Sowing Date, Genotype Choice, and Water Environment Control Soybean Yields in Central Argentina

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ABSTRACT

Soybean is one of the most important crops worldwide, and Argentina is the third largest global grain producer and the worlds´ largest meal exporter. Under the continuous challenge of increasing crop yields, especially in the central temperate region of the country, there is a growing need to optimize management in relation to the environment that each specific farm and paddock presents. Understanding the impact of available technologies and management options can help optimize crop design. Here, we identify and quantify the effect of the most relevant variables affecting soybean yield by analyzing a database that includes 53 field trials with four common commercial genotypes, reporting 50 management and environmental variables. Linear mixed-effect models revealed that two management decisions (genotype and sowing date selection) and three environmental variables (rainfall during the reproductive crop period from R1 to R7, soil type -Hapludoll vs. Argiudoll-, and water table presence -above/below 2 m of depth from the surface) helped explain ca. 40% of total yield variability, which ranged from 1675 to 7226 kg ha^{-1} and averaged 5133 kg ha^{-1}. Water table presence generated higher and more stable yields, particularly in coarse-textured Hapludolls and under low rainfall conditions. Results highlight specific management and environmental conditions that affect soybean crop yields in the region, pointing effective pathways towards yield gap reductions.

Abbreviations: AIC, Akaike's information criterion; BIC, Bayesian's information criterion; ML, maximum likelihood; MMI, multi-model inference; REML, restricted maximum likelihood; RI, relative importance.

INTRODUCTION

Soybean is one of the most important crops worldwide, with increased production and sustained demand in the last decades (FAO, 2019). World production increase has been based on both increasing yields and expanding cultivated areas. Both contributions to soybean production took place in Argentina over the last 30 years (Aizen et al., 2009; Ray et al., 2012), when genetic yield gains have achieved 44 kg ha^{-1} yr^{-1} (or 1.1% yr^{-1}; data for the central temperate region, de Felipe et al.,

2016) and cultivated area has tripled based on the addition of new agricultural land, the displacement of other extensive crops (Viglizzo et al., 2011), and the increase of double cropping schemes (Caviglia et al., 2004; Calviño and Monzon, 2009; Fischer et al., 2014). These historical events positioned Argentina as a relevant soybean source, currently representing 16% of the total global production, following United States and Brazil, which account for 34 and 32%, respectively (FAO, 2019). Argentina is also the largest global exporter of high protein soybean meal, accounting for half of the global export supply (USDA-FAS, 2019).

Now, Argentina faces the challenge of increasing crop yields, especially in the central temperate region, where exploitable yield gaps have been documented (Aramburu-Merlos et al, 2015). Improving crop productivity needs optimized management in relation to site variables (Bennett et al., 1989; Calviño and Sadras, 1999; Hatfield and Walthall, 2015), requiring a better understanding of yield responses to management decisions within the environmental context of common crop production scenarios.

Management decisions can be crucial for optimizing soybean yield, and include the selection of an adequate genotype, sowing date (Rattalino Edreira et al., 2017; Di Mauro et al., 2018), fertilization (Sucunza et al., 2018), application of fungicide (Grassini et al., 2015) and insecticide, inoculation (Legget et al., 2017), stand density (DeBruin and Pedersen, 2008; Masino et al., 2018), row spacing (Andrade et al., 2002; Andrade et al., 2019), and crop rotation schemes (Seifert et al., 2017), among others. Environmental variables known to affect yield include weather variables like temperature, solar radiation, rainfall amount (Andrade and Satorre, 2015) and distribution (Calviño et al., 2003), potential evapotranspiration (Grassini et al., 2015), and soil type (Di Mauro et al., 2018), among others. Soil quality attributes mediate water availability and nutrient provision, and while several mineral soil nutrients are known to be essential for adequate soybean yield (like N, P, K, S, Ca, Mg, Fe, Zn, Mn, and B; Borst and Thatcher, 1931; Hammond et al., 1951; Harper, 1971; Bender et al., 2015; Gaspar et al., 2017; Ciampitti and Salvagiotti, 2018) it is not completely clear to what extent they are limiting soybean yields in our focus region. There is a need to dissect and understand how all these management and environmental factors influence yield in the temperate production systems of Argentina.

A recent study in our region considering many management options and environmental conditions identified sowing date, soil type, and rainfall during the crop cycle, as the most relevant yield predictors (Di Mauro et al., 2018). These results agree with findings from similar temperate regions in the USA (Grassini et al., 2015; Rattalino Edreira et al., 2017; Mourtzinis et al., 2018) and Argentina (Calviño and Sadras, 1999; Sadras and Calviño, 2001). However, Calviño and Sadras (1999) and Di Mauro et al. (2018) did not quantify the magnitude of each effect, nor did they explore relevant interactions among factors. Important interactions like those between sowing date and water availability were found to be highly relevant in other production systems (Rattalino Edreira et al., 2017). Interestingly, earlier studies did not quantify the yield impact of shallow water tables that are accessible to crops. Today, the influence of shallow water tables to stabilize crop yields is recognized worldwide (Nosetto et al., 2009; Rizzo et al., 2018), but for our region its net effect on soybean yields is still unknown.

To explore the impact of multiple and potentially interactive management and environmental variables on soybean grain yield across the central Argentinean temperate region we conducted 53 field trials in farmer fields during three consecutive cropping years. We used linear mixed-effects models and multi-model inference techniques (MMI) (Burnham and Anderson, 2004; Smith et al., 2005) as they proved to be particularly useful to quantify multiple variable effects from experimental agricultural data (Gambin et al., 2016; Casali et al., 2018; Vitantonio-Mazzini et al., 2020). We hypothesized that the most relevant management variables are sowing date and genotype selection, while water table presence and rainfall during the crop cycle are the most important environmental controls. Based on previous evidences (Mercau et al., 2007; Rattalino Edreira et al., 2017) we also expected significant interactions between sowing date and water-related variables.

