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Modeling maize and soybean responses to climatic change and soil degradation in a region of South America

Lucía Casali[1,2] | **Juan M. Herrera**[1,3] | **Gerardo Rubio**[1,2]

[1] Instituto de Investigaciones en Biociencias Agrícolas y Ambientales (CONICET UBA), Ciudad de Buenos Aires, Buenos Aires 1417, Argentina

[2] Soil Fertility and Fertilizers, School of Agriculture, University of Buenos Aires, Av. San Martín 4453 (1417DSE), Buenos Aires, Argentina

[3] Agroscope, Plants and Plant Products, Route de Duillier 50, Nyon, Switzerland

Correspondence
Soil Fertility and Fertilizers, School of Agriculture, University of Buenos Aires, Av. San Martín 4453 (1417DSE), Buenos Aires, Argentina.
Email: rubio@agro.uba.ar

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Abstract

Climatic change effects on crop yields are expected to be crop- and site specific. Here, Decision Support System for Agrotechnology Transfer models were used to evaluate climatic change effects and mitigation strategies on maize (*Zea mays* L.) and soybean [*Glycine max* (L.) Merr.] yields in soils of the subtropical and semi-arid region of Chaco. Simulations were performed for the DK747 and A8000 genotypes, calibrated for the CERES-Maize model in a previous report and for the CROPGRO-Soybean model in the present study, respectively. Both crops markedly differ in their response to climatic change and putative levels of atmospheric CO_2 concentration. The observed significant reductions in maize yields in future climate scenarios (5–42% compared with the baseline, 1986–2010) were more associated with increased temperatures that shortened the crop cycle than with water stress. Delaying the sowing date is a feasible strategy to mitigate this effect. Projected temperature increases are expected to play a secondary role in determining soybean yields. Instead, water stress will continue to be an important constraint to soybean yield in the context of global warming, but this effect is strongly affected by rainfall regimes. Responses to raising CO_2 levels were more pronounced in soybean (+10–40%) than in maize (+2–4%). Soil degradation exacerbated the negative effects of global warming on crop yields, especially on maize, which highlights the importance of soil conservation practices. The observed high interannual climatic variability and the different sensitivities of maize and soybean to climatic variables indicate that crop diversification would be the key to improve the resilience of the agrosystems under the future scenarios.

1 | INTRODUCTION

Global climate changes are expected to continue in the future if the current trajectory of anthropogenic greenhouse gas emissions is maintained (Zhao et al., 2017). Agriculture is one of the human activities most affected by global warming because crops are directly affected by temperature and by other variables expected to change according to future scenarios such as rainfall and air CO_2 concentration (Challinor et al., 2014; Rose, Osborne, Greatrex, & Wheeler, 2016). It is assumed that those effects are crop specific due to the particular requirements of each crop (Teixeira, Fischer, van

Abbreviations: DSSAT, Decision Support System for Agrotechnology Transfer; NRMSE, normalized root mean square error; RCP, IPCC Representative Concentration Pathway

Velthuizen, Walter, & Ewert, 2013). Current predictions also indicate that the effects of climate change are site specific and not uniform across latitudes and regions (Challinor et al., 2014; Teixeira et al., 2013). Indeed, crops cultivated in subtropical regions are expected to be more severely affected than those cultivated in temperate regions (Amouzou et al., 2019; Tao & Zhang, 2011; Teixeira et al., 2013). Therefore, it is critical to quantify the impact of climate change on crop yields to assess the risks for food security and to identify strategies to mitigate the expected adverse effects.

During the past decades, maize (*Zea mays* L.) and soybean [*Glycine max* (L.) Merr.] crops have spread to areas previously considered marginal, such as the semi-arid and subhumid Chaco region, an extensive area in South America that includes part of Argentina, Paraguay, Brazil, and Bolivia (Casali, Rubio, & Herrera, 2018; Dominguez, & Rubio, 2019; Fehlenberg et al., 2017; Giménez, Mercau, Houspanossian, & Jobbágy, 2015). Along with the United States, Argentina and Brazil are among the major world exporters of maize and soybean. The expansion of the agricultural frontier was locally favored by the increase in annual rainfall (∼18% in the last decade) (Ricard, Viglizzo, & Podestá, 2015) and commodity prices and by the adoption of no-tillage, which is a more cost-effective practice than conventional tillage. The expansion process was so dramatic that it made this area one with the highest rates of deforestation in the world (Kuemmerle et al., 2017). Global studies simulating the effects of climate change on the productivity of maize and soybean show a high level of uncertainty for the Chaco region (Elliott et al., 2014; Rosenzweig et al., 2014). However, we did not find specific studies focused on the Chaco region, where maize and soybean provide the main economic support of the local communities. This lack of knowledge is particularly acute for those management strategies intended to minimize economic risks and diminish the impact of future yield constraints (Fodor et al., 2017). Irrigation practices are currently almost nonexistent in the region, so their implications for crop yield need to be considered as a potential strategy (Elliott et al., 2014). Delaying sowing dates may also be a feasible strategy to cope with climatic constraints (Saseendran, Ma, Nielsen, Vigil, & Ahuja, 2005). For maize under current climatic conditions, Maddonni (2012) reported that delaying the sowing date would improve the water balance in the critical period, but it could also increase the risk of heat stress during the reproductive periods.

Climate change impacts on agricultural production may be affected by the soil degradation process (Mullan, 2013). For example, a rise in mean temperatures may increase soil water evaporation and soil carbon losses, which, combined with a higher frequency of extreme rainfall events, may increase soil erodibility and reduce soil fertility (Lal, 2012; Nearing, Pruski, & O'neal, 2004). Soils from subtropical and tropical regions are in general more vulnerable to degradation than those from temperate regions (Ross, 1993; Rubio et al., 2019), especially in cases where native forests are converted to agricultural land (Guillaume, Damris, & Kuzyakov, 2015). Therefore, they may be more susceptible to the effects of global climate change, and considering putative soil conditions in the future may enhance the accuracy in the predictions for the agricultural consequences of climate change. Furthermore, there is a growing urgent need to design agronomic practices that mitigate the effects of climate change on crop yields and preserve the soil capacity to provide ecological services.

Agronomic simulation models are a valuable tool for studying the simultaneous effects on crop yields of multiple factors that otherwise would be very difficult to evaluate through field experiments. For example, they are highly suitable for predicting crop yields under climate change scenarios (Lobell & Burke, 2010). The Decision Support System for Agrotechnology Transfer (DSSAT) is a platform that simulates crop growth and development by integrating soil, climate, crop, and management submodels. The DSSAT models CERES-Maize and CROPGRO-Soybean have been successfully used to assess the impact of climate change and/or climate variability on agricultural productivity (e.g., Amouzou et al., 2019; Battisti et al., 2017; Ma et al., 2017) and were evaluated for different Argentine conditions with relatively low estimation errors (e.g., Casali et al., 2018; Caviglia, Sadras, & Andrade, 2013; Merlos et al., 2015). Although DSSAT models were originally developed in temperate regions, they have also been used in tropical and subtropical ones (Amouzou et al., 2019; Battisti et al., 2017; Liu et al., 2013).

