Interannual variability of seasonal rainfall in Cordoba, Argentina, evaluated from ENSO and ENSO Modoki signals and verified with MODIS NDVI data

Antonio C. de la Casa¹ · Gustavo G. Ovando¹ · Guillermo J. Díaz¹

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Abstract

El Niño–Southern Oscillation (ENSO) is an atmospheric and oceanic signal closely linked with the short-term (interannual) climate variability and, as part of the global atmospheric circulation, influences for several months the weather in different regions of the world. As a proxy of ENSO, the Southern Oscillation Index (SOI) has shown a moderate ability to predict rainfall behavior on the territory of Córdoba province, Argentina. Several studies last years have postulated for the existence of the El Niño Modoki, “a similar but different” type of El Niño, with an increasing interest in determining the characteristics of its evolution and the impact of associated teleconnections over the weather around the world. Moreover, spectral indicators such as the normalized difference vegetation index (NDVI) have also been used to monitor the ENSO cycle. The influence in a predictive way of both ENSO and ENSO Modoki over seasonal rainfall indicators: amount (PP), frequency (DPP) and maximum daily precipitation (PPmax), was analyzed during the period from 1960 to 2017 in Córdoba Province, Argentina. Complementarily, the ENSO influence on vegetation behavior was also assessed during the rainfall season by using NDVI data from MODIS-TERRA for the period 2000–2017 to verify the predictive potential of the climate signal. Before the beginning of the rainy season, the August and September SOI average (SOI_{as}) shows negative linear relationships with the rainfall attributes in almost all the territory of Córdoba that, although significant in statistical terms, are relatively weak. El Niño Modoki Index (EMI) used to represent the ENSO Modoki did not improve predictions on the rainfall behavior in Córdoba compared to SOI. Although the ENSO (SOI_{as}) explains a little portion of interannual variability on subsequent seasonal rainfall, just between 14 and 22% for the entire region, when ENSO phases’ fluctuations upon NDVI data were analyzed, a very similar scheme was established. It is important to realize these responses show a strong local dependence associated with the environment resources and agricultural scheme own of each place. These results validate the use of the ENSO as a warning signal to anticipate the productive risk of the region, particularly when the Neutral years are discarded.

Keywords Southern Oscillation Index · El Niño Modoki Index · Seasonal rainfall anomaly · Vegetation anomaly · Climate risk

Abbreviations

ENSO	El Niño–Southern Oscillation	DPP	Rainfall frequency or rainy days
SOI	Southern Oscillation Index	PPmax	Maximum daily precipitation
SOI _{as}	August and September SOI average	MODIS	Moderate-Resolution Imaging Spectroradiometer
NDVI	Normalized difference vegetation index	TERRA	Terra (EOS AM) satellite
PP	Rainfall amount	EMI	El Niño Modoki Index

✉ Antonio C. de la Casa, delacasa@agro.unc.edu.ar | ¹Facultad de Ciencias Agropecuarias, Universidad Nacional de Córdoba, Ing. Agr. Félix Aldo Marrone 746 – Ciudad Universitaria, 5000 Córdoba, Argentina.

NOA	North Atlantic Oscillation
SST	Sea surface temperature
SSTA	Sea surface temperature anomaly
MEI	Multivariate ENSO Index
ONI	Oceanic El Niño Index
PDO	Pacific Decadal Oscillation
NOI	North Oscillation Index
SMN	Servicio Meteorológico Nacional (República Argentina)
CI	Confidence interval
CI_l	Lower limit of CI
CI_u	Upper limit of CI
AX_{period}	Rainfall anomaly for a time period
AND_{period}	NDVI anomaly for a time period
T	The linear trend about time of a variable
MOD13Q1	MODIS-Terra product
MCV	Maximum composite value
BO	Córdoba Observatorio
PB	Pajas Blancas Aero
LB	Laboulaye Aero
MJ	Marcos Juárez Aero
PI	Pilar Observatorio
RC	Río Cuarto Aero
VM	Villa de María de Río Seco
VD	Villa Dolores Aero
DMI	Dipole Mode Index
IOD	Indian Ocean Dipole

1 Introduction

The atmospheric properties in each region of the world present a wide spectrum of variability including, from the ever-changing weather conditions, with a rapid transition over the course of hours and days, to the climate states evolution whose variation over time is analyzed considering either progressive trends [28, 70], periodic fluctuations [57, 61], or a climatic jump [33, 47]. In this sense, usually the rainfall time series variability is analyzed by decomposing on three timescales of short, medium and long term [26]. While the long-term variability refers to climate change, with a temporal dimension that must necessarily extend for several years, short-term variability happens from a few days to weeks, months and also including the interannual variability. In spite of the fact that it explains most of the rainfall variability, the predictive models usually assign the interannual variability a residual character [26]. Knowing the dynamics of rainfall fluctuations in a region is very important to anticipate the impact of environmental adversities and mitigate the major agricultural production climate risks, such as drought and water surplus [44].

Related to the long-term change, the climate of Córdoba Province between 1940 and 2010 presents a more humid condition today as a result of increased precipitation [20], which has a strong impact over agricultural potential of the region [19]. Also, time series of rainfall in the central region of Argentina present a medium-term modulation that has been assessed by using different methods. Lucero and Rozas [45] analyzed non-periodic fluctuations in the time series of rainfall using a wavelet function and determined that fluctuations with a time-scale of about 10 and 20 years construct the growing trend of annual rainfall of Córdoba. Following the nonlinear method of [13, 61] also shows that rainfall series in the central region of Argentina have a trend change or breaking points each 10–20 years. Furthermore, as rainfall has a direct impact on water resources of a territory, the central region of Argentina shows fluctuations both in excess and in deficiency of water with the same recurrence [16].

Among the short-term cycles reported frequently in climate studies, the quasi-biennial oscillation of equatorial stratospheric winds is one of the best known. Meanwhile, the interannual dynamics of the North Atlantic Oscillation (NOA) has also quasiperiodicities of approximately 2.2 years [46]. However, the climate fluctuation most studied at this timescale probably is El Niño–Southern Oscillation (ENSO), which is recognized as the principal large-scale climatic forcing of year-to-year precipitation variability in the Indo-Pacific region [44] and Australia [8, 64], among others. While the mechanism that determines the periodic behavior of the ENSO has no definitive explanation yet, it is an interaction phenomenon between the atmosphere and ocean and it strongly impacts short-term rainfall variability [9, 26]. The ENSO events have irregular intervals of about 2–7 years, and, as the phenomenon modifies the global atmospheric circulation, during several months the weather is affected in different regions of the world [10, 35, 39], although its impact is more noticeable in tropical regions [11].

The ENSO phenomenon with anomalies in the sea surface temperature (SST) and the associated variations of atmospheric pressure in the equatorial Pacific Ocean region, through the so-called atmospheric teleconnections [62], influence the weather conditions at seasonal scale in different regions of the world [52, 54], including Argentina [10, 55]. In Córdoba Province, the ENSO impact on rainfall produces equal or above normal values during the warm phase (El Niño) and the opposite effect during the cold phase (La Niña) which is directly associated with droughts occurrence of different duration and intensity. Indeed, negative rainfall anomalies in La Niña years explain a higher frequency of negative maize yield anomalies in the region of Córdoba [17]. With predictive purposes, various ENSO indicators such as the Multivariate ENSO Index

(MEI), the Southern Oscillation Index (SOI) and the Oceanic El Niño Index (ONI), as well as other climate indicators such as the Pacific Decadal Oscillation (PDO) and North Oscillation Index (NOI), have shown a moderate ability to predict the occurrence of rainfall in the warm semester at the territory of Córdoba Province [14]. In addition, the period between May and September is when these indicators are more linked to the occurrence of seasonal rain later [14].

Recently, two different types of El Niño events have been proposed [2, 34, 40, 63]. While El Niño is traditionally recognized as a warming of the sea surface in the eastern-to-central equatorial Pacific Ocean, the other El Niño event with the warming confined to the international dateline region can also occur. This type of El Niño has been called with different names: Central Pacific El Niño [34], dateline El Niño [40], or warm pool El Niño [38]. In this paper, the name El Niño Modoki was used, that means “something similar but different.” The global teleconnections of ENSO Modoki are also different from that of typical ENSO, and the evidence suggests they have been more frequent and persistent in the last decades [2]. They are opposite to one another, or weaker/stronger or asymmetric, depending on the region and the season of teleconnection [51]. Therefore, there is a growing interest to assess its influence on each particular territory.

