



# Trends in soil moisture content and water deficits in Argentina and the role of climate contribution

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## Abstract

Soil moisture and meteorological variables are strongly related to each other through different fluxes, constituting a complex network of interactions and feedbacks. Therefore, a better understanding of the temporal and spatial variability of soil moisture and its relationship with meteorological variables acquires a particular interest, especially under climate change conditions. Based on the gap in studies addressing this topic in Argentina, this study aimed to evaluate soil moisture content (SMC) and water deficit (DEF) annual trends between 1990 and 2019 and the contribution of different meteorological variables to those trends. To this end, simulations of SMC and DEF were performed by using a hydrological balance model, driven by meteorological observations of 51 sites distributed throughout Argentina. Since precipitation (PP) and potential evapotranspiration (PE) modulate the simulated soil moisture, annual PP and PE trends were also evaluated to assess the importance of these variables on the observed soil moisture changes. Furthermore, the regional contribution of the meteorological variables to the PE trends was assessed by means of a detrended method. Trends detected in SMC and DEF suggest an increase towards drier conditions in some areas of the country. Changes in PE were the main responsible for changes in SMC and DEF and were more relevant than changes in PP. In sites located in the center and east of the country, maximum and mean temperatures had a greater impact on PE. In sites located in the west of the country, changes in PE were mainly controlled by increases in wind speed and decreases in humidity. Examining the spatio-temporal variability of soil water and the meteorological variables that influence soil water is indispensable to assess climate-induced changes and propose feasible climate change adaptation strategies.

## 1 Introduction

Soil moisture is a key variable of the climate system as it interacts with the atmosphere through complex feedbacks by means of the energy and water balance (Seneviratne et al. 2010). The strong dependence of soil moisture on meteorological variables makes it a reservoir potentially susceptible to current and future climate change scenarios. In this sense, situations of high atmospheric evaporative demand can lead to high water deficits, which can in turn lead to the onset of drought events with potential negative consequences on agriculture. Thus, improving the understanding and documentation of the variability in soil moisture content and deficits (i.e., trends) and the contribution of the different climate variables to those changes is of great importance.

Many studies have analyzed soil moisture variability based on long-term in situ observation networks (e.g., Amenu et al. 2005), but mainly in the northern hemisphere (e.g., Dorigo et al. 2011). To analyze soil water trends, it is desirable to have in situ observation networks that ensure an

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adequate coverage of spatial variability and contain records over long periods of time. However, in regions like South America, and particularly in Argentina, there is a lack of long-term and spatially dense observations, a fact that constrains the reliability of regional analyses. Nevertheless, alternative datasets can be derived, for example, from land surface models or bucket models, hydrological balance model simulations, or satellite estimations (see Seneviratne et al. 2010). In particular, when model simulations are driven by atmospheric observations, they do not suffer from systematic errors related to atmospheric models. Several models have been developed in different regions of the world (e.g., Thornthwaite and Mather 1955; Baier and Robertson 1966; Smith 1992; Allen et al. 1998; Raes et al. 2009) as well as in Argentina (e.g., Aiello et al. 1995; Paruelo and Sala 1995; Fernández-Long et al. 2012).

Several authors have documented positive and negative trends in soil moisture (Holsten et al. 2009; Dymond et al. 2014; Wang et al. 2019; Li et al. 2019; Deng et al. 2020) as well as in soil water deficits (Thomas 2000; Robinson 2006; Cammalleri et al. 2016; Čadro et al. 2019) by focusing on global and regional scales. The explanation or contribution of different climate variables on the soil moisture trend can be as simple as a positive trend in precipitation, or via more complex interactions (see Seneviratne et al. (2010) for a complete discussion). For example, on a global scale, Deng et al. (2020) detected both negative trends (drying) in soil moisture between 1979 and 2017, which they attributed to an increase in temperature, and positive trends (wetting), which were influenced by the combined action of temperature, precipitation, and vegetation. These authors detected negative trends (drying) in most of Argentina and classified them within the most extreme category of soil moisture decline as “strong decreasing” (Deng et al. 2020). However, also in Argentina, by using model simulations, Sheffield and Wood (2008) observed an opposite behavior and detected soil moisture positive trends (wetting) between 1950 and 2000, and associated them with positive precipitation trends over that period. In agreement with the results found by Deng et al. (2020) and opposite to the ones of Sheffield and Wood (2008), Dorigo et al. (2012) documented an annual negative trend (drying) over central Argentina by analyzing trends in soil moisture over a shorter period (1988–2010) using satellite data and models.

Several authors have documented the effects of climate change on different atmospheric variables in Argentina (e.g., Skansi et al. 2013; Barros et al. 2015). The annual mean temperature in central-eastern Argentina has increased by 1 °C since 1970, while the mean annual minimum and maximum temperatures have increased by 2 °C and 0.5 °C, respectively (Müller et al. 2021). An increase in extreme temperatures (Barros et al. 2015) and in the frequency of warm days and nights has also been observed since 1970

(Müller et al. 2021). Regarding precipitation, annual trends studies differ depending on the time period analyzed. Sheffield and Wood (2008) detected positive annual precipitation trends between 1950 and 2000. Similarly, Saurral et al. (2016) detected positive trends but considering a period of 100 years, until 2013. In contrast, De Barros Soares et al. (2017) only detected significant positive trends in a region of northeastern Argentina between 1955 and 2004, whereas D’Andrea et al. (2019) did not detect significant trends in annual precipitation in central Argentina in the 1984–2014 period. However, D’Andrea et al. (2019) detected positive annual trends in potential evapotranspiration estimated by the Penman–Monteith method in several sites located in central-eastern Argentina. de la Casa and Ovando (2016) also observed positive annual trends in potential evapotranspiration in central Argentina between 2001 and 2010.

Improving the knowledge of both the temporal and the spatial variability in soil moisture is of particular interest in countries like Argentina, where the economy strongly relies on the agricultural sector. In addition, in this region, agriculture is mostly rainfed, and therefore soil moisture limits crop growth and yields. Due to the mentioned changes in climate variables in Argentina in the recent decades, combined with a lack of studies addressing long-term trends of soil moisture content and water deficits over the region and the climate contribution to these changes, the aims of this study are (1) to analyze annual trends in soil moisture content and the water deficit in Argentina for the 1990–2019 period, based on a hydrological balance model driven by meteorological observations, and (2) to analyze the contribution of different meteorological variables on the observed soil moisture changes.

## 2 Methodology

### 2.1 Study area and meteorological data

The data used in this study were collected from 51 Argentine weather stations, belonging to the Servicio Meteorológico Nacional (SMN) and the Instituto Nacional de Tecnología Agropecuaria (INTA). From each station, daily data of precipitation (PP), maximum temperature (maxT), minimum temperature (minT), actual vapor pressure (Ea), atmospheric pressure, sunshine duration (hours), and wind intensity (km/h), corresponding to the 1990–2019 period, were used. These meteorological stations were previously selected from a database of 157 sites, by removing those presenting less than 30 years of records; those having a high number of missing data (see Sect. 3.2); those not measuring any of the variables required for the analysis; or those presenting errors in the measurements, mainly due to inconsistencies in wind speed time series. The location and distribution of

the 51 sites selected are shown in Fig. 1 (for more details of meteorological stations, see also Table 3 in the Appendix).