MATERIALS AND METHODS

Study system

Experiments were sown in different locations across central Argentina (Fig. 1) during three consecutive growing seasons, 2016/17, 2017/18, and 2018/19 (referred as years 2017, 2018, and 2019, respectively). The analysis included 19 sites in 2017, 15 sites in 2018, and 19 sites in 2019, providing a total of 53 trials. The term "site" is used to define the combination of a trial at a given location and year. The location is used as a loose spatial reference to the geographical position (summarized by the town name), and involves different paddocks, farms, and/or soil types subject to different management practices. All trials were managed under no-till schemes without irrigation, following common agricultural practices for the region (Calviño and Sadras, 1999; Di Mauro et al., 2018).

Trials included four genotypes (DM40R16, DM4612, DM46R18, and DM50i17) that are commercially available from GDM (Grupo Don Mario). They were selected based on commercial relevance in the region and represent the maturity groups (MG) that are typically sown in central Argentina (DM40R16 is MG III long, DM4612 and DM46R18 are MG IV medium, and DM50i17 is MG IV long). Genotypes are STS (resistant to sulfonylurea herbicides) in all cases except DM4612. Together, these four genotypes were sown on more than 3 million hectares during the 2019 growing season in Argentina (INASE, https://www.argentina.gob.ar/sisa/informes). The number of replicates varied with sites, most of them having two (23 sites) or three (11 sites) replicates. Three sites had four replicates, and 16 sites had one replicate. Sites with single replicates were included to provide a wide range of management and environmental variables, which was the main focus of our study. Genotype evaluation power of the entire dataset was beyond the minimum requirement determined for non-replicated trials (Yan et al., 2002). Sites with two or more replicates had genotypes arranged in a randomized complete block design. Plots ranged in size from six to eight rows in width, where row spacing was different in each site, and from 200 to 240 m of length. This depended on available farming machinery at the site, and trials were sown and harvested with typical commercial planters and combines used by local farmers.

At each individual site common farmer technology and management were applied, including decisions in terms of sowing date, fertilization management, stand density, and inter-row spacing. This made trials representative of actual soybean production environments, management, and yield for the region, and are similar to previously reported studies (Di Mauro et al., 2018). Weeds and insects were chemically controlled using standard practices for the region. Soils were predominantly deep (>3 m) sandy loams (Typic Hapludoll and Entic Hapludoll), and shallower (2-3 m) clay loams (Typic Argiudoll and Aquic Argiudoll) (Soil Survey Staff, 2014). These soil types represent the most common soybean farming land of the region. Individual trials were entirely fitted within a field portion with uniform soil characteristics as indicated by local soil maps provided by the Argentinean Federal Agricultural Agency Instituto Nacional de Tecnología Agropecuaria (INTA) (GeoInta, http://visor.geointa.inta.gob.ar/) and confirmed by local observations. Sites had similar management during previous growing seasons, with previous crop being soybean in 20 trials and maize in the other 33.

For each trial, soil samples down to 2 m of depth were obtained with a hand auger before sowing to determine initial soil properties. Soil tests were more exhaustive than ones commonly carried out by farmers in the region, with the objective to detect micronutrient deficiencies. Soil tests for our study included the gravimetric content of organic matter (OM, %), and extractable P, K, S, Ca, Mg, Na, Zn, B, Mn, Fe, and Cu (ppm) for 0 to 20 cm depth. We also measured soil pH, cationic exchange capacity, sum of bases (CEC and SB, meq $100g^{-1}$), base saturation (SB/CEC), and exchangeable sodium percentage (ESP, %) at the same depth interval. Water content in soils was determined at each site to 2 m depth based on gravimetric measurements taken at 20 cm intervals and conversion to volumetric water availability (mm of water down to 2 m) using bulk density information (Black, 1965). Bulk density was taken from soil maps provided by INTA (GeoInta, http://visor.geointa.inta.gob.ar/) for each site. Water table was considered present whenever its depth was shallower than 2 m at sowing. Fertilization with P at sowing was defined in a qualitative manner (yes / no). Monthly accumulated rainfall and monthly mean temperature (°C) during the crop cycle were recorded at each site. While rainfall was measured at each site, air temperature was obtained from the closest available public weather station (less than 90 km in all cases; Mercau et al., 2007). Grain yield data was adjusted to 13.5% moisture content based on measured moisture. Harvest was performed with a commercial combine, and yield of each plot was independently obtained by weighing the tractor trailer grain tanks with sensors. Reported trials showed no major problems regarding weeds, diseases, or lodging. Coefficient of variation (CV) for yield for replicated trials ranged from 2 to 38%, with a median of 4% (86% of trials had a CV lower than 10%, and only one site, VMack1_18, presented a CV higher than 20%).

Predictor variables

Our main objective was to identify management and environmental variables that can help predict yield. The inclusion of predictors was based on several aspects, including specific interest as how to manage the crop, data availability, and enough variation across sites. Environmental variables included accumulated precipitation per month or groups of months (taking into account that from October to December when crops were in their vegetative stages, and from January to March when crops were at their reproductive stages), air temperatures (maximum, mean, and minimum), soil type according to the Soil Taxonomy criterion (Soil Survey Staff. 2014), soil water content at sowing (2 m depth), and the presence of a water table shallower than 2 m at sowing time. We also evaluated the effect of soil variables including OM, pH, P, K, S, Ca, Mg, Na, SB, CEC, base saturation, ESP, Zn, B, Mn, Fe, and Cu. The management variables included were sowing date, maturity group, row spacing, and the use (or not) of P fertilizer at sowing (Table 1).

The first step of the analysis involved data exploration following Gambin et al. (2016) and Coyos et al. (2018). Key issues considered at this stage were outliers, multicollinearity, and relationships between variables (Zuur et al., 2009). Multicollinearity among quantitative variables was evaluated by matrix correlations following Pearson method, and variance inflation factor (VIF) in R software (R Core Team, 2018, version 3.5.1; *fmsb* package; Nakazawa, 2014). Collinearity between nominal and quantitative variables was evaluated by using general linear ANOVA (*agricolae* package; Mendiburu, 2017).

