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Sunflower yield gaps and their causes in Argentina

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ABSTRACT

Context: Quantification of yield gaps and understanding their causes in sunflower (*Helianthus annuus* L.) is a key requirement for developing management strategies to take advantage of the productive potential of this crop in Argentina. The term yield gap (Yg) refers to the difference between water-limited potential yield (Yw) and actual yield (Ya).
Objective: This study quantified sunflower Yg across its full range of cropping regions of Argentina and used the results to identify potential causal factors.
Methods: This study, structured around component climate zones, proceeds in two steps. In the first, Yg is calculated by three methods according different Yw estimators: (i) yield simulations using CROPGRO-Sunflower model; (ii) top yields of comparative yield trials; and (iii) top yields of farmer's paddocks. Corresponding Ya values were estimated from national statistics. In the second, an independent database was established from the *Relevamiento de Tecnología Agrícola Aplicada.* Regression trees were used to explore associations between technological variables and estimated Yg.
Results: National sunflower Yg remained consistent across the different Yw estimation methods: 34 % via simulated yields, 40 % using comparative yield trials, and 34 % based on farmer's paddock yields. Tillage system, phosphorus fertilization, and the adoption of herbicide- resistant and high oleic cultivars were key factors in explaining the smaller sunflower Yg in Argentina.
Conclusions: Argentina has the potential to substantially increase its sunflower grain production, and key factors to increase current production were identified in this work.
Implications: Increased sunflower production could boost Argentina's exports, contributing significantly to its economy. The identified factors pave the way for designing practices that help farmers bridge the yield gap.

1. Introduction

Quantifying yield gaps (Yg) and understanding their causes in sunflower (*Helianthus annuus* L.) crop in Argentina are crucial for developing management strategies to unlock its full potential. Yield gap refers to the difference between water-limited potential yield (Yw) and actual farmer yield (Ya) (van Ittersum and Rabbinge, 1997; Evans and Fischer, 1999).

Sunflower is the fourth most important vegetable oil in the world to which Argentina, as one of the largest producers, contributes 7 % of global production (USDA, 2023; FAOSTAT, 2023). Despite its importance, the extent of sunflower Yg remains uncertain. A previous study by Hall et al. (2013) estimated sunflower Yg at 29 % of Yw for the period 2000–2007. In that assessment, regionalization of the national crop area

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was based on the advice of crop experts, while Yw was estimated from comparative yield trials (CYT).

Estimating Yw from yields of CYT or farmer's paddocks involves percentile analysis to identify top yields (Egli and Hatfield, 2014a, 2014b). This method risks overestimating Yw and Yg, especially in areas with erratic rainfall or variable soils (Shatar and McBratney, 2004; Filippi et al., 2022). Crop simulation models offer a more precise Yw estimation, but require calibration with field data from current cultivars grown without limitations (Grassini et al., 2015).

Understanding Yg causes can help to tune current crop management and, by doing so, increase sunflower production. With Yg estimates and access to crop technology information, a deeper understanding of these factors is possible (Mueller et al., 2012; Di Mauro et al., 2018; Mourtzinis et al., 2018). The *Relevamiento de Tecnología Agrícola Aplicada* from *Bolsa de Cereales de Buenos Aires* (ReTAA, 2023) provides a comprehensive database linking yield levels and technology application across Argentina. The most employed tillage system in the country is 'no-tillage' system but a proportion of the sunflower crop areas remain under 'conventional tillage' system. Tillage system impacts grain yield and fertilization response by influencing water and nutrient availability (Melaj et al., 2003). Sunflower farmers use both high oleic (HO) and conventional-oil (CO) cultivars, which differ in yield and oil quality. Conventional-oil cultivars exhibit higher grain and oil yields compared to HO cultivars (Del Gatto et al., 2015; Gaggioli et al., 2015). Nationwide, nutrient limitations restrict crop yields, with fertilizer application often below requirements (Cruzate and Casas, 2017; Leguizamón et al., 2023). Weeds are a challenge, with limited control options. Clearfield technology offers herbicide resistance for HR cultivars, while non-HR cultivars are susceptible (Tan et al., 2005).

Many management factors contribute to Yg. Regression trees, a statistical technique for linking multiple explanatory variables to a response variable in non-linear ways, have been used to identify Yg causes in farm fields (*e.g.,* Di Mauro et al., 2018; Andrade et al., 2022). This method has no assumptions about data distribution and is suitable for analyzing multi-causal variables like Yg, offering automatic variable selection, interpretable variable interactions, and handling missing data (Hastie et al., 2001; Pichler and Hartig, 2023).

This study is presented into two main sections, both utilizing regionalization from the Global Yield Gap Atlas (GYGA) project (Grassini et al., 2015; van Bussel et al., 2015; http://www.yieldgap.org/methods) based on climatic variables that determine crop growth and development. In the first section, sunflower Yg was quantified and Yw was calculated using three estimators: (i) yield simulations using a sunflower crop model, percentile analysis of (ii) regional CYT network, and (iii) farmer's paddocks. In the second section, an independent crop management database spanning six seasons, obtained after the ReTAA, was employed to explore the association between technological variables and estimated Yg through regression trees.

2. Materials and methods

2.1. Databases

A database for sunflower crop yields was developed, compiling information at various spatial scales and organizational levels: (i) CYT, (ii) farmer's paddocks, and (iii) departmental[1] level. This comprehensive database encompasses crop information from the 2009/10 to the 2015/16 cropping seasons for all climate zones (CZ) (Fig. 1). CYT information was provided by the National Cultivar Evaluation Network INTA-ASAGIR (Red INTA-ASAGIR, 2023) and member seed companies of ASAGIR (Table S1). Cazenave y Asociados, El Tejar, and AACREA (Argentine Association of Regional Agricultural Experimentation Consortia) contributed the information at the paddock yields. Lastly, departmental-level data was sourced through the Ministry of Agriculture, Livestock, and Fisheries (MAGyP, 2023).