## 2.2 Missing data

When working with observed data, the presence of missing data is usually the most relevant aspect in the selection of sites. Although the variables that describe soil water used in this study—water deficit (DEF) and soil moisture content (SMC)—do not have missing data because they are estimated from a hydrological model that does not support missing data, the input data to calculate them do have missing data. Thus, the missing data in the variables that feed the hydrological balance model used—potential evapotranspiration (PE) and PP—were evaluated. Given the number of variables used in PE estimation, the decision was to tolerate up to five missing daily data of any of the variables used in the estimation. In this way, if a variable used to calculate the PE (either temperature, actual vapor pressure, wind, or sunshine duration, used to estimate solar radiation,  $R_s$ ) has missing data, the maximum amount of missing data it can have is five data per month. As PE cannot be calculated with incomplete data sets, missing data were estimated following Allen et al. (1998). As for precipitation, while the World Meteorological Organization (WMO) does not recommend working with missing data (WMO 1989), it is possible to incorporate estimated data (WMO 2017). To avoid losing a

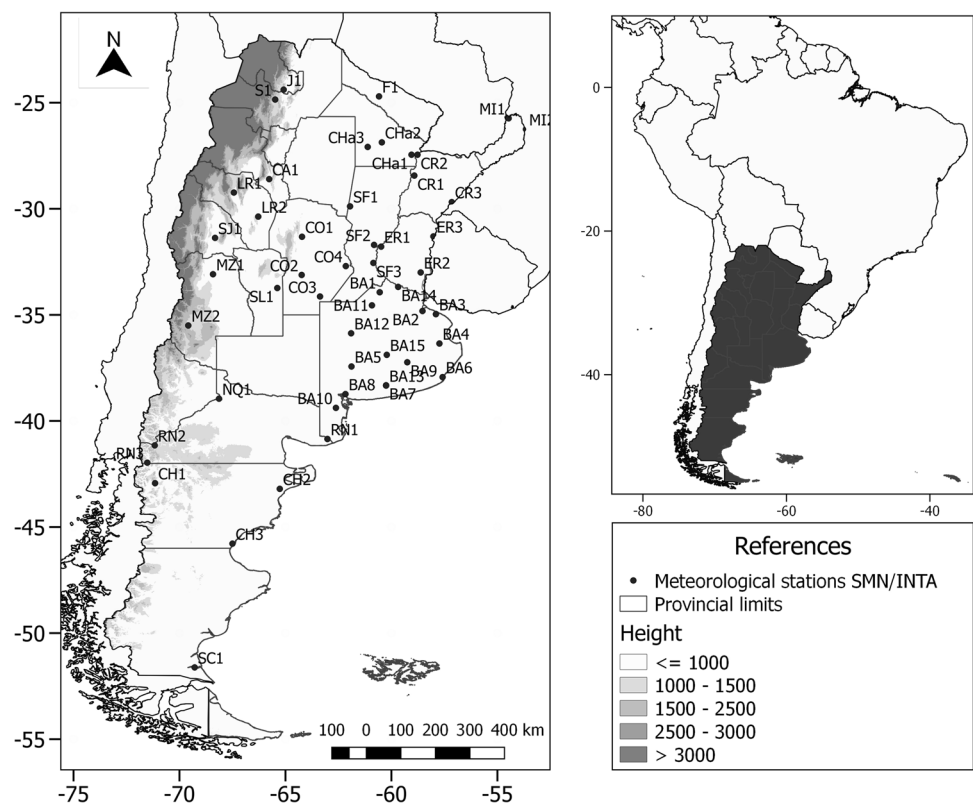
large amount of data in this work, a less strict criterion was established, and we accepted up to two missing daily PP data in each month. However, the PP data series did not contain a large number of missing data.

Once the PE and PP data series were obtained, the presence of missing data in each site was evaluated, and sites with very thinned data series were removed. The goal of this step was to avoid the use of a large number of PE data calculated with estimated values of these variables or a large number of estimated PP values. In this way, we worked only with the sites with the least number of missing data and, therefore, with the lowest number of estimated data.

## 2.3 Hydrological balance model simulations

To estimate soil moisture content, excesses, and water deficits, simulations of the BHOA model (for its acronym in Spanish: “Balance Hidrológico Operativo para el Agro”; Fernández-Long et al. 2012) were used. The BHOA is a one-layer bucket model that establishes a balance between evapotranspiration, precipitation, and soil moisture content. It is constructed from PP and PE data, and from two soil characteristics: field capacity (FC) and wilting point (WP), which allow for establishing the soil drying curve. These hydrological constants were obtained by a consensus between values determined experimentally and values estimated by different methodologies, specified in Fernández Long et al. (2018). The BHOA does not

**Fig. 1** Location of the 51 meteorological stations used in the analysis



explicitly contemplate vegetation characteristics or changes in soil properties over time. The model simulations have a daily resolution and are able to adequately represent the dynamics and variability in soil moisture content in the Pampean region (Fernandez Long et al. 2018; Spennemann et al. 2020).

The use of simplified representations of PE can lead to errors in the estimation of the impact of climate change on hydrology in general (Sheffield et al. 2012). The PE used as an input variable to the model was estimated by the Penman–Monteith method (Allen et al. 1998) (Eq. 1).

$$PE = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T+273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \quad (1)$$

where  $PE$  is the reference evapotranspiration (mm/day);  $R_n$  is the net radiation on the crop surface (MJ/m<sup>2</sup>.day);  $G$  is the soil heat flow (MJ/m<sup>2</sup>.day);  $T$  is the daily average air temperature (°C);  $u_2$  is the wind speed at 2 m high (m/s);  $e_s$  is the saturation vapor pressure (kPa);  $e_a$  is the actual vapor pressure (kPa);  $\Delta$  is the slope of the vapor pressure curve (kPa/°C); and  $\gamma$  is the psychrometric constant (kPa/°C).

This complex approach of PE estimation considers all the parameters that govern the energy exchange and heat flow of large uniform expanses of vegetation. The Penman–Monteith method requires daily data of meanT (which arise from averaging maxT and minT), wind speed at 2 m high ( $u_2$ ),  $E_a$ , sunshine duration (to obtain solar radiation), and atmospheric pressure. Some of the parameters present in Eq. 1, such as net radiation ( $R_n$ ) and  $u_2$ , were estimated following Allen et al. (1998).

As mentioned above, the input variables of the BHOA model are PP and PE, along with FC and WP data, and the output variables are the soil moisture content and water deficits and excesses, among others. When PP is greater than PE, the BHOA model simulates the soil moisture content in the root zone ( $SMC'$ ) as shown in Eq. 2, taking into account the soil moisture content of the previous day plus the fraction of precipitation remaining after subtracting the PE of the day (potential deficit, PD). Any other flux is taken into account because the model assumes that all the precipitation infiltrates into the soil (Fernández-Long et al. 2012).

$$[SMC'_t]' = SMC_{t-1} + PD \quad (2)$$

where  $SMC'_t$  is the soil moisture content on day  $t$ ,  $SMC_{t-1}$  is the soil moisture content of the previous day, and  $PD$  is the potential deficit. On the other hand, if the day has a negative PD (PE is greater than PP), soil moisture content is calculated by multiplying  $SMC_{t-1}$  by an exponential term representing the soil drying curve (Eq. 3).

$$SMC'_t = SMC_{t-1} e^{PD/CCD} \quad (3)$$

where  $PD/CCD$  is the relationship between the potential deficit and the term  $CCD$  indicates the difference between the FC and a drying limit that prevents the soil from drying out below a threshold, which depends on the texture of the soil. Excesses in this model occur when the soil moisture content exceeds the FC, and, therefore the remaining water drains (surface and subsurface runoff) (Fernández-Long et al. 2012). Then:

$$EXC = SMC_{t-1} + PD - FC \quad (4)$$

For the purposes of this study, the soil water excess (EXC) was added to the  $SMC'$  variable. This is because the incorporation to  $SMC'$  of the millimeters of water that are considered excesses according to the bucket model used allows avoiding that the  $SMC'$  variable is limited by a maximum threshold (given by the soil FC). Then, in this study, soil moisture content (SMC) is defined as:

$$SMC_t = SMC'_t + EXC \quad (5)$$

Finally, when the soil–plant system does not contain enough water to evaporate what the atmosphere demands, there is a water deficit (DEF). The variable that represents the amount of water that the soil effectively loses through evapotranspiration is the actual evapotranspiration (AE). To estimate AE, the model considers the variation in soil moisture content with respect to the previous time. If this variation is negative, the soil is drying out and therefore loses water by evapotranspiration, then:

$$AE = |\Delta SMC'_t| + PP \quad (6)$$

While, if the soil moisture variation is positive, there is recharge and the soil has enough water to deliver what the atmosphere demands, and then AE is equal to PE, and there is no DEF (Eq. 7) (Fernández-Long et al. 2012).