This paper provides an evaluation and application of the CERES-Maize and CROPGRO-Soybean models under different climate and atmospheric CO_2 concentration scenarios and crop management regimes with a focus on the semi-arid Chaco region. Our objectives were (a) to evaluate the effect of expected climate change and atmospheric CO_2 concentration scenarios on maize and soybean yields in soils with different degree of degradation and (b) to evaluate the effect of irrigation and sowing dates as possible strategies to mitigate the impact of climate change.

Core Ideas

- We studied climate change by soil degradation interactions on maize and soybean.
- Soil degradation exacerbated negative effects on crop yields, especially on maize.
- Soil conservation practices help mitigate the impacts of climate change.
- Crop diversification is essential to improve the resilience to climate change.

2 | MATERIALS AND METHODS

2.1 | Study area

The study area is located at Quimili (27°38′ S, 62°25′ W), a representative location of the semi-arid Chaco region. This region exhibits one of the highest rates of deforestation in the world (Kuemmerle et al., 2017) and is starting to show increasing signs of soil degradation (Osinaga, Álvarez, & Taboada, 2018). Historical average annual precipitation is 692 mm (Angueira, Prieto, López, & Barraza, 2007), following a monsoonal pattern with higher precipitation in summer (December–March) than in winter (June–September). Summer crops are frequently exposed to temperatures above 30 °C during the late-vegetative and reproductive stages, making them frequently affected by heat stress (Casali et al., 2018). Agricultural soils are mainly Haplustolls and Argiustolls.

2.2 | Calibration and validation of crop models

The models CERES-Maize and CROPGRO-Soybean, which are part of DSSAT v4.5 (Hoogenboom et al., 2010), were used to assess the impact of climate change, soil degradation, and agricultural practices on grain yields of maize and soybean. The CERES-Maize model has been calibrated in the study area for the cultivar DK747 in a previous report (Casali et al., 2018), whereas the CROPGRO-Soybean model was calibrated for the cultivar A8000 as part of the present study. The dataset for soybean calibration was collected from field experiments managed by the National Agricultural Technological Institute located at La María (28°03′ S, 64°15′ W), Las Breñas (27°04′ S, 61°04′ W), and Charata (27°07′ S, 61°13′ W). The experiments covered a wide range of sowing dates (2 October to 13 January) and were fertilized to avoid hydric and nutrient deficiencies. The fact that the experiments included irrigated and rain-fed conditions and covered a wide range of environmental conditions resulted in a wide variability in soybean yields (1,000–4,500 kg ha^{-1}), crop cycle length (107–207 d between sowing and full maturity), number of grains (940–2,940 grains m^{-2}), and average grain weight (0.10–0.18 g). Overall, the dataset used for calibrating the A8000 cultivar covered 41 plots. Validation of the calibrated cultivar was made with a second dataset that was collected from farmer-managed field experiments. This dataset covered a wide environmental and management range and included the following sites: Capdevila (27°23′ S, 61°30′ W), Cejolao (27°30′ S, 62°17′ W), El Colorado (27°53′ S, 62°12′ W), Las Breñas (27°6′ S, 61°6′ W), Loro Blanco (26°48′ S, 61 °12′ W), Los Frentones (26°23′ S, 61°23′ W), Otumpa (27°6′ S, 62°30′ W), Pampa del Infierno (27°36′ S, 62°23′ W), Pinedo (27°18′ S, 61°17′ W), Quimili (27°36′ S, 62°23′ W), and Roversi (27°36′ S, 61°53′ W). The data set was obtained from field experiments belonging to the Guayacán and Gancedo-La Paloma farmers groups from CREA (an association of farmers for improving techniques through the exchange of experiences) and to the Soybean Cultivation Evaluation Network from Aapresid (an association similar to CREA, which focuses on conservation agriculture and sustainability) and the National Agricultural Technological Institute. Sowing dates of these field experiments were concentrated in December and January. Precipitation during the crop cycle varied from 315 to 790 mm. Plant density was between 20 and 30 plants m^{-2}, and the distance between rows was 52 cm in most cases. The average grain yield was 3,095 kg ha^{-1}. The experiments that had one or more of the following characteristics were not considered for the model validation: (a) missing basic data such as precipitation, plant density, or sowing date; (b) precipitation values 30% or more below the average for the specific year; and (c) crop yield values 40% or more below the average of others in the same environment (because it can be attributed to measurement errors or to the incidence of pests or diseases). Overall, the dataset used for validating the CROPGRO-Soybean model for A8000 covered 51 paddocks. The accuracy of the models' outputs was assessed by the RMSE, the RMSE expression as a percentage of the observed average (normalized RMSE [NRMSE]) (Wallach, Makowski, Jones, & Brun, 2014), the adjustment index *d* (Willmott et al., 1985), and the R^2 (Steel, Torrie, & Dickey, 1980).

2.3 | Crop modeling and climate scenarios

Crop management practices used in our DSSAT simulations were set to reflect the usual practices of local farmers. The sowing date and distance between rows for both crops were 31 December and 52 cm, respectively. Crop density was 6 plants m^{-2} for maize and 24.5 plants m^{-2} for soybean. Soybean was set as the preceding crop for soybean, and maize was set as the preceding crop for maize. Maize and soybean cultivars were assumed constant for all climate scenarios. Crop residues were not incorporated, assuming no-tillage, which is the most widespread soil preparation practice in the study area. Each simulation started at the harvest date of the predecessor crop, approximately 6 mo prior to the sowing date. Initial soil nitrate availability was set at 150 kg ha^{-1}, based on soil analyses conducted locally. The initial soil water availability was set at 60% of the soil water storage capacity.

