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Resilient soybean and maize production under a varying climate in the semi-arid and sub-humid Chaco

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ABSTRACT

Food security and economic stability of many developing countries rely on the resilience of major crops to climatic variability and climatic anomalies. Since climate change forecasts predict an increasing frequency and intensity of climatic disturbances, the need to increase our knowledge about the influence of climate variability on crop productivity is especially acute for areas with fragile environments such as the semi-arid and sub-humid Chaco in South America. We used climate records from recent decades and crop growth models to: (i) identify the main climatic variables that have influenced the productivity of soybean and maize which are major crops cultivated in the area and (ii) to assess the impact of inter-annual variability of climate variables on the productivity of soybean and maize. Simulated soybean and maize grain yields indicated that farmers in Chaco should be aware of the high interannual variability in the productivity of these crops. Farmers face a different risk cropping maize and soybean depending on the location. The productivity of soybean was below production costs in 10–13% of the studied years while the corresponding values for maize were 11–14%. Diversification of crop rotations is therefore key to enhance resilience and to increase the likelihood of harnessing favorable growing conditions. Management strategies intended to conserve soil water are of paramount importance, especially for soybean where anomalies in the precipitation during the first four months after sowing was the predictor that explained the highest amount of variance in grain yield ($r = 0.58$). To mitigate the effect of temperature, which essentially is a factor out of direct control of the farmer, the main practice that arose from our study is delaying planting dates (e.g., towards late January) to avoid the occurrence of high temperatures during the critical stages of the crop.

1. Introduction

Many of the current agricultural lands were forests that were cleared out to cultivate crops in response to the increasing demand for plant-derived products (Dang et al., 2019). The demand for locally suitable management needs to be addressed because of the increasing pressure for plant products, particularly of areas that are overly sensitive to environmental degradation. If the increasing demand of plant products is not satisfied with increases in production, the expansion of agricultural frontiers at the expense of natural environments may continue in the future. One of the biggest challenges in designing strategies is that such areas, by definition, lack a sufficient agricultural history to provide guidance about best practices adapted to local conditions.

The Chaco region, which covers large areas of Argentina, Brazil, and Paraguay, registers one of the highest rates of deforestation in the world (Kuemmerle et al., 2017). Despite high deforestation rates, Chaco is still dominated by native forests (Marchesini et al., 2020). In terms of climate, it can be divided into two subregions: the Sub-humid Chaco which has a subtropical sub-humid climate with annual precipitations between 750 and 950 mm (1901–2011) and the Semiarid Chaco which

Abbreviations: DAS, days after sowing; ΔMT_{1-4}, average maximum temperature from January to April; $\Delta MT_{filling}$, average maximum temperature during grain filling; $\Delta D30_{50-100}$, number of days with maximum temperatures above 30 °C during the period 50 and 100 DAS; $\Delta D35_{50-100}$, number of days with maximum temperatures above 35 °C during the period 50 and 100 DAS; ΔP_{12-4}, precipitation anomaly from December to April; $\Delta WS_{s\text{-}h}$, water stress index from sowing to harvest; ΔQs-h, photothermal coefficient between sowing and harvest (ΔQs-h); $\Delta P/PET_{0-50}$, ratio between accumulated precipitation and potential evapotranspiration between 0 and 50 DAS.

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has a subtropical semi-arid climate with an average annual precipitation between 500 and 750 mm (1901–2011) (Naumann et al., 2004). Precipitations are concentrated in the summer season, and they present a great interannual variability in both subregions, but specially in the Semiarid Chaco. This regime allows rainfed farming with high risks of droughts and heat-stress (Ricard et al., 2015). Because the highest annual temperatures coincides with the rainy season, limitations to crop growth and productivity were mainly attributed to water deficits (Giménez et al., 2015; Pérez-Carrera et al., 2008). Agricultural development and sustainability in the Chaco region is therefore conditioned by the precipitation and thermal regime and requires adequate planning and proper resource management (Gorleri, 2005). Although exploitable yield gaps in the Chaco region have been documented (Merlos et al., 2015), improving crop productivity needs optimized management in relation to sites' characteristics (Casali et al., 2018). For example, Cammarano et al. (2019) showed that in the Mediterranean basin the impact of future climate on barley productivity is negative but some locations will be less affected than others.

Food security and economic stability of many developing countries such as those in the Chaco region depend on the resilience of major crops to climatic variability (Hansen et al., 2019; Kahiluoto et al., 2019). Whereas resilience represents the capacity of farming systems to maintain sufficient and nutritious food production in the face of environmental perturbations (Bullock et al., 2017; Kahiluoto et al., 2019), climate variability is how the climate fluctuates above or below an average long-term value according to Dinse (2009). Resilience has emerged as a key tool for conceptualizing the vulnerability of farming systems to variations in the environmental conditions (Douxchamps et al., 2017). Metrics comprise production and nutritional diversity as well as socio-economic stability of food supply (Bullock et al., 2017). The study of crop responses to the local climatic variability makes it possible to anticipate the risks involved and to help design strategies to sustain high levels of resilience and productivity (Ray et al., 2015). Studies based on historical climate variability are helpful in detecting trends, determining interactions, quantifying impacts, and conceptualizing hypotheses (Burnham et al., 2011). This is essential because the management of crops needs to ensure that agricultural systems are sufficiently resilient to cope with the impacts of climate change. Water demand patterns of cultivated systems not necessarily follow the seasonality and interannual variability of rainfall (Giménez et al., 2020). Past climate data may be particularly useful in areas without agricultural history records since they can be coupled to agronomic simulation models to study the association between local climate variability and crop yield. Through this approach, grain yields can be estimated and management strategies compatible with local climatic conditions can be evaluated. This approach has already been used in areas with a long agricultural history (e.g., Bell and Fischer, 1994; Lal et al., 1999; Lobell et al., 2013, 2005). For example, Lobell et al. (2013) using APSIM and 46 years of climate data from the Midwestern United States, found a negative and marked response in maize yield to temperatures above 30 °C, and a relatively weak response to precipitation. Studies about the relationship between climate variability and crop yields usually considers anomalies of climatic variables rather than raw data. Climate anomalies are mainly estimated using three approaches: (i) by comparing the annual value of the variable with the mean across all the available years [e.g., Burnham et al. [18]]; (ii) by comparing the annual value with the previous year [e.g., Ray et al. [17], Giménez et al. [19]]; or (iii) by comparing the annual value with the linear trend during the entire studied period [e.g. Burnham et al. [18]]. Most studies on the association between historical climate variability and agricultural productivity focused on only one crop, probably because the main goal was to elucidate physiological mechanisms. However, the decision of which crops to grow and how to distribute the agricultural area among different crops that share the same growing season can have important consequences on the resilience of agricultural systems.

Since the semi-arid and sub-humid Chaco regions have a short agricultural history (<10–15 years), there are no reliable datasets that capture the effects of climatic variability on crop yields. In this sense, simulation models are a valuable tool for understanding the adaptation of the main crop to the local environment (Battisti et al., 2017; Cammarano et al., 2020; Casali et al., 2021). Using this approach and climate records from recent decades, the objectives of this study were: (i) to identify the main climatic variables influencing the productivity of soybean and maize and (ii) to assess the impact of inter-annual variability in climate variables on the productivity of soybean and maize.

2. Materials and methods

2.1. Study area

The study was conducted in two representative areas of the semi-arid and sub-humid Chaco Region: Quimili (27°38'S, 62°25'W) and Las Breñas (27°04′S, 61°04′W), respectively. This region exhibits one of the highest rates of deforestation in the world (Kuemmerle et al., 2017). The cleared areas are mainly cultivated with maize and soybean (Dominguez and Rubio, 2019).