While a thorough knowledge of rainfall variability is still far from being reached, the predictability of short-term component based on their relationship with atmospheric and oceanic state of the equatorial Pacific offers some concrete possibility to reduce the level of risk and uncertainty in agricultural production. As strategic information, this knowledge can be used to establish in advance the most appropriate agricultural or environmental management guidelines according to each likely climate scenario [24]. Also, climate indices like SOI, PDO, MEI, etc., are useful to develop models for rainfall forecasting, as Abbot and Marohasy [1] have shown for Queensland, Australia, by using artificial neural networks.

The normalized difference vegetation index (NDVI) is a spectral indicator widely used to represent the presence, vigor and productivity of vegetation in a region [48]. Its use in remote sensing has allowed to identify and quantify the different types of vegetation present in a territory [22, 25], classify the cropped areas with different species [6], as well as to assess the impact of drought in various regions of the world [30, 37] and Argentina [59]. As a proxy of vegetation, spectral indicators like NDVI have also been useful to monitor the ENSO cycle [23, 41, 43, 58, 66].

The interannual variability of the quantity, frequency and intensity of precipitation is closely linked to the dynamics of the ENSO phases in the central region of Argentina. After establishing the relationship between the ENSO and seasonal rainfall in advance, and considering the

major influence of water on the state and productivity of vegetation in a climate between subhumid and semiarid, the spectral data of NDVI have potential to confirm the effective range of the ENSO signal over this territory.

Even though the characteristic modes of ENSO influence over rainfall in the central region of Argentina are partially known, the particular objectives of this work were to validate the predictive capacity of this atmospheric–oceanic fluctuation in advance of rainfall start on more specific rainfall attributes, related not only to total quantity, but also to the frequency of events and their intensity. Then, looking for improving the predictive capacity of traditional ENSO over precipitation, the relationship between ENSO Modoki and rainfall variability was also explored, as well as the most opportune time of the year to establish a reliable predictor. As a proxy of vegetation, spectral NDVI data were also used to assess alternatively the effective range of the ENSO signal, to verify the predictive potential of this information from a more holistic perspective. In the Materials and Methods section, the data and their corresponding calculation are presented. This was structured into four parts: (1) rainfall indexes, (2) the Southern Oscillation Index (SOI), (3) the Enso Modoki Index (EMI), used to assess the state of ENSO, and finally (4) the normalized difference vegetation index (NDVI) to assess the condition of vegetation. Then, in the Results and Discussion section the following subjects are evaluated: (1) the ENSO and ENSO MODOKI influence on rainfall regime, (2) the ENSO influence on seasonal rainfall using SOI as a proxy and (3) the ENSO influence on vegetation using NDVI as a proxy.

2 Materials and methods

2.1 Rainfall data

The rainfall records analyzed in this study were obtained from the network of surface meteorological stations operated by the Servicio Meteorológico Nacional (SMN) in the province of Córdoba, Argentina. Figure 1 shows a map with the geographical location of these stations in the region.

The influence of both ENSO and ENSO Modoki on the rainfall regime of Córdoba was evaluated from daily rainfall data of the period 1960–2017 that were added, according to the seasonality of rainfall in the region, for the trimester October–November–December (indicated with the ond extension) and for all the warm semester from October to March (indicated by the ondjfm extension). In addition to the warm semester, cumulative rainfall values were also considered between October and April (Oct–Apr), October and May (Oct–May), November and April (Nov–Apr) and November and May (Nov–May), to assess more extensively

Fig. 1 Geographical location of the weather stations in the province of Córdoba, Argentina, whose meteorological data were used in this study: Córdoba Observatorio (BO); Laboulaye Aero (LB); Marcos Juárez Aero (MJ); Pilar Observatorio (PI); Río Cuarto Aero (RC); Villa de María de Río Seco (VM); and Villa Dolores Aero (VD)

the ENSO influence on rainfall and vegetation during the rainy season through the region.

The ENSO influence on the rainfall pattern over time was assessed by two time series: one between 1960 and 1999 ($n=40$) and the other from 2000 to 2017 ($n=18$). The latter also corresponds to the period with NDVI data used to verify the scope of the relationship between ENSO signal and rainfall. As the correlation for the entire 58-year period can be considered the reference value, those coefficients calculated for shorter periods were analyzed in terms of their membership with respect to the confidence interval of the long-term correlation ($p < 0.05$).

The confidence interval (CI) of correlation coefficient (r) was calculated through the $\dot{Z}$ value that was obtained with the following expression [56]:

$$\dot{Z} = \frac{1}{2} \ln \frac{(1+r)}{(1-r)} \quad (1)$$

Then, the lower limit of CI (CI_l) with a 95% of probability ($p < 0.05$) was obtained as:

$$CI_l = \text{TanH} \left(\dot{Z} - \frac{1.96}{\sqrt{n-3}} \right) \quad (2)$$

and the upper limit of CI (CI_u) as:

$$CI_u = \text{TanH} \left(\dot{Z} + \frac{1.96}{\sqrt{n-3}} \right) \quad (3)$$

Three attributes of the rainfall regime were assessed in this study: the amount or total cumulative value (PP), the frequency of events or rainy days (DPP) and the maximum value of daily rainfall during the period (PPmax) [15]. The latter one is an indicator that has been used as a substitute to explore the rainfall intensity [7, 21, 50].

The rainfall information of different localities was expressed in terms of the rainfall anomaly for the trimester or semester period (AX_{period}) that, due to the long-term trend for some attributes, was calculated each year as the difference between the trimester October–November–December (X_{ond}) or the semester October–November–December–January–February–March (X_{ondjfm}), and the linear trend for each rainfall variable with respect to time (T) from the initial to final year of the analyzed period, according to the following general expressions:

$$AX_{\text{ond}} = X_{\text{ond}} - T_{\text{ond}} \quad (4)$$

$$AX_{\text{ondjfm}} = X_{\text{ondjfm}} - T_{\text{ondjfm}} \quad (5)$$

where X is either the total rainfall (PP), rainy days (DPP) or the maximum daily rainfall (PPmax) during the period and T the linear trend about time.

2.2 ENSO status: Southern Oscillation Index (SOI)

The Southern Oscillation Index (SOI) was used here as a proxy to characterize the ENSO phenomenon [14, 17]. The SOI represents the variation of atmospheric pressure on two opposite sectors in the Tropical Pacific Ocean, according to the following expression [8]:

$$\text{SOI} = 10 \times \left[\frac{\text{AP}_{\text{Tahiti}} - \text{AP}_{\text{Darwin}}}{\text{DEdif}} \right] \quad (6)$$

where AP is the atmospheric pressure anomaly resulting from the difference between the monthly value and the long-term average (base period 1933–1992) at Tahiti and Darwin; DEdif is the standard deviation of the difference for the same base period. The SOI time series were obtained from the Australian Government—Bureau

of Meteorology [4]. Following the Australian Bureau of Meteorology, sustained negative values of the SOI below -8 indicate El Niño episode and positive values of the SOI above $+8$ are typical of a La Niña episode. SOI values between those limits are considered as Neutral cases.

Monthly SOI values were used as a rainfall predictor individually, and also they were aggregated from bimonthly, three-monthly, and so on to annual period (January and February, from January to March, from January to April, and so on). Then, discarding January SOI value, the process was repeated beginning from February. At last, the final integration was from September to December, to analyze the ENSO influence just before the rainy season begins in the study region.

To check for any change in the frequency of the ENSO phases during the period with radiometric information, the confidence intervals of El Niño, La Niña and Neutral status during the period of climatic character were calculated. The exact values of the bilateral, lower and upper confidence ends (π_l, π_u), which define the confidence interval (CI) of the relative frequency value (π),

$$\text{CI: } \pi_l \leq \pi \leq \pi_u \quad (7)$$

can be calculated using [56]:

$$\pi_l = \frac{x}{x + (n - x + 1)F} \quad \text{with} \quad F(df_1 = 2(n - x + 1), df_2 = 2x); \quad (8)$$

and

$$\pi_u = \frac{(x + 1)F}{n - x + (x + 1)F} \quad \text{with} \quad F(df_1 = 2(x + 1), df_2 = 2(n - x)) \quad (9)$$

where x represents the number of cases under the established condition, n is the size of the sample and F the value of the Fisher's distribution with the respective degrees of freedom (df).