$$AE = PE \quad (7)$$

It is considered that when AE is lower than PE plants begin to suffer from water stress, so the water deficit (DEF) is expressed as the difference between PE and AE:

$$DEF = PE - AE \quad (8)$$

## 2.4 Estimation of the annual trend

The daily values of SMC and DEF obtained when executing the model were gathered (for the case of soil water deficits) and averaged (for soil moisture content plus excesses) on a monthly basis. In this way, monthly data series were obtained for the period 1990–2019. Trends were estimated for the annual values (mm year<sup>-1</sup>). Annual time series arise from an accumulation or an average of monthly values and,

because of that, the missing months have a great impact on the annual or seasonal final value, especially when the variable accumulates. Therefore, and considering that only stations with few estimated PE and PP data were preserved, annual trends were calculated with the complete database, including the values estimated by the model.

Trends in DEF and SMC were estimated using the non-parametric Mann–Kendall test (Mann, 1945; Kendall, 1975), with a threshold for statistical significance of 0.1. This test is best suited when the data do not have a normal distribution (Yue et al., 2002), and is one of the most used tests in the detection of trends in environmental, climatic, or hydrological data series (Yue et al., 2002; Fernández-Long et al. 2013; Asfaw et al., 2018; Zuo et al., 2019). This methodology identifies the existence of upward or downward trends but does not quantify them. Because of that, the magnitude of the slope when a trend was detected was determined by the Sen slope (Sen, 1968). This estimator is statistically robust and unbiased. Both the Mann–Kendall test and the Sen slope admit are feasible with missing data.

## 2.5 Climate contribution to soil moisture trends

To find the variable responsible for the changes observed in SMC and DEF, annual trends on PP and PE were also analyzed. In addition, a detrended analysis of variables that

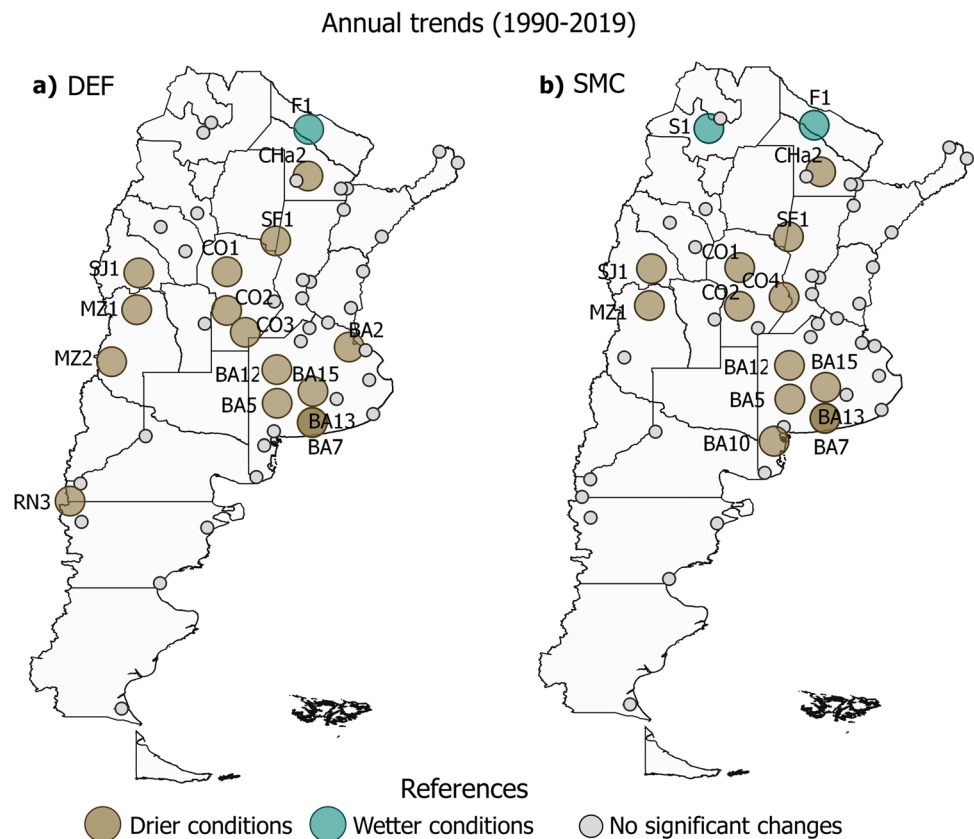
influence PE estimation was computed (Xu et al. 2006; Liu et al. 2010). The variables evaluated were meanT, maxT, minT, wind speed, Rs (estimated from sunshine duration), and Ea (as a measure of atmospheric humidity). Temporal trends of each variable were removed by subtracting the linear function given by the Sen slope of the variable in the period 1990–2019 and its intercept. Once the individual annual trend was eliminated, the annual PE was recalculated. Results from detrend analysis were also complemented by the annual trend analysis of all the variables that influence PE estimation, using the same procedure described in the previous section.

## 3 Results

### 3.1 Annual trend analysis

DEF increased in almost all sites, with significant responses (Fig. 2a), indicating the occurrence of increasingly dry conditions. In total, 16 sites (31%) showed significant changes. The trends observed were positive in 15 of them, suggesting greater soil water deficits. Only one site recorded a significant negative trend in DEF, in the north of the country (site F1). Sites with trends towards drier conditions were situated in the center-west (sites MZ1, MZ2, and SJ1) and center of

**Fig. 2** Annual trends for the 1990–2019 period in **a** water deficit (DEF) and **b** soil moisture content (SMC). Brown circles indicate significant trends to drier conditions, while blue circles indicate significant trends to wetter conditions. Gray circles indicate no significant changes





Argentina (sites CO1, CO2, CO3, and SF1) and in the west of Buenos Aires province (sites BA5, BA7, BA12, BA13, and BA15).

The trends in SMC were less than in DEF, but they also suggested increasingly dry conditions in most cases (Fig. 2b). In 11 sites, 21% of the cases analyzed showed significant trends in SMC, and most were negative, except for two stations in the north of the country (Fig. 2b). Negative trends indicate, in this case, a reduction in the soil water content. Regarding water deficits, the stations located in the center of the country showed significant trends towards drier conditions of lower water availability, although they did not always show significant changes in both variables. Some sites showed significant responses in DEF and not in SMC, as in the case of site MZ2 in the west and site CO3 in the center of Argentina.

The results allowed the detection of certain areas in which changes were clearer and more consistent in both variables. The sites located in the central region of the country experienced decreases in SMC and increases in DEF. These changes show a lower availability of soil water with time in this area. This spatial pattern is visible given the number of meteorological stations located in this region of the country. Results also showed a wide spatial representativeness in the province of Buenos Aires (constituted by all the sites with the acronym BA), although, while the west of the province experienced significant changes in deficiencies, no evident pattern of decrease in SMC was observed.