Climate data for the crop simulations were derived from a multi-climate model ensemble. We used mean values of daily observations across four general circulation models, with the best performance according to a previous report

TABLE 1 Original and modified soil parameters for the three soil profiles used in the simulations

	Not degraded				Moderately degraded				Degraded			
Horizon	Ap	IIAC	IIC1	IIC2	Ap	IIAC	IIC1	IIC2	Ap	IIAC	IIC1	IIC2
Depth, cm	**0–15**	**15–47**	**47–77**	**77–200**	**0–10**	**10–42**	**42–72**	**72–195**	**0–5**	**5–37**	**37–67**	**67–190**
Clay, %	15	7	9	9	15	7	9	9	15	7	9	9
Sand, %	31	52	48	46	31	52	48	46	31	52	48	46
Organic C, %	**1.32**	**0.58**	**0.32**	**0.32**	**1.18**	**0.52**	**0.28**	**0.28**	**1.06**	**0.47**	**0.2**	**0.2**
Total N, %	0.13	0.09	0.05	0.04	0.13	0.09	0.05	0.04	0.13	0.09	0.05	0.04
Curve number	**73**				**83**				**93**			

Note. Soil characteristics that were modified to generate the degraded soils are bolded.

in the study site (Secretaría de Ambiente y Desarrollo Sustentable de la Nación, 2014). In this report, the performance of 27 models belonging to the CMIP5 base (Stouffer, Taylor, & Meehl, 2011; Taylor, Stouffer, & Meehl, 2012) (available at 3cn.cima.fcen.uba.ar) was evaluated for several Argentinean regions through the Unique Model Validation Index approach. This index varies between 0 and 1, with values close to 1 indicating the best performances. According to this approach, the four best models for our study site were CNRM-CM5, CMCC-CM, CSIRO-Mk-6-0, and MRI-CGCM3, with IUVM values of 0.9, 0.78, 0.71, and 0.70, respectively. These models provide daily rainfall, daily maximum and minimum temperature, and the other climate data required to run DSSAT. The predictive capacity of the multimodel ensemble was verified through correlation analysis with data obtained from a local (Quimili) meteorological station for the period 1994–2010. The results were satisfactory (R^2 = .99, .97, and .93 for monthly means of maximum and minimum temperatures and precipitation, respectively).

Our simulations were carried out in seasonal mode and considered three time horizons: (a) baseline climate (1986–2010), (b) near future (2015–2039), and (c) far future (2075–2099). We considered two IPCC Representative Concentration Pathways (RCPs) scenarios that modulate contrasting conditions that may occur in the future: RCP 4.5 (which assumes some stabilization in the emissions of greenhouse gases) and RCP 8.5 (which reflects the current trajectory of CO_2 emissions) (IPCC, 2014) (Figure 1). Because the model does not estimate solar radiation values, they were calculated using the Hargreaves and Samani (1985) equation. Simulations were conducted under a baseline concentration of CO_2 (360 μmol mol^{-1}) and under a range of higher concentration levels (van Vuuren et al., 2011) (550, 425, 525, 450, and 800 μmol mol^{-1} in the scenario 1986–2010, 2015–2039 RCP 4.5, 2075–2099 RCP 4.5, 2015–2039 RCP 8.5, and 2075–2099 RCP 8.5, respectively). The inclusion of CO_2 treatments for the historical weather data was made only for comparative purposes and to conduct statistical analysis that allows the proper partition of variance.

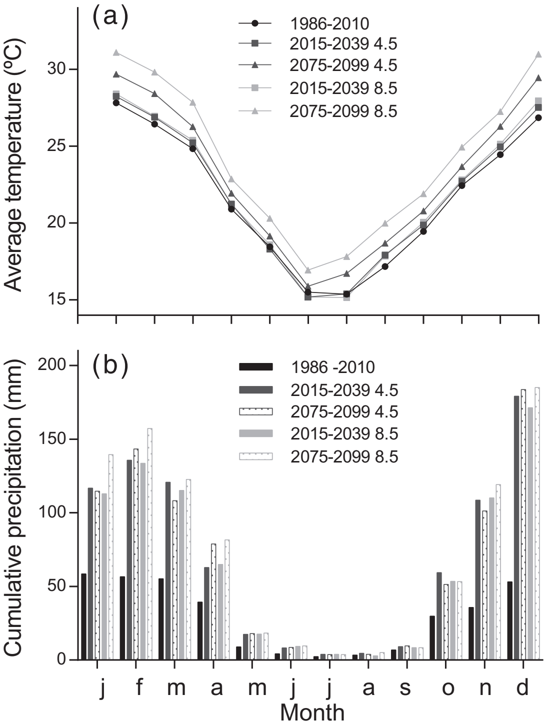

FIGURE 1 (a) Average monthly temperature and (b) cumulative monthly precipitation in Quimili in five climate scenarios generated by the multi-model ensemble: baseline period (1986–2010), near future (2015–2039), and far future (2075–2099) under two emission scenarios (RCP 4.5 and 8.5)

2.4 | Soils

The soil used for our simulations was an Entic Haplustol 7 de Agosto series, which is the main soil in Quimili according to the Santiago del Estero Geographic Information System (SigSE) (Angueira et al., 2007). The pristine condition of this soil, as described in the SigSE data base, was assumed to represent nondegraded soils (Table 1). Two additional simulated soils were generated to represent moderately degraded and degraded soil conditions. For this purpose, the properties considered key to define the course of the degradation process due to agricultural activities (Seybold, Herrick, & Brejda, 1999) were modified from the pristine condition (i.e., 10 and 15% reduction in the percentage of organic C and 5 and 10 cm reduction in the depth of the surface horizon, respectively, for the moderately degraded and degraded soil condition) (Table 1). Additionally, the curve number was increased by 10 and 20 units for the two degraded conditions. This curve number is a dimensionless soil-water retention parameter from DSSAT that varies from 0 to 100 and estimates the infiltration and runoff rates (Ritchie, 1998).

2.5 | Crop management strategies

Two crop management strategies were evaluated: sowing date and irrigation. There were three sowing date treatments (conventional, 31 December; early, 10 December; and late, 20 January) and two irrigation levels (nonirrigated and irrigated). The irrigated treatment was generated with DSSAT through automatic watering whenever soil moisture reached 50% of the total water storage capacity, and the total water storage capacity was brought to a value of 100%.

2.6 | Statistical analyses

Factorial ANOVAs were performed considering the climate scenarios, CO_2 levels, soils conditions, sowing dates, and irrigation levels. The outputs of the model were analyzed separately for current and elevated CO_2 levels for the two irrigation levels and for the three sowing dates.

3 | RESULTS

3.1 | Climate change scenarios

The multi-model ensemble predicted significant increases in average monthly temperatures for the future climate scenarios (Figure 1). Increases in maximum temperatures averaged 0.2 and 1.3 ˚C for the less dramatic (RCP 4.5) and 0.4 and 2.3 ˚C for the most dramatic scenario (RCP 8.5) in the near and distant future, respectively. Regarding minimum temperatures, the multi-model ensemble predicted average increases of 0.4 ˚C and an average increase of 1.6 ˚C for the RCP 4.5 scenario in the near and distant future, respectively. For the RCP 8.5 scenario and the same periods, the increases are predicted to be 0.5 and 3.1 ˚C, respectively. Regarding total annual rainfall, the predictions do not show clear trends across climate scenarios and time periods. In terms of seasonality, climate predictions for the future scenarios indicate rainfall increases over the baseline period during the late spring and summer months (November–February) (Figure 1).