Statistical analysis and model selection

Data were analyzed using linear mixed-effects models to assess the influence of different predictors on grain yield (*lme4* package, lmer function; Bates et al., 2015). We applied the top-down strategy for the model selection process (Zuur et al., 2009; Gambin et al., 2016; Coyos et al., 2018; Vitantonio-Mazzini et al., 2020).

After data exploration, we proposed a “beyond optimal model” which included different variables that presented association with grain yield. These variables were classified into management and environmental. Each overall partial regression coefficient (β+) was considered a fixed effect, reflecting the influence of a predictor on grain yield across all sites. Once the “beyond optimal model” was defined, an optimal structure of the random component was obtained based on REML estimates. The random structure used block nested within site plus genotype. By including block nested within site as random effects, our models estimated different intercepts for each block and site to account for the hierarchical data structure. The same applied for the genotype random term. For sowing date and rainfall from January to

March (J-M), we tested models with both linear and curvilinear response. Curvilinear response was explored by fitting a second-order polynomial function ($Y_i = \alpha + \beta_1 \times X_i + \beta_2 \times X_i^2 + \varepsilon_i$). We found model improvement (i.e., lower AIC) when considering some curvilinear relations, therefore we present models with coefficients β_1+β_2 in those cases. We used visual analysis of the residual errors against fitted values for all yield predictors, and no clear heterogeneity of error variance was evident. We also tested heterogeneity of error variance with a Levene's test, and no significant differences were found.

We searched for the optimal fixed structure based on ML estimations and multi-model inference (MMI), originated from the information theory approach (Burnham and Anderson, 2004). Aligned on the context and our objectives, AIC is the appropriate tool for model selection when compared to others indicators such as BIC, or hypothesis testing (Aho et al., 2014; Burnham et al., 2011). Because models have different fixed effects (but with same random structure) we used ML estimation instead of REML. The final model was presented using REML estimation.

We also calculated a "weight of evidence" (Akaike weight, ω_i), and a "measure of importance" for each possible predictor (based on relative importance; RI) in R software (*MuMIn* package, importance function; Bartón et al., 2018). The Akaike weights (ω_i) represent the probability for a model *i* to be the actual "best model" given a set of considered models (Burnham and Anderson, 2004). In many contexts, the AIC selected "best model" will include and exclude some variables, yet this inclusion/exclusion does not distinguish differential evidence of importance for all predictors in itself. In consequence, RI provides a much more representative estimate of evidence for all predictors (Burnham and Anderson, 2004).

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Proportional change in variance (PCV) at different grouping levels (site, genotype, and residual) was calculated as described in Merlo et al. (2005). PCV monitors changes specific to each variance component. That is, how the inclusion of additional predictor(s) has reduced (or increased) the variance component at different levels. Proportional change in variance is calculated as (equation 2):

$$PCV = \frac{V_{N-1} - V_{N-2}}{V_{N-1}} \qquad \text{(Equation 2)}$$

where V_{N-1} is the variance in the null model and V_{N-2} is the variance in the final model with predictors. Positive values indicate a reduction in the variation among groups (e.g., sites) given by the incorporation of predictors.

R^2 of adjusted models were obtained following the methodology described in Nakagawa and Schielzeth (2013) for generalized linear mixed models. Both marginal and conditional R^2 were calculated. Marginal R^2 (R^2_m) represents the variance explained by fixed factors and is given by (equation 3):

$$R_m^2 = \frac{\sigma_f^2}{\sigma_f^2 + \sum_{l=1}^{\mu} \sigma_l^2 + \sigma_\varepsilon^2} \qquad \text{(Equation 3)}$$

where σ_f^2 is the variance calculated from the fixed effect components of the linear mixed model, σ_l^2 is the variance component of the lth random factor, and σ_ε^2 is the residual variance. Equation 3 can be modified to express conditional R^2 (R^2_c) (equation 4):

$$R_c^2 = \frac{\sigma_f^2 + \sum_{l=1}^{\mu} \sigma_l^2}{\sigma_f^2 + \sum_{l=1}^{\mu} \sigma_l^2 + \sigma_\varepsilon^2} \qquad \text{(Equation 4)}$$

which represents the variance explained by the entire model (fixed and random factors) (Nakagawa and Schielzeth, 2013). Because predictor variables have different units and scales, the analysis was conducted with standardized variables using z-scores. Yet, figures and predictor effects are recalculated and presented in their original units and scales for easier visualization.

RESULTS

Management and environmental variations across sites

The 53 trials reported here displayed a wide variability of management and environmental conditions as well as grain yields. The variables that were initially considered showed a large variation across time and space (Table 1). Grain yield ranged from 1675 to 7226 kg ha^{-1}, with an average of 5133 kg ha^{-1} (Fig. 2), matching typical yields for soybean as a single crop in the region (Di Mauro et al., 2018).

Among explored environmental variables (Table 1), those in the fixed components that were more likely to contribute to the optimal model were soil type, presence of a water table at sowing, rainfall from January to March, soil Ca, soil P, and soil pH. Interestingly, variations in soil type implied variations in the availability of several other soil nutrients (K was higher in Hapludolls; Mg, Mn, and Cu were higher in Argiudolls; $p<0.05$). There was no trend suggesting differential management with soil type and were also distributed at comparable geographical coordinates. Similarly, management variables in the fixed component that were more likely to contribute to the optimal model were sowing date and maturity group. The rest of the explored variables (Table 1) showed no apparent association with yield.

Data exploration also suggested potential interactions between sowing date and maturity group, soil type x water table and rainfall from January to March x water table, consequently all these interactions were included into the "beyond optimal model". Finally, despite some correlations between pH, soil P and Ca, and rainfall from January to March, there was no evidence of multicollinearity among quantitative predictors of interest, and therefore they were all included in the analysis.

