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Environmental and management variables explain soybean yield gap variability in Central Argentina

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ABSTRACT

Assessing yield gap (Yg) is required to identify opportunities for future yield increases. Central Argentina is one of the most productive soybean regions in the world. In this region, soybean is planted after a winter fallow period (from now on soybean as single crop) or after the harvest of a winter crop (from now on soybean as second crop). Information regarding options for obtaining even higher yields is limited. The objectives of this paper are: i) to estimate Yg of soybean as single or second crop, ii) to identify management and environmental variables associated with soybean Yg variability, and iii) to assess the spatial distribution of soybean Yg. A farmers' survey with ~22,500 field observations from 2003 to 2015 was compiled. Water-limited yield potential (Ywlim) was estimated as the 95th percentile of actual farmers' yield (Ya) across years. Yield gap was the difference between Ywlim and Ya, expressed as a percentage of Ywlim. Factors associated with Yg were evaluated using regression trees. Ordinary kriging was used to explore spatial patterns of Yg. Average Ywlim were 5095 and 4337 kg ha^{-1} for single and second crop, respectively. Average Yg were 28.7 and 33.5% for single and second crop, respectively. Yield gap showed a wide range of variation. Management accounted for 66 and 91% of explained variation in Yg for single and second crop, respectively. Gap closing for single crop was associated with earlier planting and maize as previous crop. Gap closing for second crop was associated with foliar fungicide utilization, P fertilization, and earlier planting. Single crop Yg was spatially auto-correlated, whereas no auto-correlation was observed for second crop. The spatial structure of single crop was represented by an exponential model, with 81% of total variation explained by the spatial structure and a maximum range of auto-correlation of approximately 120 km. This result is consistent with the observed spatial auto-correlation of variables explaining Yg in single crop. Our approximation allowed the characterization of the magnitude, possible explaining factors, and spatial dependence of soybean Yg in one of the most productive regions in the world. Although average gaps are relatively small compared to those in other regions, there are still opportunities for future yield improvements.

1. Introduction

The increase in global crop production will play a crucial role to satisfy food demand in coming years (Godfray et al., 2010). Attaining this goal requires increasing yield per unit land area given that new farming land is currently lacking (Foley et al., 2011). One alternative for increasing yield is closing yield gaps (Yg) at the farm level. Estimating Yg at farm level requires comparing actual farmers' yield (Ya) to some measure of potential yield (or water-limited yield potential in rainfed cropping systems, Ywlim) (Van Ittersum et al., 2013). Potential yield can be estimated by crop models, maximum-yield field experiments, or maximum farmers' yields. These three measures of potential yield, when compared to Ya, allow the calculation of model-based Yg, experiment-based Yg, and farmer-based Yg, respectively (Lobell et al., 2009). Even though model-based Yg analysis is the standard approximation (Van Ittersum et al., 2013; Van Wart et al., 2013a), farmer-

Abbreviations: Ya, actual farmers' yield; Ywlim, water-limited yield potential; Yg, yield gap

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based analysis has been also widely used for global or regional analysis of different field crops (i.e. Licker et al., 2010; Egli and Hatfield, 2014a,b; Tanaka et al., 2015; Ernst et al., 2016). Our general objective was to assess farmer-based Yg for soybean production. According to Lobell et al. (2009) farmer-based Yg analysis is only appropriate in intensively managed cropping systems and when analyzing many fields, in order to increase the chances of attaining at least one field with yield close to potential. We focused our analysis on ~22,500 field observations from a subgroup of farmers with high level of technology adoption from the Central region of Argentina. The estimation of farmer-based Yg provides an important measure of opportunities to improve crop production under current cropping systems technology.

Yield gap analysis can help to identify regions or production systems where highest priority should be given to successfully increase crop productivity (van Oort et al., 2017). The possibilities of increasing yield are highest in situations where Yg is large enough (> 20%) (Lobell et al., 2009). Bhatia et al. (2008) showed model-based soybean Yg of 54% for farmers in India. Zhang et al. (2016) found model-based Yg of 16% in soybean across years with different levels of water supply in China. Egli and Hatfield (2014a) found that average soybean farmer-based Yg ranged from 9 to 24% across three states in the U.S. Midwest across a 40-yr period. Grassini et al. (2015a) and Rattalino Edreira et al. (2017) showed that model-based combined with farmer-based Yg estimations of soybean producers in U.S. were 32 and 22% under rainfed conditions, respectively. Sentelhas et al. (2015) found that average soybean model-based Yg was 13% in rainfed systems of Brazil. Aramburu Merlos et al. (2015), using Global Yield Gap Atlas approach (www.yieldgap.org), represented the first attempt to evaluate soybean Yg in Central Argentina and found an average of 25% model-based Yg under rainfed conditions. However, information regarding potential causes (management or environmental factors) of Yg variation and spatial distribution within Central Argentina are scarce. Yield gap analysis has recently been expanded to double cropping systems to identify possibilities of yield improvement or design new farming systems (Guilpart et al., 2017). However, information regarding environmental causes of Yg of soybean as second crop after the harvest of a winter crop in Argentina is currently limited (Andrade and Satorre, 2015).