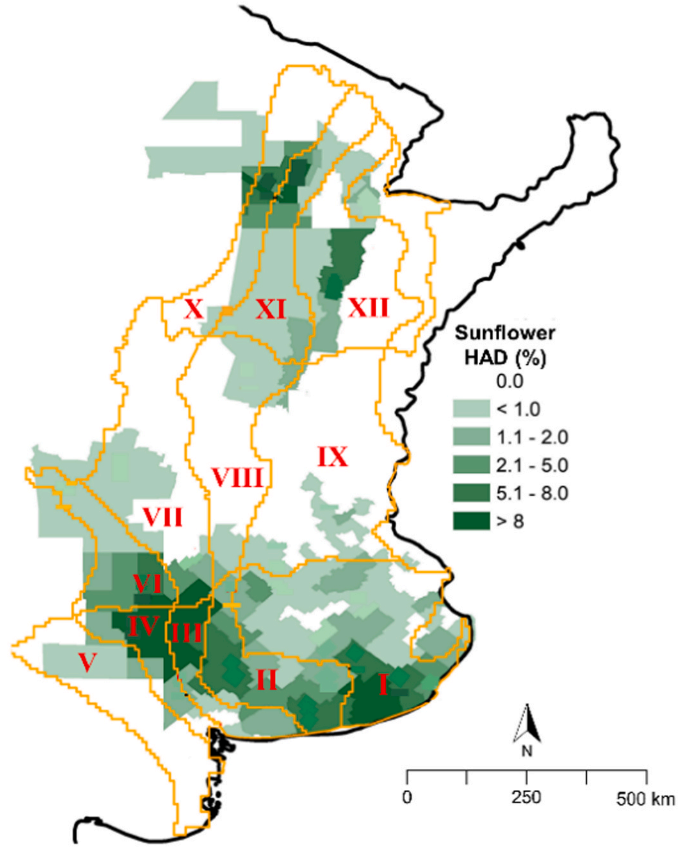

Fig. 1. Climate zones (CZ) (GYGA) identified by Roman numerals and outlined with yellow lines and sunflower average harvest area density per department (HAD, % of total department area) for the 2009/10–2015/16 period. The HAD values were calculated based on information from the Ministry of Agriculture, Livestock, and Fisheries.

For the second section of the study, exploring the causes of Yg through an analysis of technological variables linked to sunflower yield levels, an independent database derived from the ReTAA by *Bolsa de Cereales de Buenos Aires* was used. The ReTAA has collected technological and production information of Argentina's main grain crops by telephone interview of qualified informants. Initially every two years since 2010/11 cropping season but annually from 2016/17 to 2018/19. The data is geo-referenced and contains crop yields in response to inputs and management practices, referred to as the "technological setups". The collected information covers tillage system (no-tillage and conventional tillage); cultivars: high oleic (HO), conventional-oil (CO), herbicide-resistant (HR), and non-HR; sowing seed density; types and rates of applied fertilizers herbicides, insecticides, and fungicides, specifying active ingredients and quantities applied. Yield gap can be calculated for each of these "technological setups". This analysis focuses on data from 2010/11, 2012/13, 2014/15, 2016/17, 2017/18, and 2018/19 cropping seasons.

2.2. Quantification of the yield gaps

Yield gaps estimations were made using as a cornerstone for climate regionalization the methodology developed within the framework of the GYGA (www.yieldgap.org). Within the GYGA methodology, explicit criteria are employed to delineate homogeneous CZ (Fig. 1). Each CZ corresponds to a particular combination of growing degree days, aridity index, and temperature seasonality (van Wart et al., 2013b).

[1] The second-level subdivisions of the provinces of Argentina are called departments.

Furthermore, the GYGA protocol establishes the use of locally calibrated and validated simulation models for estimating Yw.

2.2.1. Procedures for Yg calculation

For each cropping season, Yw was determined through three approaches: (i) yield simulations using the CROPGRO-Sunflower model from the DSSAT platform (Rodriguez et al., 2023), (ii) percentile analysis of yields of regional CYT network, and (iii) percentile analysis based on farmers' paddock yields. Estimation of Ya was based on information provided by the Ministry of Agriculture, Livestock, and Fisheries (MAGyP, 2023). The Yg was calculated as the difference between Yw and Ya (Lobell et al., 2009). Since three Yw estimators were available, three methods were established to estimate Yg:

$$\textbf{Method 1}: \mathrm{Yg}\ \left(\mathrm{kg\ ha^{-1}}\right) = \mathrm{Yw\ yield\ simulations–Ya} \quad (1)$$

$$\textbf{Method 2}: \mathrm{Yg}\ \left(\mathrm{kg\ ha^{-1}}\right) = \mathrm{Yw\ based\ on\ CYT\ yields–Ya} \quad (2)$$

$$\textbf{Method 3}: \mathrm{Yg}\ \left(\mathrm{kg\ ha^{-1}}\right) = \mathrm{Yw\ based\ on\ farmer's\ paddocks\ yields–Ya} \quad (3)$$

The Yg expressed as a percentage was calculated for all three methods using Eq. (4), where the Yw value varies depending on the method employed:

$$\mathrm{Yg}(\%) = \left(\frac{\mathrm{Yw} - \mathrm{Ya}}{\mathrm{Yw}}\right) * 100 \quad (4)$$

Other authors often express Yg as a percentage of Ya rather than as a percentage of Yw (Fischer et al., 2014). Method 1 involved simulations using the CROPGRO-Sunflower model, adding complexity compared to methods 2 and 3. For this reason, it is separately described below.