3.2 | Maize

Simulated maize yields were significantly affected by CO_2 levels, climate scenarios, and soil degradation (Table 2). The effect of CO_2 enrichment was low (average +2.7%), whereas the effect of climate scenarios was more prominent (Figure 2). Compared with the 1986–2010 period, the average maize yields under RCP 4.5 were 6 and 20% lower in 2015–2039 and 2075–2099, respectively (Figure 2), whereas under RCP 8.5 the average maize yields were 7 and 43% lower in 2015–2039 and 2075–2099, respectively. These decreases in crop yields were associated with the shortening of the crop cycle prompted by higher temperatures (Figure 3). For example, the crop cycle was 17 d shorter (i.e., −16%) in the scenario of highest temperatures (2075–2099; RCP 8.5) compared with the 1986–2010 period.

Soil degradation × climate scenario was the only statistically significant interaction between the studied factors (Table 2). Whereas in the 1986–2010, 2015–2039/4.5, and 2015–2039/8.5 scenarios no significant effect of soil degradation was detected on maize yields, both RCP emission scenarios associated with the distant future (i.e., 2075–2099) were sensitive to the soil condition. In 2075–2099/4.5, maize yields were 1 and 7% lower in moderately degraded and degraded soil compared with the nondegraded condition, whereas in 2075–2099/8.5 maize yields were 4 and 14% lower, respectively.

Specific simulations were performed to evaluate the effects of anticipating or delaying sowing dates 20 d before or after December 31 (i.e., the sowing date considered optimal nowadays) under rainfed conditions and 360 μmol mol^{-1} air CO_2. Obtained results indicated a significant effect of sowing date on the grain yield of maize and that climate scenarios and soil degradation levels modified this effect (Table 3). Delaying sowing dates led to significant increases in maize yields. As compared with sowing on 31 December, sowing on 10 December and 20 January caused an 18% decrease and an 18% increase in yields, respectively (Figure 4). The largest effect was observed in the 2075–2099/RCP 8.5 scenario, in which maize yield increased by 40% when maize was sown on 20 January compared with 31 December. In contrast, in the 1986–2010 period, the yield difference between these sowing dates was 12%. The duration of the grain filling period was also significantly affected by the sowing date, which for the 2075–2099/RCP 8.5 scenario rose from 31 d for those plants sown on 31 December to 37 d on those sown 20 d later. Regarding the interaction sowing date × soil, maize sown early (10 December) showed a significantly lower yield (−15%) in the degraded soil than in the other two soils. In contrast, no significant effects of soil condition were observed in the other two sowing dates.

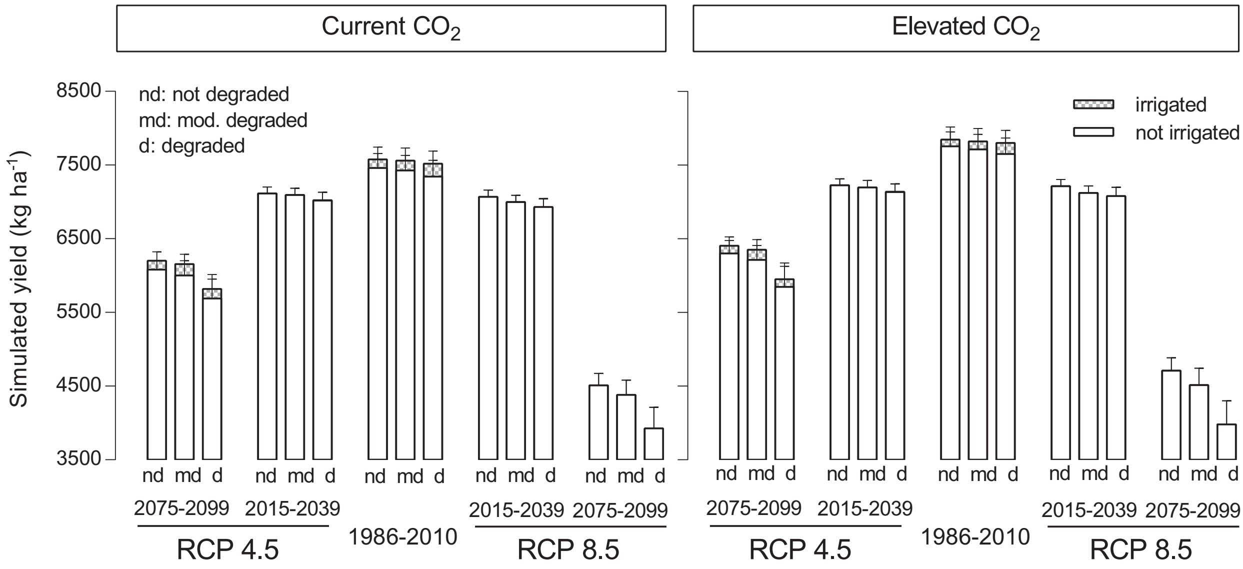

FIGURE 2 Maize yields (+ SEM) simulated by the CERES-Maize model in three soils (not degraded, moderately degraded, and degraded) under two irrigation treatments (rainfed and irrigated), five climate scenarios (baseline period, 1986–2010; near future, 2015–2039; far future, 2075–2099), and two emission scenarios for each future scenario (RCP 4.5 and 8.5). In all cases, the sowing date was 31 December, and the simulations were run with the baseline level of CO_2 (360 μmol mol^{-1}) and with the increased levels (550, 425, 525, 450, and 800 μmol mol^{-1} in the scenarios 1986–2010, 2015–2039/RCP 4.5, 2075–2099/RCP 4.5, 2015–2039/RCP 8.5, and 2075–2099/RCP 8.5)