Identifying management and environmental variables associated with Yg is critical for decision-making regarding Yg closure. Different techniques can be utilized to this end. Regression trees have been used to explore explanatory variables of wheat Yg (Ernst et al., 2016). However, regression tree approach has been successfully utilized to identify variables associated with yield of different crops. For instance, they were utilized to explore factors associated to yield variability in wheat (Lobell et al., 2005), maize (Tittonell et al., 2008), rice (Tanaka et al., 2015), sugarcane (Ferraro et al., 2009) and soybean (Mourtzinis et al., 2018; Zheng et al., 2009). This approach has several advantages for being used to analyze field surveys at regional scale (De'Ath and Fabricius, 2000). Briefly, regression trees are easy to interpret, variable selection is unbiased, non-linear relationships between variables can be unraveled, and there are no distributional assumptions of the response variable. Additionally, the trees handle both categorical and continuous variables and allow missing data. Therefore, a regression tree approach will be utilized to explore management and environmental explaining factors of soybean Yg across ~22,500 field observations in Central Argentina.

Yield gap analysis could be conducted under different spatial scales (Sadras et al., 2015). Previous studies focused on methodologies to scale up location-specific Yg estimations to larger spatial areas (van Bussel et al., 2015; Van Wart et al., 2013a,b). This protocol, based on determining homogeneous areas with respect to environmental conditions, was used in Yg analysis in Argentina (Aramburu Merlos et al., 2015). An interesting alternative is to incorporate a geostatistical approach at more detailed spatial scales (e.g. farms or paddocks) to improve the spatial resolution and accuracy of regional Yg analysis (Lobell and Ortiz-Monasterio, 2006; Steinbuch et al., 2016). Therefore, we propose this alternative method to identify spatial patterns in Yg magnitude through geostatistical techniques. Mapping this variability can help the development of spatially specific agronomic strategies aimed at closing Yg for specific areas as was shown for maize in Bangladesh (Schulthess et al., 2013) and Africa (Van Dijk et al., 2012).

There is a clear need to synthesize crop yield, climate, soil and management data from different areas to identify crop production limitations (Lobell and Asner, 2003). Yield gap analysis using farmers' survey constitutes an opportunity to achieve this objective (Beza et al., 2017). Local studies are needed to understand and dissect the role of agricultural system characteristics and biophysical conditions in closing Yg (Rattalino Edreira et al., 2017). In this context, we used field observations across the main soybean production area of Central Argentina to accomplish the following objectives: i) estimate soybean Yg, ii) identify environmental and management variables associated with soybean Yg; and iii) explore spatial distribution of soybean Yg across Central Argentina.

2. Materials and methods

2.1. Study area and farmers' survey description

The study area is part of Central Argentina, and soybean is the main crop in this area. Soybean can be planted after a fall/winter fallow period (April–September) with the previous crop being another summer crop (e.g. soybean or maize) that grew during the previous warm growing season (September–April). Therefore, soybean is planted after a fall/winter fallow period which begins after previous summer crop harvest. Usual planting dates range from October to mid-December. This soybean crop is referred as "single crop". Alternatively, soybean can be planted after a winter grain crop is harvested or after a cold-season grass crop is dried with herbicide or used directly as animal feed. The most common winter grain crop in this region is wheat (*Triticum aestivum* L.), while the cold-season grass crop can also be wheat (terminated before full maturity) or rye-grass (*Lolium multiflorum*). Winter crops for grain are usually harvested in late November to December, while grass crops are dried/fed earlier. Soybeans are therefore planted from early December to mid-January. This soybean crop is referred as "second crop".

The study area has a monsoonal climate with rainfall concentrated in the summer season (December-February) (Hall et al., 1992). There is substantial interannual rainfall variability associated with the El Niño Southern Oscillation phenomenon (Podestá et al., 1999). Soils are predominantly Mollisolls (USDA, 1975) having no major physical or chemical limitations.

Farmers' surveys under analysis were provided by farmers' members of Southern Santa Fe Region of Argentine Association of Regional Consortiums for Agricultural Experimentation (AACREA). Soybean yield and management data were compiled from 2003 to 2015. Post-2003 data were entirely based on no-till conditions and herbicide-resistant GMO soybean production. The widespread and rapid adoption of a no-till management strategy and Roundup Ready® soybean germplasm (Monsanto Company, St. Louis, MO) represent major changes in production technology (Satorre, 2011). The timeframe analyzed ensured that approximately the same overall technology was used to avoid abrupt productive leaps across years, while also allowed the construction of a sufficient large climatic data set. Each observational unit corresponded to a specific field in a particular year. All fields were managed with available farmer technology under no-till and rainfed conditions. Separate farmers' surveys were maintained for single (n = 15,522) and second soybean crops (n = 7,112).

Management variables extracted from farmers' surveys were: previous crop, sowing date, row spacing, plant population, maturity group, nutrient rate applied by fertilization, and fungicide and insecticide use (Table 1). Each observation was georeferenced using the closest

Table 1
Characterization of soybean crop (as single or second crop) of Central Argentina according to management variables. Management data corresponds to farmer members of Southern Santa Fe Region of Argentine Association of Regional Consortiums for Agricultural Experimentation (AACREA).