Model selection

The proposed "beyond optimal model" included two management variables (sowing date and maturity group) and its interaction, and six environmental variables (soil type, water table, rainfall from January to March, soil Ca, soil P, and soil pH), and the interactions soil type x water table and rainfall from January to March x water table, giving a total of eleven predictors (Table 2). The optimal fixed structure, based on MMI, included six of these predictors. These were sowing date, soil type, water table, rainfall from January to March, and the interactions soil type x water table and rainfall from January to March x water table. The model with the lowest AIC or "best model" (model A) has a ω_i of 0.25 and predictors included presented a RI of 100% (Table 2). In agreement with this, models with fixed effects showed an important improvement in terms of AIC when compared to the model without fixed effects (or "null model"; Table 2), indicating the relevance of considered predictors. Including these predictors improved model accuracy from 0.86 to 0.92 (Table 2).

The model without fixed-effects predictors, which explored the random variation associated with random terms, indicated that 77% of the total yield variation was related to site-to-site differences, followed by 3% related to genotype-to-genotype variations (Table 3). These results agree with the wide yield variation observed across sites (Fig. 2). The residual variation of the model was 14% of the total variance (Table 3). Similar results were observed in the model without standardization.

By including management and environmental predictors, the "best model" (model A) explained a large portion of the total variability (Table 3). The fixed-effect predictors of the "best model" decreased the site-to-site variation in crop yield (PCV_S) by 27%. This indicated that part of the variation in the model without fixed effects was caused by considered management and environmental variables (Table 3). The residual of the final model improved as evidenced by a residual variance reduction (32%; Table 3). Similar results were observed in the model without standardization.

Influence of predictor variables

Final model (model A) included only one management variable (sowing date), and five environmental variables (soil type, water table, rainfall from January to March, the interaction of soil type x water table, and the interaction of rainfall January to March x water table). Sowing date, a management variable that can be easily modified by farmers, appeared with a high RI (100%; Table 2). The presence of an accessible water table at sowing and soil type, environmental variables that can be easily scouted by farmers, also showed a high RI (100%; Table 2).

We further examined the estimates of regression coefficients (β+) for the final model. This allowed quantifying the particular influence of each predictor variable on grain yield. The use of standardized variables allowed us to compare the influence of different predictors. Sowing date showed an accelerating negative effect on grain yield (Fig. 3A). The initial slope showed that the yield loss was -8.81 kg ha^{-1} day^{-1} of delay in sowing (Table 4). Results showed that the optimum period for sowing lasts until October 30th (90% of maximum yield) with an average decrease of -39 kg ha^{-1} day^{-1} after this date. Interestingly, there was no evidence of interaction with maturity group, indicating that the yield of all maturity groups we studied responded similarly.

Increased rainfall from January to March showed a positive yield response, although the magnitude of the effect depended on the presence of an available water table at sowing (Fig. 3B). The average response of grain yield to rainfall during this period was 6 kg of yield mm^{-1} at sites without water table, and close to 1 kg of yield mm^{-1} at sites with available water table at sowing (Table 4; Fig. 3B). The large rainfall range explored (48 to 508 mm) helped determine yield differences of ~3000 and ~500 kg ha^{-1} without and with an accessible water table at sowing, respectively (Fig. 3B). Therefore, fields in the region with an accessible water table presented higher and more stable yields, regardless of rainfall amount from January to March. These results highlight the relevant yield effect of rainfall during soybean reproductive stages (occurring during these months), but also show that the presence of accessible water tables in the explored conditions can compensate for the lack of rainfall in this period.

The presence of an accessible water table at sowing displayed an overall positive effect on grain yield that was six times higher in magnitude in the coarse-textured Hapludoll compared to the Argiudoll soil type (1708 vs. 276 kg ha^{-1}; Fig. 3C;

Table 4). Interestingly, with the presence of an influencing water table the average yield was similar for both soil types, being 5382 and 5298 kg ha^{-1} for Argiudolls and Hapludolls, respectively (Fig. 3C). The presence of an accessible water table masked the lower yields of Hapludolls compared to Argiudolls, which were -1515 kg ha^{-1} when water tables were not present at an accessible depth. Soil type and water table also affected the site-to-site yield stability. Hapludolls had higher yield variability than Argiudolls when an accessible water table did not exist, and the presence of an accessible water table reduced yield variability in both soil types.

Genotypes random effects, or BLUPs, indicated DM46R18 was the genotype promoting the highest positive yield effect across sites, followed by DM40R16, DM50I17, and DM4612 (Table 4). A yield difference of ca. 400 kg ha^{-1} was evident when comparing the highest and lowest yielding genotypes, indicating the relevance of adequate genotype selection for maximizing yield.

DISCUSSION

Dissecting the relative importance of crop management x environment interactions is not trivial (Gambin et al., 2016; Rattalino Edreira et al., 2017). Developing tools to guide farmers' decisions for closing exploitable yield gaps under different conditions is critical (Zhang et al., 2020). In the present study we identified and quantified the yield influence of important predictors for soybean yield in the central temperate region of Argentina, where soybean is cultivated under contrasting technical, management, and environmental conditions. Identified yield predictors were based on variables that can be optimized based on observed variability. Our model satisfactorily described the spatial and temporal variation in grain yield (r^2 = 0.92), which ranged from 1675 to 7226 kg ha^{-1} (Fig. 2).

In the context of maximizing yield per unit of land area we found one specific management decision with a strong yield effect. Sowing date showed an optimum period to prevent drastic yield losses until October 30th. After this sowing date an important yield penalty (-39 kg ha^{-1} day^{-1}) unfolds, similar to that reported before in Argentina (Andrade, 1995), the United States (Grassini et al., 2015; Rattalino Edreira et al., 2017), and Brazil (Zanon et al., 2016). With another approach, Di Mauro et al. (2018) highlighted the advantages of early sowings for maximizing soybean yields in the study region but suggested a later threshold (November 25th) before yield losses occur. This management predictor can be easily considered by farmers to optimize yields. Based on our results, earlier sowings are recommended across all the explored soil types and environmental conditions that we covered.