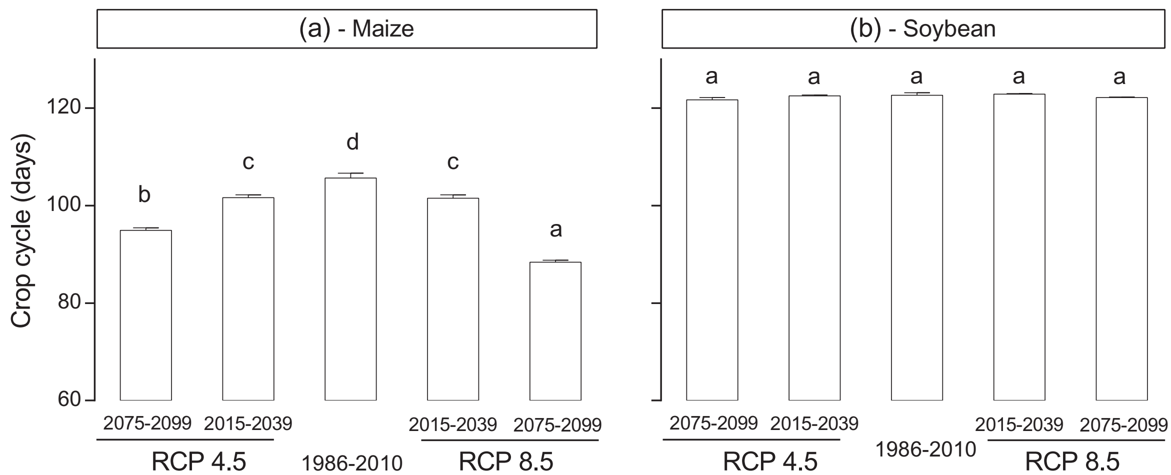

FIGURE 3 (a) Crop cycle length simulated by CERES-Maize and (b) CROPGRO-Soybean under five climate scenarios (baseline period, 1986–2010; near future, 2015–2039; far future, 2075–2099) and two emission scenarios for each future time period (RCP 4.5 and 8.5). In all cases, the sowing date was 31 December, and the simulations were run with the baseline level of atmospheric CO_2 concentration (360 μmol mol^{-1}) under a nondegraded soil. Bars represent SEM. In the mean comparison test for each crop, a < b < c < d; the same letter indicates no significant differences between the climate scenarios at a level of .05 using the Tukey test

3.3 | Soybean

The simulated soybean phenological and yield data for the calibrated A8000 (Supplemental Table S1) were in good agreement with the measured data. The NRMSE values were below 20% for the different simulated phenological and growth variables (Supplemental Table S2), indicating a "good" to "excellent" agreement between observed and predicted values (Jamieson, Porter, & Wilson, 1991). In particular, the number of days to R1 and R7 was simulated with great accuracy, with NRMSE values of 10.9 and 4.1% and a difference of just one day (Supplemental Table S2). Yield was simulated satisfactorily, with an NRMSE of 18%, an R^2 of .69 and an overestimation of 9.4% of the observed average (Supplemental Table S2).

Simulated soybean yields were significantly affected by the climate scenario, CO_2 level, soil degradation, and irrigation treatments and by the interactions irrigation × climate scenario and CO_2 level × climate scenario (Table 2). Among these factors and in contrast to maize, the level of CO_2 was one

TABLE 2 *F* values and significance levels of the simulated maize and soybean yields as affected by climate scenarios (C), soils (S), irrigation (I) treatments and CO_2 levels (L)

	C	S	I	L	I × L	I × S	L × C	I × C	L × S	C × S	I × L × C	I × L × S	I × C × S	L × C × S	I × L × C × S
Maize															
F value	687	14	1.3	14.6	0.01	0.01	0.5	0.5	0.05	2.47	0.004	0.004	0.01	0.04	0.000
p value	**	***	ns	***	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns
Soybean															
F value	17.8	6.1	59.4	1461	0.1	0.7	74.9	15	0.25	0.16	0.07	0.000	0.08	0.02	0.0004
p value	**	***	***	***	ns	ns	***	***	ns	ns	ns	ns	ns	ns	ns

[**]Significant at the .01 probability level.
[***]Significant at the .001 probability level.

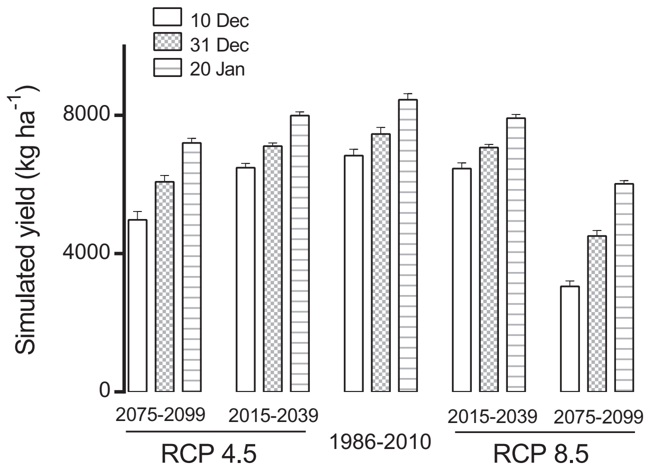

FIGURE 4 Simulated maize yield by the CERES-Maize model for three sowing dates (10 and 31 December and 20 January) and five climate scenarios (baseline period, 1986–2010; near future, 2015–2039; far future, 2075–2099) and two emission scenarios for each future scenario (RCP 4.5 and 8.5). In all cases, the simulations were run with the current level of atmospheric CO_2 concentration (360 μmol mol^{-1}), rainfed conditions, and under a nondegraded soil. Bars represent SE

of the main factors regulating soybean yield. In general, elevated CO_2 levels led to higher yields (Table 2; Figure 5). Compared with the current CO_2 levels, yield increased by 24, 10, 13, 22, and 40% in the scenarios 1986–2010, 2015–2039/RCP 4.5, 2015–2039/RCP 8.5, 2075–2099/RCP 4.5, and 2075–2099/RCP 8.5, respectively (Figure 5). Given the important effects of CO_2 levels on soybean yields and that this factor showed significant interactions with the climate scenarios (Table 3), we performed independent ANOVAs for current and elevated CO_2 levels (Table 4); accordingly, the results are shown for each CO_2 concentration.

3.3.1 | Current CO_2 level

Under the current CO_2 level, irrigation effects on soybean yields were modulated by the climate scenario (Table 4). Irrigation significantly increased yields by 12 and 7% for the 1986–2010 and 2075–2099/RCP 4.5 periods, respectively (Figure 5), whereas no significant effects were observed for the other climate scenarios. The positive effects of irrigation on soybean yields were observed under the three soil conditions (Table 4), averaging 4, 4, and 5% for the nondegraded, moderately degraded, and severely degraded soils, respectively (Figure 5). Averaging all treatments, degraded and moderately degraded soil conditions decreased soybean yields by 3 and 2%, respectively. As mentioned above, the effects of the different climate scenarios on soybean yields differed between rainfed and irrigated conditions. Under irrigated conditions, the 2075–2099 RCP/4.5 scenario was the only one in which

TABLE 3 *F* values and significance level of the effects of climate scenarios, soils, and sowing dates on simulated grain yield of maize

	Climate Scenario (C)	Soil (S)	Sowing date (P)	C × S	C × P	S × P	C × S × P
F value	457.3	16.3	591.5	0.75	13.2	6	0.22
p value	***	***	***	ns	***	***	ns

Note. The simulations were carried out under rainfed conditions and with the current level of CO_2 (360 μmol mol^{-1}).
***Significant at the .001 probability level.