Changes of greater magnitude were observed with more frequency in DEF than in SMC (Table 1). The magnitude of these changes is given by the percentage of change over time (slope) with respect to the annual mean value of DEF or SMC in that site (Relative change, Table 1). In the case of DEF, the most important changes occurred mainly in the center of the country, with variations of 2.5% or over per year. The greatest change was observed in site BA12, with a slope of  $10.9 \text{ mm year}^{-1}$ , which corresponds to an increase of 3.2% in its average value per year in the period 1990–2019. In addition, other sites with significant changes in annual water deficiencies in the center of the country were SF1, CO1, CO2, and CO3, with increases of 11.4 mm, 15.0 mm, 10.7 mm, and 7.8 mm per year respectively (equivalent to 1.7%, 2.2%, 1.5%, and 1.6% with respect to their average). In terms of SMC, the site with the highest degree of change was SJ1, in the west of the country.

### 3.2 Contribution of meteorological variables to changes in soil moisture.

Important changes in PE were observed during the 1990–2019 period; on the contrary, during the same period, there were almost no significant changes in PP (Fig. 3). Although the PP is highly determinative of soil

water content, in this study, no strong signal from PP trends was observed. PE increased in the central, central-west, and central-east regions of the country. PE showed a decrease only in the southern sites (Patagonian region) and in the F1 site in the north of the country (Fig. 3). In sites where decreases in DEF or SMC were observed, PE consistently increased (Table 1), whereas, in site F1, a lower PE corresponded to lower water deficits and greater soil moisture content (increase in SMC) (Table 1). PP accompanied this trend towards drier conditions only in two sites, with significant negative trends (Table 1). Therefore, changes in PE were the main ones responsible for generating changes in soil moisture.

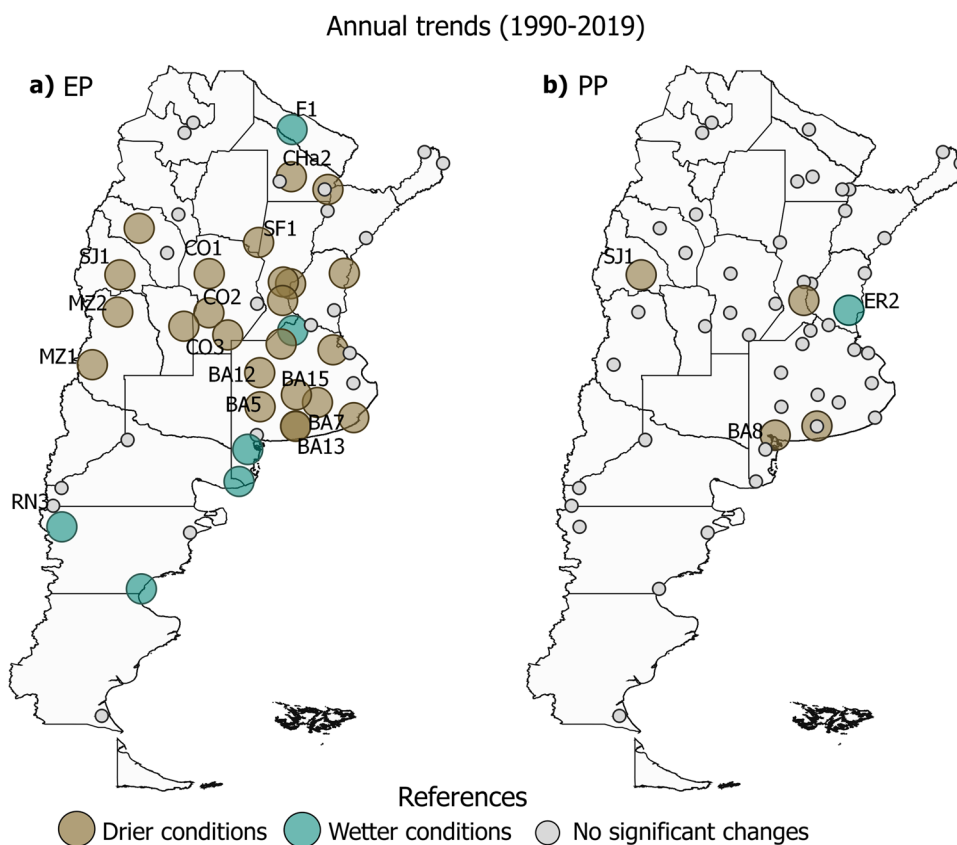
The results of the PE detrend analysis suggest a greater impact of maxT and meanT—accompanied by negative trends in actual vapor pressure ( $E_a$ ) (lower relative humidity)—on PE in sites with significant changes in soil moisture located in the center and east of the country (Table 2, group I). Solar radiation ( $R_s$ ) was of secondary importance in these sites. Temperatures, radiation, and humidity all increased PE over the time period studied. This can be observed in Table 2, since the slope of PE after eliminating the trends in these variables is always lower than the original. Therefore, each variable contributed to increasing PE. Figure 4a shows the scatter plot between the original PE's slopes and the modified PE's slopes. The effect of the variables on PE can be easily observed from the distance of the points from the 1:1 line. A greater distance from the 1:1 line is observed in cases where the trends in maxT and meanT were eliminated (Fig. 4a). On the other hand, when the minT trend was removed, there was no impact, placing all the points near the 1:1 line (Fig. 4a). Humidity and solar radiation (estimated by sunshine duration) showed an important influence on PE, although lower than that of maxT and mean T (Fig. 4c and d). Humidity in those sites had negative trends, while radiation had positive trends (see Appendix, Table 3).

In sites located in the west of the country (MZ1, MZ2, SJ1, and RN3), changes in PE were mainly controlled by increases in wind speed and decreases in humidity ( $E_a$ ) (Table 2, group II). When the trends in wind or humidity were eliminated, the PE slopes were lower than the original. Therefore, both variables contributed to increasing PE in these sites between 1990 and 2019. Figure 4b shows that the wind impact on PE was only relevant in a few sites, located in the west of the country (group II), and that most points are close to the 1:1 line. It is interesting to note that while the wind changed significantly in the period studied (see Appendix, Table 4), it only influenced the PE of sites located in the west of the country and had no major influence on the PE of sites in central and eastern Argentina. At group II sites, maxT and minT had no impact on PE (Table 2).

**Table 1** Annual trend slope (mm year<sup>-1</sup>), annual value (mm), and relative change (as the percentage of change with respect to the annual value) of water deficits (DEF), soil moisture content (SMC), potential evapotranspiration (PE), and precipitation (PP), in sites with significant trends (\*) in DEF and/or SMC

Site	DEF			SMC			PE			PP		
	Slope (mm year <sup>-1</sup> )	Annual (mm)	Relative change (%)	Slope (mm year <sup>-1</sup> )	Annual (mm)	Relative change (%)	Slope (mm year <sup>-1</sup> )	Annual (mm)	Relative change (%)	Slope (mm year <sup>-1</sup> )	Annual (mm)	Relative change (%)
FI	-12*	684	-1.8	1*	117	0.9	-7.9*	1512	-0.8	3.0	968	0.3
SI	-0.6	644	-0.1	0.5*	104	0.5	2.2	1264	0.1	4.1	741	0.6
CHa2	10.7*	626	1.7	-1.3*	117	-1.1	7.7*	1455	0.6	-8.0	942	-0.8
SF1	11.4*	666	1.7	-1*	116	-0.8	10.2*	1453	0.7	-6.9	960	-0.7
CO1	15*	696	2.2	-1.4*	109	-1.2	8.5*	1476	0.7	-6.0	861	-0.7
CO2	10.7*	691	1.5	-1.3*	107	-1.2	5.1*	1494	0.5	-5.1	847	-0.6
CO3	7.8*	478	1.6	-1.0	126	-0.8	4.8*	1290	0.4	-4.4	933	-0.5
CO4	9.8	435	2.3	-2*	230	-0.9	4.5	1279	0.3	-12.4	931	-1.3
BA12	10.9*	345	3.2	-1.3	163	-0.8	10.0*	1192	0.9	-6.7	999	-0.7
BA2	5.1*	420	1.2	-0.2	136	-0.2	3.7*	1179	0.3	-1.4	1026	-0.1
BA5	6.4*	495	1.3	-0.5	115	-0.5	4.8*	1201	0.6	-5.1	793	-0.6
BA7	5.9*	489	1.2	-0.8	145	-0.6	4.0*	1208	0.5	-8.4*	792	-1.1
BA13	12.8*	500	2.6	-1.8*	146	-1.2	7.1*	1259	0.7	-7.5	838	-0.9
BA15	8.6*	367	2.3	-0.9*	143	-0.6	5.0*	1138	0.6	-6.3	913	-0.7
BA10	0.5	692	0.1	-0.8*	59	-1.3	-1.2*	1147	-0.3	-3.7	471	-0.8
SJ1	12.6*	1411	0.9	-0.5*	32	-1.7	9.4*	1510	0.6	-3.6*	99	-3.6
MZ2	8.4*	1051	0.8	-0.4	65	-0.6	6.6*	1368	0.5	-2.1	321	-0.7
MZ1	6.1*	1090	0.6	0.0	55	0.0	6.1*	1354	0.5	0.2	264	0.1
RN3	2.4*	390	0.6	0.0	95	0.0	0.8*	826	0.1	-5.7	929	-0.6