Variable	Type	Units	Explored range	
			Single crop	Second crop
Previous crop	Qualitative		maize, soybean, sorghum, sunflower, peanut, summer grass.	wheat, barley, rape, pea, oats, chickpea, winter grass.
Sowing date	Quantitative	date	October 1st–January 1st	November 1st–January 1st
Row spacing	Quantitative	m	0.17–0.70	0.17–0.52
Plant population	Quantitative	pl m^{-2}	17–76	14–100
Maturity group	Qualitative	000 to X	II–VIII	II–VIII
Rates of N applied	Quantitative	kg ha^{-1}	0–32	0–32
Rates of P applied	Quantitative	kg ha^{-1}	0–59	0–70
Rates of S applied	Quantitative	kg ha^{-1}	0–33	0–33
Rates of Zn applied	Quantitative	kg ha^{-1}	0–38	0–38
Rates of Ca applied	Quantitative	kg ha^{-1}	0–30	0–30
Use of fungicide	Qualitative	Yes/No		
Use of insecticide	Qualitative	Yes/No		

Table 2
Location and environment characterization of the study area within Central Argentina. Location, soil type and water table presence data were provided by farmers' members of Southern Santa Fe Region of Argentine Association of Regional Consortiums for Agricultural Experimentation (AACREA). Climatic data was estimated using national public statistics. For more details about climatic variables estimation please see Material and methods.

Variable	Type	Units	Explored range
Latitude	Quantitative	Degrees	−33.4 to −27.7
Longitude	Quantitative	Degrees	−65.3 to −62.8
Soil type[a]	Qualitative	Soil taxonomy classification	Argialbolls, Hapludolls, Natralbolls, Alfisolls.
Water table presence	Qualitative	Yes/No	
Accumulated rainfall	Quantitative	mm	
October			2–334
November			0–294
December			3–406
January			8–312
February			0–390
March			0–524
Accumulated radiation[b]	Quantitative	MJ m^{-2}	
October			396–766
November			512–838
December			582–882
January			376–872
February			324–923
March			350–665
Mean air Temperature[b]	Quantitative	°C	
October			13–26
November			18–29
December			20–32
January			21–33
February			18–33
March			11–30

[a] Soil type is according to Soil Taxonomy Classification (USDA, 1975).
[b] Estimations for second crop were from the December – March period.

location and characterized according to environmental variables. Environmental variables considered were soil type according to the Soil Taxonomy criterion (USDA, 1975), topographic elevation, water table presence, monthly accumulated rainfall and radiation, and monthly mean temperature. Regarding the climatic variables, the inclusion of more variables could have added too much complexity to the interpretation of the results. Also, we chose climate variables that are most commonly available from standard weather stations, easily available to growers, and relevant to crop yield determination. For example, maximum and minimum air temperature could have been also included in the analysis. However, these variables can be considered redundant due to show a high degree of collinearity. In this sense, we summarized their effects using mean air temperature. Soil type and water table presence were obtained from farmers' surveys. Climatic variables were estimated according to the geographic location of each observation using public data (Grassini et al., 2015b). Monthly accumulated rainfall and radiation, and monthly mean temperature were derived from nearby public weather stations of National Institute of Agricultural Technology of Argentina (http://inta.gob.ar) (Aramburu Merlos et al., 2015; Verón et al., 2015). In cases of missing radiation records, they were derived from the Prediction of Worldwide Energy Resource dataset from the National Aeronautics and Space Administration (http://power.larc.nasa.gov). Recent papers showed a good agreement between satellite and measured radiation data (Aramburu Merlos et al., 2015; Bai et al., 2010; White et al., 2011). For soybean as single crop, all climatic variables were estimated for the period of October to March. For soybeans as second crop, rainfall was estimated for the period of October to March, and radiation and temperature were estimated for December to March. Ranges of climatic variables are shown in Table 2.

2.2. Actual yield, water-limited yield potential, and yield gap estimation

Actual farmers' yield corresponds to soybean seed yield (kg ha^{-1}) of each field for a given year and location expressed at 13.5% moisture. Water-limited yield potential was estimated by fitting a quantile linear regression for the 95th percentile to Ya across years (Egli and Hatfield, 2014a,b). Using this estimation method, rather than selecting the 95th percentile of highest yielding field, is required to de-trend observed yield data from the expected yield increase observed during the analyzed period (de Felipe et al., 2016). The linear model was fitted using the *quantreg* package in the R environment (Koenker, 2013). We were interested in quantify Yg magnitude of each type of soybean crop. Therefore, separately for soybeans as single and second crop, Yg was calculated as the difference between Ywlim and Ya, expressed as the percentage of Ywlim.

2.3. Management and environmental variables explaining soybean Yg variability

Regression tree analysis was performed to explore possible management/environmental associations with Yg. Regression trees were constructed using JMP software (version 13.1.0, SAS Institute Inc., Chicago, IL, USA). Briefly, regression trees explain variation of a dependent variable (i.e. Yg) by repeatedly splitting the data into more homogeneous groups, using combinations of explanatory variables (e.g. sowing date and soil type, among others). The algorithm defines a threshold value of the explanatory variable that splits data into groups showing homogeneity within them. Each optimal split should maximize the LogWorth statistic. This is a measurement of statistical significance defined as $-\log10$ (p-value). Five hundred observations were established as the minimum population of each terminal node.

