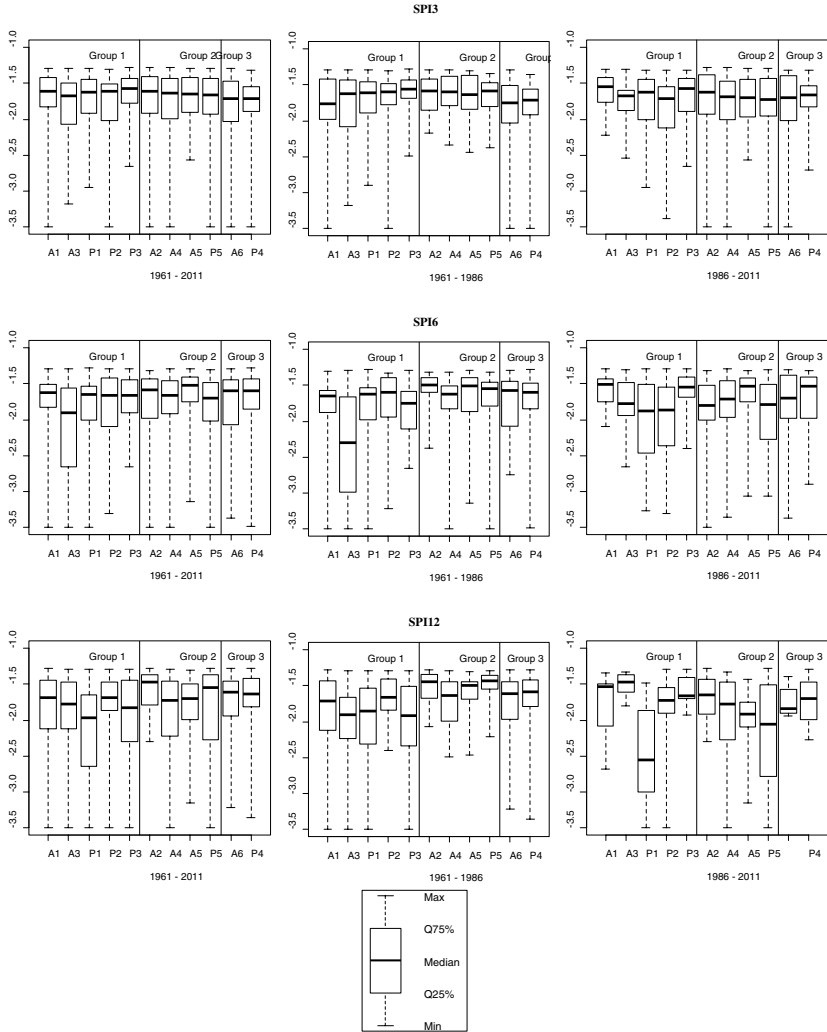


Fig. 3.7 Boxplots of the SPI of drought months ($SPI < -1.28$) at the 11 rain gauges over three time windows: the entire period (*left column*, 1961–2011); the first half (*center column*, 1961–1986); and the second half (*right column*, 1987–2011)

stations with rainfall lower than the median in a given region and dry months were determined as those with an index over 0.8

Changes in Drought Severity

Figure 3.7 shows the SPI below -1.28 threshold (severe drought, see Table 3.3) at different time-scales over three time windows: entire period (left column, 1961–2011); first half (center column, 1961–1986); second half (right column, 1987–2011). The three groups of rain gauges in each diagram are the same as in Fig. 3.6. The rain gauges are identified by the horizontal axes and values of SPI are represented in the vertical axes.

The previous figure clearly shows that, especially for the smallest time scale (SPI3 and SPI6), no significant changes (in terms of median values and of the variability of the SPI samples) are detected in the drought severity when comparing the results for the different time windows (entire period and first and second half of the entire periods). For the time scale of 12 months (SPI12) a slight increase in the variability of the phenomenon in the more recent period (1986–2011) may be noticed (greater distance between Q25 and Q75 %).

Conclusions

An exploratory approach aiming at analyzing the occurrence rates of the droughts in Northern Argentina and in Paraguay was carried out by applying a Kernel occurrence rate estimation method coupled with bootstrap confidence band construction. To identify the droughts events the standardized precipitation index (SPI) was applied to the monthly rainfall series at 11 rain gauges at different time scales (3, 6, and 12 consecutive months).

The results achieved, despite proving the suitability of the approach, did not reveal any trend towards an increase or a decrease either in the frequency of the droughts or in their severity, most probably due to the insufficient number of rainfall series that were analysed coupled with the relatively small length of the rainfall samples. Accordingly, the next step of the study should expand the procedure by applying it to more data, which will also allow a more detailed characterization of the droughts in the study area.

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