2.2. Crop modeling

The models CERES-Maize and CROPGRO-Soybean, which are part of DSSAT v4.5 (Hoogenboom et al., 2010), were used to assess the effect of climatic variables on maize and soybean grain yields. Both models were calibrated previously for the study area with the maize hybrid DK747 and the soybean genotype A8000 (Casali et al., 2021). Crop management parameters were parametrized according to the most frequently practices used by local farmers. These were sowing date 31st of December, distance between rows 52 cm and plant densities 245,000 and 60,000 plants ha^{-1} for soybean and maize, respectively. Each simulation started at the harvest date of the preceding crop, approximately six months before the sowing date of the target crop. Crop residues were not incorporated into the soil, assuming no-till practices, which is the usual soil-preparation method in the study area. The initial soil water content was set to 60% of the soil water storage capacity.

Soil data were obtained from the SigSE database (Angueira et al., 2007). The most representative soil profile for each location was used in the simulations: August 7 soil series (Entic Haplustol) for Quimili and Tizón series (Oxic Haplustol) for Las Breñas (Table 1).

Daily climatic data (i.e., maximum and minimum temperature, solar radiation, and precipitation) from weather stations of INTA (National Agricultural Technology Institute) were used for Las Breñas while precipitation for Quimili was provided by the "Sociedad Rural" (i.e. an association of farmers) and maximum and minimum temperature and solar radiation were retrieved from NASA-POWER (https://power.larc.nasa.gov/data-access-viewer/). We used all available climatic records: 1994–2014 (21 y) for Quimili and 1967–2014 (48 y) for Las Breñas to maximize the likelihood of detecting anomalies. To minimize the sources of variation and to focus on the identification of climatic effects on crop productivity, all simulations were carried out using the same soil initial conditions and management practices. Thus, the only parameter that changed from year to year were the climatic conditions. For the same reason, simulations were carried out without nutritional limitations, including nitrogen.

2.3. Mixed models

We tested to which extent variations in climate conditions (maximum and minimum temperatures, precipitation, and solar radiation) and extreme events translate into anomalies in the grain yield of soybean and maize. The anomalies of simulated grain yields and climatic indices were estimated as deviations from an overall trend. Yearly values of climatic indices were estimated for a time period corresponding to the growing season of the crops, according to the following formula:

Table 1
Analytical data of the two soil profiles used in the simulations.

	Quimili: Entic Haplustol "7 de Agosto" series				Las Breñas: Oxic Haplustol "Tizón" series						
Horizon	Ap	IIAC	IIC1	IIC2	Ap12	A	Bw1	Bw2	C	Ck1	Ck2
Depth (cm)	0–15	15–47	47–77	77–200	0–19	19–34	34–51	51–81	81–123	123–144	144–200
Clay (%)	15	7	9	9	31.5	35.6	36.1	33.7	29.3	27.5	22.4
Sand (%)	31	52	48	46	21.6	16.2	17.7	24.4	18.5	17.7	18.6
Organic C (%)	1.32	0.58	0.32	0.32	1.25	0.59	0.27	0.12	–	–	–
Total N (%)	0.13	0.09	0.05	0.04	0.13	0.01	–	–	–	–	–

$$\Delta x_i = \frac{x_i}{\mu} \tag{1}$$

where ΔX_i is the anomaly of the variable *x* for the year *i*, x_i is the mean value for the growing season for the year *i*, and μ is the overall mean for all the years with available climatic records. For the overall trend, we used 21 years of data from Quimili and 48 years of data from Las Breñas.

Linear mixed models were used to define the models that best described the relationship between the anomalies in the simulated grain yield and the anomalies in the climatic indices. These models have the advantage that can be used with unbalanced data and can cope well with missing observations (Smith et al., 2005). Although the goal was to fit a parsimonious multivariate model to the data, we began by developing simple models for each group of similar climatic variables. This was done to get more detailed insights on the characteristics and severity of limitations imposed by each type of climatic variable. The groups were:

a. *Temperature and evapotranspiration*. Maximum and minimum temperature (°C) were considered for different periods between January and April, and during different phenological phases. In soybean the phases were five: VE-R1, R1-R5, R5-R7, E-R7 and planting to harvest. In maize, the phases were six: VE-V6, V6 to floral induction, floral induction to R1 (i.e., anthesis), R1 to beginning of grain filling, grain filling and planting to harvest. Evapotranspiration (mm) was estimated according to the Hargreaves' approach (Hargreaves and Samani, 1985) for four periods (0–50, 0–150, 50–100 and 100–150 days after sowing; DAS). Here and also for the other groups, the rationale of using months, crop growth stages, and DAS (i.e., three different temporal scales) was to minimize the risk of missing critical information about the constraints because of mismatches between temporal scales and climatic events. In total, 27 variables for soybean and 29 variables for maize were calculated for this group of parameters.
b. *Solar radiation* (MJ m^{-2}). It was estimated for the same periods described above. In addition, a photothermal ratio was calculated as the ratio between solar radiation and the average temperature above the base temperature (i.e., in soybean 6 °C and in maize 8 °C). In total, 10 variables for soybean and 12 for maize were calculated for this group.
c. *Heat stress.* Several indices were generated based on the days and the degree-days (°C) above six thresholds temperatures (20, 25, 30, 35, 40, and 45 °C) for four periods of the crop cycle (0–50, 0–150, 50–100, and 100–150 DAS). In total, 48 variables for both maize and soybean were calculated for this group.
d. *Water availability and water stress index*. Accumulated precipitation (mm) in different periods between December and April, and during different phases defined by the phenological stages of the crop were considered in the simulations. In addition to simpler direct measurements, agro-climatic indices were estimated as the ratio between evapotranspiration according to Hargreaves (mm) and accumulated precipitation (mm) in four periods (0–50, 50–100, 100–150 and 0–150, DAS). We additionally considered a water stress index included in DSSAT. This index takes into account the ratio of crop's water uptake and transpiration potential (Ritchie, 1998). Therefore, it can quantify stress conditions not only based on water availability but also accounting for crop's water demand. We calculated this for different periods between December and April, and for different phases defined by the phenological stages of the crops. In total, 34 variables for soybean and 37 variables for maize were calculated for this group.

The anomalies from these environmental variables were calculated to identify the most explanatory variables within each of the five groups, Pearson's correlation coefficients between the anomalies of the simulated crop yields and the anomalies of the environmental variables were evaluated. Once the main explanatory variables of yield within each group were determined, mixed models were fitted. The mixed models were of the type:

$$\text{Grain yield anomaly} = \mu + \text{climatic predictor anomaly} + \text{year} + e \tag{2}$$

where μ is the average grain yield anomaly, climatic predictor anomaly is the anomaly of the climatic variable, year is the effect of year, and *e* is a residual comprising variation unexplained by the previous components. The predictor anomaly was set as a fixed effect factor while the year was set as a random factor. The most informative climatic predictors within each group of similar variables were evaluated to identify a parsimonious multiple constraint model for each crop. In the group solar radiation for soybean, none of the variables showed significant correlation with crop yields. Therefore, we run the multiple constraint models without a predictor from the solar radiation group. The structure of these models was the same as that of simple models but considering more than one predictor. In this case, the climatic predictor was set as a fixed effect factor while the year was set as a random factor.

The lme4 package (Bates et al., 2015) of the R software (R Development Core Team, 2019) was used to analyze the mixed effects of the relationships between anomalies in soybean and maize grain yield and climatic predictors. We followed an established protocol (Zuur et al., 2010) to check for (i) outliers, (ii) homogeneity of variance, (iii) normal distribution, (iv) independence, and (v) type of relationship between the candidate predictor and the response variable. To verify the assumption of homoscedasticity, the graphs of standardized residuals were visually inspected for each of the predictive variables. To verify the assumption of normality, qq-plots were inspected to compare the distribution of the residuals of the model (which was assumed to be normal) with the theoretical normal distribution. Possible spatial trends were also controlled by evaluating the homogeneity of variances between the two sites that we considered (Quimili and Las Breñas).