2.2.1.1. Method 1: yield gap from simulated Yw

2.2.1.1.1. Selection of weather stations and soils. Selection of weather sources and data quality control followed the GYGA guidelines (Grassini et al., 2015; http://yieldgap.org/methods). Daily maximum and minimum temperature and precipitation data were derived from INTA (National Institute for Agricultural Technology; http://siga2.inta.gov.ar/) and SMN (National Weather Service; http://www.smn.gov.ar/) weather stations. Data from NASA-POWER (http://power.larc.nasa.gov/) were used as source of daily incident solar radiation.

Following van Bussel et al. (2015), weather stations used for this study, hereafter termed reference weather stations (RWS), were selected based on sunflower-specific harvested area within a buffer zone area of 100 km radius centered on each RWS and clipped by the CZ where the RWS was located. RWS were iteratively selected starting with the one with the greatest harvested area coverage until reaching ca. 50 % of sunflower-harvested area and more than 70 % coverage by the CZ where the RWS were located. The iterative selection process, resulted in the identification of 10 RWS (Figure S1), collectively covering 75 % of the national sunflower harvest area. Consequently, the quantification of sunflower Yg was made possible in seven CZs—specifically in CZ **I**, **II**, **IV**, **VI**, **VII**, **XI**, and **XII**—deemed representative of the broader sunflower cropping area in Argentina.

Dominant soil series were identified for each RWS buffer based on data provided by the Soil Institute of INTA (http://geointa.inta.gov.ar/). Dominant soil series (two to three per RWS) were selected based on (i) province-level soil maps (1:50,000 and 1:100,000), and (ii) farmer's preference for growing sunflower in specific soils.

2.2.1.1.2. Simulated cropping systems and Yg upscaling to national level. Simulations were performed using the revised CROPGRO-Sunflower with genetic coefficients developed for local cultivars (Rodriguez et al., 2023). Crop management practices for each RWS were retrieved from local informants. One renowned informant was identified per RWS and asked to provide all management practices required for the Yw simulation. Requested information included: dominant crop sequences, soil type, sowing dates, cultivar name and cycle length, and plant population density. To obtain the average sunflower Yw at the RWS level from the 2009/10 to the 2015/16 cropping seasons, continuous crop sequences were simulated. This involved considering water availability at the beginning of each crop season, factoring in both residual moisture from the preceding harvest and the balance during fallow periods. Adhering to the protocol proposed by van Bussel et al. (2015), each simulation-soil combination was weighted based on its relative contribution to the total harvested area within the influence zone of the corresponding RWS. This approach enabled the estimation of the average sunflower Yw at the RWS level.

The Yg was calculated at the RWS spatial scale as the difference between Yw and Ya for each season, spanning seven cropping seasons from 2009/10–2015/16. The Ya for each RWS was estimated using reported yields from departments (MAGyP, 2023) within the RWS's influence zone. Finally, Yg estimates were scaled up to CZ and the national level based on each RWS's relative contribution to the sunflower harvested area. This method enabled the estimation of Yg in seven CZs across Argentina, deemed highly representative of the entire sunflower harvested area in the country (Fig. 3, A).

2.2.1.2. Methods 2 and 3: estimation and upscaling of the Yg using Yw derived from percentile analyses based on CYT and farmer's paddock yields. The Yw estimation based on CYT was performed by calculating the 90th percentile of yields recorded in each cropping season within the same department. The analyzed cropping seasons spanned from 2009/10–2015/16. Notably, each reported yield value in a CYT represents the average yield of a cultivar, typically based on four replicates per trial. The purpose of calculating the 90th percentile was to represent the performance of the best available cultivars in each cropping season. This choice was made because CYT often includes low-yielding cultivars, which could impact our Yw estimation if other summary measures, such as the average of CYT yields, were employed.

The Yw estimation based on farmer's paddock yields followed the methodology proposed by Egli and Hatfield (2014a, 2014b). This methodology consisted of calculating the 95th percentile of yields recorded in each cropping season within the same department. Using the 95th percentile instead of the 90th percentile (used in CYT) result in a smaller amount of yield data for estimating Yw. This is useful in the case of farmer's paddocks since they cover a larger area than CYT plots, and a smaller number of farmer's yields can adequately represent Yw. The cropping seasons considered for this analysis also ranged from 2009/10–2015/16.

For methods 2 and 3 the difference between Yw and Ya for each crop season (seven crop seasons from 2009/10–2015/16) was calculated at the departmental spatial scale. Finally, Yg estimates at the departmental scale were scaled up to the CZ level and then to the national level, based on the relative contribution of each department and CZ to the sunflower harvested area. Utilizing available data, Yg quantification was performed across a total of eight CZ using Methods 2 and 3 (Fig. 3 B, and C).

2.3. Determination of Yg causes through the ReTAA database analysis

2.3.1. Disaggregation of the ReTAA database and scale spatial analysis

Commencing with the georeferenced information from each informant, we proceeded to aggregate ReTAA data at the departmental level. The variables reported in the ReTAA were grouped into those related to i) tillage system, ii) crop characteristics, iii) crop nutrition, or iv) crop protection (Table 1). A detailed description of the variables reported in the ReTAA can be found in the supplementary material (see section "S2. Description of the variables reported in the ReTAA").

A new estimation of Yg from the ReTAA database was conducted; however, this Yg was not included in the initial part of the study because: (i) it spans a different time frame, from 2010/11–2018/19, (ii) for the initial cropping seasons, data were collected every two cropping

Table 1
Variables surveyed in the Relevamiento de Tecnología Agrícola Aplicada (ReTAA) by climate zone (GYGA) and their respective abbreviations. The classification of these variables in a classic crop yield analysis scheme is also presented: tillage system, crop characteristics, crop nutrition, or crop protection. The rationale for selecting only CZ I, II, IV, X, and XII is detailed in section 2.4.3. For the actual yield variable, the number of observations is indicated, followed by the range of observed yields enclosed in parentheses.