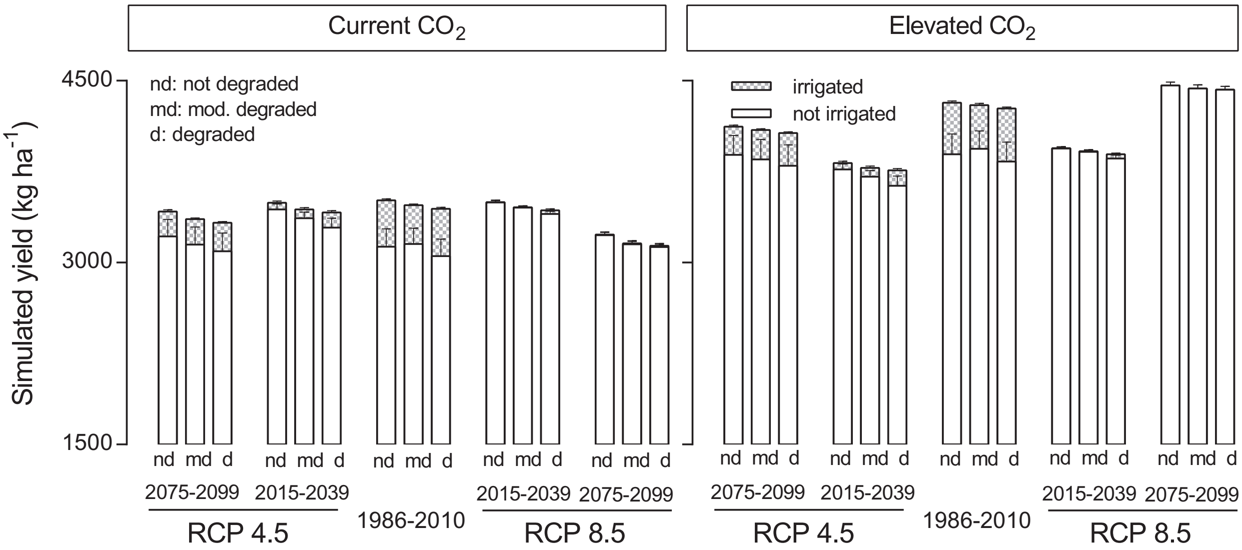

FIGURE 5 Soybean yields (± SE) simulated by the CPOPGRO-Soybean model in three soils (not degraded, moderately degraded, and degraded) under two irrigation treatments (rain-fed and irrigated), five climate scenarios (baseline period, 1986–2010; near future, 2015–2039; far future, 2075–2099) and two emission scenarios for each future scenario (RCP 4.5 and 8.5). In all cases, the sowing date was 31 December, and the simulations were run with the current level (360 μmol mol^{-1}) and increased levels (550, 425, 525, 450, and 800 μmol mol^{-1}) of CO_2 in the scenarios 1986–2010, 2015–2039/RCP 4.5, 2075–2099/RCP 4.5, 2015–2039/RCP 8.5, and 2075–2099/RCP 8.5

soybean yields showed significant differences (a 9% reduction) compared with the reference period. Within the nonirrigated situations, soybean yield was 8 and 11% significantly higher in the 2015–2039/RCP 4.5 and 8.5 treatments than in 1986–2010, respectively (Figure 5).

Sowing dates consistently affected soybean yields across the different climate scenarios and soil degradation treatments, as shown by the nonsignificant interactions between them (Table 5). In contrast to maize, delaying soybean sowing dates led to significant decreases in crop performance, even though the duration of the crop cycle was not affected (Figure 3). Compared with 31 December, sowing on 10 December or 20 January caused an increase of 6% and a decrease of 19% in soybean yields, respectively (Figure 6).

3.3.2 | Elevated CO_2 levels

Soybean yields under high CO_2 levels were significantly affected by climate scenarios, irrigation, and the interaction between them but remained unaffected by the soil condition (Table 4). The effects of the climate scenario did not follow a clear pattern in terms of RCP or in terms of the evaluated period of years (Figure 5). In line with current CO_2 results, under elevated CO_2, irrigation significantly increased yields by 11 and 7% for the 1986–2010 and 2075–2099/RCP 4.5 scenarios, respectively, compared with rainfed conditions. In the other climatic scenarios, irrigation effects were not statistically significant (Figure 5). Under rainfed conditions, climate scenarios effects were only significant for the 2075–2099/8.5 treatment, with a 14% yield increase compared with 1986–2010. On the other hand, under irrigated conditions the climate scenarios 2015–2039/4.5, 2015–2039/8.5, and 2075–2099/4.5 compared with the reference period showed yield decreases of 12, 9, and 5%, respectively.

The effects of sowing dates differed between climate scenarios (Table 5; Figure 6). No differences between the 10 December and 31 December sowing dates were found in all tested climate scenarios. Instead, sowing on 20 January compared with 31 December decreased yields by 16, 20, 21, 16, and 15% in 1986–2010, 2015–2039/4.5, 2015–2039/8.5, 2075–2099/4.5, and 2075–2099/8.5, respectively.

TABLE 4 *F* values and significance levels of simulated soybean yield as a function of climate scenarios, soils, and irrigation

	Climate Scenario (C)	Soil (S)	Irrigation (I)	I × C	I × S	C × S	C × S × I
Current CO_2							
F value	16.99	4.85	30.77	7.62	0.19	0.09	0.04
p value	***	***	***	***	ns	ns	ns
Elevated CO_2							
F value	69.24	1.83	28.98	7.74	0.17	0.08	0.04
p value	***	ns	***	***	ns	ns	ns

Note. The simulations were run with the current level of CO_2 (360 μmol mol^{-1}) and with a range of increased atmospheric CO_2 levels (550, 425, 525, 450, and 800 μmol mol^{-1} in the scenarios 1986–2010, 2015–2039/RCP 4.5, 2075–2099/RCP 4.5, 2015–2039/RCP 8.5, and 2075–2099/RCP 8.5. In all cases, the sowing date was 31 Dec. ns, not significant.
***Significant at the .001 probability level.

4 | DISCUSSION

The marked seasonality of the rainfall regime has determined the historical prevalence of summer crops in the subtropical and semi-arid Chaco. According to the multi-model climatic ensemble considered in this study, the advantages of summer crops will be maintained in the future under the expected global change, whereas winter crops will still have little chance of success due to the extreme scarcity of winter rains (Figure 1). Although no significant changes in the total annual amount of rainfall are expected, the seasonal pattern will be further accentuated according to climate predictions, with an increasing rain concentration in summer. Climate models also predicted an increase in the mean maximum and minimum temperatures, suggesting that crops will face a greater heat stress and a larger water demand, especially in summer (Figure 1).