2.3 ENSO Modoki status: ENSO Modoki Index (EMI)

To characterize and assess the ENSO Modoki phenomenon, [2] proposed the El Niño Modoki Index (EMI) based on the sea surface temperature anomaly (SSTA) in different regions of the Pacific Ocean. While conventional El Niño is characterized by strong anomalous warming in the eastern equatorial Pacific, El Niño Modoki is associated with strong anomalous warming in the central tropical Pacific and cooling in the eastern and western tropical Pacific [51]. This particular SSTA pattern is different from what happens during typical El Niño events. Because of the unique tripolar nature of the SSTA during El Niño Modoki, the index is defined as follows:

$$\text{EMI} = [\text{SSTA}]_A - 0.5x[\text{SSTA}]_B - 0.5x[\text{SSTA}]_C \quad (10)$$

where the brackets in Eq. (10) represent the area-averaged SSTA over each of the region A (165°E – 140°W , 10°S – 10°N), B (110°W – 70°W , 15°S – 5°N) and C (125°E – 145°E , 10°S – 20°N), respectively. Time series of EMI for this analysis were extracted from Japan Agency for Marine-Earth Science and Technology (Japan Agency for Marine-Earth Science and Technology [29]). Then, monthly EMI values were aggregated and analyzed exactly in the same way as SOI.

2.4 Normalized difference vegetation index (NDVI) data

Spectral vegetation indices have been developed to relate reflectance from leaves or canopies with vegetation characteristics and conditions [27]. The normalized difference vegetation index (NDVI) is the most frequently used vegetation index for developing vegetation cover estimation models [32]. The NDVI data were used as a proxy of vegetation in this study. Data of NDVI from MODIS-TERRA satellite, launched in 2000, with a 250 m spatial resolution, have both a good temporal coverage of 18 years by 2018 and an appropriate spatial detail.

The NDVI is a dimensionless index that expresses the presence and density of vegetation, calculated according to the following equation [27]:

$$\text{NDVI} = \frac{\rho_{\text{nir}} - \rho_r}{\rho_{\text{nir}} + \rho_r} \quad (11)$$

where ρ_r and ρ_{nir} are reflectance values corresponding to red and near-infrared wavelengths, respectively.

The product MOD13Q1 was used in this study, which is a composition of 16 days using the maximum composite value (MCV) algorithm. The spatial resolution is 250 m, and the images are radiometric and geometrically corrected, and available for the entire series of 16-day images from July 2000 until July 2018. Only 25 pixels of each site around the meteorological station were extracted to analyze. In each place, those pixels that presented a correlation less than 0.75 with respect to the rest of the set were discarded, looking for preserving the spatial homogeneity of the information.

The NDVI data for Córdoba city (BO) were extracted to the north of the city, next to the Pajas Blancas (PB) airport, to avoid the influence of the big city. The 16-day NDVI values were averaged on a monthly basis to make them compatible with SOI data. The series was then depurated by removing every datum that showed anomalous values according to the immediately precedent and subsequent NDVI data. Very few data had to be excluded. Finally, the anomaly of NDVI ($\text{AND}_{\text{period}}$) was expressed as the difference of NDVI and the linear trend, for both the trimester and for the semester and jfm, according to the following expressions:

$$\text{AND}_{\text{ond}} = \text{NDVI}_{\text{ond}} - T_{\text{ond}} \quad (12)$$

$$AND_{ondjfm} = NDVI_{ondjfm} - T_{ondjfm} \quad (13)$$

3 Results and discussion

3.1 ENSO and ENSO Modoki influence on the rainfall regime in Córdoba

Looking for a suitable indicator to predict the rainfall behavior from the ENSO signal, a necessary condition is that the relationship must hold a high, significant and stable correlation over time. However, other relevant aspects to consider are the timing of the signal relative to the onset of rains, their ability to describe the phenomenon in a comprehensive manner and the geographic scope that holds the relationship. For this purpose, Fig. 2 shows graphically the procedure used, looking for a suitable indicator to anticipate the rainfall characteristics at Córdoba Province. Moreover, as there is a growing recognition that there exist two different types of El Niño, it is likely that ENSO Modoki can provide greater capacity to explain rainfall variability in Córdoba, so the El Niño Modoki Index (EMI) was also used to explore its effects.

Given that the rainy season in the central region of Argentina is of a monsoonal type, with about 80% of the annual average rainfall recorded from October to March, Fig. 2 shows the correlation between SOI and the accumulated rainfall for the trimester from October to December, at the beginning of rainy season [12], and also for the full rainy semester. For this analysis, the SOI and EMI data were calculated for different periods: from each month individually to bimonthly sequences, three-monthly, etc., completing the annual period. The scanning was done in advance to the start of rains, first forward by adding the SOI or EMI information 1 month at a time, and then backward, discarding the posterior month while year progresses. Moreover, to capture the occurrence of the phenomenon in a comprehensive manner for all rainfall indicators, only those correlation values of a significant nature are presented for each lapse and place.

Although Villa Dolores (VD) shows less evidence of association with SOI in Fig. 2, it shares some similar features of precipitation regime with the rest of sites in Córdoba. Because the rainy season starts toward the end of the year in VD, it is likely that the October and November information will not be particularly useful there [12]. The SOI signal for places in eastern and central Córdoba more humid areas shows a consistent and widespread association, particularly for the total amount of rainfall and the frequency of events. The relationship is negative

in character, but its intensity is moderate only, since for any variable and analyzed lapse the correlation reaches an upper limit of -0.54 (for APPmax_{ond} in RC). Although the correlation coefficients are quite low, they are not very different from those [60] obtained when predicting the monsoon rains in India using more complex neural network models.

Assessing the temporal change of the correlation between the SOI of each particular month with the following seasonal precipitation, signal intensity increases as the rainy period approaches, reaching maximum values from August to October, depending on the site [14]. Considering monthly correlation values for APP_{ondjfm} only, the maximum in Marcos Juárez (MJ), Villa de María Río Seco (VM) and Pilar (PI) occurs in August, in Córdoba (BO), Río Cuarto (RC) and Villa Dolores (VD) is over September and for Laboulaye (LB) it happens in October.

With predictive purposes, it is interesting that after October the correlation for November and December tends to be equal to or less than for the previous months, so that their inclusion does not contribute effectively to improve the prediction. This behavior is most noticeable by considering the chromatic representation of Fig. 2. For all rainfall indexes, the signal intensity increases as the first months of the year are discarded and, on the other hand, November and December SOI data do not increase the correlation. Thereby, the inclusion of this information is not useful for the purpose of constructing a potential predictor. This temporal dependence about SOI is especially valuable for developing more accurate rainfall forecast models [1].

While the correlation between monthly SOI and EMI data for the whole period from January 1960 to December 2017 reaches a value of -0.452 (data not shown), showing some dependence inverse between both indices, when the analysis was repeated using EMI data instead of SOI, the ENSO Modoki signal did not improve the predictive capacity over rainfall behavior during the subsequent rainy season, as Table 1 shows. Not only the coefficients of correlation are equal or lower than those of SOI for almost all rainfall attributes, but in VD the relationships between EMI and precipitation have been completely missing. Also, rainfall intensity in LB shows a negative correlation, instead of positive as is expected for EMI in this region. The highest frequency and persistence of the El Niño Modoki signal in recent years [36, 71] have not influenced rainfall over the study region in a particular way, as Table 1 shows when the different periods are compared. For this reason, the information about the relationship between EMI and rainfall is not included onwards.