Variable	Abbreviation	Classification	CZ I	CZ II	CZ IV	CZ X	CZ XII
Actual yield (Ya) (Mg ha^{-1})	-	-	135 (1.0–3.4)	180 (1.1–3.2)	56 (1.0–3.1)	101 (1.0–3.0)	87 (0.9-3.5)
Tillage system (% under no tillage)	Till system	Tillage system	X	X	X	X	X
Adoption of High Oleic cultivars (HO)	HO Cultivar	Crop characteristics	X	X	X	X	X
Adoption of herbicide-resistant cultivars (HR)	HR Cultivar	Crop characteristics -protection	X	X	X	X	X
Seed density	Seed density	Crop characteristics	X	X	X	X	X
Nitrogen (N) post-sowing fertilization	N Fert	Crop nutrition	X	X	X	X	X
N rate fertilization	N Rate Fert	Crop nutrition	X	X	X	X	X
Phosphorus (P) fertilization at sowing	P Fert	Crop nutrition	X	X	X	X	X
P rate fertilization	P Rate Fert	Crop nutrition	X	X	X	X	X
Fallow herbicide	Fallow herb	Crop protection	X	X	X	X	X
Pre-emergent herbicide application	Pre E Herb	Crop protection	X	X	X	X	X
Post-emergent herbicide application	Post E Herb	Crop protection	X	X	X	X	X
Post emergent insecticide application	Insecticide	Crop protection	X	X	X	X	X
Post emergent fungicide application	Fungicide	Crop protection				X	X

seasons, and (iii) the limited quantity of data only allowed Yg estimation in 5 CZ (see **Section 2.3.2**). The calculation of Yw and Yg was conducted at the departmental spatial scale. The methodology involved estimating Yw based on the 95th percentile of reported Ya by ReTAA in each department and cropping season (i.e., employing the same method used for estimating Yw from farmer's paddocks in the initial part of this study). Concurrently, Yg was calculated as the difference between Yw and each individual Ya value. Subsequently, the Yg values were upscaled at the CZ scale to enhance result interpretability. Figure S5 shows the variability observed in Yw and Ya within each CZ.

2.3.2. Analysis of the relationship between technological variables and Yg

The technological information now associated with each Yg value at the departmental level was aggregated to the CZ spatial scale, using a grouping of departments with similar agro-ecological characteristics. In cases where a department straddled the boundary of two CZ, it was categorized within the CZ that covered more than 50 % of its area. Fig. 2 shows the georeferenced ReTAA informants and their spatial alignment within the CZ of Argentina. Climate zones with less than 25 technological setups were excluded from scrutiny, leaving five CZ in Argentina for analysis: **I**, **II**, **IV**, **X** y **XII** (Table S2). It is important to note that these CZ can be considered representative of the entire sunflower harvested area in Argentina.

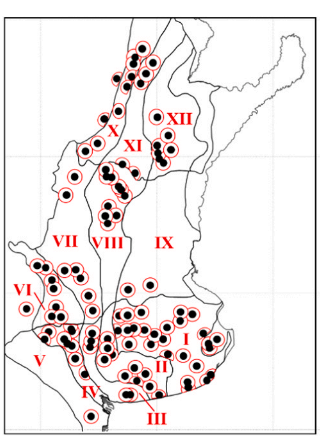

Fig. 2. Informants (black dots) and their zone of influence (red circles) from the Relevamiento de Tecnología Agrícola Aplicada (ReTAA) for the period 2010/11–2018/19 georeferenced within the climate zones (GYGA), identified by Roman numerals.

Regression trees were constructed to explore associations between technological variables and Yg. This analysis, being descriptive in nature, utilized the complete dataset within each CZ for tree fitting. Regression trees were fitted in R (R Development Core Team, 2023) using the *rpart* package (Therneau et al., 2015). Briefly, the *rpart* algorithm works by recursively splitting the dataset, creating subsets until meeting a predetermined termination criterion. The splitting criterion utilized in the *rpart* algorithm was based on the Gini index (Breiman et al., 1983; Mourtzinis et al., 2018). The result of this procedure is a tree-shaped plot (Figure S2), where each split generated nodes, named according to their position. Terminal nodes contain the final predictions for the response variable, and the sizes of both intermediate and terminal nodes follow predefined criteria.

In this study, Yg values were used as the response variable, and all technological variables detailed in Table 1 were explanatory variables. To ensure sufficient statistical power, we required at least 5 % of the total observations in each CZ for each terminal node (Rattalino Edreira et al., 2017; Di Mauro et al., 2018). To avoid overfitting and improve interpretability, the maximum depth of the tree was set a priori at 10 total nodes. The explanatory power of the regression tree was quantified using the coefficient of determination (R^2) and the root mean square error (RMSE). Additionally, the p-values of the nodes in the regression trees were obtained through the R package *sctest* (Zeileis et al., 2002).

The relative variable importance within each regression tree was determined using the "variable.importance" function of the *rpart* package. This function provides a measure of the importance of each variable in the model (regression tree), aiding in identifying the most relevant or influential variables in the tree's decision-making. Variable importance was determined by the extent of improvement in the impurity measure (Gini index in our analysis) achieved by dividing the tree nodes with that variable. A greater improvement indicates a higher variable importance.

3. Results

3.1. Spatial and temporal variation in Ya and Yw across Argentina

The national average Ya (2009/10–2015/16) stood at 2.10 Mg ha^{-1} in Argentina (Table 2), and varied significantly across years and regions (Table S3). Climate zones situated in the northern part of the country (*i. e.* **XI** y **XII**, Fig. 1) showed smaller Ya and higher coefficients of interannual variation than the central and southern regions. Climate zone **I** presented the highest Ya, slightly differing from the Ya observed in CZs **II**, **III**, **VI** y **VII** (Table S3). The national average Yw was 3.19, 3.52, and 3.19 Mg ha^{-1} for method 1, 2 and 3, respectively (Table 2). Yw values

Table 2
Average national actual yield (Ya), water-limited yield potentials (Yw) based on three methods, and yield gaps (Yg) for sunflower in Argentina. Method 1 (Yw estimates using CROPGRO-Sunflower model); method 2 (Yw based on 90th percentile from yields of CYT); method 3 (Yw based on 95th percentile from farmer's paddocks yields).