Simulated maize yields in the semi-arid Chaco clearly diminished under the evaluated RCP climate scenarios. Under the extreme scenario (2075–2099/RCP 8.5), yield decline was particularly severe: −43% compared with the baseline period. This decline was more associated with increased temperatures than with water stress because the rising temperatures (Figure 1) led to shorter growing periods with fewer days for grain filling (Figure 3) and lower yields (Figure 2). Because certain limitations of the CERES-Maize model in simulating the effects of heat stress have been reported (e.g., Gabaldón-Leal et al., 2016), even a more severe effect of heat stress than the one predicted here might take place. Evidence on the prevalence of temperature over water deficit as the main factor responsible for future yields comes from the low impact of irrigation in all future scenarios, contrasting with the more pronounced positive responses in the baseline control (Figure 2). In sharp contrast to maize, both RCP climatic scenarios exerted a relatively minor influence on soybean yield (Figure 5). Mixed results appeared when analyzing the role of water as a limiting factor for soybean yields. The robust and positive response to irrigation observed in the baseline period confirms that water availability has been the main local limiting factor for soybean yields. However, the predicted increase in rainfall in future scenarios would lead to a dilution of water as a major constraint, which explains the lower response to

TABLE 5 *F* values and significance level of the simulated soybean yield as a function of climate scenarios, soils, and sowing dates

	Climate scenario (C)	Soil (S)	Sowing date (P)	P × C	P × S	C × S	C × S × P
Current CO_2							
F value	15.35	5.41	238.8	1.9	0.08	0.14	0.02
p value	***	***	***	ns	ns	ns	ns
Elevated CO_2							
F value	43.89	3.96	211.5	2.19	0.17	0.15	0.02
p value	***	*	***	*	ns	ns	ns

Note. The simulations were performed under rainfed conditions, and with the current (360 μmol mol^{-1}) and elevated levels of atmospheric CO_2 (550, 425, 525, 450, and 800 μmol mol^{-1} for the 1986–2010, 2015–2039/RCP 4.5, 2075–2099/RCP 4.5, 2015–2039/RCP 8.5, and 2075–2099/RCP 8.5 scenarios. ns, not significant.
*Significant at the .05 probability level.
***Significant at the .001 probability level.

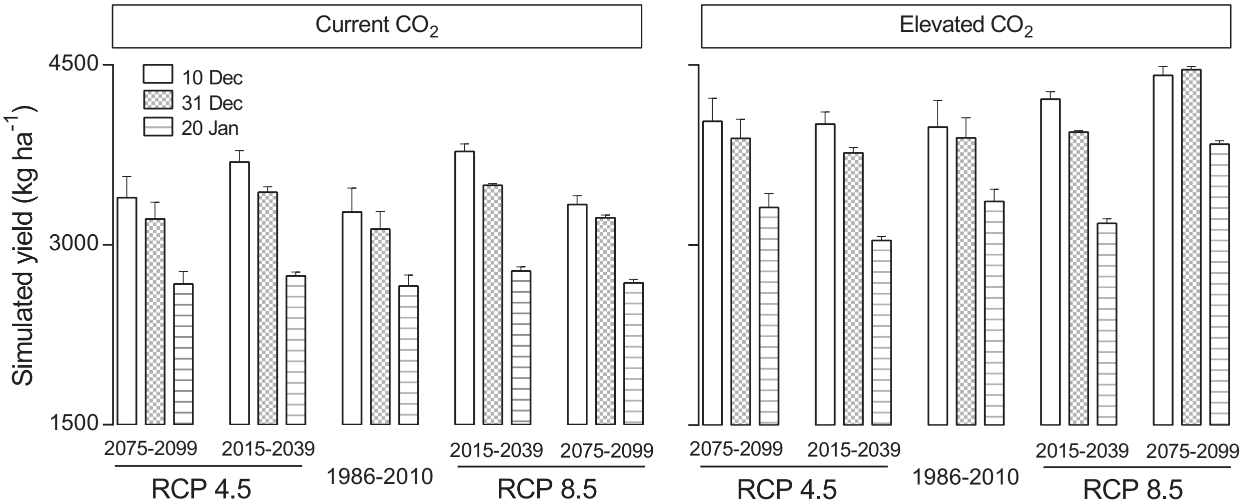

FIGURE 6 Soybean yield simulated by the CROPGRO-Soybean model in nondegraded soil with three sowing dates (10 and 31 December and 20 January) and under five climate scenarios (baseline period, 1986–2010; near future, 2015–2039; and far future, 2075–2099) and two emission scenarios for each future scenario (RCP 4.5 and 8.5). The simulations were performed without irrigation, with the current level of CO_2 (360 μmol mol^{-1}) and with the elevated CO_2 levels (550, 425, 525, 450, and 800 μmol mol^{-1}) in the scenarios 1986–2010, 2015–2039/RCP 4.5, 2075–2099/RCP 4.5, 2015–2039/RCP 8.5, and 2075–2099/RCP 8.5. Bars represent SEM

irrigation. Moreover, no positive responses to irrigation are predicted for the more severe scenario (RCP 8.5), which may be associated with increased rainfall in the critical periods of January and February (Figure 1). Our findings are in line with previous works that identified temperature as the main factor defining maize performance in the context of global change, with a prevalence of declines in yields (Bassu et al., 2014; Rose et al., 2016; Tao & Zhang, 2011). They are also consistent with recent modeling and meta-analysis reports, which observed a greater sensitivity to rising temperatures in maize than in soybean (Justino et al., 2013; Rose et al., 2016; Zhao et al., 2017).

Previous reports from both CO_2 enrichment experiments and modeling studies indicated that CO_2 enrichment enhanced maize (a C4 plant) yields under drought, but under well-watered conditions yield responses were less consistent (Meng et al., 2016; Twine et al., 2013). In our simulation with maize, irrigation had a minor effect on yields, whereas CO_2 levels had a very moderate effect (<3%). In contrast to maize, soybean (a C3 plant) showed strong and positive responses to elevated CO_2 levels, with yield gains being up to 40% in the 2075–2099/RCP 8.5/800 μmol mol^{-1} CO_2 scenario. The high response of C3 plants to CO_2 enrichment is well documented and is related to the photosynthetic pathway (e.g., Fodor et al., 2017; Twine et al., 2013). Substrate saturation of the photosynthetic enzymes from C4 plants occurs at about 400 μmol mol^{-1}, a value very close to the current ambient CO_2 level (Fodor et al., 2017). This C3/C4 difference in photosynthetic behavior is captured by the DSSAT models (Hoogenboom et al., 2010).