2.4. Yield gap spatial pattern analysis

The spatial pattern of Yg for single and second crop was assessed for those locations having at least five years of Yg estimates. This subsetting constrained the spatial analysis to a sub-region with highest density of data. Location geographical coordinates were projected to planar coordinates using UTM zone H20. A random field approach for a continuous variable in a continuous R^2 space was adopted to describe the spatial patterns of Yg (Goovaerts, 1997). The spatial trend of Yg at large scale across space was explored by fitting smooth non-parametrical regressions between the Yg and both planar spatial coordinates and topographic elevation of each site. Distributional and random field assumptions (stationarity and continuity) of Yg were also explored. The auto-correlation of Yg (residual in case a significant trend is detected) was assessed by building a direct omnidirectional variogram. The variogram was explored at a maximum extent of 220 km (i.e. less than one third of the diagonal of the bounding box of sampled area), and a spatial resolution of 14 km that guarantee at least 30 paired observations for each lag-distance class. The sample semi-variance at each lag-distance was estimated according to the robust method proposed by Cressie and Hawkins (1980) (Eq. (1)).

$$2\gamma_{CH}(h) = \frac{1}{C_h}\left[\left(\frac{1}{N_h}\sum_{1}^{N(h)} \quad |Z_{xi} - Z_{xj}|^{\frac{1}{2}}\right)^4\right] \tag{1}$$

where γ(h) represents the semi-variance calculated for a specific spatial lag-distance class h, and Z represents the random variable at different locations. In this case, the estimated Yg at sites X_i and X_j, N_h is the number of all pairs of sites separated by distance class h, and C_h is a correction factor for bias in the Z variable calculated as Eq. (2).

$$C_h = 0.457 + \frac{0.494}{N_h} + \frac{0.494}{N_h^2} \tag{2}$$

For each soybean crop, different models (i.e. exponential, spherical and Gaussian) were fitted by the weighted least squares method and selected according to the residual sum of squares after obtaining the two empirical omnidirectional direct variograms. Then, using the regionalized spatial model (trend + auto-correlation) characterizing the particular spatial structure of each crop, we used ordinary kriging interpolation to predict Yg in a new grid finer than the original (∼2/3 finer than the spatial resolution employed in the original sampling). To build the predicted map of Yg for each soybean crop, we focused on the same sub-region with high density of data to avoid zones without near data. To manipulate spatial objects, the *sp* (Bivand et al., 2013) and *rgdal* packages (Bivand et al., 2016) were used in the R environment. To calculate the empirical semivariograms, fit the models, and apply the interpolation techniques, the *gstat* R package was used (Pebesma, 2004).

Table 3
Summary statistics related to soybean actual farmers' yield, water-limited yield potential and yield gap from soybean crops (as single or second crop) of Central Argentina during 2003–2015.

	95^{pth}	75^{pth}	Median	25^{pth}	5^{pth}	Average
Actual farmers' yield (kg ha^{-1})						
Single crop	5156	4421	3786	2979	1625	3635
Second crop	4430	3692	3010	2262	1141	2941
Water-limited yield potential (kg ha^{-1})						
Single crop	5306	5252	5089	4980	4816	5095
Second crop	4611	4544	4343	4141	4007	4337
Yield gap (%)						
Single crop	68.0	41.4	25.7	13.4	0.0	28.7
Second crop	78.0	48.5	30.6	15.6	0.0	33.5

3. Results

3.1. Actual yield, water-limited yield potential, and yield gap

Average Ya of soybean single crop was 3635 kg ha^{-1}, and ranged from 1625 to 5156 kg ha^{-1} (Table 3). Average Ya of second crop was 2941 kg ha^{-1}, ranging from 1141 to 4430 kg ha^{-1} (Table 3).

Water-limited yield potential differed between soybean as single and second crop. Single crop Ywlim ranged from 4816 to 5306 kg ha^{-1} (Table 3), with a linear increase of 54 kg ha^{-1} yr^{-1} for the period under analysis ($p < 0.001$, data not shown). Second crop Ywlim ranged from 4007 to 4611 kg ha^{-1} across years, showing a linear increase of 67 kg ha^{-1} yr^{-1} ($p < 0.001$, data not shown) (Table 3).

Average soybean Yg was 28.7 and 33.5% for single and second crop, respectively (Table 3). Yield gaps ranged from 0 to 68% and from 0 to 78%, respectively (Table 3).

3.2. Management and environmental variables explaining soybean yield gap variability

3.2.1. Soybean as single crop

The final regression tree for soybean as single crop explained 25.8% of the total variation in observed Yg (Supplementary Table 1; Fig. 1). Management variables accounted for 66% of the explained variation while environmental-location variables accounted for the remaining 34% (Table 4). There were 20 terminal nodes, with average Yg at terminal nodes ranging from 11 to 52% (Fig. 1).