Argentinean soybean production systems are predominantly rainfed (Hall et al., 1992). For the range of maturity groups and sowing dates commonly used, soybean reproductive stages are achieved between January to March (Santachiara et al., 2017), and the rainfall during this period proved to be critical for maximizing yields, especially where water tables were not accessible. This is not surprising since this is the period when crops experience the highest water demands (Calviño and Sadras, 1999) and also determine the number of seeds per unit land area that will be harvested (Egli and Yu, 1991; Rotundo et al., 2012). Previous studies described positive water table effects on soybean yield, with an optimum depth ranging from 1.2 and 2.2 m depth (Nosetto et al., 2009). Our results showed that the crops with water tables less than 2 m below the surface at sowing had reduced yield variability across a wide rainfall range, most likely resulting from the capillary supply of water to crops. Soybean crops sowed into soils with water tables deeper than 2 m below the surface had greater dependency on rainfall, especially during the reproductive period of the crop. Rizzo et al. (2018) highlighted that the presence of shallow water tables under maize crops are leading to higher and more stable yields in central United States. The results for soybean in central Argentina in this analysis agree with those findings for maize in the United States.

We explored a wide range of soil variables to search for nutrient limitations across sites with large yield differences. We expected that some nutrients could help explain part of those differences, but our analysis showed that soil type was more relevant than any specific nutrient. Although some nutrients varied with soil type (i.e., K was higher in Hapludolls, and Mg, Mn, and Cu were higher in Argiudolls), soil type helped to capture functional soil properties that may escape what is captured by individual indicators (like nutrient concentrations in our case). Physical effects on water supply was the most likely underlying mechanism of soil type effects.

By exploring yields within the two most representative but texturally different soil types (Alvarez and Lavado, 1998) used for soybean in central Argentina, we identified a key contrast regarding water supply to crops, manifested by the soil type x water table interaction. While soybean crops grown on sandier Hapludolls had ~1500 kg ha^{-1} lower yields than crops grown on Argiudolls when water tables were not accessible, this yield difference disappeared where those water tables were less than 2 m deep (Nosetto et al., 2009). These observations reflect the lower water holding capacity that Hapludolls have compared with Argiudolls (80-180 vs. 150-250 mm from 0 to 2 m depth) under unsaturated conditions (no accessible water tables), but their higher capacity to store and transport water once they approach saturation (water tables becoming accessible). This is expected for sandier soils given their large volumetric fraction involved in storage above field capacity (Hillel, 2003). While the observed yield differences found between Hapludolls and Argiudolls are in accordance with the general observation of higher dependency on real time precipitations at soils with restricted water holding capacity and availability (Calviño and Sadras, 1999), they highlight how this restriction flips to a comparative advantage with shallow water tables in the case of sandy soils.

Our results showed that maturity group choices had little impact on crop yield variability, in agreement with Santachiara et al. (2017) reporting that widely used maturity groups in central Argentina have different strategies for yield determination but reach similar yield levels. Genotype selection can be optimized to increase yields across a wide range of environment and management scenarios. The genotypes tested represent a small sample of commercial germplasm currently available in Argentina, and span six years of genetic improvement between DM46R18 and DM4612, which were released in 2018 and 2012, respectively. We found an average yield difference of 414 kg ha^{-1} for these two varieties, which is in general agreement with the reported genetic gain for the region of 44 kg ha^{-1} yr^{-1} (de Felipe et al., 2016).

In summary, our study explored a wide range of management decisions and environmental variables that could help optimize soybean yields and anticipate part of their yield variability. However, not all predictors had a high impact on yield. Variables like sowing date, genotype selection, rainfall during reproductive stages, presence of an accessible water table, and soil type drive soybean yields under current farming conditions. Soybean production in the central temperate region of Argentina will benefit further from a deeper understanding of the interactive effects of soil types and water table conditions on yields. These are aspects that can be easily anticipated, helping not only farmers but others in the soybean production and supply chain to optimize their actions.

CONCLUSIONS

We identified management and environmental predictors that are relevant for soybean yield in our region and quantified the magnitude of their effect. Management decisions related to genotype selection and sowing date are very important. Genotype selection can increase yields by 400 kg ha^{-1}, and optimum sowing date may be preserved until October 30th (with an average decrease of 39 kg ha^{-1} day^{-1} after this date).

Environmental variables including soil type, the presence of a water table less than 2 m from the surface, and rainfall during the reproductive crop periods all helped explain yield variability. The availability of a water table helped obtain more stable and higher yields regardless of rainfall and soil type. Soil variables like pH, Ca, and P were not relevant to differentiate sites with contrasting soybean grain yield.

AUTHOR CONTRIBUTIONS:

Lucas N Vitantonio-Mazzini: methodology, formal analysis, writing, review and editing. **Damián Gomez:** data curation, formal analysis. **Brenda L. Gambin:** methodology, writing, review and editing. **Guido Di Mauro:** data curation, writing. **Rodrigo Iglesias:** data curation, funding acquisition. **Jerónimo Costanzi:** funding acquisition. **Esteban G. Jobbágy:** writing, review and editing. **Lucas Borras:** conceptualization, funding acquisition, writing, review and editing.

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FIGURE CAPTIONS

Fig. 1. Map of the center temperate region of Argentina showing the location of tested sites. Empty red circles indicate trials sown in 2016/2017 (n: 19), empty red squares represent trials sown in 2017/2018 (n: 15), and empty red triangles indicate trials sown in 2018/2019 (n: 19). Solid lines show province boundaries, and broken lines describe annual rainfall isohyets (700, 900, and 1100 mm yr^{-1}) based on data from 1970 to 2000.