**Fig. 3** Annual trends for the 1990–2019 period in **a** Penman–Monteith potential evapotranspiration (PE) and **b** precipitation (PP). Brown circles indicate significant trends to drier conditions, while blue circles indicate significant trends to wetter conditions. Gray circles indicate no significant changes



## 4 Discussion

An increase towards drier soil conditions was detected in some regions of Argentina for the 1990–2019 period, but without major changes in precipitation. This result is not consistent with the results of Sheffield and Wood (2008), who observed positive trends in soil water in Argentina (wetter conditions) between 1950 and 2000, and an increase in precipitation. The difference in our results could be related to the time period analyzed, as shown by Minetti et al. (2003) and de Barros Soares et al. (2017), who also detected positive trends in precipitation by using time periods similar to those of Sheffield and Wood (2008). Nevertheless, studies analyzing precipitation trends in central eastern Argentina in more recent periods (1984–2014) (D’Andrea et al. 2019) agree with our results.

It is worth mentioning that the soil moisture content formulation (SMC, Eq. 5) in the BHOA model includes the excess term (EXC, Eq. 4), with the purpose that the SMC is not limited by the field capacity in the upper bound. However, this could be showing higher values of SMC when comparing with other data sources, because it includes, although not explicitly, runoff variables (i.e., surface, and subsurface) inside the SMC. Despite this, the annual trends towards drier conditions detected in our study are also consistent with those found by Deng et al. (2020) and Dorigo

et al. (2012), who analyzed satellite estimations of soil moisture over time periods similar to the one used in our study. It is important to highlight that both independent data sources (i.e., satellite estimations vs. hydrological balance model) are consistent in showing the same sign in soil water trends. Therefore, on an annual time scale, surface soil moisture from satellite estimations and point scale soil moisture in the root zone from BHOA simulations, which are driven by observations, can spatially complement each other.

An interesting feature to mention is that annual DEF experienced more important and more frequent relative changes than annual SMC (see Table 1). This result could be related to the influence of excesses on annual SMC. In this way, as SMC contains water excesses, these could have countered moments of lack of water, i.e., water deficits. The role of excesses in SMC could be related to an increase in the frequency and intensity of extreme precipitation events, particularly in the center and east of the country (Barros et al. 2015; Camilloni 2018), affecting EXC and thus SMC. However, further studies are needed to confirm this assumption. It is possible that this growing trend in water excesses, together with DEF negative trends, may have been responsible for smoothing out the observed annual SMC trends.

The evidence of soil moisture content and water deficit trends suggests the possible existence of trends in different meteorological variables like PP and those used in the



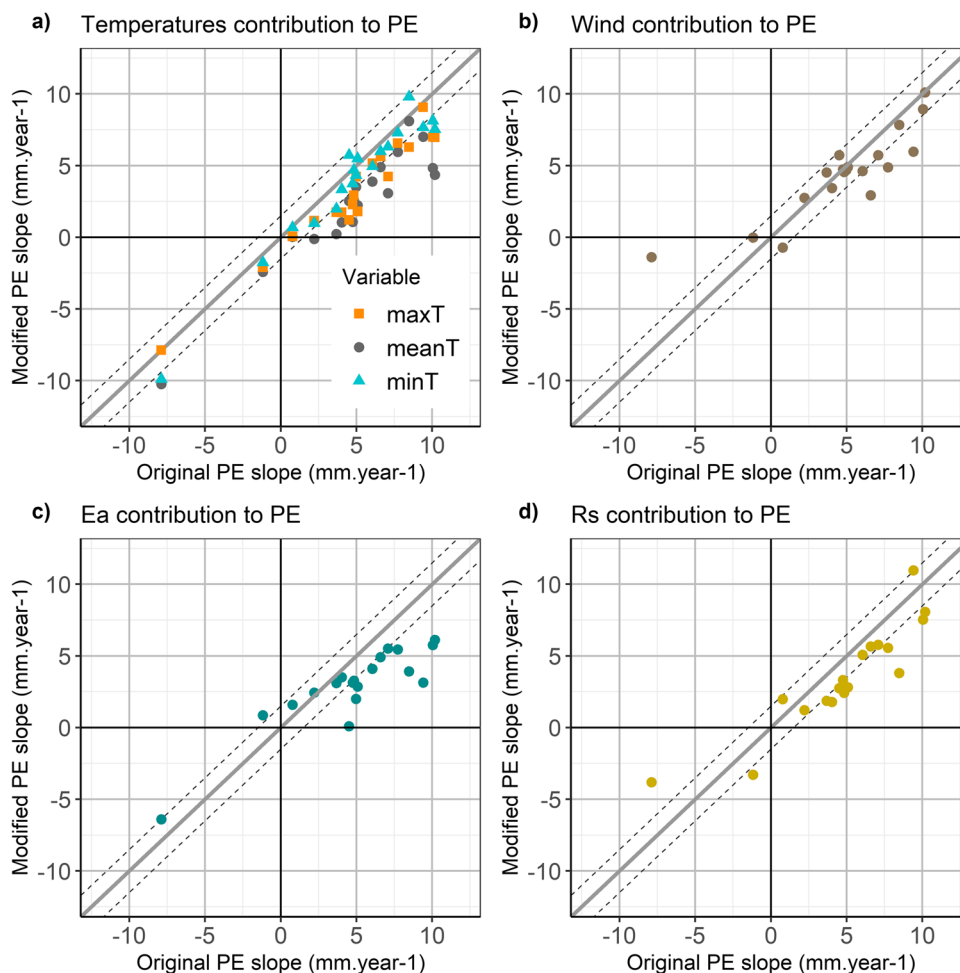
**Table 2** Potential evapotranspiration (PE) slopes ( $\text{mm year}^{-1}$ ) for the period 1990–2019. The values of the original PE slopes and the modified PE slopes (with PE recalculated after detrend in meanT, maxT, minT, Rs, Ea, and wind) are shown. Upward arrows indicate that the variable contributed to an increase in PE between 1990 and 2019, while down arrows indicate a negative contribution to PE. The shaded numbers indicate the most important differences between the original and modified slopes for each site. Horizontal lines divide groups of sites, while site F1 is different from all sites