Sowing date was the primary splitting node ($p < 0.001$; Fig. 1) and explained approximately 50% of explainable Yg variation (Table 4). Average Yg was 25.6% and 42.5% for sowing dates previous and after the 25th of November, respectively. Previous crop explained 6.2% of explainable Yg variation in single crop soybean (Table 4); Yg was 8.1% lower in fields having maize as previous crop compared to other crops ($p < 0.001$; Fig. 1). Phosphorus and Zn fertilization also decreased Yg

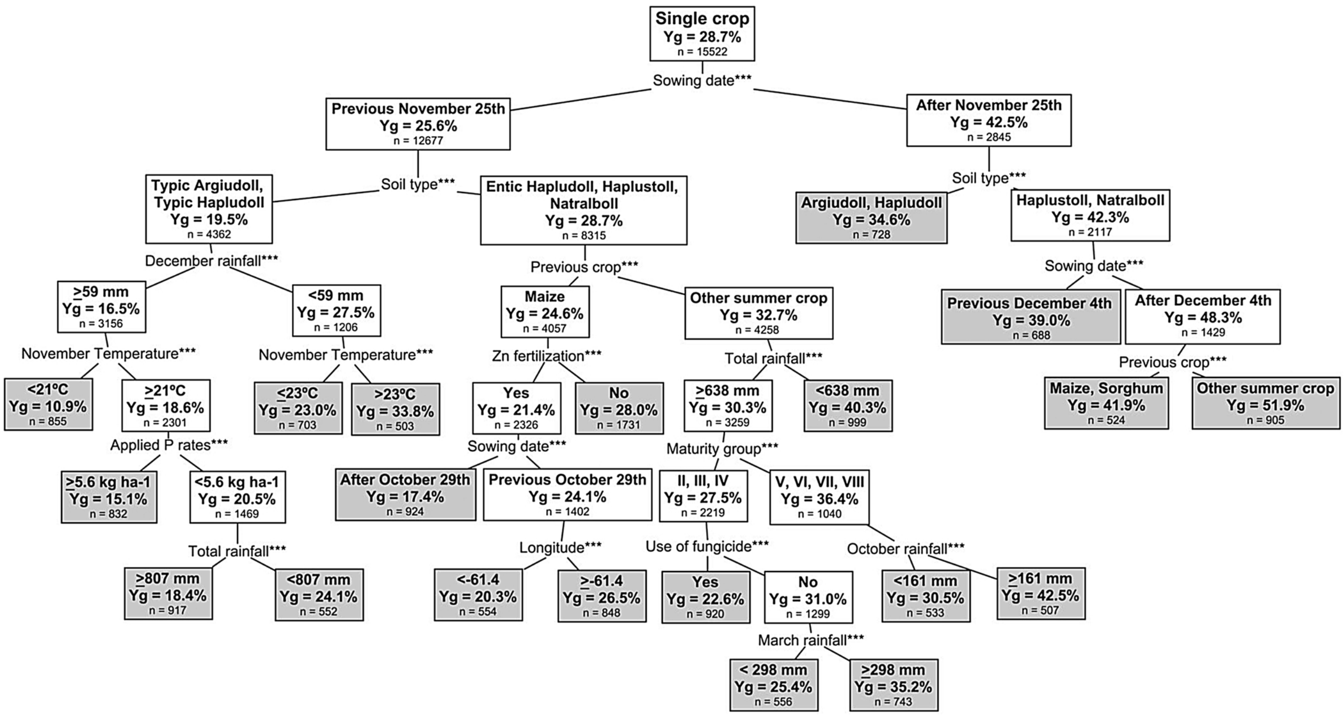

Fig. 1. Regression tree model for single crop soybean yield gap (Yg) in Central Argentina. Yield gap is expressed as percentage of water-limited yield potential. *** $p < 0.001$. p-values were estimated using the LogWorth statistic. Terminal nodes are represented as gray boxes.

Table 4
Relative soybean yield gap variability (%) explained by management/environmental variables using regression trees. Relative variability is referred to the total variability explained by the model for each crop. Overall, regression trees explained 25.8 and 30.7% of total variation in yield gaps for soybeans as single and second crop, respectively.

Variable	Single crop % explained variation	Second crop % explained variation
Sowing date	49.6	14.0
Previous crop	6.2	6.9
Fertilization	3.9	18.2
Maturity group	3.5	0.0
Use of fungicide	2.3	51.8
Σ Management	65.5	90.9
Rainfall	12.4	4.9
Temperature	3.9	0.0
Longitude	0.8	4.2
Soil type	17.4	0.0
Σ Environment – Location	34.5	9.1

compared to cases with no fertilization ($p < 0.001$; Fig. 1). Maturity group and fungicide application accounted for 5.8% of explainable Yg variation in single crop soybean (Table 4). Maturity groups II–IV showed lower Yg than V–VIII (27.5 and 36.4% respectively; $p < 0.001$; Fig. 1). However, early maturity groups showed Yg decreases associated with fungicide application ($p < 0.001$; Fig. 1).

Among environmental variables, soil type was the most important factor both in early and late planting date ($p < 0.001$; Fig. 1), explaining 17.4% of explainable Yg variation (Table 4). Rainfall and air temperature accounted for 16.3% of explainable Yg variation for the single crop soybean (Table 4). Generally, Yg decrease was observed under environments with better water supply and cooler temperatures ($p < 0.001$; Fig. 1).