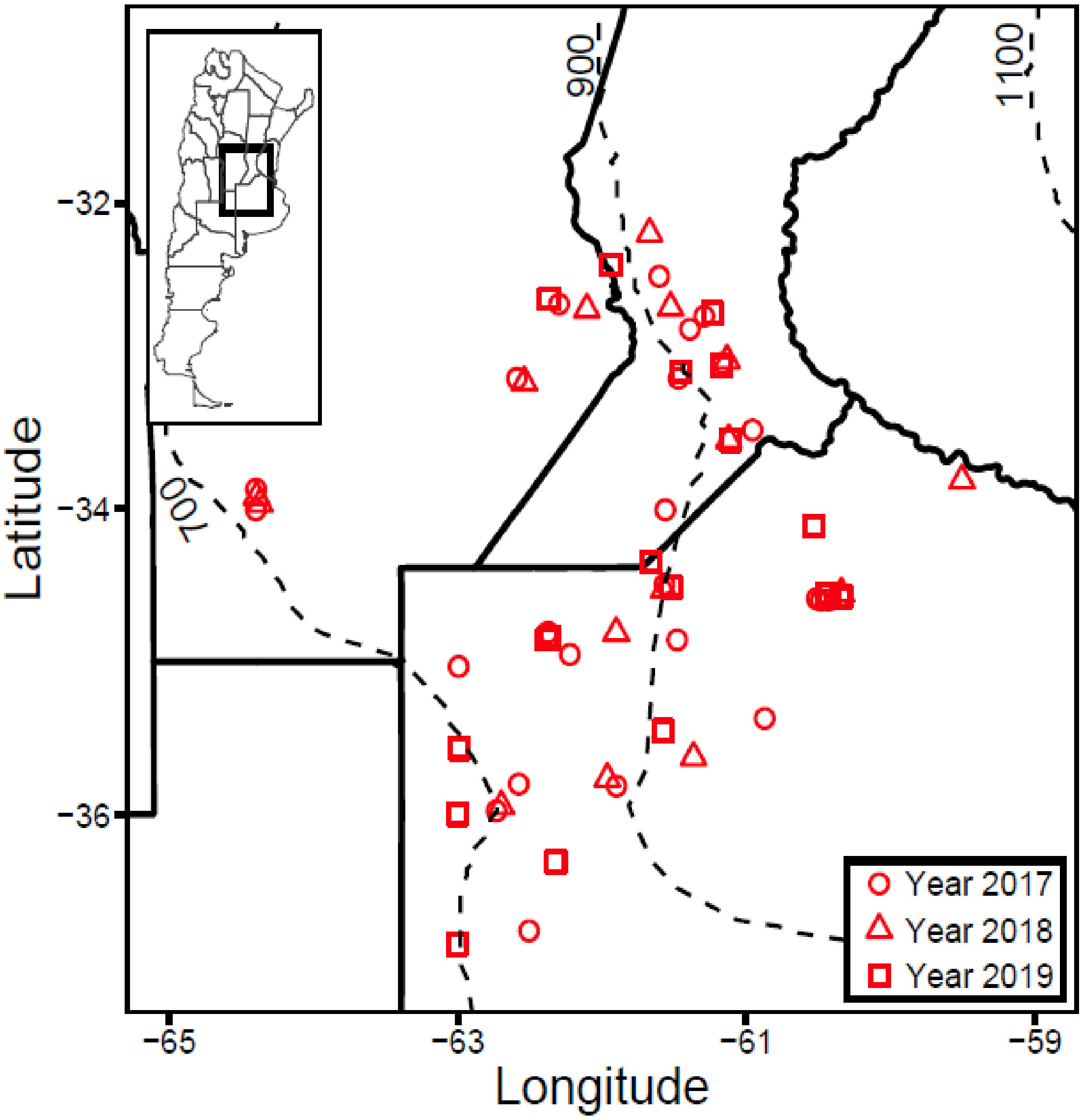

Fig. 2. Boxplot of adjusted grain yield (13.5% moisture) for the 53 trials. The red dash line reflects the yield mean of all tested trials, averaging 5133 kg ha^{-1}.