The temporal correlation between the residues was evaluated with the auto-correlation function (ACF). Multicollinearity between predictors in multivariate models was assessed with VIF (Variance Inflation Factor) from the R package "car" (Fox and Weisberg, 2018) and following the criterion that VIF values less than 10, rules out multicollinearity problems. To select predictors for the final model, we followed the top-down strategy of model selection and multi-model inference (Burnham et al., 2011). The multi-model inference approach does not rely on the assumption that there is a unique "true model" but rather that several plausible hypotheses in the form of models can be examined simultaneously to identify one that better summarize which "effects" (represented by predictors) can be supported by the available data. Selection of model predictors was based on the AIC (Akaike

Information Criterion) criteria (Burnham et al., 2011). Goodness of fit of mixed models was assessed with the R^2 of adjusted models (Nakagawa and Schielzeth, 2013). According to this approach, the marginal R^2 represents the variance explained by fixed factors, while conditional R^2 represents the variance explained by the entire model (fixed and random effects).

3. Results

3.1. Climatic characterization

During the 1995–2015 growing season of summer crops (January-April) in Quimili, the mean ± standard error maximum and minimum temperatures were 30.8 ± 1.3 °C and 19.7 ± 1.2 °C, respectively. These values were rather similar in Las Breñas for 1968–2015, 31.1 ± 1.3 °C and 19.3 ± 0.9 °C, respectively (Fig. 1). Solar radiation during the crop cycle averaged 19.4 ± 1.1 MJ m^{-2} in both locations, whereas average precipitation during the crop cycle was lower in Quimili (430.9 ± 143.4 mm) than in Las Breñas (519.9 ± 168.5 mm).

3.2. Soybean

Average simulated soybean grain yields for Quimili and Las Breñas during the study periods were 2519 and 2476 kg ha^{-1}, respectively (Fig. 2). Within the temperature group, the average maximum temperature from January to April (ΔMT_{1-4}) was identified as the best predictor of soybean yield anomalies (r = 0.48) (Fig. 3). This period covers almost entirely the crop cycle from sowing to physiological maturity. In the years in which the ΔMT_{1-4} was 3 °C above the average maximum temperature of 31°C for that period, the simulated soybean yield was 600 kg ha^{-1} lower than the average of the whole studied period (Fig. 3).

In terms of the variables related to heat stress, correlations indicated that the number of days with more than 35°C during the period 50–100 DAS ($\Delta D35_{50-100}$), which coincides with the phenological phases R4 - R6, was the best predictor of soybean yield anomalies (r = 0.62). The simulated grain yield of soybean was consistently below average when $\Delta D35_{50-100}$ was greater than 2.5, what means that the number of days during the period between 50 and 100 DAS with maximum temperatures above 35 °C was higher than 20 (Fig. 3). The $\Delta D35_{50-100}$ index showed a greater association with the grain yield than the same heat stress index calculated for other periods of the crop cycle. None of the variables related to solar radiation was significantly associated with anomalies in the grain yield of soybean as already mentioned in materials and methods.

Among the variables related to water availability, the precipitation anomaly from December to April (ΔP_{12-4}) (Fig. 3) was the predictor that explained the highest amount of variance in the simulated yield anomalies (r = 0.58). An asymptotic model fitted the data better than a linear one (data not shown), probably because responses to precipitation diminished after reaching a certain threshold (Fig. 3). The threshold values beyond which further increases in precipitation no longer resulted in increases in soybean grain yield were 562 mm in Quimili and 639 mm in Las Breñas. These thresholds corresponded approximately to the average of accumulated precipitation between December and April.

Among the different periods for which the DSSAT's water stress index was estimated, the index for the entire crop cycle showed the higher association (r = 0.92) with the simulated yield anomaly of soybean. Values lower or higher than 0.05 (the average of DSSAT's water stress index in all studied years) were generally associated with grain yields above or below, respectively, the average grain yield for the whole dataset. The water stress index estimated for shorter periods of the crop cycle showed a lower but still significant correlation with the simulated yield anomaly (i.e., r = 0.87 in R5-R7 and r = 0.72 in R1-R5). The DSSAT water stress index was mainly influenced by three climatic variables: the amount of precipitation from December to April (R^2 =0.42), the average maximum temperature between January and April (R^2 = 0.39), and the number of days with a maximum temperature higher than 35 °C between 50 and 100 DAS (R^2 = 0.40) (Fig. 4). When the slopes of the three relationships were compared, the higher slope was found for the average maximum temperature between January and April (slope = 0.0383). The slopes of the relationships between water stress index and precipitation and between water stress index and heat stress, were considerably lower (−0.0003 and 0.0078, respectively).

The predictors with the highest explanatory power for each group of variables were considered together in multivariate models (Table 2) that allowed the identification of the most influential factors affecting soybean grain yields. Among the models that were considered (Table 2), model 1 showed the higher overall fit. This model included variables previously identified within the groups for temperature and evapotranspiration, heat stress and water stress index: ΔMT_{1-4}, $\Delta D35_{50-100}$ and $\Delta WS_{s\text{-}h}$. These variables showed additive relationships between them (Table 2). No variables from the solar radiation and water availability groups were retained by this model. Model 2 included the same three variables plus the variable ΔP_{12-4}. When $\Delta WS_{s\text{-}h}$ was removed from the model (model 5 in Table 2), the AIC value increased dramatically (from −135 to −32), whereas removing ΔMT_{1-4} and $\Delta D35_{50-100}$ had a lower impact on AIC (from −135 to −123). These results indicate that $\Delta WS_{s\text{-}h}$ was the variable with the highest association with soybean yield, followed by the variables ΔMT_{1-4} and $\Delta D35_{50-100}$.

3.3. Maize

Simulated maize yields during the 1994–2014 period in Quimili and 1967–2014 in Las Breñas averaged 7026 and 7314 kg ha^{-1}, respectively (Fig. 2). Among the variables of the temperature group, the maximum temperature during grain filling ($\Delta MT_{filling}$) showed the highest correlation with the simulated maize yield anomaly (r = 0.74) (Fig. 5) followed by the average maximum temperature between sowing and harvest (r = 0.67). In the years in which the $MT_{filling}$ was above the average of 31°C, the simulated maize yield was 1792 kg ha^{-1} lower than the average of the whole studied period (Fig. 5).

Among the evaluated variables within the heat stress group, the number of days with maximum temperatures above 30°C between 50 and 100 DAS ($\Delta D30_{50-100}$) had the highest correlation (r = 0.6) with maize grain yield anomalies. As expected, the greater the $\Delta D30_{50-100}$ anomaly, the lower the anomaly value in the simulated grain yield of maize (Fig. 5). When $\Delta D30_{50-100}$ exceeded the average number of days with maximum temperatures above 30°C for the evaluated period at each site (24 and 29 days in Quimili and Las Breñas, respectively), maize grain yields were lower than the average grain yield in 93% of the studied years while in 7% of the years yields they were higher than the long-term average. In those years when $\Delta D30_{50-100}$ was 50% above the average for each site, maize yield was reduced by more than half compared to the long-term average. Maximum temperatures during other periods of the crop cycle (i.e., 0–50, 0–150, and 100–150 DAS) and other temperature thresholds (range tested: 20–45 °C) showed lower correlation values with maize grain yields. Among the solar radiation group, the photothermal coefficient between sowing and harvest ($\Delta Q_{s\text{-}h}$) was the best predictor of the anomalies in the grain yield of maize.