As shown in Fig. 2, although there are other alternatives to combine the SOI values that could marginally improve the signal somewhere and for some precipitation

Fig. 2 Heat map representing color-coded levels of correlation coefficient between average of Southern Oscillation Index (SOI) ranging at different starting (in abscissa) and ending month (lag in ordinate), and the anomalies of total rainfall (PP), rainy days (DPP) and daily maximum precipitation (PPmax) for the trimester

October–November–December (ond) and the semester October–November–December–January–February–March (ondjfm) during the period 1960–2017 in Córdoba, Argentina. Only the r statistically significant ($p < 0.05$) is shown

Table 1 Correlation coefficients between Southern Oscillation Index (SOI) (above) and El Niño Modoki Index (EMI) (below) of August–September (left) and July–August–September (right) with anomalies of total amount (APP), rainy days (ADPP) and maximum

daily rainfall (APPmax) of October–November–December (ond) and semester October–November–December–January–February–March (ondjfm) for different periods in Córdoba, Argentina

Period		APP		ADPP		APPmax		APP		ADPP		APPmax	
		ond	ondjfm	ond	ondjfm	ond	ondjfm	ond	ondjfm	ond	ondjfm	ond	ondjfm
SOI _{as}													
BO	1960–1999	-0.249	-0.278	-0.337	-0.288	-0.264	-0.231	-0.240	-0.261	-0.314	-0.260	-0.249	-0.214
	2000–2017	-0.262	-0.638	-0.182	-0.552	-0.029	-0.358	-0.240	-0.629	-0.216	-0.597	0.016	-0.316
	1960–2017	-0.251	-0.374	-0.301	-0.338	-0.174	-0.272	-0.242	-0.359	-0.294	-0.327	-0.151	-0.245
LB	1960–1999	-0.521	-0.383	-0.355	-0.333	-0.147	0.100	-0.508	-0.408	-0.304	-0.301	-0.173	0.097
	2000–2017	-0.182	-0.386	-0.213	-0.450	0.209	0.357	-0.221	-0.385	-0.308	-0.512	0.217	0.401
	1960–2017	-0.398	-0.377	-0.310	-0.369	-0.006	0.153	-0.406	-0.394	-0.306	-0.369	-0.021	0.156
MJ	1960–1999	-0.459	-0.486	-0.305	-0.339	-0.275	-0.171	-0.433	-0.473	-0.270	-0.318	-0.278	-0.160
	2000–2017	-0.340	-0.370	0.068	-0.233	-0.062	-0.256	-0.351	-0.399	-0.020	-0.312	-0.001	-0.223
	1960–2017	-0.428	-0.453	-0.204	-0.302	-0.214	-0.192	-0.414	-0.452	-0.206	-0.314	-0.201	-0.174
PI	1960–1999	-0.272	-0.465	-0.236	-0.377	-0.179	-0.183	-0.233	-0.437	-0.171	-0.309	-0.148	-0.102
	2000–2017	-0.385	-0.365	-0.469	-0.525	-0.408	-0.472	-0.362	-0.388	-0.524	-0.582	-0.367	-0.435
	1960–2017	-0.301	-0.435	-0.294	-0.421	-0.239	-0.236	-0.268	-0.423	-0.258	-0.394	-0.204	-0.166
RC	1960–1999	-0.537	-0.522	-0.181	-0.226	-0.650	-0.356	-0.512	-0.508	-0.153	-0.186	-0.654	-0.372
	2000–2017	-0.322	-0.293	-0.357	-0.462	-0.236	0.137	-0.301	-0.292	-0.373	-0.453	-0.214	0.072
	1960–2017	-0.483	-0.447	-0.228	-0.305	-0.539	-0.206	-0.463	-0.441	-0.211	-0.273	-0.544	-0.243
VD	1960–1999	-0.121	-0.246	0.021	-0.031	-0.101	-0.219	-0.122	-0.239	0.003	-0.031	-0.104	-0.240
	2000–2017	0.001	-0.357	-0.067	-0.208	-0.115	-0.160	-0.048	-0.422	-0.115	-0.209	-0.173	-0.169
	1960–2017	-0.089	-0.278	-0.008	-0.092	-0.105	-0.205	-0.105	-0.291	-0.034	-0.091	-0.121	-0.225
VM	1960–1999	-0.564	-0.447	-0.339	-0.332	-0.228	-0.264	-0.537	-0.437	-0.293	-0.316	-0.242	-0.268
	2000–2017	-0.290	-0.350	-0.352	-0.321	0.063	-0.153	-0.353	-0.409	-0.458	-0.432	0.093	-0.196
	1960–2017	-0.496	-0.415	-0.341	-0.328	-0.153	-0.233	-0.494	-0.426	-0.331	-0.347	-0.158	-0.247
EMI _{as}													
BO	1960–1999	0.137	0.056	0.225	-0.121	0.068	0.035	0.117	0.014	0.211	-0.166	0.049	0.012
	2000–2017	0.302	0.352	0.089	0.367	0.200	0.094	0.273	0.329	0.095	0.369	0.213	0.094
	1960–2017	0.156	0.113	0.183	-0.049	0.100	0.052	0.137	0.075	0.179	-0.085	0.091	0.036
LB	1960–1999	0.177	-0.175	0.031	-0.065	0.234	-0.394	0.137	-0.232	0.017	-0.095	0.242	-0.411
	2000–2017	0.056	0.151	0.206	0.376	-0.417	-0.551	0.025	0.159	0.162	0.354	-0.400	-0.514
	1960–2017	0.124	-0.085	0.069	0.063	0.001	-0.433	0.092	-0.121	0.047	0.032	0.021	-0.435
MJ	1960–1999	0.426	0.208	0.231	-0.072	0.317	-0.222	0.385	0.149	0.236	-0.106	0.282	-0.264
	2000–2017	0.238	0.186	0.049	0.345	0.121	0.253	0.195	0.151	0.070	0.343	0.168	0.236
	1960–2017	0.371	0.202	0.172	0.042	0.264	-0.116	0.335	0.149	0.186	0.014	0.251	-0.159
PI	1960–1999	0.115	0.048	0.172	-0.074	0.028	-0.030	0.086	0.011	0.170	-0.104	0.013	-0.055
	2000–2017	0.310	0.324	0.247	0.372	0.262	0.535	0.300	0.317	0.223	0.384	0.260	0.516
	1960–2017	0.146	0.111	0.176	0.041	0.080	0.052	0.123	0.080	0.172	0.021	0.065	0.027
RC	1960–1999	0.282	0.142	0.161	-0.006	0.480	0.185	0.257	0.093	0.161	-0.040	0.449	0.137
	2000–2017	0.183	0.169	0.135	0.153	0.177	-0.148	0.158	0.157	0.102	0.127	0.135	-0.161
	1960–2017	0.247	0.137	0.154	0.044	0.384	0.078	0.227	0.101	0.147	0.011	0.361	0.048
VD	1960–1999	-0.053	-0.096	-0.007	-0.090	0.134	-0.092	-0.078	-0.114	-0.009	-0.111	0.098	-0.099
	2000–2017	-0.216	0.105	-0.183	-0.125	-0.095	0.157	-0.212	0.122	-0.154	-0.115	-0.124	0.162
	1960–2017	-0.098	-0.055	-0.056	-0.104	0.081	-0.048	-0.113	-0.065	-0.048	-0.113	0.050	-0.054
VM	1960–1999	0.320	0.062	-0.015	-0.174	0.273	0.172	0.284	0.013	-0.055	-0.220	0.276	0.140
	2000–2017	0.231	0.303	0.260	0.260	-0.155	0.141	0.229	0.326	0.297	0.291	-0.153	0.169
	1960–2017	0.293	0.124	0.030	-0.084	0.176	0.166	0.267	0.093	0.005	-0.114	0.184	0.148

References: In red, bold and cursive the coefficients with statistical significance ($p < 0.05$); in green the coefficients are inside the confidence interval; in blue and orange the coefficients are outside the confidence interval

features in particular, a good predictor for all region can be set from the SOI values of July, August and September, looking for to anticipate the behavior of rainfall in the immediate subsequent season. The October information, which is also potentially valid, belongs to a period where rainfall is part of the estimate, and, as such, it is

not considered appropriate to be included. Thus, the two indicators analyzed to predict the behavior of rain immediately subsequent are the SOI average for the trimester July–August–September and for the period of August–September. For comparative purposes, Table 1 shows the correlation between these ENSO signals with

the different properties of rainfall regime evaluated, and it is included also those coefficients obtained from the ENSO Modoki signal to verify its worse performance.