3.2.2. Soybean as second crop

The final regression tree for second crop soybeans explained 30.7% of the total variation in observed Yg (Supplementary Table 1; Fig. 2). Of the explained variation, environmental variables had lower importance than management variables in explaining Yg variation for the second crop soybean (Table 4). There were 10 terminal nodes, with average Yg at terminal nodes ranging from 14 to 62% (Fig. 2).

Fungicide application was the primary splitting node. Average Yg was 27.9 and 50.1% for applied vs. not applied fungicide cases, respectively ($p < 0.001$; Fig. 2). In cases that fungicides were not applied, P fertilization had a significant role in reducing Yg from 61.9 to 39.3% for non-fertilized and fertilized cases, respectively ($p < 0.001$; Fig. 2). Fields having fungicide application showed Yg variation associated with sowing date and previous crop ($p < 0.001$). Low Yg was observed when soybean was sown prior to December 7th and after the harvest of a winter crop (e.g. wheat and barley for grain) compared to a winter grass for pasture or as cover crop ($p < 0.001$; Fig. 2). Accumulated rainfall during December accounted for 4.9% of explainable Yg variation in second crop (Table 4). Yield gap reductions were associated with increases in December rainfall greater than 138 mm ($p < 0.001$; Fig. 2).

3.3. Yield gap spatial analysis across Central Argentina

In both types of soybean crops, we were unable to detect any significant spatial trend for the mean Yg across latitude, longitude, and/or topographic elevation in the studied region. The sampled variogram indicates a strong spatial Yg auto-correlation for the single soybean crop (Fig. 3A). However, there was no spatial auto-correlation in the Yg of the second crop (Fig. 3B). The spatial structure of single crop soybean was well represented by an exponential model with 81% of total variation explained by the spatial structure (nugget = 34.48 and sill = 181.63) and a maximum range of auto-correlation of ~120 km (Fig. 3A). The error for the fitted model was very low (RSS < 0.001). The spatial variation of Yg for the single crop soybean was predicted using ordinary kriging since there were no significant models for mean response (trend). The predicted map indicates zones with low Yg (< 20%) and well-defined zones with large Yg (> 40%; Fig. 4A). In

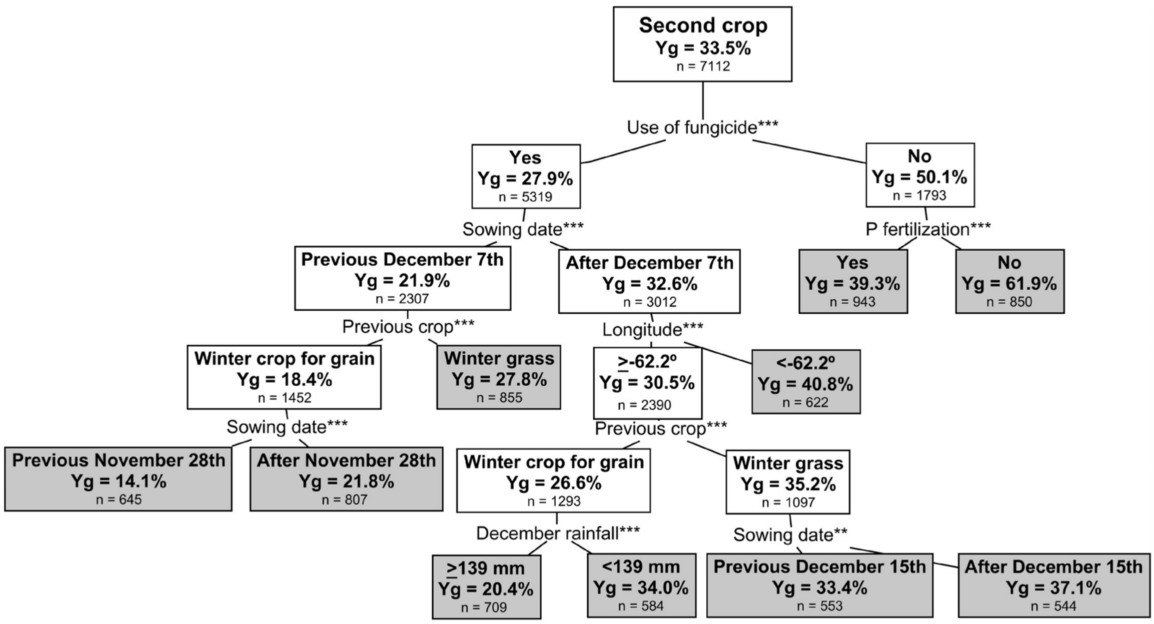

Fig. 2. Regression tree model for second crop soybean yield gap (Yg) in Central Argentina. Yield gap is expressed as percentage of water-limited yield potential. *** $p < 0.001$; ** $p < 0.01$. p-values were estimated using the LogWorth statistic. Terminal nodes are represented as gray boxes.