Variables from the water availability group had lower correlation values with the grain yield anomalies of maize than those from the temperature, heat stress, and solar radiation groups (Fig. 5). Within the water availability group, the predictor that explained the highest amount of variance in the grain yield anomalies of maize was $\Delta P/PET_{0-50}$ (ratio between accumulated precipitation and potential evapotranspiration between 0 and 50 DAS) (r = 0.37) which averaged 0.51 in Quimili (ΔP_{0-50} = 227 mm and ΔPET_{0-50} = 440 mm), and 0.58 in Las Breñas (ΔP_{0-50} = 261 mm and ΔPET_{0-50} = 445 mm). On the other hand, none of the variables related to the water stress index showed a significant association with the simulated maize yield.

When evaluating multivariate models, the most parsimonious model (i.e., model 1in Table 3) included the four predictors that were identified

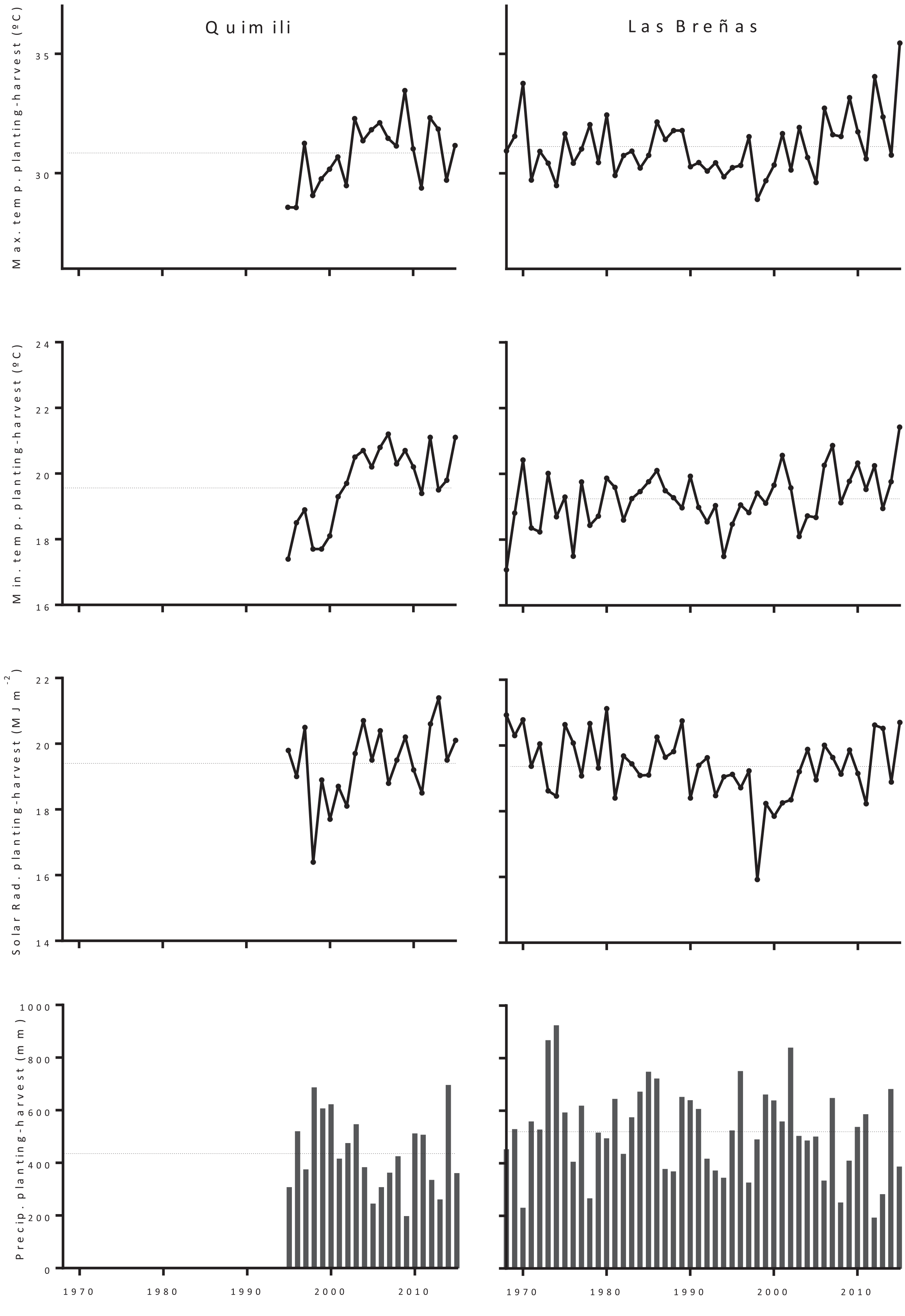

Fig. 1. From top to bottom: average maximum temperature, minimum temperature, solar radiation and accumulated precipitation during the crop cycle (January-April) in Quimili between 1995 and 2015 (left) and in Las Breñas between 1968 and 2015 (right). The dotted line indicates the average values in each case.

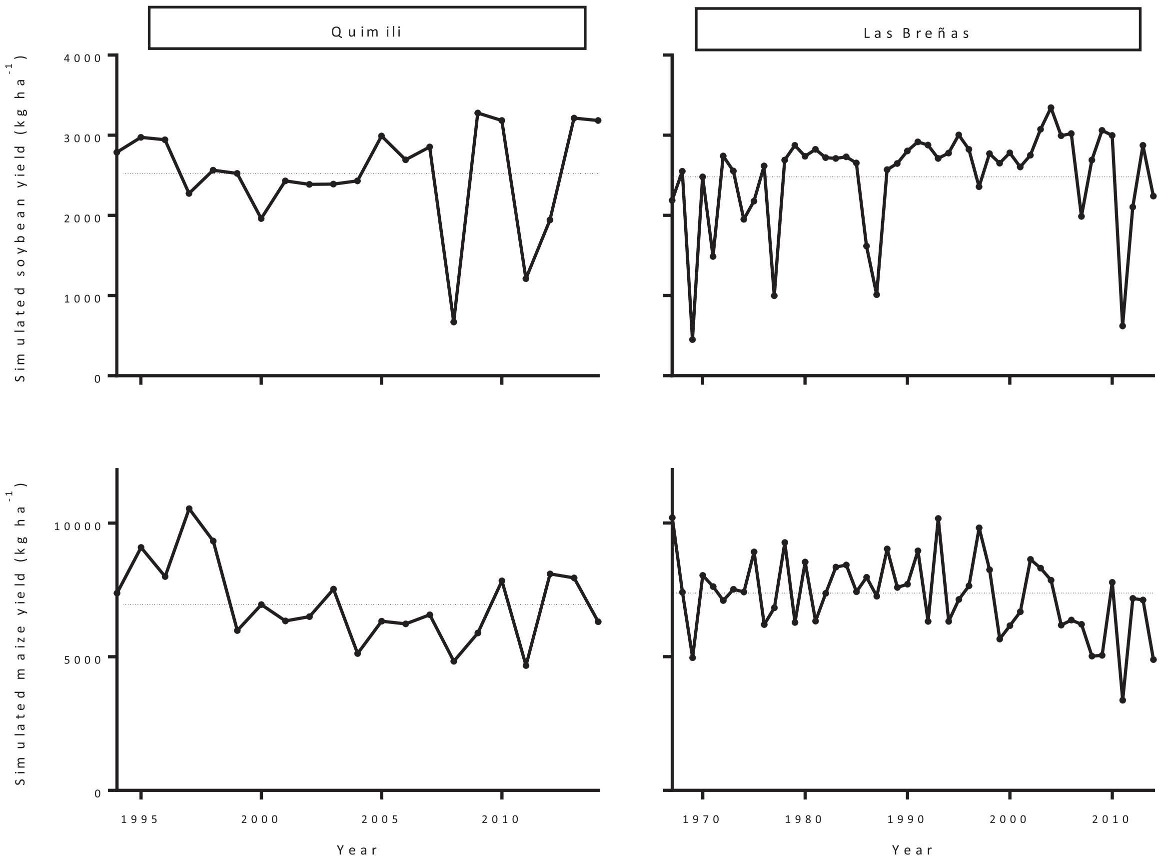

Fig. 2. Yield simulated by CROPGRO-Soybean and CERES-Maize models for soybean (top) and maize (bottom) respectively, in Quimili (left) and Las Breñas (right). The average is indicated with a dotted line.