Similarly, Chan et al. [5] showed that when the Indian Ocean Dipole (IOD) reaches its peak phase, the regional rainfall anomalies increase over subtropical La Plata Basin while they decrease over central Brazil, in austral spring. Also, they found that the associated low-level anomalous anticyclone next to the coast of Brazil increased the moisture flux and gives rise to the anomalously high precipitation over Uruguay and northern Argentina.

Table 1 displays the indifference of the SOI contribution in July for a predictive purpose. As was to be expected due to the high correlation between the two indicators ($r=0.979$), no main differences are detected between them and, for that reason, only the August and September SOI average (SOI_{as}) data are analyzed later on because of its greater simplicity and proximity to the start of the rainy cycle.

Except in some isolated cases, the ENSO signal affects inversely all those features used to represent the rainfall regime: quantity, frequency and intensity. Moreover, ENSO is also useful as a proxy to estimate the behavior of precipitation in the region of both the initial trimester of rainfall and the whole semester. Villafuerte et al. [67] also found that interannual variations in extreme precipitation indices are influenced greatly by the ENSO over Philippines. Thus, it is possible to project this information to describe every year the behavior of precipitation before the start of the rainy season in the region, which is suitable to both support the decision of seeding and anticipate the rainfall characteristics during summer crop season.

Also, SOI_{as} presents a relatively stable behavior along time. According to Table 1, the signal intensity shows only little variations in the different periods considered. If the coefficient of correlation for the whole period 1960–2017 is considered as the climatic long-term behavior, then a confidence interval can be established. For most meteorological stations and rainfall attributes analyzed, the coefficients corresponding to the shorter periods (1960–1999 and 2000–2017) present values that are included in the respective confidence intervals, which suggests that the relationship has maintained some temporal stability. This result is of particular interest when the SOI–PP relationship is evaluated in the most recent period that includes the spectral information since, in spite of its small extension, it looks appropriate to represent the climatic behavior.

Contrary to [51], who found that the ENSO Modoki events significantly, and distinctly, affect seasonal rainfall in Africa, EMI does not show a superior predictive capacity than SOI in Córdoba territory. With correlations equal to or lesser than the SOI produced for each site and period,

these results confirm that the ENSO Modoki signal does not improve the ENSO traditional signal to predict rainfall behavior in Córdoba.

3.2 ENSO influence on the rainfall regime in Córdoba using SOI as proxy

Having identified a reliable and appropriate predictor of the subsequent seasonal rainfall, the specific predictive capacity of this signal is now assessed using a linear regression analysis to establish how much interannual variability is able to explain. Figure 3 presents scatter plots between the average SOI of August and September immediately before the start of the rainy season and the amount of rain, the frequency of events and the maximum daily amount for the trimester (October–November–December) and semester (from October to March) subsequent in Córdoba, Argentina.

While dispersion is important, as indicated by the relatively low determination coefficients, negative linear relationships are established and geographically widespread throughout the territory. Except in VD, discarded for lack of statistical significance, and in LB when maximum daily rainfall is evaluated, this scheme is repeated throughout the region and for different features of rainfall. This scheme about the rainfall and SOI relationships is just contrary to the Indo-Pacific region [44, 67].

Making a comprehensive interpretation of all this information, when the intensity of ENSO signal increases (decreases) during La Niña (El Niño) events, it is likely that the rainfall anomaly in the trimester and semester subsequent takes progressively more negative (positive) values. Also, if only positive values of SOI during the cold phase are considered, we can expect that the decline in rainfall in the central region of Argentina would possibly be accompanied by a decrease in the frequency of cases, extending the periods between soil water recharge, as well as by a decrease in the intensity of the events, which may result in an incomplete refill of soil water content, all of which constitutes a negative combination that tends to aggravate an emerging drought condition. As was indicated by Rivera and Penalba [53], the ENSO information is useful for a seasonal rainfall prediction in South America and can be applied particularly to forecast droughts under La Niña conditions.

An easy way to implement alternatives to reduce the estimation error is to classify the SOI-averaged August–September (SOI_{as}) in the three particular categories of the events: El Niño ($SOI_{as} < -8$), La Niña ($SOI_{as} > 8$) and Neutral. This procedure produces results similar to those obtained using the monthly SOI values of the entire year for the categorization of the ENSO phases (Table 2). As shown in Fig. 4, although the statistical evaluation of Villa

Fig. 3 **a** Scatter plot between Southern Oscillation Index of August–September (SOI_{as}) and the anomaly of rain for trimester October–November–December (APP_{ondr} , green triangles) and semester October–November–December–January–February–March (APP_{ondjfm} , black cross) subsequent in Córdoba since 1960–2017. $R^2 > 0.067$ is significant ($p < 0.05$). **b** Scatter plot between Southern Oscillation Index of August–September (SOI_{as}) and the anomaly of rainy days for trimester October–November–December ($ADPP_{ondr}$, green triangles) and semester October–November–December–January–February–March ($ADPP_{ondjfm}$, black cross) subsequent in Córdoba since 1960 to 2017. $R^2 > 0.067$ is significant ($p < 0.05$). **c** Scatter plot between Southern Oscillation Index of August–September (SOI_{as}) and the anomaly of maximum daily rainfall for trimester October–November–December ($APPmax_{ondr}$, green triangles) and semester October–November–December–January–February–March ($APPmax_{ondjfm}$, black cross) subsequent in Córdoba since 1960 to 2017. $R^2 > 0.067$ is significant ($p < 0.05$)

Dolores is not significant ($p < 0.05$), the determination coefficients of the linear relations between the SOI and precipitation increase systematically and almost duplicate when Neutral years are excluded. Concurrently, as the extraction of 57% of Neutral cases increases only slightly the slope, the linear relationship can be considered as stable because this filtering does not change its inclination. A higher predictive accuracy in terms of determination coefficient increase is repeated for the frequency of rainfall, though the R^2 values are mostly lower in this case.

3.3 ENSO influence on vegetation using NDVI as proxy

3.3.1 ENSO phases' frequency in the analyzed period

The NDVI MODIS information from the TERRA satellite, with data available from 2000, was analyzed until 2018. Despite this short period of data availability, the results represent satisfactorily the long-term correlation between rainfall and ENSO (Table 1). In the same way, since frequency of ENSO events in the period 1960–2017 allows to calculate its respective confidence intervals, it was established that the relative frequency values of the El Niño, La Niña and Neutral states for the most recent interval 2000–2017 are within the confidence interval of the expected long-term behavior. Table 2 presents the relative frequency results obtained, where in addition to the classification obtained for the different phases using SOI_{as} as the index, the status of the phenomenon for the all calendar year was also considered, using the modal value of the 12 months classified according to each of the three ENSO categories as a criterion.

The results obtained from SOI_{as} , both in the long-term (58 years) and for the shorter and most recent period (18 years), are included inside the frequency interval of the annual classification in the period between 1960 and 2017. In addition, when using SOI_{as} a tendency is observed

to increase the identification of El Niño and La Niña cases, to the detriment of the Neutral years. This confirms that the frequency values of El Niño, La Niña and Neutral events in the period with radiometric information not only are very similar to those of climatic character, but they are also within the confidence interval of the long-term relative frequency.

3.3.2 Relationship between seasonal rainfall and NDVI

Modulated by ENSO, atmospheric conditions influence the rainfall regime in Córdoba so that, when El Niño (La Niña) phase is presented, it is more likely an increase (decrease) in the amount of rainfall, the number of events and also their intensity. This periodic disturbance to a wetter or drier weather condition must necessarily have an impact on vegetation, whose status and dynamics can now be characterized from spectral indicators like NDVI [3, 23, 30]. Therefore, the NDVI variation configures evidence to verify the predictive capacity of the atmospheric and oceanic signal of ENSO from a more holistic perspective [41, 49].

As was established by [72], ENSO is globally the leading climatic driver of interannual variability of NDVI during the vegetation growing season, especially over southern and eastern Africa, eastern Australia, northeastern Asia and northern South America. However, although rainfall is closely linked to the vegetation growth, other environmental and productive factors can also modify the NDVI expression locally [42, 65]. In order to evaluate this hypothesis, first a correlation and regression analysis between the PP and NDVI values during the warm semester is performed as shown in Fig. 5. Moreover, the seasonal analysis was extended so that accumulated rainfall and NDVI are also considered from October to April, October to May, November to March, November to April and November to May. Likewise, due to the delay that vegetation growth experiences with respect to rainfall occurrence, the seasonal analysis was carried out by lagging the NDVI accumulation in relation to the rainfall record [31, 68]. Thus, the relationship between the PP and the NDVI was analyzed considering exactly the same time period (i) for both variables, with a delay of the NDVI of 1 month ($i + 1$) and for a delay of the NDVI of 2 months ($i + 2$) with respect to the rainfall record (i).