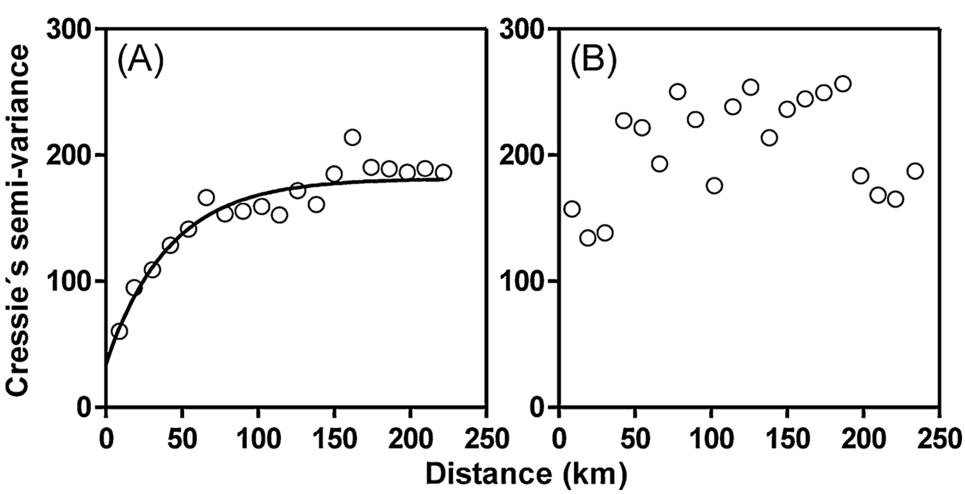

Fig. 3. Sample omnidirectional and direct variograms of yield gaps for soybeans as single (A) or as second (B) crop to describe the local spatial auto-correlation. Gamma was estimated by the robust method proposed by Cressie-Hawkings. In panel “A”, the continuous line represents the fitted exponential model (nugget = 34.48, sill = 181.62 and range = 120 km; RSS = 0.00008).

addition, due to the high density of points within the predicted area, the estimated standard error by ordinary kriging was very low near the observed points (< 7%), and it was also relatively low even in areas with lower observed points density (12–14%; Fig. 4B).

4. Discussion

Our approximation using field observations enabled a realistic and parsimonious characterization of the magnitude, possible determinants, and spatial dependence of soybean Yg in one of the most productive regions in the world. Soybean Yg was close to 30% of Ywlim but ranged from 0 to 68% and from 0 to 78% for soybean as single or second crop, respectively. The Yg magnitude estimated using our farmers' survey and approximation was similar to other reports for the region. Using a crop modeling approach, Aramburu Merlos et al. (2015) estimated soybean Yg close to 25% for this region. Our estimate of 33.5% Yg for second crop soybeans did not differ from the previously reported in this region for this type of soybean crop (Andrade and Satorre, 2015). The relative importance of management and environmental factors determining Yg were different when comparing single vs. second crop soybeans. This difference probably accounts for the contrasting spatial distribution of Yg between single and second crops in Central Argentina. Our study expands on previous knowledge identifying environmental conditions and, more importantly, agronomic management variables associated with soybean Yg variation. This information is critical for farmer's decision-making to reduce Yg.

Optimizing agronomic management could reduce Yg for both single and second crops. However, the relative importance of agronomic management variables in explaining variation in Yg was lower for single compared to second crops, at 66.5% vs. 90.8% of explained variation, respectively. Earlier planting date was associated with reduced Yg in single crop soybeans. This relationship was also described in previous analyses in the United States (Grassini et al., 2015a; Rattalino Edreira et al., 2017) and Brazil (Zanon et al., 2016). Previous crop was the second most important management factor responsible for variation in Yg for single crop soybeans; fields including maize as previous crop showed reduced Yg. This result reinforces the importance of maize rotation for soybean productivity as reported in previous studies (Marburger et al., 2016; Mourtzinis et al., 2017; Seifert et al., 2017). For soybeans as second crop, fungicide application was the most important management factor associated with Yg variation. Therefore, a yield-protective action became relevant due to effects on Ya (Bluck