Method	Ya (Mg ha^{-1})[a]	Yw (Mg ha^{-1})[a]	Yg (Mg ha^{-1})[b]
1	2.10 (21 %)	3.19 (34 %)	1.09 (34 %)
2		3.52 (23 %)	1.42 (40 %)
3		3.19 (17 %)	1.09 (34 %)

[a] Number between brackets shows the coefficient of variation (in %).
[b] Number between brackets shows Yg as a percentage of Yw.

were smaller in CZ's located in the northern part of the country compared to those in the central and southern regions, particularly for methods 2 and 3. However, with method 1 (Yw estimates based on yield simulations), yields in different zones were similar (Table S4). In terms of the interannual coefficient of variation (CV), method 1 recorded the highest value, while method 3 recorded the lowest (Table 2).

3.2. Yield gaps of sunflower crop in Argentina

The national average Yg varied across methods: 34 % for methods 1 and 3 %, and 40 % for method 2 (Fig. 3, A, B, and C). This corresponds to Yg values of 1.09; 1.42 and 1.09 Mg ha^{-1} for methods 1, 2, and 3, respectively. Significant variation in Yg was observed among CZ, method 1 (Fig. 3, A) revealed larger Yg in northern CZ **XI** (53 % or 1.65 Mg ha^{-1}) and **XII** (54 % or 1.67 Mg ha^{-1}) compared to southern CZ **I**, **II**, and **IV**, where gaps ranged between 26 % and 46 % or 0.84–1.41 Mg ha^{-1}. For method 2 (Fig. 3, B), percentage Yg were also larger in CZ **XI** y **XII** (50 % for both), while gaps in other CZ varied between 33 % and 43 %. However, method 2 did not show a consistent trend in Yg in megagrams per hectare based on CZ, fluctuating between approximately 1.10 and 1.90 Mg ha^{-1} (Table S5). Finally, with method 3 (Fig. 3, C), percentage Yg were also larger in CZ **XI** and **XII** compared to other CZ (except CZ **IV**). But expressed in kilograms per hectare, Yg were similar across CZ, ranging between 0.94 and 1.10 Mg ha^{-1} approximately (Table S5).

3.3. Association between technological variables and Yg

Regression trees identified and ranked the most important variables influencing Yg in each CZ (Fig. 4, Figure S6, Table 3). These regression trees enabled a moderate variability explanation, ranging from 29 % to 48 %. The tillage system emerged as one of the management variables strongly associated with Yg. Larger adoption of no-tillage system was consistently linked to smaller Yg. It consistently occupied a position between the first and fourth nodes in the regression tree model for all CZ, except for CZ **I** (Fig. 4. A; Figure S6). Similarly, in CZs **II**, **IV**, **X** and **XII**, the tillage system ranked among the top two most important variables (Table 3). Among the crop characteristics, the adoption of HR and HO cultivars proved to be the most crucial in explaining Yg. Smaller Yg values were associated with high and moderate adoption of HR and HO cultivars. It consistently ranked among the top six most influential factors across all CZ (Fig. 4. B; Figure S6). It's worth noting that HR cultivars contribute not only to crop characteristics but also to crop protection (Table 1). Within the crop nutrition, the P fertilization (P Fert and P Rate Fert variables) emerged as crucial in explaining sunflower Yg in Argentina (Table 3). Phosphorus fertilization rates greater than 8.5–14 kg ha^{-1} (the range for all CZ) were consistently associated with smaller Yg. Concerning N nutrition (N Fert and N Rate Fert variables), this factor was less important than P nutrition; however, it ranked among the six most important variables in all zones (Table 3).

Regarding weed protection, the importance of the variable adoption of HR cultivars in explaining Yg has already been previously highlighted within crop characteristics variables. The application of herbicides in fallow, pre-emergence, and post-emergence periods was found to be of minor importance in explaining Yg overall. As for insect protection, post-emergence insecticide application was associated with larger Yg in CZ **I** and **XII**. The application of post-emergence fungicides (crop disease protection) could only be analyzed in CZ **X** y **XII** due to data availability (Table 1). No association of this variable with larger or smaller Yg values