Site	Group	PE	Modified PE slope without trend in:					
			meanT	maxT	minT	Rs	Ea	Wind
F1	-	-7.89	-10.24	-7.87	-9.90	↓-3.82	-6.40	↓-1.39
S1	I	2.21	↑-0.11	1.16	0.98	1.22	2.43	2.74
CHA2	I	7.72	↑5.95	6.56	7.29	↑5.56	↑5.45	↑4.88
SF1	I	10.18	↑4.36	↑6.98	7.54	8.07	↑6.12	10.11
CO1	I	8.47	8.11	6.28	9.79	↑3.81	↑3.92	7.84
CO2	I	5.08	↑2.23	↑1.80	5.49	↑2.82	↑2.86	4.90
CO3	I	4.75	↑1.08	↑2.29	3.74	3.31	3.13	4.74
CO4	I	4.51	↑2.54	↑1.21	5.72	2.75	↑0.10	5.72
BA12	I	10.05	↑4.84	↑7.00	8.12	7.53	↑5.77	8.94
BA2	I	3.67	↑0.23	1.74	1.98	1.87	3.11	4.52
BA5	I	4.82	↑2.56	↑2.93	4.70	↑2.42	3.27	4.55
BA7	I	4.02	↑1.05	↑1.74	3.33	↑1.79	3.51	3.43
BA13	I	7.09	↑3.07	↑4.24	6.31	5.78	5.52	5.73
BA15	I	4.98	↑3.52	4.23	4.33	↑2.82	↑1.99	4.68
BA10	I	-1.18	-2.41	-2.09	-1.76	↑-3.29	↓0.86	-0.02
SJ1	II	9.41	7.01	9.07	7.67	10.96	↑3.14	↑5.90
MZ2	II	6.59	↑4.90	5.64	5.98	5.67	↑4.9	↑2.92
MZ1	II	6.06	↑3.89	5.17	4.95	5.07	↑4.10	↑4.62
RN3	II	0.78	0.04	0.06	0.68	1.97	1.60	↑-0.72

formulation of PE (see Eq. 1). Consequently, the behavior of PE and PP (1990–2019) was analyzed, and the results showed significant annual trends in PE and almost no significant changes in precipitation, as mentioned earlier (see also Fig. 3). As changes in PE were the main responsible for changes in soil water, a detrend analysis was carried out to determine which meteorological variables were more important in modulating the PE trend. Positive trends in temperature and solar radiation and a negative trend in humidity were the main causes of the positive trend in PE in the center and east of Argentina, with a consequent decrease in SMC. Similar results in PE (also using the Penman–Monteith formulation) and PP were documented by D’Andrea et al. (2019) in central-eastern Argentina. These authors documented that the decreasing trend in relative humidity could have been the main cause of PE trends, having more weight than temperature, by using a forward stepwise regression analysis. Despite the differences, both methodological approaches agree in pointing to humidity as one of the variables responsible for PE trends. Similar results have been documented in China by Liu et al. (2010), who, through a detrend analysis, observed that an increasing trend in air temperature and, to a lesser extent, a decreasing trend in relative humidity, were the main causes for the increasing annual trends of PE, also estimated by the Penman–Monteith method.

Wind speed increased significantly both in sites in the center and east and in sites in the west of Argentina. However, changes in PE were explained by trends in this variable only in the west (see Appendix, Table 4). This is possibly related to the existence of spatial variability in the sensitivity of PE to meteorological variables. Many studies have analyzed PE sensitivity in different parts of the world, showing widespread results. For example, Liu et al. (2010) studied the sensitivity of PE to meteorological variables in the Yellow River basin in China and found that it varied in different regions of the basin: in the upper basin, PE was more sensitive to solar radiation, and in the west portion it was more sensitive to air temperature, whereas, in the middle basin, the northwest portion was more sensitive to wind speed and the south portion was more sensitive to relative humidity. Interestingly, the northwest portion of the middle basin of the Yellow River presents climatic characteristics similar to those of the sites in the west of Argentina used in this study, where the greatest changes were due to trends in wind speed. In the Tibetan Plateau, PE was most sensitive to solar radiation, and to a lesser extent to mean temperature (Hu et al. 2021); while in the Changjiang basin in China, PE showed the lowest sensitivity to wind speed, and it was most sensitive to relative humidity (Gong, et al. 2006). In addition, the sensitivity of PE may vary with seasons (Gong et al. 2006; Zeng et al. 2021), but since we worked with annual data, this

**Fig. 4** Scatter plot between original PE slope and modified PE slope after eliminating trends in **a** temperatures (maxT, minT, and meanT); **b** wind; **c** vapor pressure (Ea); and **d** solar radiation (Rs)



variability was not taken into account. Therefore, a significant trend in a meteorological variable does not determine the cause of the changes in PE by itself; a high sensitivity of PE to that variable is also required, and that will depend on the site conditions.

## 5 Conclusions

In this study, annual trends of SMC and DEF and the climate contribution to those trends were analyzed in 51 sites distributed throughout Argentina for the 1990–2019 period. This was performed based on simulations from a relatively simple water balance model (BHOA). Our results showed that, in general, DEF significantly increased (i.e., positive trend) in almost all sites. Significant SMC trends occurred in fewer sites and with a minor relative change in comparison to DEF, but also suggesting an increase in drier conditions (i.e., negative trends) in most cases.

PE trends were the main responsible for inducing changes in SMC, as almost no significant changes in PP were detected. In central-eastern Argentina, which is the core

agricultural region, PE increased mainly due to the increase in maxT and meanT, followed by increases in solar radiation and decreases in humidity. In the sites located in the west of the country, PE increased due to increases in wind and a decrease in humidity. Because temperature turned out to be one of the most important drivers of the increase in PE in central eastern Argentina, projected increases in temperature documented by the IPCC (2021) could imply higher PE scenarios and, therefore, higher DEF and lower SMC. According to the results obtained in this study, increasingly drier conditions are expected to continue to occur in this region of the country.

Finally, examining the spatio-temporal variability in soil water and how the meteorological variables affect it is indispensable to assess climate-induced changes and propose feasible climate change adaptation strategies. This is particularly important in countries like Argentina with predominantly rainfed agriculture, as crop yields strongly depend on precipitation and, thus, on soil moisture conditions. Thus, soil water negative trends could have a negative impact on crop yields. Depending on the time of occurrence, they could have a higher or lower impact on this economic

activity. Corn and soybean production are sensitive to drier summers, while winter crops such as wheat and barley are sensitive to water soil scarcity, especially during spring months. Advancing in the understanding of soil moisture behavior and the seasonality of its changes is essential to

propose feasible climate change adaptation strategies in the agricultural sector. Therefore, further studies are needed to evaluate the seasonality trends of soil moisture content and water deficits to complement this study.