within each group of variables. Similarly, to soybean, the predictors had additive effects while interactions between them did not significantly increase the explanatory power. The relative ranking of these variables was determined according to the AIC values of each model after removing the target variable from the complete model. The variable with the highest predictive power was ΔMT during grain filling ($\Delta MT_{filling}$), whose removal increased AIC by 23.2 units. It was followed by $\Delta Q_{s\text{-}h}$ and $\Delta P/PET_{0\text{–}50}$, whose removal increased AIC by 14.6 and 6.5, respectively. The heat stress variable ($\Delta D30_{50\text{–}100}$) was relatively less relevant since its removal led to an increase of only 2.2 AIC units.

4. Discussion

4.1. Impacts on soybean and maize grain yield

As expected, there were both coincidences and divergences in the influence of climatic variables on yield anomalies between soybean and maize. One of the main coincidences was that their yields were influenced in a higher extent by the maximum temperature rather than by average temperatures. This effect was observed through both the average daily maximum temperatures and the number of days with temperatures above certain thresholds, whose timing and values showed some variation between both species. In the case of soybean, the average daily maximum temperatures during the entire crop cycle ($\Delta TM_{1\text{–}4}$) showed a closer association with yield ($r = 0.5$) than the same parameter considered within shorter periods. Maximum temperatures emerged as a robust predictor of soybean yields on its own since none of the variables related to solar radiation was significantly associated with soybean yield anomalies. Similarly, Bhatia et al. (2008) found a weak association between solar radiation during the crop cycle and the simulated grain yields of soybean under limited water supply conditions.

In the case of maize and in agreement with previous field experiments (e.g., Badu-Apraku et al., 1983; Peters et al., 1971), the maximum sensitivity to the average daily maximum temperatures was observed during the grain-filling period ($\Delta MT_{filling}$ $r = 0.74$). Higher average maximum temperatures resulted in a shorter crop cycle (Fig. 6). A shorter crop cycle implies that crops intercept less solar radiation, fix less carbon, spend less time during grain filling (as observed in our simulations) and ultimately attain less grain yields. Unlike what was observed for soybean, radiation appeared as a major factor explaining grain yield anomalies in maize as indicated by the impact of the photothermal quotient in the multivariate summary model (Table 3).

Another coincidence between both species was that, among the group of heat stress variables, the highest correlation with yield anomalies was the number of days with maximum temperatures above specific thresholds during the same period: 50–100 DAS. However, the temperature threshold that showed the highest correlation was higher in soybean than in maize (35 vs 30 °C), what suggests a higher tolerance of soybean to heat stress. In the case of soybean, the period of maximum sensitivity to high temperatures coincided with the phenological stages R4-R6 and the observed temperature threshold is in line with Gibson and Mullen (1996), who found that soybean yields decrease dramatically with diurnal temperatures above 35ºC from flowering to the beginning of grain filling. The effects of high temperatures on soybean yields have been attributed to their impacts on the rate of photosynthesis and respiration (Andrade and Satorre, 2015; Jones et al., 2003; Lal et al., 1999). Regarding maize, the period of maximum sensitivity to high temperatures occurred during the flowering period, which was reported as the most sensitive period to several types of stress (e.g., thermal, hydric, and light) in determining the number of grains and ultimately the grain yield of maize (Ceglar et al., 2016; Grant et al., 1989; Kiniry and Ritchie, 1985; Schoper et al., 1987). In the specific case of heat

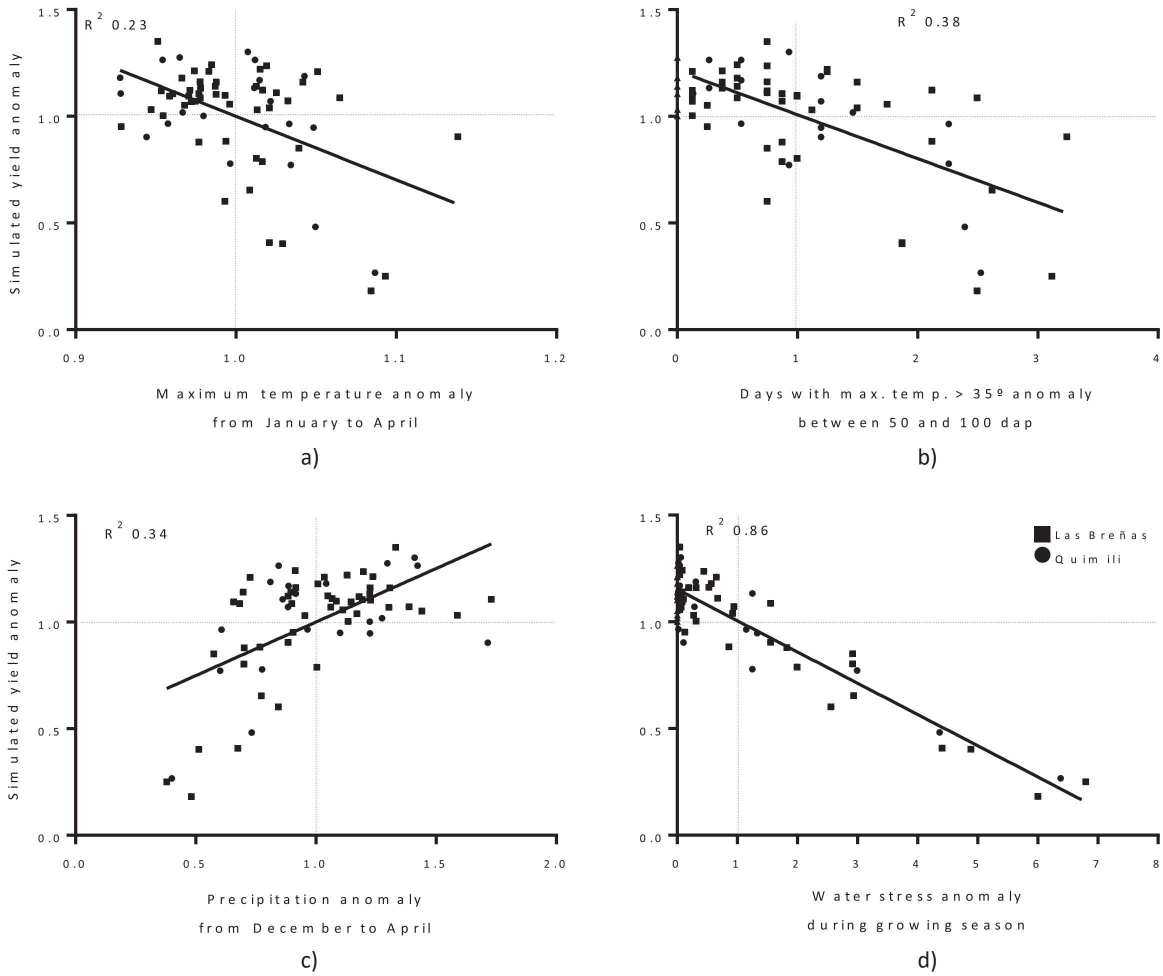

Fig. 3. Anomaly of soybean yield simulated by CROPGRO-Soybean as a function of a) anomaly of maximum temperature between January and April; b) anomaly of days with maximum temperature above 35ºC between days 50 and 100 after planting; c) anomaly of accumulated precipitation between December and April; and d) anomaly of water stress between planting and harvest. The anomaly is represented as a straight line of the linear regression between both variables and the corresponding R^2 value. The squares indicate the values corresponding to Las Breñas, while the circles those of Quimili. Triangles indicate the zeros, which were not considered in the regression analysis. The correlation was highly significant ($p < 0.001$). Dotted lines indicate the anomaly with value 1. The anomaly was calculated in relation to the mean values corresponding to 21 and 48 years of data in Quimili and Las Breñas, respectively. Example: a value of 1 on the x-axis indicates that in that year the maximum temperature coincided with the historical average and a value of 1.1 indicates that it was 10% higher.