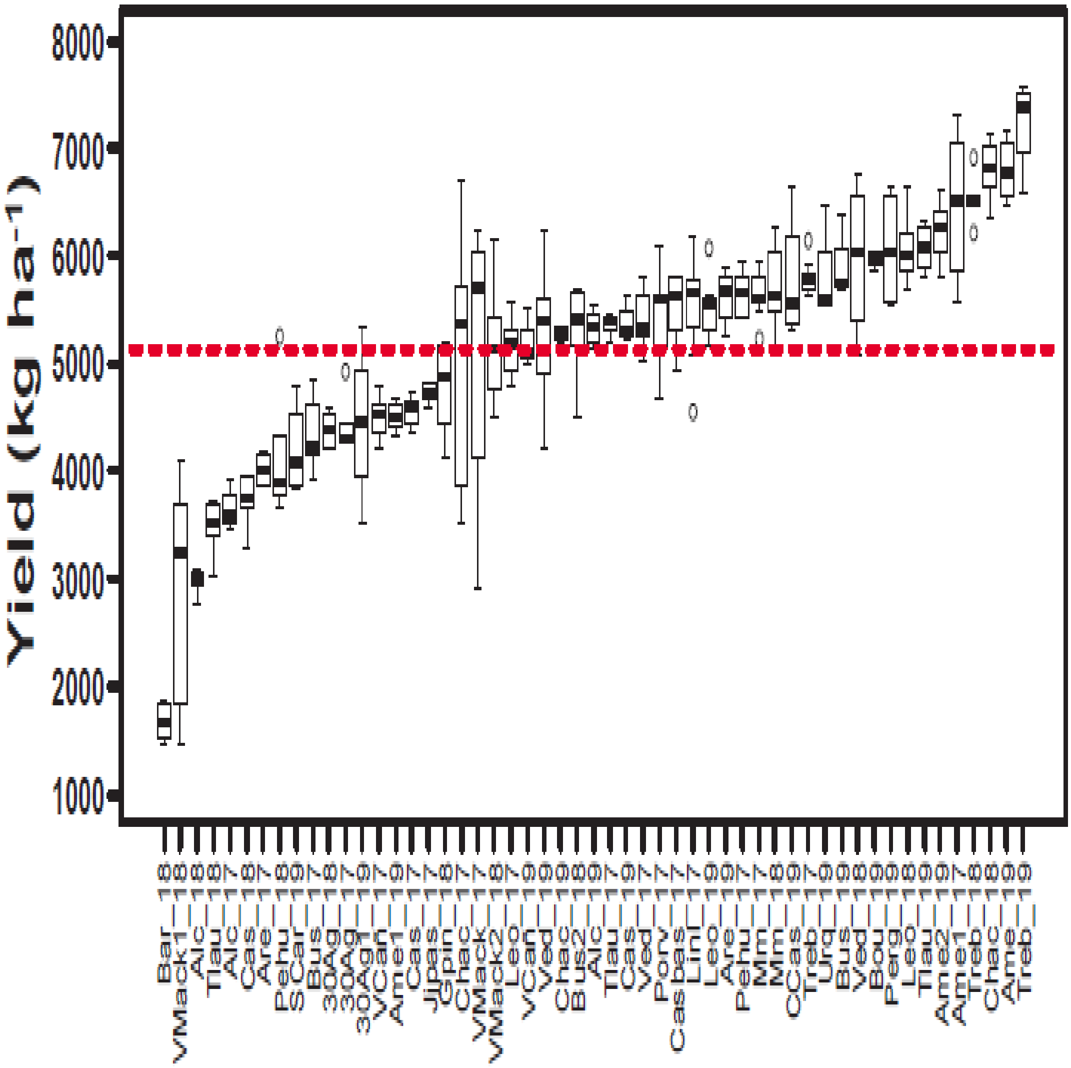

Fig. 3. Yield response to sowing date (Fig. 3A), to rainfall from January to March (J-M) (Fig. 3B), and to each soil type x water table combination (Fig. 3C). In Fig. 3A the red solid line reflects the effect of sowing date. In Fig. 3B the red and black dashed line reflects the effect of rainfall at sites with the presence of a water table and with no water table at sowing, respectively (Fig. 3B). In Fig. 3B empty red circles indicate sites with presence of water table, and empty black show sites with no water table at sowing (Fig. 3B). In Fig. 3C the blue and green dash lines reflect the effect of a water table present at sowings at sites with an Argiudoll and Hapludoll soil, respectively. Observed yields were corrected with random effects.

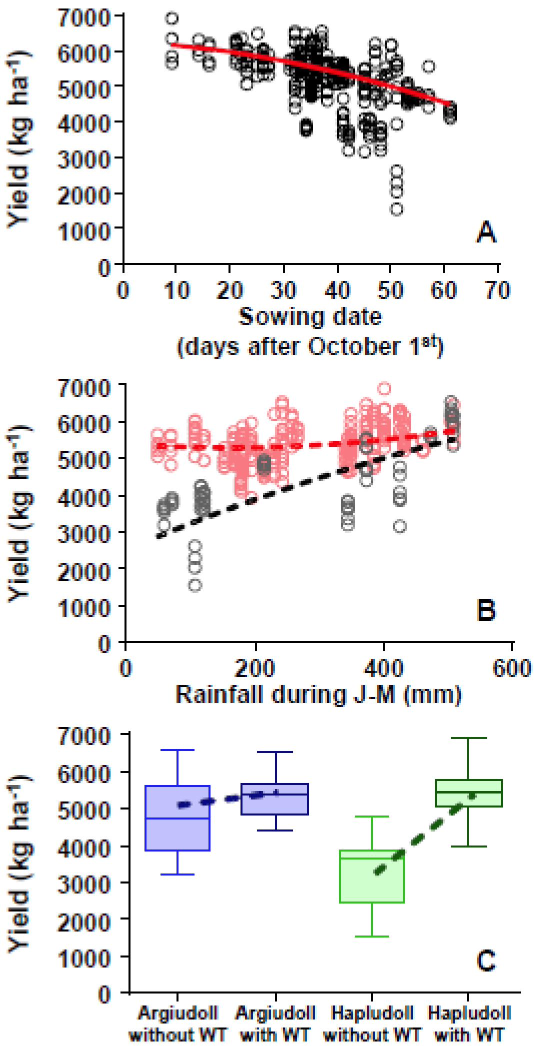

Table 1. Description of environmental and management variables explored in 53 sites, together with their unit and explored range. Figure 1 provides a geographical distribution of all sites across the region. ESP stands for exchangeable sodium percentage and CEC for cationic exchange capacity. Maturity group III_L refers to III long, IV_M refers to IV medium, and IV_L refers to IV long.

Variable		Type	Unit	Explored range
Environmental				
Accumulated rainfall		Quantitative	mm	
	October			7 to 340
	November			13 to 320
	December			18 to 282
	January			22 to 322
	February			0 to 195
	March			5 to 202
	October to December			59 to 656
	January to March			48 to 508
	January to February			27 to 390
	February to March			5 to 323
	December to January			112 to 495
	October to March			261 to 1163
Max. air temperature		Quantitative	°C	
	December			26.6 to 32.8
	January			27.6 to 32.7
	February			26.6 to 32.6
	March			23.2 to 30.5
Mean air temperature		Quantitative	°C	
	December			20.8 to 24.7
	January			22.0 to 25.4
	February			20.5 to 25.0
	March			17.4 to 22.4
Min. air temperature		Quantitative	°C	
	December			13.8 to 17.2