A particularly useful feature of DSSAT is the ability to simulate soil water dynamics. For example, Liu et al. (2013) showed that the CERES-Maize and CROPGRO Soybean models provide reasonable predictions of water dynamics and crop yields in Mollisols managed with either conventional or conservation tillage practices. Our simulations conducted in Mollisols indicated that soil degradation accentuated the negative effects of climate change, especially on maize yields (Figure 2). Compared with the baseline period, maize grown on degraded soils showed yield reductions of 7, 8, 23, and 48% in 2015–2039/RCP 4.5, 2015–2039/RCP 8.5, 2075–2099/RCP 4.5, and 20752099/RCP 8.5, respectively. The yield decline of maize in the degraded soils averaged 21%. Maize yields in nondegraded soils were on average 18% lower compared with the baseline period in the corresponding four future climate scenarios (6, 7, 18, and 40%). In contrast, soil degradation effects on soybean yields were restricted to the nonirrigated treatment in all climate scenarios, which suggests that soil degradation impaired the water supply to the crop and that irrigation would have masked that effect. The higher impact of soil degradation on maize compared with soybean might be explained by their higher nutrient and water demand. Overall, the obtained results indicated that the impact of soil degradation varied according to the magnitude of this degradation and to the climatic scenario. However, as clearly explained by Powlson, Stirling, Thierfelder, White, and Jat (2016), soil conservation practices should be seen as contributing to climate change mitigation, regardless of their effect on crop yields. They deliver other services, such as soil carbon sequestration and a consistent improvement in soil quality, which greatly increase soil resilience to climate change, avoiding irreversible damages such as soil losses through erosion (Powlson et al., 2016). In the particular case of the deforested soils of semi-arid Chaco, conservation practices seem to be imperative, taking into account their inherent fragility and the need to ensure an appropriate physical environment for water conservation and root exploration (Rubio et al., 2019).

The date of sowing exerted remarkable effects on simulated maize yields (Figure 4). The more extreme the climate change scenario was, the greater the benefit of delaying the sowing date among the range tested here. Delaying sowing until 20 January increased maize yield by 29% compared with 10 December in the 1986–2010 period and by 27–134% in the four future climate scenarios. Late sowing implies that maize plants are exposed to lower temperatures and consequently have a longer growth cycle and grain filling period (Saseendran et al., 2005). Although in general the best soybean performance was verified under the intermediate sowing dates, in some cases early dates yielded more than the intermediate dates. The divergent effects of changing sowing dates on maize and soybean yields are not unexpected given the greater sensitivity of maize to the rising temperatures. The contrasting results between both crops extend observations made by Olesen et al. (2011) and Teixeira et al. (2013), which identified the change in crop calendars as key adaptive solutions to reducing the negative impacts of climate change on agriculture.

Effective mitigation of climate change is highly relevant for maintaining agricultural production and future food security, especially in areas where crop growing conditions are expected to be less favorable. Several crop management strategies emerge from our simulations as tools to alleviate the consequences of climate change in the semi-arid Chaco. As mentioned, delaying the sowing date arises as a relatively simple tool to help in handling global warming for maize cropping systems. Instead of changing sowing dates, irrigation may be a tool for sustaining soybean yields depending on the rainfall regimes, as shown by the RCP scenarios. In terms of genotype selection or crop breeding, the obtained results for maize show that traits associated with longer maturity periods and higher grain filling rates should be introduced to mitigate climate change effects (Ma et al., 2017). For soybean, traits associated with drought tolerance, such as deeper root systems or reducing sensitivity of grain filling period to water deficit, are useful features that guide crop breeders in developing new genotypes (Battisti et al., 2017). Climate change adaptation strategies need to be locally relevant to be viable. In this sense, the findings of this study have important implications for climate change adaptation in the Chaco region. They can be beneficial to assign priorities for adaptation strategies, including alternative sowing dates and adoption of irrigation and soil conservation practices, for the two most grown crops. Insights presented here can be used to set breeding goals for the development of new hybrids and varieties, particularly to account for the multiple stresses that soybean and maize will face in Chaco. Furthermore, management strategies coping with climate variability proved to be critical to cope with the threat of climate change in this region. Our study also shows methodological limitations that should be addressed. Future research will be supported by the availability of more synergistic and holistic research frameworks that include reliable quantification of uncertainty and tools for performing simulation at appropriate levels of spatial complexity. Such a framework, relying on modeling and local characteristics will lead to better methods for linking simulation to real-world adaptation options. For this, it is also critical to increase the collection of local information of the environment, such as weather data, from more sites and the impact of rehabilitation practices for degraded soils. Because diversification proved to be a key adaptation strategy, local results from experiments testing alternative cropping systems (e.g., integrated crop–livestock–forestry systems) are currently lacking but may be highly helpful to extend the scope of recommendations beyond maize and soybean.

5 | CONCLUSIONS

In this study, we showed agricultural management practices and crop breeding strategies to alleviate global change effects in the subtropical and semi-arid Chaco region. Maize yields were severely reduced in the predicted future climate scenarios, and this appeared to be mainly related to temperature increases that shortened the crop cycle. By reducing the exposure to heat stress, delaying sowing date is a feasible management strategy to mitigate those effects. Surprisingly, irrigation had only minor effects on maize yield under the climate change scenarios. Simulations with soybean indicated that, unlike maize, the crop will benefit from a significant increase in atmospheric CO_2 concentration, even in the scenario with higher temperatures (2075–2099/RCP 8.5). Projected temperature increases are expected to play a secondary role in determining soybean yields. Instead, water stress will continue to be an important constraint to soybean yield in the context of global warming, but this effect seems to be strongly affected by the rainfall regimes in the future scenarios. Finally, soil degradation exacerbated the negative effects of global warming on crop yields. Obtained results highlight the importance of soil conservation practices by offering evidence that global warming consequences will be more severe in degraded soils. The observed high interannual climatic variability and the different sensitivity of soybean and maize to climatic variables indicates that monocultures should be avoided in order to decrease the risk of severe crop failure all over the farm. In this sense, cropping sequence diversification appears to be the key to improve the resilience of the agrosystem and to increase the probability of harnessing favorable growing conditions, as observed in other regions (e.g., Gaudin et al., 2015).

CONFLICT OF INTEREST

The authors declare no conflicts of interest related to this report.

ORCID

Juan M. Herrera https://orcid.org/0000-0002-9398-7224
Gerardo Rubio https://orcid.org/0000-0001-8419-2473

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

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