## Appendix

**Table 3** Meteorological stations used in this study. Name, latitude, longitude, and height are detailed

Code	Name	Lat	Long	Height (m)	Code	Name	Lat	Long	Height (m)
F1	Las Lomitas	-24.7	-60.6	130	RN2	Bariloche AERO	-41.2	-71.2	840
S1	Salta AERO	-24.9	-65.5	1221	SL1	Villa Reynolds AERO	-33.7	-65.4	486
LR1	Chilecito AERO	-29.2	-67.4	945	CR3	Paso de los Libres AERO	-29.7	-57.2	70
CA1	Catamarca AERO	-28.6	-65.8	454	MI1	Iguazú AERO	-25.7	-54.5	270
CR1	Bella Vista INTA	-28.4	-58.9	70	CO4	Marcos Juarez AERO	-32.7	-62.2	114
SF1	Ceres AERO	-29.9	-62.0	88	MZ1	San Martín (Mendoza)	-33.1	-68.4	653
CO1	Córdoba AERO	-31.3	-64.2	474	CHa2	Pcia. Roque Saenz Peña INTA	-26.9	-60.5	90
ER1	Paraná AERO	-31.8	-60.5	78	CHa3	Las Breñas INTA	-27.1	-61.1	102
ER2	Guauguaychú AERO	-33.0	-58.6	21	BA10	Hilario Ascasubi INTA	-39.4	-62.6	22
CO2	Río Cuarto AERO	-33.1	-64.2	421	SJ1	San Juan INTA	-31.4	-68.3	618
BA1	Pergamino INTA	-33.9	-60.6	65	SF2	Sauce Viejo AERO	-31.7	-60.8	18
CO3	Laboulaye AERO	-34.1	-63.4	137	BA11	Junín AERO	-34.6	-60.9	81
BA2	Ezeiza AERO	-34.8	-58.5	20	BA12	Pehuajó AERO	-35.9	-61.9	87
BA3	La Plata OBS	-35.0	-57.9	23	CR2	Corrientes AERO	-27.5	-58.8	62
MZ2	Malargüe AERO	-35.5	-69.6	1425	SF3	Oliveros INTA	-32.6	-60.9	26
BA4	Dolores	-36.4	-57.7	9	LR2	Chamical AERO	-30.4	-66.3	461
BA5	Coronel Suarez AERO	-37.4	-61.9	233	ER3	Concordia AERO	-31.3	-58.0	38
BA6	Mar del Plata AERO	-37.9	-57.6	21	CHa1	Resistencia AERO	-27.5	-59.1	52
BA7	Barrow INTA	-38.3	-60.3	120	BA13	Tres Arroyos	-38.3	-60.3	115
BA8	Bahía Blanca AERO	-38.7	-62.2	83	BA14	San Pedro INTA	-33.7	-59.7	28
NQ1	Neuquén AERO	-39.0	-68.1	271	J1	Jujuy AERO	-24.4	-65.1	905
CH2	Trelew AERO	-43.2	-65.3	43	RN1	Viedma AERO	-40.9	-63.0	7
CH3	Comodoro Rivadavia AERO	-45.8	-67.5	46	MI2	Bernardo de Irigoyen AERO	-26.3	-53.7	815
SC1	Río Gallegos AERO	-51.6	-69.3	19	BA15	Olavarría AERO	-36.9	-60.2	166
CH1	Esquel AERO	-42.9	-71.2	797	RN3	El Bolsón AERO	-42.0	-71.5	337
BA9	Tandil AERO	-37.2	-59.3	175					

**Table 4** Slopes of the annual trend of water deficits (DEF) ( $\text{mm year}^{-1}$ ), soil moisture content (SMC) ( $\text{mm year}^{-1}$ ), potential evapotranspiration (PE) ( $\text{mm year}^{-1}$ ), precipitation (PP) ( $\text{mm year}^{-1}$ ), mean temperature (meanT) ( $^{\circ}\text{C year}^{-1}$ ), maximum temperature (maxT) ( $^{\circ}\text{C year}^{-1}$ ), minimum temperature (minT) ( $^{\circ}\text{C year}^{-1}$ ), solar radiation (Rs) ( $\text{MJ m}^{-2} \text{ year}^{-1}$ ), actual vapor pressure (Ea) ( $\text{hPa year}^{-1}$ ), and wind ( $\text{km h}^{-1} \text{ year}^{-1}$ ). Slopes marked with \* indicate they were statistically significant

Site	Annual trends									
	DEF	SMC	EP	PP	meanT	maxT	minT	Rs	Ea	Wind
F1	-12*	1*	-7.9*	2.98	0.04*	0.00	0.06*	-0.04*	0.03	-0.2*
S1	-0.6	0.5*	2.2	4.10	0.03*	0.03*	0.03*	0.01	0.00	-0.02*
CHa2	10.7*	-1.3*	7.7*	-7.99	0.02*	0.03*	-0.01	0.02*	-0.05*	0.11*
SF1	11.4*	-1*	10.2*	-6.88	0.05*	0.06*	0.05*	0.02*	-0.05*	0.01
CO1	15*	-1.4*	8.5*	-6.03	0.00	0.05*	-0.02	0.06*	-0.06*	0.02*
CO2	10.7*	-1.3*	5.1*	-5.15	0.02*	0.05*	-0.01	0.03*	-0.02	0.01
CO3	7.8*	-1.0	4.8*	-4.39	0.04*	0.06*	0.02	0.02*	-0.02	0.00
CO4	9.8	-2*	4.5	-12.39	0.02	0.06*	-0.03	0.02	-0.06*	-0.12*
BA12	10.9*	-1.3	10.0*	-6.74	0.06*	0.07*	0.04	0.04*	-0.06*	0.1*
BA2	5.1*	-0.2	3.7*	-1.44	0.03*	0.04*	0.03*	0.02*	-0.01	-0.06*
BA5	6.4*	-0.5	4.8*	-5.11	0.02*	0.04*	0.01	0.04*	-0.02	0.02
BA7	5.9*	-0.8	4.0*	-8.4*	0.04*	0.06*	0.02*	0.03*	-0.01	0.02
BA13	12.8*	-1.8*	7.1*	-7.5	0.04*	0.06*	0.02	0.02*	-0.02	0.06*
BA15	8.6*	-0.9*	5.0*	-6.3	0.01*	0.02*	0.01	0.03*	-0.03*	0.03*
BA10	0.5	-0.8*	-1.2*	-3.7	0.02*	0.02*	0.02	0.03*	0.03	-0.05*
SJ1	12.6*	-0.5*	9.4*	-3.6*	0.04*	0.01	0.06*	-0.02	-0.11*	0.06*
MZ2	8.4*	-0.4	6.6*	-2.09	0.02*	0.03*	0.02*	0.01	-0.02*	0.10*
MZ1	6.1*	0.0	6.1*	0.20	0.04*	0.04*	0.04*	0.01	-0.05*	0.04*
RN3	2.4*	0.0	0.8*	-5.72	0.02*	0.04*	0.00	-0.02	0.02*	0.07*

**Author contribution** All authors contributed to the study conception and design and to the final version of this manuscript. Data processing and analysis were performed by M. Peretti. The first draft of the manuscript was written by M. Peretti, and all authors commented on previous versions of the manuscript. The supervision of the findings of this research was done by M. E. Fernandez Long. All authors read and approved the final manuscript.

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**Data availability** The datasets analyzed during the current study are available from the corresponding author on reasonable request.

**Code availability** All the analyses of data carried out in this study were developed by using the Rstudio software. The *wql* library was used for the statistical analysis of trends. The analysis codes are available on request.

## Declarations

**Ethics approval** Not applicable.

**Consent to participate** Not applicable.

**Consent for publication** Not applicable.

**Competing interests** The authors declare no competing interests.

## References

- Aiello JL, Kuba J, Forte Lay JA (1995) Software AGROAGUA. In: Agrosoft'95 - Feira e Congresso de Informática Aplicada à Agropecuária e Agroindústria. Juiz de Fora, Brasil
- Allen RG, Pereira LS, Raes D, Smith M (1998) Crop evapotranspiration - guidelines for computing crop water requirements - FAO Irrigation and drainage paper 56. Food and Agriculture Organization of the United Nations, Rome
- Amenu GG, Kumar P, Liang XZ (2005) Interannual variability of deep-layer hydrologic memory and mechanisms of its influence on surface energy fluxes. *J Clim* 18:5024–5045. <https://doi.org/10.1175/JCLI3590.1>
- Baier W, Robertson GW (1966) A new versatile soil moisture budget. *Can J Plant Sci* 299–315
- Barros VR, Boninsegna JA, Camilloni IA et al (2015) Climate change in Argentina: trends, projections, impacts and adaptation. *Wiley Interdiscip Rev Clim Chang* 6:151–169. <https://doi.org/10.1002/wcc.316>
- Čadro S, Uzunović M, Cherni-Čadro S, Žurovec J (2019) Changes in the water balance of Bosnia and Herzegovina as a result of climate change. *J Agriculture For* 65:19–33. <https://doi.org/10.17707/agricultforest.65.3.02>
- Camilloni IA (2018) Argentina y el cambio climático. *Cienc Invest* 68:5–10
- Cammalleri C, Micale F, Vogt J (2016) Recent temporal trend in modelled soil water deficit over Europe driven by meteorological observations. *Int J Climatol* 36:4903–4912. <https://doi.org/10.1002/joc.4677>
- D'Andrea MF, Rousseau AN, Bigah Y et al (2019) Trends in reference evapotranspiration and associated climate variables over the last 30 years (1984–2014) in the Pampa region of Argentina.