	January			16.0 to 19.6
	February			13.3 to 19.0
	March			11.1 to 16.0
Soil type		Qualitative	Soil taxonomy classification	Argiudolls, Hapludolls
Soil water at planting		Quantitative	mm	112 to 228
Water table		Qualitative	Yes/No	
Soil organic matter		Quantitative	%	1.2 to 4.1
Soil pH		Quantitative		5.2 to 6.7
Soil phosphorus		Quantitative	ppm	6 to 80
Soil potassium		Quantitative	ppm	197 to 897
Soil sulfur		Quantitative	ppm	1.1 to 59.4
Soil calcium		Quantitative	ppm	60 to 2,212
Soil magnesium		Quantitative	ppm	109 to 339
Soil sodium		Quantitative	ppm	9 to 151
Soil sums of bases		Quantitative	meq $100g^{-1}$	5 to 15
Soil base saturation		Quantitative	%	47 to 100
Soil ESP		Quantitative	%	0.3 to 6.4
Soil CEC		Quantitative	meq $100g^{-1}$	7 to 28
Soil zinc		Quantitative	ppm	1 to 4
Soil boron		Quantitative	ppm	0.2 to 1.8
Soil manganese		Quantitative	ppm	16 to 231
Soil iron		Quantitative	ppm	80 to 262
Soil copper		Quantitative	Ppm	0.6 to 3.4
Management				
Sowing date		Quantitative	days	October 10th to December 1st
Maturity group		Qualitative	000 to X	III_L, IV_M, IV_L
Row spacing		Quantitative	m	0.35, 0.38, 0.42, 0.52
Fertilization with P		Qualitative	Yes/No	

Table 2. Akaike's Information Criterion (AIC) for mixed effects models of the potential effect of management and environmental variables on grain yield in soybean. The table describes the best 10 models (A to J; from a total of 830 possible models) plus the model without fixed effects (null model). Each column represents a different predictor variable. Uncross cells indicate variables that were not included in a particular model. AIC measures the relative goodness of fit of a given model and the ΔAIC column indicates the difference between a model's AIC and that of the best-fitting model. The ω column express the probability of being the best model among all possible models. R^2_m represents the variance explained by fixed factors, while R^2_c represents the variance explained by the entire model. RI represents de relative importance of each predictor. J stands for January and M for March. See materials and methods section for further details.

Model	Management variables			Environmental variables								Model statistics				
	Sowing date	Maturity group	Sowing date x maturity group	Soil type	Water table	Rainfall J-M	Soil type x water table	Rainfall J-M x water table	Ca	P	pH	AIC	ΔAIC	ω	R^2_m	R^2_c
A	+			+	+	+	+	+				510.8	0.0	0.25	0.36	0.92
B	+			+	+	+	+	+		+		512.3	1.5	0.12	0.35	0.92
C	+			+	+	+	+	+	+			512.6	1.8	0.10	0.36	0.92
D	+			+	+	+	+	+			+	513.0	2.1	0.09	0.36	0.92
E	+			+	+	+	+	+	+	+		514.1	3.3	0.05	0.36	0.92
F	+	+		+	+	+	+	+				514.4	3.6	0.04	0.35	0.92
G	+			+	+	+	+	+		+	+	514.5	3.7	0.04	0.35	0.92
H	+			+	+	+	+	+	+		+	514.8	4.0	0.03	0.36	0.92
I				+	+	+	+	+				515.2	4.3	0.03	0.32	0.92
J	+	+		+	+	+	+	+		+		516.0	5.1	0.02	0.35	0.92
Null												610.6	99.8	0.00	-	0.86
RI	*100*	*6*	*0*	*100*	*100*	*100*	*100*	*100*	*22*	*3*	*18*					

(%)	0

Table 3. Variance components (VC), for all random effects, proportional change in variance (PCV), and variance inflation factor (VIF) for the model without fixed effects and the final model at z-scores and non-standardized.

Random effects	Model without fixed effects (z-scores)	Final model (z-scores)	Model without fixed effects	Final model
Site (S)	0.91468	0.66877	1,039,527	760,051
Genotype (G)	0.03549	0.03331	40,339	37,856
Block (B)	0.07065	0.07063	80,304	80,284
Residual	0.16458	0.11160	187,038	126,835
PCV_S	-	27 %	-	27 %
PCV_G	-	6 %	-	6 %
PCV_B	-	0 %	-	0 %
$PCV_{Residual}$	-	32 %	-	32 %
VIFs		< 4.0		< 4.0

Table 4. Mixed-effects model estimates with their standard errors (SE) of the influences of environmental and management predictors on grain yield and their units. WT stands for water table, J for January and M for March. β_1 and β_2, describe parameters of a second-order polynomial function fitted to yield and each predictor. The estimated base model included Argiudoll as soil type, and absence of water table.

Fixed effects			Final model (z-scores)	Final model	Units
Intercept			-0.03 ± 0.47	4120 ± 1193	kg ha^{-1}
Sowing date	β_1		-0.34 ± 0.12	-8.81 ± 53.56	kg ha^{-1} day^{-1}
	β_2		-0.03 ± 0.07	-0.33 ± 0.74	
Rainfall J to M	β_1	with no WT	0.70 ± 0.16	7.41 ± 7.59	kg ha^{-1} mm^{-1}
	β_2	with no WT	-0.05 ± 0.20	-0.003 ± 0.01	
Rainfall J to M x water table	β_1	with WT	0.11 ± 0.20	-1.27 ± 8.33	kg ha^{-1} mm^{-1}
	β_2	with WT	0.06 ± 0.20	0.004 ± 0.01	

Water table	for Argiudoll	0.26 ± 0.54	276 ± 1022	kg ha^{-1}
Water table x soil type	for Hapludoll	1.34 ± 0.46	1708 ± 487	kg ha^{-1}
Soil type	for Hapludoll	-1.42 ± 0.31	-1515 ± 333	kg ha^{-1}

Table 5. List of tested commercial genotypes, their maturity group, cycle length, and yield effect. Maturity group III_L refers to III long, IV_M refers to IV medium, and IV_L refers to IV long.

Genotype	Maturity group	Cycle differences to R7	Yield difference over mean
		days	kg ha^{-1}
DM40R16	III_L	0	75
DM4612	IV_M	4	-183
DM46R18	IV_M	4	231
DM50i17	IV_L	8	-123