Figure 5a shows the relationship between the accumulated values of PP and NDVI during the warm semester, for NDVI values delayed by 1 month with respect to rainfall. The seasonal rainfall influence on the accumulated NDVI value was analyzed by a linear model, whose coefficients were obtained empirically by correlation and regression, both considering the complete set of information to represent regional behavior, and for each place in particular.

Table 2 Relative frequency of events classified as La Niña, Neutral and El Niño using the SOI index for all calendar year (SOI_{year}) and for August–September (SOI_{as}), with the confidence interval superior (CIs) and inferior (Cli) and the respective F values of CIs (F_s) and Cli (F_i) for the period 1960–2017

		1960–2017		2000–2017	
		SOI_{year}	SOI_{as}	SOI_{year}	SOI_{as}
<i>La Niña</i>					
F_s	1.820				
F_i	2.172				
CIs	0.29	0.17	0.19	0.17	0.17
Cli	0.09				
<i>Neutral</i>					
F_s	1.767				
F_i	1.678				
CIs	0.78	0.66	0.57	0.78	0.61
Cli	0.52				
<i>El Niño</i>					
F_s	1.820				
F_i	2.172				
CIs	0.29	0.17	0.24	0.06	0.22
Cli	0.09				

In addition, to take into account long-term changes in the variables, both rainfall and NDVI values were expressed as an anomaly with respect to the linear trend, as Fig. 5b shows. The assessment of the relationship between the anomaly of both rainfall and NDVI for other seasonal periods and the delay effect is presented in Table 3.

As Fig. 5a shows, dispersion is large for the region as a whole, with a coefficient of determination (R^2) that, although very significant in statistical terms ($p < 0.001$), is relatively low (between 0.06 and 0.18), depending on the seasonal period and delay considered. However, an increase in seasonal rainfall has a positive effect on vegetation growth in the region as expected. When the linear relationship is established for values corrected by the trend in Fig. 5b, while the result of about 0.16 for the warm semester with 1-month lag in NDVI is very close to the value obtained for the variables without trend, for the other periods the R^2 in general is higher (between 0.11 and 0.28), validating the time trend influence over these variables.

Furthermore, when these variables were fitted by a polynomial of second degree, the t values for the first- and second-degree terms are statistically significant and the R^2 results slightly higher also, which point out a certain nonlinear character of the relationship, with a tendency of the NDVI to decrease above a maximum rainfall record or, at least, not increasing. Using geographically weighted regression, [65] determined for Northern Nigeria that the relationship between NDVI and rainfall is clearly not linear.

The saturation behavior that NDVI signal presents in these relatively more humid environments was pointed out also by [49] for Africa, noting that the vegetation response to climate is complex and not completely known. Meanwhile, drought events that are represented by negative rainfall anomalies are translated into a progressive decline of biomass production (NDVI).

This general behavior has nuances and differences when each place is analyzed separately. This is difficult not only because of the climatic/environmental condition of each site, but also because of aspects linked to the particular agricultural management, from double cropped more intensively areas to sectors covered by natural vegetation or fallow. These contrasts are useful, however, to discriminate between different agricultural uses and land cover through the analysis of time series of NDVI [18, 69].

As shown in Fig. 5b, while PB, PI, VD and LB present linear relationships statistically significant ($p < 0.05$), with R^2 higher than for all the regions, in MJ, RC and VM, for its part, the relationship cannot sustain formally. Just to emphasize some aspects of interest, while the seasonal rainfall at PB is within the regional range values (between 400 and 1100 mm), the radiometric information is notably lower than for the other sites. The land surrounding Córdoba airport (PB) is not cultivated so that the predominant vegetation (shrub and pasture) have NDVI values below those of cropped areas. In addition, the absence of agricultural activity confers to these radiometric data a character more directly linked to rainfall, reaching a R^2 significantly higher than the regional value and a statistically significant relationship in this area.

To the east of the region, the highest water availability throughout the year in MJ, even with the addition of water from underground layer, can explain the NDVI's independent behavior with respect to the warm season rainfall. Likewise, NDVI data of MJ in Fig. 5a reach the highest values in the region, indicating here the major productive capacity. On the other hand, VD is located in a relatively more arid sector to the west of the region, so that, with a lower rainfall range (between 400 and 800 mm) and for a higher water atmospheric demand, vegetation shows more strong response to rainfall occurrence. The linear relationship is statistically significant for VD and has the highest angular coefficient, indicating that each mm of rainfall produces a greater NDVI increase.

3.3.3 Relationship between seasonal NDVI and SOI

The period with radiometric information analyzed between 2000 and 2017 not only preserves a correlation structure for the response of rainfall to ENSO which is similar to the long term, but also convincingly reproduces the

Fig. 4 Linear slope (**b**) and the coefficient of determination (R^2) for the relationship between the SOI of August–September and total rainfall (above) and rainy days (below) for the trimester October–

November–December and the warm semester in different sites of Córdoba, Argentina

relative frequency of the different ENSO phases that the phenomenon presents on a climatic scale. According to the linear relationships in Fig. 6 for the periods from October to March and from November to April, a configuration similar to the relationship between seasonal rainfall and

ENSO is observed, with positive anomalies of NDVI during the El Niño events and negative ones during the opposite phase. This description is sustained in particular when the analysis involves the information as a whole (without discriminating between sites), although the R^2 is low and

Fig. 5 **a** Scatter plot between accumulated values of rainfall between October and March and the NDVI with 1-month ($i+1$) lag (from November to April) for the different sites in the period 2000–2017. In each place and for the entire region, the points were

adjusted to straight lines whose regression and determination coefficients are presented also. **b** As above but for the anomaly of rainfall and NDVI [** statistically significant ($p < 0.05$)]

Table 3 Coefficients of regression (a: intercept; b: slope) and determination (R^2) for the linear relationship between seasonal rainfall anomaly and accumulated NDVI anomaly for different periods (i),and with 1-month ($i+1$) and 2-month ($i+2$) lag, for each site and the entire region. Also Fisher's F statistic and its probability level