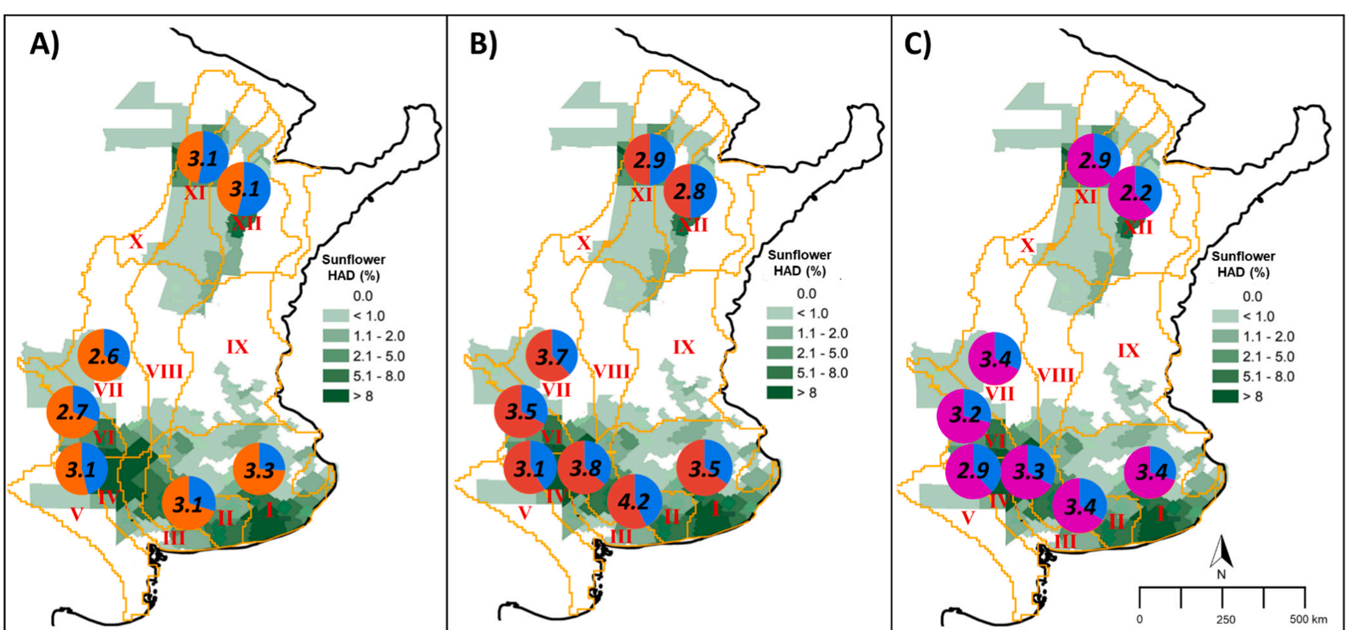

Fig. 3. Yield gap maps for sunflower crop across climate zones (CZ) (GYGA) in Argentina. Climate zones are delimited by yellow lines and identified by Roman numerals. Green shaded areas indicate sunflower average harvest area density per department (HAD, % of total department area) for the 2009/10–2015/16 time period. Yw was estimated by: A) simulations with CROPGRO-Sunflower (method 1), B) 90th percentile based on CYT yields (method 2) and C) 95th percentile based on farmer's paddocks yields (method 3). Water-limited yield potential (Yw, Mg ha^{-1}, in numbers) for CZ level in numbers in each pie chart. Actual yields (orange for A, red for B and pink for C) and yield gaps (blue) are shown, both relative to the Yw (Mg ha^{-1}, in numbers), in each pie chart.

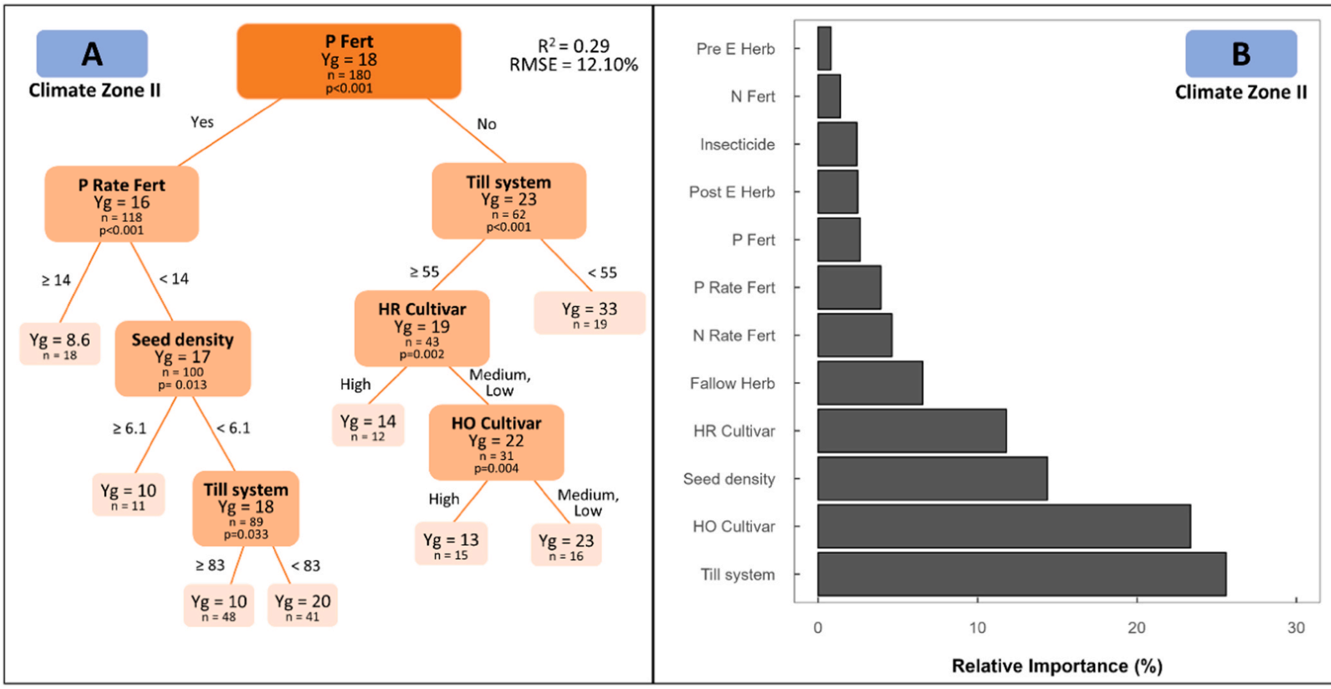

Fig. 4. **A)** Example of regression tree analysis for the climate zone (GYGA) II. The response variable was Yg expressed as a percentage of Yw, while the explanatory variables were those detailed in Table 1. The number associated with "till system" represents the percentage of no tillage. **B)** Variable importance scores for each predictor included in the fitted regression tree model.

Table 3
Top-six ranking of variable importance for the 5 CZs (GYGA) obtained from the fitted regression trees. A color code has been used to facilitate the visualization of variables across the table. The table also presents the number of data (n) used for model fitting, the coefficient of determination (R^2), and the root mean square error (RMSE).