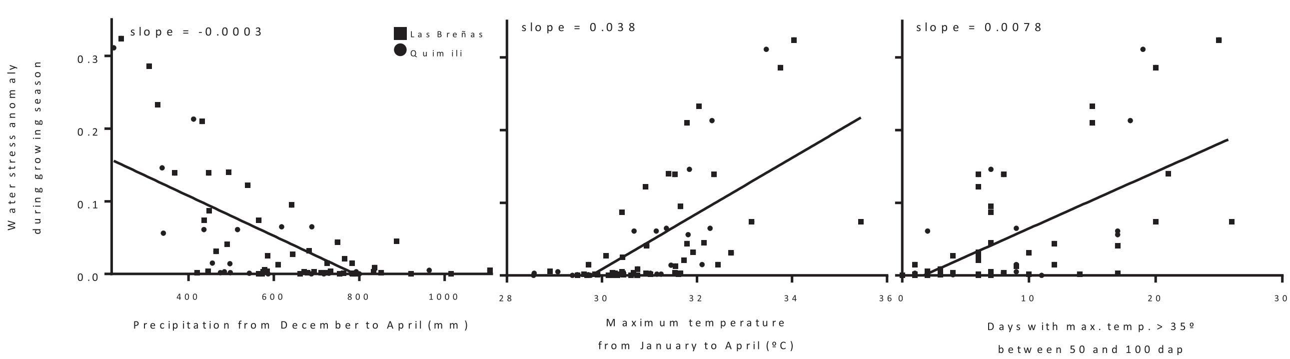

Fig. 4. Water stress between planting and harvest simulated by CROPGRO-Soybean as a function of accumulated precipitation from December to April (left), maximum temperature from January to April (center) and days with maximum temperature above 35ºC between days 50 and 100 after planting (right). The squares indicate the values corresponding to Las Breñas, while the circles to those to Quimili. The lines of the linear regressions between the variables and the corresponding slopes are presented. The three correlations were highly significant ($p < 0.001$).

stress, Rattalino Edreira and Otegui (2012) found more severe effects on the grain yield of maize when it occurred around flowering than during grain filling. The maximum temperature threshold for heat stress of 30 °C, identified in our maize simulations, agree with Lobell et al. (2013), Schlenker and Roberts (2009), and Lobell et al. (2011).

Among the water stress parameters, the best predictors for soybean and maize yields were those directly influenced by temperature, which highlights the critical contribution of this factor. In the case of soybean,

Table 2
General structure of some of the linear mixed models considered to predict the anomaly in the grain yield of soybean simulated by the CROPGRO-Soybean model at a locality of the Semi-Arid Chaco (Quimili) and a locality of the Subhumid Chaco (Las Breñas) for 1994–2014 and 1967–2014, respectively. The models differ in the predictors included and in the relationships between the predictors (additive or interactive). They are ordered from best to worst goodness of fit according to the Akaike information criterion (AIC).

Removed variables	Models	AIC	Weigth	marg. R^2	cond. R^2
1. $\Delta pp_{12\text{–}4}$	ΔSim Yield$_i = \Delta MT_{1\text{–}4} + \Delta D35_{50\text{–}100} + \Delta WS_{p\text{-}h}+ (\text{Year})_i + \epsilon_i$	-135.1	0.264	0.89	0.93
2. None	ΔSim Yield$_i = \Delta MT_{1\text{–}4} + \Delta D35_{50\text{–}100} + \Delta pp_{12\text{–}4} + \Delta WS_{p\text{-}h}+ (\text{Year})_i + \epsilon_i$	-133.1	0.097	0.89	0.93
3. $\Delta D35_{50\text{–}100}$	ΔSim Yield$_i = \Delta MT_{1\text{–}4} + \Delta pp_{12\text{–}4} + \Delta WS_{p\text{-}h}+ (\text{Year})_i + \epsilon_i$	-125.7	0.002	0.88	0.93
4. $\Delta MT_{1\text{–}4}$	ΔSim Yield$_i = \Delta D35_{50\text{–}100} + \Delta pp_{12\text{–}4} + \Delta WS_{p\text{-}h}+ (\text{Year})_i + \epsilon_i$	-123.7	< 0.001	0.87	0.94
5. $\Delta WS_{p\text{-}h}$	ΔSim Yield$_i = \Delta MT_{1\text{–}4} + \Delta D35_{50\text{–}100} + \Delta pp_{12\text{–}4} + (\text{Year})_i + \epsilon_i$	-32.0	< 0.001	0.51	0.69

ΔSim Yield: anomaly of soybean yield simulated by CROPGRO-Soybean; ΔMT1-4: anomaly of maximum temperature between January and April; ΔD3550-100: anomaly of the number of days with maximum temperature above 35ºC between days 50 and 100 after planting; Δpp12-4: anomaly of accumulated rainfall between December and April; ΔWSp-h: anomaly of water stress between planting and harvest; amd ϵi: error. The anomalies were calculated in relation to the average values corresponding to 21 and 48 years of data in Quimili and Las Breñas, respectively.