Region	Oct–Mar			Oct–Abr			Oct–May			Nov–Abr			Nov–May		
	i	$i+1$	$i+2$	i	$i+1$	$i+2$	i	$i+1$	$i+2$	i	$i+1$	$i+2$	i	$i+1$	$i+2$
Region															
b	0.0005	0.0005	0.0005	0.0005	0.0006	0.0006	0.0006	0.0007	0.0008	0.0006	0.0006	0.0006	0.0007	0.0008	0.0009
R^2	0.113	0.167	0.112	0.135	0.181	0.176	0.141	0.227	0.245	0.197	0.178	0.195	0.197	0.239	0.278
F	15.867	24.944	15.674	19.310	27.410	26.473	20.303	36.387	40.342	30.407	26.806	30.055	30.432	38.984	47.774
P	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
LB															
b	0.0005	0.0007	0.0006	0.0006	0.0006	0.0006	0.0005	0.0006	0.0007	0.0007	0.0007	0.0009	0.0005	0.0007	0.0010
R^2	0.106	0.225	0.187	0.131	0.198	0.204	0.092	0.177	0.222	0.210	0.256	0.355	0.151	0.250	0.369
F	1.906	4.641	3.679	2.409	3.952	4.102	1.618	3.440	4.563	4.250	5.511	8.793	2.840	5.335	9.372
P	0.186	0.047	0.073	0.140	0.064	0.060	0.222	0.082	0.048	0.056	0.032	0.009	0.111	0.035	0.007
MJ															
b	−0.0001	0.0000	−0.0002	0.0001	0.0000	0.0000	0.0002	0.0003	0.0003	0.0001	−0.0001	0.0003	0.0002	0.0002	0.0006
R^2	0.007	0.000	0.048	0.007	0.001	0.000	0.015	0.037	0.056	0.004	0.004	0.038	0.024	0.032	0.152
F	0.110	0.005	0.807	0.117	0.011	0.004	0.241	0.609	0.952	0.070	0.060	0.630	0.392	0.526	2.865
P	0.744	0.944	0.382	0.737	0.918	0.951	0.630	0.447	0.344	0.795	0.809	0.439	0.540	0.479	0.110
PB															
b	0.0006	0.0008	0.0010	0.0007	0.0009	0.0010	0.0009	0.0011	0.0011	0.0008	0.0010	0.0009	0.0010	0.0011	0.0010
R^2	0.339	0.518	0.582	0.420	0.607	0.603	0.502	0.621	0.622	0.583	0.648	0.618	0.630	0.657	0.634
F	8.196	17.168	22.288	11.606	24.720	24.302	16.105	26.197	26.341	22.394	29.454	25.937	27.299	30.713	27.669
P	0.011	0.001	0.000	0.004	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
PI															
b	0.0007	0.0007	0.0006	0.0008	0.0008	0.0007	0.0009	0.0009	0.0008	0.0008	0.0008	0.0006	0.0009	0.0009	0.0007
R^2	0.344	0.418	0.339	0.414	0.485	0.433	0.415	0.468	0.379	0.502	0.548	0.365	0.487	0.549	0.341
F	8.400	11.471	8.190	11.304	15.072	12.201	11.337	14.088	9.764	16.147	19.400	9.191	15.205	19.480	8.286
P	0.010	0.004	0.011	0.004	0.001	0.003	0.004	0.002	0.007	0.001	0.000	0.008	0.001	0.000	0.011
RC															
b	0.0003	0.0004	0.0004	0.0001	0.0003	0.0004	0.0001	0.0004	0.0008	0.0004	0.0004	0.0002	0.0005	0.0006	0.0007
R^2	0.052	0.102	0.061	0.006	0.059	0.061	0.010	0.087	0.129	0.115	0.071	0.015	0.139	0.103	0.093
F	0.871	1.815	1.039	0.092	1.003	1.035	0.163	1.518	2.372	2.085	1.228	0.241	2.582	1.836	1.634
P	0.365	0.197	0.323	0.766	0.332	0.324	0.692	0.236	0.143	0.168	0.284	0.630	0.128	0.194	0.219
VD															
b	0.0015	0.0015	0.0012	0.0015	0.0015	0.0013	0.0015	0.0017	0.0015	0.0016	0.0014	0.0012	0.0016	0.0016	0.0014
R^2	0.347	0.423	0.347	0.367	0.433	0.398	0.338	0.437	0.443	0.430	0.492	0.353	0.400	0.492	0.400
F	8.509	11.746	8.512	9.289	12.207	10.578	8.180	12.417	12.708	12.048	15.491	8.739	10.651	15.491	10.645
P	0.010	0.003	0.010	0.008	0.003	0.005	0.011	0.003	0.003	0.003	0.001	0.009	0.005	0.001	0.005
VM															
b	0.0005	−0.0001	−0.0003	0.0002	0.0001	0.0002	0.0003	0.0006	0.0009	0.0000	−0.0001	0.0002	0.0002	0.0004	0.0008
R^2	0.071	0.003	0.024	0.010	0.003	0.009	0.025	0.081	0.140	0.001	0.005	0.017	0.010	0.033	0.163
F	1.215	0.040	0.395	0.164	0.047	0.151	0.418	1.404	2.604	0.014	0.078	0.281	0.163	0.546	3.126
P	0.287	0.843	0.538	0.691	0.831	0.702	0.527	0.253	0.126	0.906	0.783	0.603	0.692	0.471	0.096

References: Coefficients in red (orange) with statistical significance $p < 0.05$ ($p < 0.1$)

Fig. 6 Scatter plot between the Southern Oscillation Index of August–September (SOI_{as}) and rainfall anomaly (APP) for the warm semester **(a)** and for the period from November to April **(b)**, in Córdoba, Argentina. Also shown the relationship with NDVI anomaly

(AND) accumulated during the period (i) and with 1-month ($i+1$) and 2-month ($i+2$) lag [** statistically significant ($p < 0.05$); * statistically significant ($p < 0.10$)]

denotes a strong local influence. While in some places the relationship fits well, as in PB, in others this dependency does not exist at all, as in RC. Table 4 depicts the information for three periods from October to April, October to May and November to May, for the entire region and also each site. In addition, the association is strengthened when the radiometric information is delayed with respect to the rainfall record (from October to March), so that the accumulated NDVI values from November to April and even more between December and May show a more dependent relation with SOI_{as} .

Likewise, the delay effect in the response of vegetation is corroborated when other seasonal periods of accumulation are evaluated, which results in relationships even more correlated with SOI_{as} . In this sense, incorporating the radiometric information of April and May tends to increase the correlation, suggesting that the effective period of vegetation growth continues until after March. In the opposite direction, discarding the October information also increases the correlation and denotes that the seasonal growth of vegetation would start just after October.

Erasmí et al. [23] did not find significant correlations between NDVI and SOI in Indonesia when analyzing the relationship for the period from 1982 to 2006, but, using sea surface temperature (SST) as the ENSO index, the correlation was significant although very low. For the central region of Argentina, while the SOI cannot be discarded as a seasonal rainfall predictor, and to anticipate the vegetation behavior as well, the analysis of SOI_{as} predictive capacity for each particular site results in a more complex mosaic. The independence of the NDVI about the ENSO signal is verified for MJ, which is consistent in some way because the warm semester (from October to March) rainfall does not have a significant influence here, as shown in Fig. 5. However, when other periods are considered in Table 4, as from November to April or to May, while the cumulative rainfall values show the inverse influence of the ENSO in a significant way, the NDVI values do not replicate this behavior at all.

In PB, the SOI_{as} is a consistent indicator to anticipate the behavior of both the seasonal rainfall and the NDVI; considering different seasonal periods and delay times, the predictive behavior is very generalized. Just in the center of the region, the predictive scheme for PI looks very similar to PB, but is less generalized. Even though rainfall information in Villa Dolores (VD) responds straight to the ENSO signal, this influence does not translate to the spectral information. This behavior is probably due to the fact that agriculture over there is carried out under irrigation.

During the period 2000–2017, the ENSO signal loses the predictive capacity in Río Cuarto, at least in statistical terms, for all seasonal lapses and delays considered. Nor does the relationship between the ENSO and the total

rainfall amount reach statistical support, although it shows the negative trend expected for the entire region.

According to these results, it follows that while the ENSO phenomenon modulates short-term changes in the rainfall regime of Córdoba, Argentina, its effect is diluted a little when the impact is projected on the status and dynamics of vegetation. While the SOI_{as} variation at regional scale can explain between 14 and 22% of annual variability of total rainfall for different seasonal periods, for accumulated NDVI values with 1 or 2 months of lag the range diminishes between 7 and 18% only. The evidence presented here suggests a consistent predictive relationship between the SOI_{as} and the rainfall regime in the central region of Argentina, so that the ENSO indicator provides a valuable information in advance about the seasonal behavior of quantity, frequency and, to a lesser extent, intensity of rainfall, useful to mitigate both the environmental and agricultural risk.

When the relationship between the SOI and the accumulated NDVI is established instead, the same behavior is expressed roughly but reaching a lower degree of accuracy. Although the expected trend does not contradict (that is, an increase (decrease) in available water in El Niño (La Niña) years would produce the consequent increase (decrease) in biomass), other factors inherent to vegetation growth are not considered at all (initial biomass, previous soil moisture, soil type, temperature conditions, degradation, agricultural management, etc.) and thus restrict the scope of the radiometric information. Moreover, an apparent nonlinear nature of the relationship between NDVI and rainfall regime may also contribute to dilute this dependence, especially when 1-year El Niño occurs and the rainfall increase does not translate necessarily into more vegetation coverage or biomass.

4 Conclusions

The Southern Oscillation Index of August–September (SOI_{as}) as a proxy of El Niño–Southern Oscillation (ENSO) is a signal linked with the rainfall regime in Córdoba, Argentina, both for the trimester from October to December and for the semester from October to March subsequent. The relationship is even more consistent when the accumulation period is after October and includes the months of April and May. Instead, the El Niño Modoki Index (EMI), used to represent the ENSO Modoki, showed lower correlation coefficients with the rainfall regime and did not improve the predictions about the subsequent rainfall behavior.