CZ / Ranking	I	II	IV	X	XII
1	P Fert	Till system	P Rate Fert	HR Cultivar	Till system
2	HR Cultivar	HO Cultivar	Till system	Till system	P Fert
3	HO Cultivar	Seed density	HO Cultivar	Fallow Herb	HO Cultivar
4	N Fert	HR Cultivar	N Rate Fert	N Rate Fert	Insecticide
5	P Rate Fert	Fallow Herb	HR Cultivar	HO Cultivar	N Fert
6	Insecticide	N Rate Fert	Seed density	P Rate Fert	HR Cultivar
n	135	180	56	101	87
R^2	0.33	0.29	0.47	0.33	0.48
RMSE (*Yg%*)	11.9	12.1	12	16	12

was found. Additionally, this variable ranked low in importance in the two analyzed CZ (Figure S6, C2 and D2).

4. Discussion

This study contributes important insights into the magnitude and underlying causes of Yg in sunflower crops of Argentina. It establishes that estimates of national Yg range between 34 % and 40 % of Yw, depending on the methodology employed. These values are larger than those of Hall et al. (2013), who estimated a national Yg of 29 % during 2000–2007. In absolute terms, Yg are 1.10–1.42 (1.20 mean) and 0.75 Mg ha^{-1}, respectively. The explanation is found in changes of Ya and Yw. While Hall et al. (2013) determined a national Ya of 1.85 Mg ha^{-1}, our estimate for the later period (2010–2016) was 2.10 Mg ha^{-1}. Thus, despite an observed increase in the Ya of sunflower across decades, the Yg also increased, highlighting the potential for further yield improvements in Argentina's sunflower production. The Yw values estimated in this study are 3.20–3.50 (3.30 mean) Mg ha^{-1}, while Hall et al. (2013) estimated a Yw of 2.6 Mg ha^{-1}.

Aramburu Merlos et al. (2015), using simulation models to estimate Yw (method 1), found that in Argentina, the Yg for wheat and maize was 41 %, and for soybean, it was 32 %. In comparison, our assessment of sunflower, using the same methodology, resulted in a Yg of 34 %, suggesting that sunflower crop exhibits an intermediate gap between wheat-maize and soybean in Argentina. On a global scale, the sunflower crop in Argentina presented a moderate Yg. Argentina's sunflower Yg surpassed those reported for some major high-technology cereal--producing regions, *e.g.*, wheat in Germany and maize in Nebraska, USA, which exhibit gaps of ~20 % (Grassini et al., 2011; van Wart et al., 2013a). Conversely, sunflower Yg in Argentina is considerably smaller than those reported for smallholder production systems in Sub-Saharan Africa, where gaps reach up to 80 % of the Yw (Tittonell and Giller, 2013; Kassie et al., 2014).

Water-limited potential yield estimation based on CYT yields, method 2, showed the highest national Yw value and, consequently, the highest national Yg compared with model simulations, method 1, and farmeŕs paddock yields, method 3. The Yw values obtained through method 2 in each of the CZ did not surpass the yields of the top decile of CYT reported by Hall et al. (2013) for similar zones. While Hall et al. (2013) argue that the top decile of CYT should not be considered a benchmark for Yg analysis due to its exceptional nature (i.e. the best cultivars available), we contend that it is an appropriate reference. The yields of the top decile in our database were associated with the 3–4 highest-yielding cultivars in each department and cropping season. This is optimal, as Yw, by definition, should be calculated based on the best available cultivars. However, it is important to note that, due to other factors, there may be an overestimation of Yw when using CYT. These factors include i) the absence of border effect in CYT (which is present at the farmer's paddocks and results in a reduction in average yield), ii) harvesting is done more carefully in CYT plots, leading to lower grain losses compared to the farmer scale (Calviño et al., 2019; Rodriguez et al., 2019). Furthermore, as previously mentioned, methods relying on percentile analysis carry the risk of overestimating Yw, especially in areas where rainfall is variable, and soils exhibit great variability (Agrawal et al., 2008; Licker et al., 2010; Hall et al., 2011).

On the contrary, method 3, also relying on percentile analysis but based on farmer's paddock yields, resulted a smaller Yg compared to method 2. However, method 3 introduces two significant risks. Firstly, there is the potential of overestimating Yw, particularly in regions with variable rainfall and diverse soils, as discussed earlier. Secondly, there is also the risk of underestimating Yw if none of the farmers adopt management practices aimed at achieving Yw (Fischer et al., 2009; Sadras et al., 2015). Economic, structural, or cultural factors can deter farmers from optimal practices like using high-yielding cultivars, proper fertilization, or effective weed control. In such cases, the yields of farmers may not accurately reflect Yw (Tittonell et al., 2008; Pradhan et al., 2015). This underestimation issue is less likely with the CYT approach (method 2), where management practices for Yw attainment are generally implemented (Agrawal et al., 2008; Hall et al., 2013).

When comparing the outcomes of method 1 (Yw based on simulations) with method 3 (Yw based on farmer's paddocks), a notable similarity was observed in the values obtained. Despite observing moderate variability across the zones, the estimated Yg for each zone showed a high correlation (Figure S4). Notably, Egli and Hatfield (2014) also calculated maize Yw in the USA using the analysis of percentiles of observed farmer's paddock yields. Their findings suggested that these values were lower than those estimated through simulation models (Grassini et al., 2011). Although Egli and Hatfield (2014a) did not suggest a rationale for the disparities between observed Yw and simulated Yw, it is crucial to highlight that studies estimating Yw and Yg using simulation models (Aramburu Merlos et al., 2015; Filippi et al., 2022) often lack a detailed description of the calibration and evaluation procedures of such models. In this study, a rigorous model calibration and evaluation was conducted, which is described in full detail by Rodriguez et al. (2023).