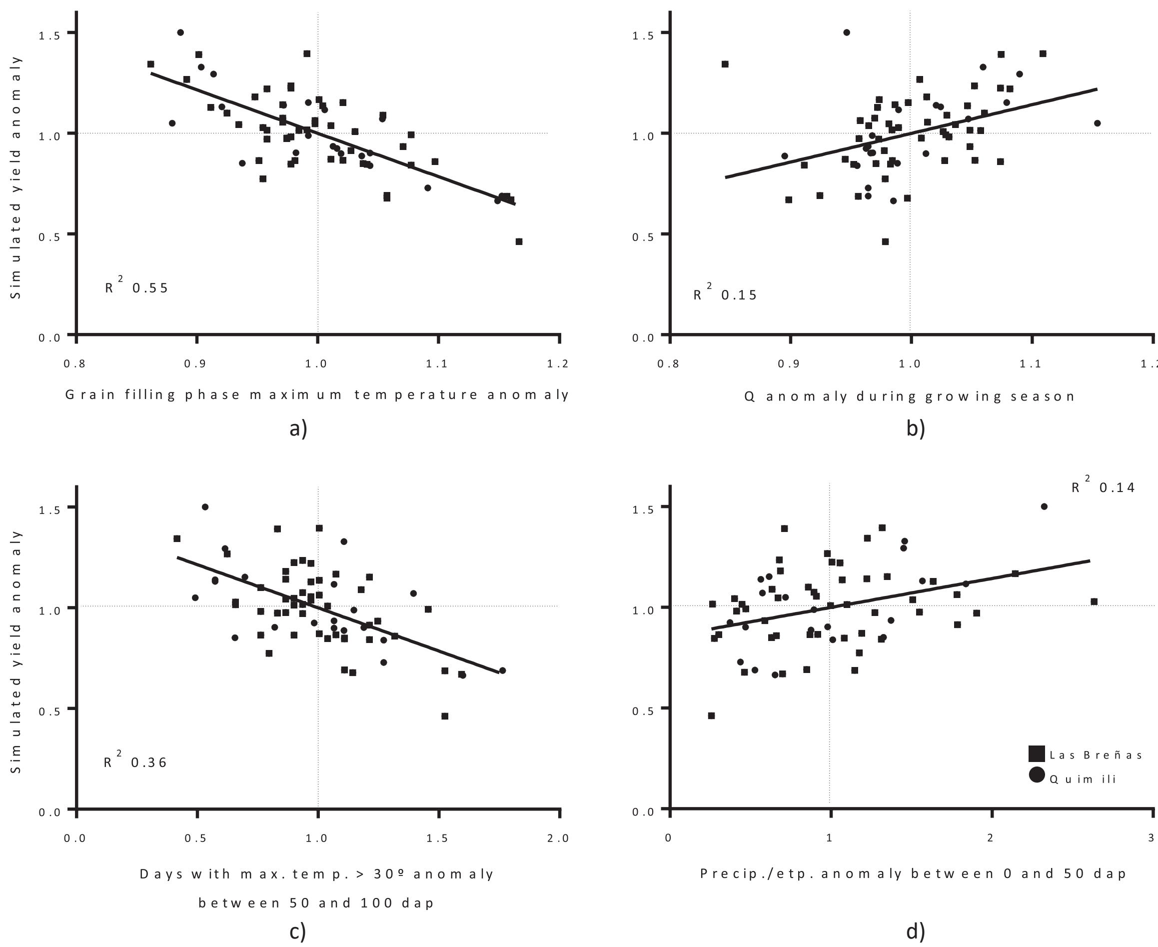

Fig. 5. Anomaly of maize grain yield simulated by CERES-Maize as a function of a) anomaly of the maximum temperature during grain filling phase; b) anomaly of the photothermal quotient (Q) between planting and harvest; c) anomaly of the number of days with maximum temperature above 30 °C between days 50 and 100 after planting; d) anomaly of the relation between accumulated rainfall and accumulated evapotranspiration according to Hargreaves between days 0 and 50 from planting. The line of the linear regression between both variables and the corresponding R^2 value is presented. The squares indicate the values corresponding to Las Breñas, while the circles those of Quimili. The correlation was highly significant ($p < 0.005$). Dotted lines indicate the anomaly with value 1. The anomaly was calculated in relation to the mean values corresponding to 21 and 48 years of data in Quimili and Las Breñas, respectively.

the DSSAT water stress index ($\Delta EH_{s\text{-}h}$), which considers precipitations, water uptake and plant transpiration (tightly regulated by temperature), showed the highest correlation ($r = 0.70$–0.92) with yield anomalies. The greater impact of precipitation was observed during the period from December (i.e., one month before sowing) to April ($\Delta P_{12\text{–}4}$). This indicates that besides water availability during the critical period, as previously observed by Giménez et al. (2015) in the Chaco region, water stored in the soil before sowing and water availability during the whole crop cycle were also important determinants of the effects of precipitation anomalies on soybean productivity. Regarding maize, a ratio combining precipitation and evapotranspiration at the early growth stages of maize (0 and 50 DAS; $\Delta P/PET_{0\text{–}50}$) was the best water-associated predictor of the anomalies in the grain yield of maize, outperforming the DSSAT water stress index. This indicates that the effects of the low precipitation levels on maize yield were regulated by the atmospheric demand. When the ratio was greater than 0.5, maize

Table 3
General structure of some of the linear mixed models considered to predict the anomaly in the grain yield of maize simulated by the CERES-Maize model in a locality of the Semi-Arid Chaco (Quimili) and a locality of the Subhumid Chaco (Las Breñas) for 1994–2014 and 1967–2014, respectively. The models differ in the predictors included and in the relationships between the predictors (additive or interactive). They are ordered from best to worst goodness of fit according to the Akaike Information Criterion (AIC).

Removed variables	Models	AIC	Weigth	marg. R^2	cond. R^2
1. None	ΔSim Yield$_i$ = $\Delta MT_{filling}$+ $\Delta D30_{50-100}$ + $\Delta pp/etp_{0-50}$ + ΔQ_{s-c}+ (Year)$_i$ + ϵ_i	-103.6	0.139	0.64	0.92
2. $\Delta D30_{50-100}$	ΔSim Yield$_i$ = $\Delta MT_{filling}$ + $\Delta pp/etp_{0-50}$ + ΔQ_{s-c}+ (Year)$_i$ + ϵ_i	-101.4	0.048	0.61	0.91
3. $\Delta pp/etp_{0-50}$	ΔSim Yield$_i$ = $\Delta MT_{llenado}$+ $\Delta D30_{50-100}$ + ΔQ_{s-c}+ (Year)$_i$ + ϵ_i	-97.1	0.006	0.59	0.90
4. $\Delta pp/etp_{0-50}$ and $\Delta D30_{50-100}$	ΔSim Yield$_i$ = $\Delta MT_{llenado}$+ ΔQ_{s-c}+ (Year)$_i$ + ϵ_i	-95.2	0.002	0.57	0.89
5. ΔQ_{s-c}	ΔSim Yield$_i$ = $\Delta MT_{llenado}$+ $\Delta D30_{50-100}$ + $\Delta pp/etp_{0-50}$ + (Year)$_i$ + ϵ_i	-89.0	$<$ 0.001	0.59	0.88
6. $\Delta MT_{filling}$	ΔSim Yield$_i$ = $\Delta D30_{50-100}$ + $\Delta pp/etp_{0-50}$ + ΔQ_{s-c}+ (Year)$_i$ + ϵ_i	-80.4	$<$ 0.001	0.48	0.86
7. ΔQ_{P-H} and $\Delta MT_{filling}$	ΔSim Yield$_i$ = $\Delta pp/etp_{0-50}$ + $\Delta D30_{50-100}$ + (Year)$_i$ + ϵ_i	-61.5	$<$ 0.001	0.38	0.75

ΔSim yield: anomaly of maize grain yield simulated by CERES-Maize; ΔMT filling: anomaly of maximum temperature during grain filling; ΔD3050-100: anomaly of the number of days with maximum temperature above 30ºC between days 50 and 100 after planting; Δpp/etp0-50: anomaly of the relation between accumulated precipitation and accumulated evapotranspiration according to Hargreaves between days 0 and 50 after planting; ΔQp-h: anomaly of the photothermal quotient between planting and harvest; and ϵi error. The anomalies were calculated in relation to the average values corresponding to 21 and 48 years of data in Quimili and Las Breñas, respectively.