- Theor Appl Climatol 136:1371–1386. <https://doi.org/10.1007/s00704-018-2565-7>
- de Barros SD, Lee H, Loikith P et al (2017) Can significant trends be detected in surface air temperature and precipitation over South America in recent decades? *Int J Climatol* 37:1483–1493. <https://doi.org/10.1002/joc.4792>
- de la Casa AC, Ovando GG (2016) Variation of reference evapotranspiration in the central region of Argentina between 1941 and 2010. *J Hydrol Reg Stud* 5:66–79. <https://doi.org/10.1016/j.ejrh.2015.11.009>
- Deng Y, Wang S, Bai X et al (2020) Variation trend of global soil moisture and its cause analysis. *Ecol Indic* 110:105939. <https://doi.org/10.1016/j.ecolind.2019.105939>
- Dorigo WA, Wagner W, Hohensinn R et al (2011) The International Soil Moisture Network: a data hosting facility for global in situ soil moisture measurements. *Hydrol Earth Syst Sci* 15:1675–1698. <https://doi.org/10.5194/hess-15-1675-2011>
- Dorigo W, De Jeu R, Chung D et al (2012) Evaluating global trends (1988–2010) in harmonized multi-satellite surface soil moisture. *Geophys Res Lett* 39:3–9. <https://doi.org/10.1029/2012GL052988>
- Dymond SF, Kolka RK, Bolstad PV, Sebestyen SD (2014) Long-term soil moisture patterns in a Northern Minnesota forest. *Soil Sci Soc Am J* 78:S208–S216. <https://doi.org/10.2136/sssaj2013.08.0322nafsc>
- Fernandez Long ME, Gattioni NN, Spennemann PC (2018) Inter-comparación y validación de simulaciones de la humedad del suelo en la Pampa Húmeda. *Actas XVII Reun Argentina Agrometeorol* 19 al 21 septiembre 2018, San Luis, Argentina 78–79
- Fernández-Long ME, Spescha L, Barnatán I, Murphy G (2012) Modelo de balance hidrológico operativo para el agro (BHOA). *Rev Agron Ambient* 32(1–2):31–47
- Gong L, Xu C, Yu, Chen D, et al (2006) Sensitivity of the Penman-Monteith reference evapotranspiration to key climatic variables in the Changjiang (Yangtze River) basin. *J Hydrol* 329:620–629. <https://doi.org/10.1016/j.jhydrol.2006.03.027>
- Holsten A, Vetter T, Vohland K, Krysanova V (2009) Impact of climate change on soil moisture dynamics in Brandenburg with a focus on nature conservation areas. 2076–2087
- Hu S, Gao R, Zhang T, et al (2021) Spatio-temporal variation of reference evapotranspiration and its climatic drivers over the tibetan plateau during 1970–2018. *Appl Sci* 11: <https://doi.org/10.3390/app11178013>
- IPCC (2021) *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press.
- Li X, Liu L, Li H, et al (2019) Spatiotemporal soil moisture variations associated with hydro-meteorological factors over the Yarlung Zangbo River basin in Southeast Tibetan Plateau. *Int J Climatol* 39:188–206. <https://doi.org/10.1002/joc.6202>
- Liu Q, Yang Z, Cui B, Sun T (2010) The temporal trends of reference evapotranspiration and its sensitivity to key meteorological variables in the Yellow River Basin, China. *Hydrol Process* 24:2171–2181. <https://doi.org/10.1002/hyp.7649>
- Minetti JL, Vargas WM, Poblete AG et al (2003) Non-linear trends and low frequency oscillations in annual precipitation over Argentina and Chile, 1931–1999. *Atmosfera* 16:119–135
- Müller GV, Lovino MA, Sgroi LC (2021) Observed and projected changes in temperature and precipitation in the core crop region of the humid pampa, Argentina. *Climate* 9:1–25. <https://doi.org/10.3390/cli9030040>
- Paruelo JM, Sala OE (1995) Water losses in the Patagonian steppe: a modelling approach. *Ecology* 76:510–520. <https://doi.org/10.2307/1941209>
- Raes D, Steduto P, Hsiao TC, Fereres E (2009) *AquaCrop – The FAO crop model to simulate yield response to water AquaCrop Reference Manual*. Ref Man
- Robinson PJ (2006) Implications of long-term precipitation amount changes for water sustainability in North Carolina. *Phys Geogr* 286–296. <https://doi.org/10.2747/0272-3646.27.4.286>
- Saurral RI, Camilloni IA, Barros VR (2016) Low-frequency variability and trends in centennial precipitation stations in southern South America. *Int J Climatol* 37:1774–1793. <https://doi.org/10.1002/joc.4810>
- Seneviratne SI, Corti T, Davin EL et al (2010) Investigating soil moisture-climate interactions in a changing climate: a review. *Earth-Science Rev* 99:125–161. <https://doi.org/10.1016/j.earscirev.2010.02.004>
- Sheffield J, Wood EF (2008) Global trends and variability in soil moisture and drought characteristics, 1950–2000, from observation-driven simulations of the terrestrial hydrologic cycle. *J Clim* 21:432–458. <https://doi.org/10.1175/2007JCLI1822.1>
- Sheffield J, Wood EF, Roderick ML (2012) Little change in global drought over the past 60 years. *Nature* 491:435–438. <https://doi.org/10.1038/nature11575>
- Skansi MM, Brunet M, Sigró J et al (2013) Warming and wetting signals emerging from analysis of changes in climate extreme indices over South America. *Glob Planet Change* 100:295–307. <https://doi.org/10.1016/j.gloplacha.2012.11.004>
- Smith M (1992) CROPWAT A computer program for irrigation planning and management. *FAO Irrig Drain Pap* N° 46 133
- Spennemann PC, Fernández-long ME, Gattinoni NN, Cammalleri C (2020) Journal of Hydrology : Regional Studies Soil moisture evaluation over the Argentine Pampas using models, satellite estimations and in-situ measurements. *J Hydrol Reg Stud* 31:100723. <https://doi.org/10.1016/j.ejrh.2020.100723>
- Thomas A (2000) Climatic changes in yield index and soil water deficit trends in China. 71–81
- Thorntwaite CW, Mather JR (1955) *The water balance*. Publ Climatol VIII, (1)104 p Drexel Inst Tech, New Jersey USA
- Wang L, Xie Z, Jia B, et al (2019) Contributions of climate change and groundwater extraction to soil moisture trends. *Earth Syst Dyn Discuss* 1–37. 10.5194/esd-2019-26
- WMO (1989) Calculation of monthly and annual 30-year standard normals. *World Clim Program* 14
- WMO (2017) *Directrices de la Organización Meteorológica Mundial sobre el cálculo de las normales climáticas* No 1203. 32
- Xu C, Yu, Gong L, Jiang T, et al (2006) Analysis of spatial distribution and temporal trend of reference evapotranspiration and pan evaporation in Changjiang (Yangtze River) catchment. *J Hydrol* 327:81–93. <https://doi.org/10.1016/j.jhydrol.2005.11.029>
- Zeng P, Sun F, Liu Y et al (2021) Changes of potential evapotranspiration and its sensitivity across China under future climate scenarios. *Atmos Res* 261:105763. <https://doi.org/10.1016/j.atmosres.2021.105763>

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