This study has identified multiple technological factors that contribute to the Yg in sunflower crop in Argentina. Phosphorus fertilization stands out as a key factor across diverse regions, mirroring the overall scenario of this work where nutrient input to the crop falls substantially below the amount removed by grain harvest. Regression trees explained moderate Yg variability (30–48 %), exceeding values reported for analysis of soybean Yg in the USA by Mourtzinis et al. (2018) (10 %-34 %). The adoption of a no-tillage system was associated with smaller Yg. This association likely stems from several factors, including its contribution to increased soil water holding capacity and greater water availability for the crop (Brandt, 1992; Melaj et al., 2003).

Lower Yg values were observed in association with high and medium levels of HR cultivar adoption. This observation could have two explanations: i) During the 2011–2019 period, HR cultivars exhibited equal or larger Ya than non-HR cultivars, as indicated by data from the National Cultivar Evaluation Network INTA-ASAGIR (Figure S8). Consequently, the adoption of HR cultivars could be related to choosing cultivars with larger yield potential, translating into larger Ya and, therefore, smaller Yg. ii) The second possible explanation is that HR cultivar adoption is associated with crop protection through more effective weed control. In contrast, the adoption of HO cultivars may have a more indirect explanation. While HO cultivars generally have smaller yield potential than CO cultivars (Del Gatto et al., 2015; Gaggioli et al., 2015). Based on this premise, one might anticipate that technological approaches predominantly adopting HO cultivars would be associated with larger Yg. However, our results contradict this expectation. We observed a consistent association between HO cultivar adoption and smaller Yg across all analyzed CZ. In our analysis, the adoption of HO cultivars is possibly correlated with other variables not recorded in the ReTAA (for example, sowing date, fallow duration, fertilization with nutrients such as Boron (B), Potassium (K), and Zinc (Zn), among others) that could explain a reduction in Yg.

The four variables related to crop nutrition (P Fert, P Rate Fert, N Fert, N Rate Fert) showed a direct association with Yg across all analyzed zones (CZ). Phosphorus fertilization rate emerged as the most significant link to Yg. These findings align with those reported by Parra et al. (2003) and Sainz Rozas et al. (2012), in CZ **I**, **II**, **III**, **IV**, and **X**. These authors demonstrated that, in these zones, agricultural activity without adequate nutrient replenishment has resulted in a significant decrease in soil P levels limiting crop yields. This observation mirrors the results obtained in this study, where it was noted that nine analyzed CZ exhibited negative P and N balances (Figure S7). Nitrogen crop nutrition had relatively less importance than P nutrition in explaining Yg in all CZ analyzed. On a global scale, Mueller et al. (2012) demonstrated that global crop production could increase between 45 % and 70 % for most crops by closing the Yg through nutrition and water management improvements.

As for the relevance of crop protection technologies, the results are less clear. The application of insecticides to the crop explained part of the Yg in the CZ **I** and **X**, but contrary to expectations, the application of insecticides was associated with larger values of Yg than the non-application of insecticides. One hypothesis regarding these results is that the "yes" level would indicate scenarios, for example, years and/or sites within a CZ, where insect damage caused a reduction in crop Ya despite the application of insecticides. Weed control had less relative importance than other factors in explaining sunflower Yg (Satorre and Andrade, 2021), except for the adoption of HR cultivars. Finally, disease protection, evaluated through the application of fungicides, showed low importance in the two CZ analyzed (**X** y **XII**).

The most significant limitation of our approach in analyzing the causes of Yg is that there are potential explanatory variables for sunflower Yg that are not recorded in ReTAA database. Some of these variables include sowing date (De la Vega and Hall, 2002a, b); bird damage (Bucher and Aramburú, 2014); incidence and severity of fungal diseases (Markell et al., 2015); the preceding crop (Salado-Navarro y Sinclair, 2009); occurrences of extraordinary adversities (Sierra et al., 1993; www.ora.gob.ar) and the characterization of cultivars considering aspects such as yield potential, resistance or tolerance to other biotic adversities, susceptibility to lodging, cycle length, among others (De la Vega and De la Fuente, 2010).

5. Conclusions

Yield gap assessment performed in this study indicates that Argentina has the potential to substantially increase grain production of sunflower. This study provides novel insights into the association between sunflower Yg and its causes. Tillage system, P fertilization, and the adoption of herbicide-resistant cultivars were key factors in explaining sunflower Yg in Argentina. It is crucial to focus future initiatives on constructing more detailed crop management databases (including bird damage, incidence and severity of fungal diseases, and cultivar characterization, among others) to enhance the understanding of other potential causes of Yg in sunflower and other extensive crops in Argentina. Despite limitations, this study makes a significant contribution to bridging the sunflower Yg in Argentina.

CRediT authorship contribution statement

Ignacio Martin Rodriguez: Writing - original draft, Visualization, Investigation, Formal analysis, Data curation. Antonio Juan Hall: Writing - review & editing, Supervision, Methodology, Investigation, Conceptualization. **Juan Pablo Monzon:** Writing - review & editing, Supervision, Investigation, Funding acquisition, Conceptualization. **Jorge Luis Mercau:** Writing - review & editing, Supervision. Methodology, Investigation, Conceptualization. **Sofia Gayo:** Writing - review & editing, Data curation. **Monica Lopez Pereira:** Writing - review & editing, Investigation, Conceptualization. **Anibal Cerrudo:** Writing - review & editing, Investigation, Formal analysis. **Henan Urcola:** Writing - review & editing, Conceptualization. **Carolina Troglia:** Writing - review & editing, Data curation. **Sebastian Zuil:** Writing - review & editing, Supervision, Data curation, Conceptualization. **Maria Paolini:** Writing - review & editing, Data curation. **Gustavo Martini:** Writing - review & editing, Data curation. **Pablo Cipriotti:** Writing - review & editing, Writing - original draft, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of Competing Interest

The authors declare no conflict of interest. The paper contents have not been previously published nor are under consideration for publication elsewhere. All co-authors have contributed to the paper and have agreed to be listed as co-authors.

Data availability

Data will be made available on request.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.fcr.2024.109480.

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