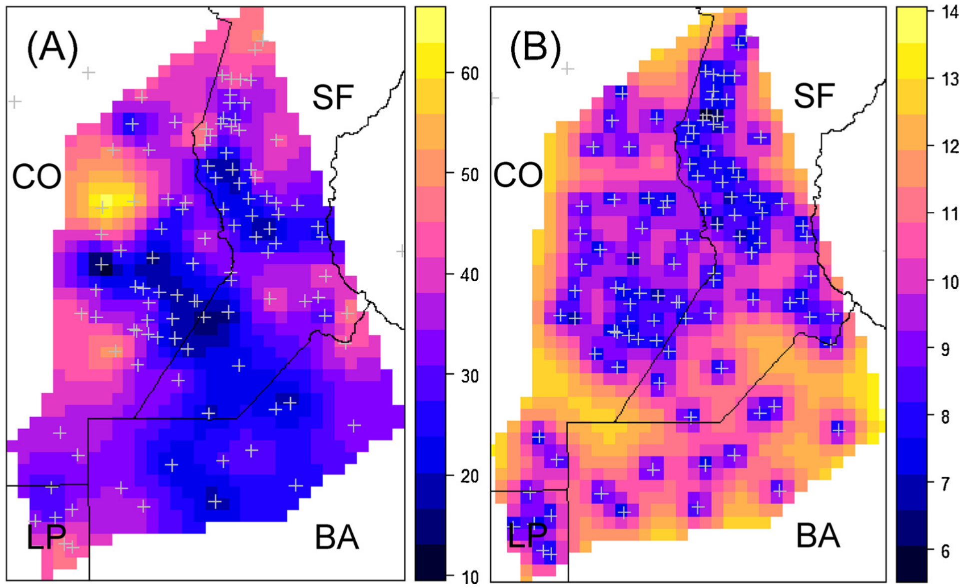

Fig. 4. Interpolated map of yield gap (expressed as percentage of water-limited yield potential) for single crop soybean by ordinary kriging (A) and its associated standard prediction error (B) in the highest-productivity soybean region in Central Argentina. Different codes represent the Argentinean provinces, BA: Buenos Aires; CO: Córdoba; SF: Santa Fe and LP: La Pampa.

et al., 2015; Villamil et al., 2012). Phosphorus fertilization was associated with reduced Yg in fields where fungicides were not applied. This trend was consistent with Ya increases observed in studies conducted in Argentina (Calviño and Sadras, 1999) and the U.S. (Grassini et al., 2015a) in association with fertilization management.

Our results also contribute to unraveling the main environmental factors determining Yg. Soil type was the main factor associated with soybean single crop Yg. Reduced Yg was observed in fields with favorable soil types like Argiudolls and Hapludolls soils (USDA, 1975) compared to fields having other soil types. Similar results were observed in Yg analysis conducted in irrigated maize systems of the U.S., where reduced Yg was associated with favorable soil types (Farmaha et al., 2015). Despite this general trend, previous studies indicate that soil properties can affect crop Ya and thus Yg magnitude. For example, Bacigaluppo et al. (2011) showed that organic matter content and saturated hydraulic conductivity affect Ya in Argiudoll soils of Central Argentina. Therefore, soil properties recorded *in situ* could contribute to the fine-tuning of predictive models quantifying Yg in single crop soybean. For these systems, a cooler November was also associated with reduced Yg on the most productive soil types and when having the earliest planting dates in the season. This might be associated with favorable conditions during crop development. As expected under rainfed systems, rainfall was associated with reduced Yg for both single and second crops. In contrast, more rainfall in March was associated with increased Yg in single crop soybean. This month coincides with harvest maturity of soybeans in single crop. Therefore, Yg increases might be attributed to harvest diseases due to water excess in harvest season (Penalba et al., 2009).

Local spatial auto-correlation was remarkably different between both soybeans as single and second crop. There was a significant spatial correlation structure explaining approximately 80% of Yg variation at distances no farther than 120 km for single crop soybeans, while there was no significant spatial auto-correlation for second crop. The main putative environmental reason for this zonal or local patchiness in Yg is local edaphic conditions. Using soil data available for this region (Cruzate et al., 2012), soil type showed a spatial range of variation similar to that observed for Yg in the single crop soybean. The lack of spatial auto-correlation for soybean as second crop has two potential explanations suggested from the data. First, the number of fields sampled was lesser compared to that for the single crop. Although the spatial sampling coverage was very similar between both soybean crops, the number of second crop fields sampled was notably lower than that for single crop. In fact, the bounding box or spatial surveyed area was practically the same in both crops. Second, the absence of autocorrelation structure in second crop could be related to higher relative importance of management vs. environmental variables associated with Yg variation. Agronomic management does not usually follow a defined spatial pattern, while environmental variables do follow a more defined spatial pattern.

5. Conclusions

Our results showed soybean Yg close to 30% of Ywlim. However, soybean Yg ranged from 0 to 68% and from 0 to 78% for soybean as single or second crop, respectively. There were differences in factors associated to Yg variability between single and second crop types. Single crop Yg variability was associated with both environmental and management variables. In contrast, management variables explained > 90% of Yg variability for the second crop. Therefore, different productive strategies emerge for closing Yg for these two soybean production alternatives. Local spatial auto-correlation was remarkably different between both crops, with a significant spatial correlation structure explaining ~80% of Yg variation at distances no farther than 120 km for the single crop. In contrast, no spatial correlation was found for soybean as second crop. Our approximation using ~22,500 field observations allowed us to characterize the magnitude, possible explaining factors, and spatial dependence of soybean Yg in one of the most productive regions in the world. Although average Yg are relatively small compared to other regions, there are still opportunities for future yield improvements.

Our results can be extrapolated to other rainfed soybean production regions with the appropriate considerations. Particularly, three aspects of our research justify its applicability to other regions and contexts: (i) opportunities of yield improvement found in this paper can be adopted for other rainfed soybean production regions and/or farming systems with comparable technology adoption; (ii) interaction between management and environment explored in our research may help to generate new hypotheses regarding potential causes of soybean Yg in other production regions; and (iii) our approach of utilizing data from, and analyzing at the level of, farmers' fields proves to be a valid method that can be utilized to explore Yg in other crops and that can also be contrasted to the most common method of crop modeling Yg assessment thus far.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.eja.2018.04.012.

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