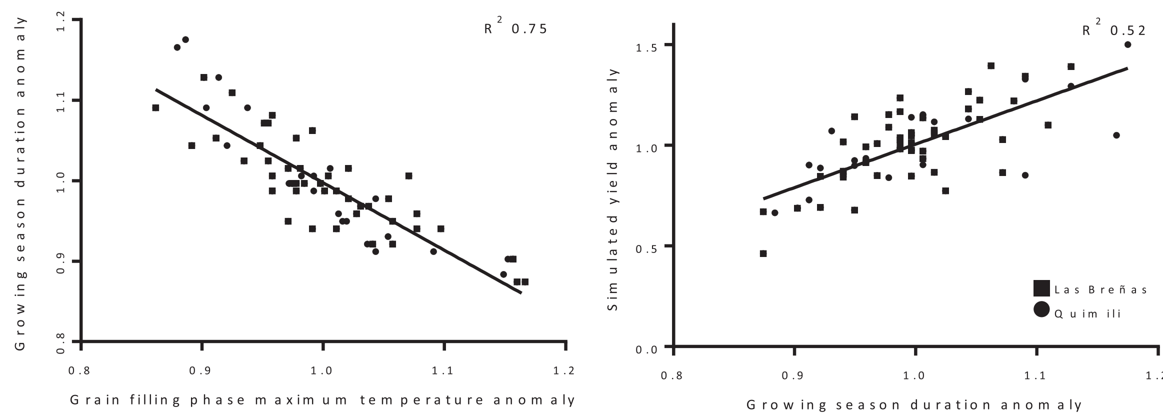

Fig. 6. Anomaly of the days between planting and harvest of maize, simulated by the CERES-Maize model, as a function of the anomaly of the maximum temperature during the grain filling phase (right); and anomaly of the maize yield simulated by CERES-Maize, as a function of the anomaly of the days between planting and harvest (left). The lines of the linear regression between the variables and the corresponding R^2 values are presented. The squares indicate the values corresponding to Las Breñas, while the circles indicate those of Quimili. Both correlations were highly significant ($p < 0.001$). The anomaly was calculated in relation to the mean values corresponding to 21 and 48 years of data in Quimili and Las Breñas, respectively.

yields were above average in all years, except in two years. It is also noteworthy that whereas the best water availability predictor for maize was linked to a restricted period of the crop cycle (i.e., 0–50 days), for soybean the best predictor was an index that covered from one month before sowing to physiological maturity. This suggest that in maize the major impact of drought was through effects on germination, establishment, and plant density whereas drought at later stages had a lower influence on yield anomalies. The differences between soybean and maize may be explained by differences in rooting depth (Fernandez and Rubio, 2015).

Finally, the multivariate models that summarized the major climatic parameters retained most predictors identified within each group of variables. For soybean, the most parsimonious model indicated that ΔTM_{1-4}, $\Delta D35_{50-100}$ and the DSSAT's water stress index measured throughout the crop cycle (ΔEH_{s-h}) were the most relevant predictors of yield anomalies (Table 2). In the case of maize, the parameters of the multivariate models with the highest predictive power were the maximum temperatures during grain filling ($\Delta MT_{filling}$), followed by the photothermal quotient (ΔQ_{s-h}) and $\Delta P/PET_{0-50}$.

4.2. Future implications

A note of caution should be observed in relation to the results of this study. Following the proposed objective of identifying the main climatic variables influencing maize and soybean yields in the region, the only source of variation of our simulations were the climatic parameters. The crop sanitary and nutritional conditions were maintained constant and assumed to be at the optimum level. Therefore, the representativity of the results would be maximal without severe sanitary issues under a recommended nutrient management and would be reduced as sanitary and nutritional conditions differ significantly from them. Several managements strategies aimed to mitigate the negative climatic effects on crop grain yields can be envisaged from our study. Simulated soybean and maize grain yield across 69 campaigns were 2497 and 7170 kg ha^{-1}, respectively. This indicates that both crops are suitable for the climatic conditions of the semi-arid and sub-humid Chaco. However, local farmers should be aware of the high interannual variability in grain yields that stem from the intrinsic climatic variability. Our results indicated that they should expect fluctuating economic results, however with a prevalence of positive economic outcomes. In such sense, Fig. 2 data allows to estimate the economic outcomes based on production costs expressed in kg of grain. For example, if a production cost of 1800 kg of soybean is assumed, negative results (yields lower than production costs) occurred in 10% and 13% of the studied years in Quimili and Las Breñas, respectively. For maize, assuming a production cost equivalent to a grain yield of 5000 kg ha^{-1} is assumed, negative economic outcomes were observed in 14% and 11% of the years in Quimili and Las Breñas, respectively. Therefore, farmers in the area assume a lower risk by cropping soybean than maize in Quimili and maize rather than soybean in Las Breñas. Given the different sensitivity of soybean and maize to climatic variables, having only one crop on the farm should be avoided to reduce the risk of serious crop failures affecting the whole operation. In this regard, crop diversification appears to be the key to improving agrosystem resilience and to increase the probability of harnessing favorable growing conditions, as observed for other regions (e.g. Gaudin et al., 2015). The proportion of each crop should be determined according to both a general scheme valid in the long term and to information gathered in the specific campaign. For example, the proportion of soybean could be increased in those years with relative higher soil water contents before sowing.

Obtained results are in line with a recent work in the same study site that showed that both crops markedly differ in their response to climatic change projected for the near (2015–2039) and the far (2075–2099) future (Casali et al., 2021). Significant reductions in maize yields in future climate scenarios (5–42% compared to the baseline 1986–2010) were more associated with increased temperatures that shortened the crop cycle than with water stress. In contrast, projected temperature increases are expected to play a secondary role in determining soybean yields and water stress will continue to be an important constraint to soybean yield in the context of global warming (Casali et al., 2021). Several reports suggest that the interannual climate variability in the Chaco Region is strongly influenced by ENSO (El Niño-Southern Oscillation) (Magrin et al., 2007; Patiño and Vicentini, 2007; Tiedemann, 2011), whose intensity and frequency is expected to increase by global climate change (Cleland et al., 2007). In addition, a higher incidence of diseases in maize crops have been reported during El Niño periods (Torres, 2001). Therefore, future trials in the area should consider the need to acquire biotic stress data which is currently unavailable. Ceglar et al. (2016) found remarkable spatial differences in the contribution of different meteorological drivers to crop yield variability and in the timing of the maximum impact; the exact timing of critical periods for grain yield determination in maize and the most influential variables were highly variable across France. Similarly, the results of this study for the Chaco region show that it is necessary to perform local studies, as the present one, to identify constraints to crop productivity and suitable strategies for the adaptation of local agricultural systems.

Management strategies intended to conserve soil water are of critical relevance in this region as indicated by the role of water-related variables on simulated grain yields, especially soybean. Available strategies that help reduce evaporation rates and ultimately increase soil water conservation include no-tillage, optimized fertilization, rotations with crops that leave large amounts of residues, and efficient weed control. Supplementary irrigation arises as alternative options for increasing water availability, especially for soybean. On the other hand, the identification of the periods of greater sensitivity to climatic parameters obtained in our simulations provide a guide to adjust crop management strategies. For example, the high relevance of the soil water content at sowing time suggests that practices that minimize soil water consumption before sowing soybean can be helpful. For instance, previous crops should be terminated at least one month before sowing soybean. To mitigate the effect of high temperatures, which is essentially a factor beyond the direct control of the farmer, the main practice that emerges from our simulations is to delay sowing dates (e.g., to late January) to avoid heat stress during critical stages of the crop [57].

In terms of plant breeding, new crop varieties should have genetic profiles that alleviate losses from the multiple environmental constraints that are encountered during the crop lifecycle. At least three breeding goals for the local climate conditions emerged from our simulations: (i) maize genotypes with longer grain-filling periods may confer advantages to cope with high temperatures; (ii) genotypes with greater water use efficiency; (iii) improved photosynthetic traits in maize since the photothermal quotient was retained in the models summarizing the main drivers in grain yield anomalies. The integration of mechanistic understanding, genetic variation, and genome-scale breeding will be essential to achieve these goals. Using crop models to elucidate mechanistic responses and to design crop ideotypes is an important step to raise genetic yield potential in a target environment. Crop ideotypes optimized for local climate could provide plant breeders with a road map for selection of the target traits and their optimal combinations for crop improvement and genetic adaptation.

CRediT authorship contribution statement

Lucía Casali: Methodology, Investigation, Formal analysis, Validation, Writing – original draft, **Juan M. Herrera**: Methodology, Formal analysis, Validation, Writing – review & editing, Supervision, **Gerardo Rubio**: Conceptualization, Validation, Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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