The relationships between SOI_{as} and different attributes of rainfall regime are mostly linear and of inverse character.

Table 4 Coefficients of regression (a: intercept; b: slope) and determination (R^2) for the linear relationship between SOI_{as} and seasonal rainfall (PP) and accumulated NDVI for different periods (i), and with 1-month ($i+1$) and 2-month ($i+2$) lag, for each site and the entire region. Also Fisher's F statistic and its probability level

	Oct–Abr				Oct–May				Nov–May			
	PP i	ND i	ND $i+1$	ND $i+2$	PP i	ND i	ND $i+1$	ND $i+2$	PP i	ND i	ND $i+1$	ND $i+2$
<i>Region</i>												
<i>a</i>	0.602	0.000	0.001	0.001	0.569	0.001	0.001	0.001	0.605	0.001	0.001	0.001
<i>b</i>	−7.224	−0.005	−0.007	−0.010	−6.831	−0.007	−0.009	−0.012	−7.255	−0.007	−0.010	−0.011
R^2	0.172	0.047	0.090	0.146	0.159	0.060	0.126	0.181	0.201	0.090	0.146	0.146
<i>F</i>	25.765	6.064	12.206	21.190	23.499	7.892	17.923	27.321	31.106	12.206	21.190	21.276
<i>P</i>	0.000	0.015	0.001	0.000	0.000	0.006	0.000	0.000	0.000	0.001	0.000	0.000
<i>LB</i>												
<i>a</i>	0.628	0.001	0.001	0.001	0.632	0.001	0.001	0.001	0.759	0.001	0.001	0.001
<i>b</i>	−7.542	−0.010	−0.010	−0.013	−7.588	−0.011	−0.012	−0.016	−9.102	−0.010	−0.013	−0.016
R^2	0.123	0.098	0.107	0.177	0.123	0.106	0.157	0.212	0.188	0.107	0.177	0.213
<i>F</i>	2.236	1.743	1.926	3.444	2.246	1.897	2.983	4.314	3.716	1.926	3.444	4.333
<i>P</i>	0.154	0.205	0.184	0.082	0.153	0.187	0.103	0.054	0.072	0.184	0.082	0.054
<i>MJ</i>												
<i>a</i>	0.646	0.000	0.000	0.000	0.533	0.000	0.000	0.000	0.582	0.000	0.000	0.000
<i>b</i>	−7.751	−0.001	−0.002	0.000	−6.394	−0.003	−0.003	−0.002	−6.981	−0.002	0.000	−0.002
R^2	0.194	0.003	0.010	0.000	0.148	0.008	0.017	0.008	0.228	0.010	0.000	0.010
<i>F</i>	3.862	0.053	0.166	0.006	2.777	0.129	0.280	0.133	4.726	0.166	0.006	0.161
<i>P</i>	0.067	0.821	0.689	0.939	0.115	0.725	0.604	0.720	0.045	0.689	0.939	0.694
<i>PB</i>												
<i>a</i>	0.965	0.001	0.001	0.002	0.936	0.001	0.002	0.002	0.944	0.001	0.002	0.002
<i>b</i>	−11.576	−0.012	−0.016	−0.021	−11.237	−0.015	−0.020	−0.022	−11.326	−0.016	−0.021	−0.019
R^2	0.278	0.265	0.403	0.533	0.269	0.320	0.447	0.529	0.317	0.403	0.533	0.523
<i>F</i>	6.168	5.757	10.816	18.250	5.881	7.540	12.958	18.003	7.413	10.816	18.250	17.514
<i>P</i>	0.024	0.029	0.005	0.001	0.028	0.014	0.002	0.001	0.015	0.005	0.001	0.001
<i>PI</i>												
<i>a</i>	0.619	0.000	0.001	0.001	0.588	0.001	0.001	0.001	0.631	0.001	0.001	0.001
<i>b</i>	−7.428	−0.005	−0.008	−0.010	−7.061	−0.006	−0.010	−0.012	−7.571	−0.008	−0.010	−0.009
R^2	0.183	0.050	0.160	0.275	0.175	0.078	0.209	0.276	0.248	0.160	0.275	0.194
<i>F</i>	3.585	0.839	3.041	6.081	3.390	1.352	4.230	6.092	5.270	3.041	6.081	3.854
<i>P</i>	0.077	0.373	0.100	0.025	0.084	0.262	0.056	0.025	0.036	0.100	0.025	0.067
<i>RC</i>												
<i>a</i>	0.406	0.000	0.000	0.001	0.396	0.000	0.001	0.001	0.362	0.000	0.001	0.001
<i>b</i>	−4.877	−0.001	−0.005	−0.006	−4.753	−0.002	−0.006	−0.010	−4.348	−0.005	−0.006	−0.008
R^2	0.107	0.001	0.069	0.062	0.108	0.013	0.101	0.110	0.096	0.069	0.062	0.069
<i>F</i>	1.926	0.022	1.194	1.050	1.930	0.217	1.794	1.969	1.701	1.194	1.050	1.193
<i>P</i>	0.184	0.885	0.291	0.321	0.184	0.647	0.199	0.180	0.211	0.291	0.321	0.291
<i>VD</i>												
<i>a</i>	0.432	0.000	0.000	0.001	0.416	0.000	0.001	0.001	0.434	0.000	0.001	0.001
<i>b</i>	−5.188	−0.003	−0.006	−0.008	−4.990	−0.003	−0.007	−0.009	−5.212	−0.006	−0.008	−0.009
R^2	0.204	0.009	0.047	0.126	0.214	0.011	0.059	0.146	0.249	0.047	0.126	0.151
<i>F</i>	4.113	0.146	0.786	2.303	4.368	0.170	0.996	2.733	5.317	0.786	2.303	2.851
<i>P</i>	0.060	0.707	0.389	0.149	0.053	0.686	0.333	0.118	0.035	0.389	0.149	0.111
<i>VM</i>												
<i>a</i>	0.517	0.000	0.000	0.001	0.483	0.001	0.001	0.001	0.520	0.000	0.001	0.001
<i>b</i>	−6.206	−0.006	−0.004	−0.010	−5.792	−0.006	−0.008	−0.015	−6.243	−0.004	−0.010	−0.011
R^2	0.179	0.063	0.026	0.106	0.149	0.047	0.075	0.179	0.161	0.026	0.106	0.119
<i>F</i>	3.500	1.070	0.431	1.905	2.805	0.784	1.306	3.482	3.078	0.431	1.905	2.169
<i>P</i>	0.080	0.316	0.521	0.186	0.113	0.389	0.270	0.080	0.098	0.521	0.186	0.160

Table 4 (continued)References: Coefficients in red (orange) with statistical significance $p < 0.05$ ($p < 0.1$)

When a phase La Niña (El Niño) occurs, positive (negative) values of SOI_{as} depict negative (positive) anomalies of rain that involve lower (higher) amount, frequency and intensity of the events. For both the trimester and the semester subsequent, rainfall estimates increase their accuracy when the Neutral years are discarded from the analysis.

Both the correlation structure between the rainfall regime and the ENSO in the region and the frequency of ENSO events for the period 2000–2017 are appropriate to represent the long-term climate behavior. The relationship between the SOI_{as} and NDVI maintains a configuration which is similar to the ENSO influence over rainfall, and, despite the fact that some loss of accuracy was determined in this case, the NDVI information as a proxy of the vegetation presents an adequate capacity to highlight the influence of ENSO, particularly at a regional scale. For a local scale instead, the relationship of the ENSO with the NDVI has a more confusing interpretation as many environmental and agricultural management factors interact on the growth of vegetation.

Thus, while this information would help to reduce the uncertainty of interannual rainfall variability, as well as to enhance the early warning system on food and agriculture in the region [43], only a small part of the total variability can be explained from the ENSO signal (between 10 and 20% of total). Finally, the radiometric information of NDVI verifies very closely the influence the ENSO exerts on the rainfall regime, at least when the entire region is considered. While the spatial and temporal extent of influence of SOI and MEI on rainfall and NDVI was identified in this study, the teleconnection mechanisms between SOI and MEI with other climate drivers should be the subject of further research.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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