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RESEARCH ARTICLE

Assessing management factors limiting rice production in Venezuela

João Vitor Santos de Souza[1] · Cintia Piovesan Pegoraro[1] · Camille Flores Soares[1] · Isabela Bulegon Pilecco[1] · Vitória Signor[1] · Lauren Machado Lago[1] · Bruna Pinto Ramos[1] · Marcel Angel Guevara · Maria Carolina Bitencourt[2] · Wilmer Iván Chacón Martinez[2] · Daniel Alejandro Brito Herrera[5] · Tarmar Lopez[5] · Mauricio Fornalski Soares[1] · Eduardo Lago Tagliapietra[1] · Gonzalo Rizzo[4] · Giovana Ghisleni Ribas[3] · Nereu Augusto Streck[1] · Alencar Junior Zanon[1]

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Abstract

Rice once played a strategic role for food security in Venezuela, but economic stagnation and the onset of hyperinflation in 2016 led to a sharp decline in production. Today, the country imports about 45% of its rice needs. Despite this critical situation, no previous studies have quantified rice yield potential or yield gap analyses in Venezuela, leaving an important research gap regarding the country's capacity to achieve self-sufficiency. The objectives of this study were threefold: (i) to determine the rice yield potential and yield gap for the wet and dry seasons, (ii) to identify the biophysical and management factors causing the yield gap, and (iii) to estimate whether it is possible to achieve rice self-sufficiency by closing the yield gap in Venezuela. Yield potential was estimated using the Oryza v3 simulation model, and yield gaps were analyzed based on 401 farmer field surveys conducted over seven agricultural years (2018–2024). Additional production potential was assessed under scenarios of agricultural intensification and cropland expansion and compared with projections of rice demand until 2040. Results showed that the yield potential of irrigated rice ranged between 8.1 and 9.8 Mg ha^{-1} in the wet season and between 10.4 and 10.9 Mg ha^{-1} in the dry season. Yield gaps averaged 53% in the wet season and 59% in the dry season, with main constraints related to crop establishment methods and preceding summer crops. These findings highlight substantial opportunities to increase national production through improved agronomic practices. The novelty of this study lies in providing the first comprehensive and data-based assessment of rice yield gaps in Venezuela, combining crop modeling, farm surveys, and future demand scenarios. The results demonstrate that by intensifying rice-based systems and investing in research, rural credit, and infrastructure, Venezuela could achieve self-sufficiency and double domestic rice production by 2040.

Keywords *Oryza sativa* L. · Yield gap · Crop management · Rice self-sufficiency

1 Introduction

In the coming years, global agriculture will face one of its greatest challenges, caused by rapid population growth and the resulting need to meet the high demand for food (Fanzo et al. 2024). It is estimated that global food demand will increase by 35 to 56% between 2010 and 2050, while the number of people at risk of hunger could rise from 811 million in 2020 to over 1.5 billion by 2050 under pessimistic socioeconomic and climate scenarios (Van Dijk et al. 2021). Given the scenario of decreasing arable land and climate change, yield increases and more efficient resource use are key prerequisites to ensure the sustainability of agricultural

✉ João Vitor Santos de Souza
joaosouzaagro@hotmail.com

[1] Federal University of Santa Maria, Hall #77, Roraima Avenue 1000, Santa Maria, Rio Grande do Sul , Brazil

[2] United Nations Industrial Development Organization, Caracas, Venezuela

[3] University of São Paulo (Esalq-USP), Padua Dias Avenue, n#11, Piracicaba, São Paulo, Brazil

[4] Faculty of Agronomy, University of the Republic, General Eugenio Garzón Ave 780, Montevideo 12900, Uruguay

[5] National Foundation of Irrigated Rice (FUNDARROZ), Eduardo Chollet Avenue, n#3301, Araure, Portuguesa, Venezuela

ecosystems (Gaffney et al. 2019; Cassman and Grassini 2020; Yuan et al. 2021, 2022).

Rice (*Oryza sativa* L.) cultivation plays a critical role in ensuring self-sufficiency in Venezuela and has been recognized by the United Nations Industrial Development Organization (UNIDO) as one of the five priority agro-industrial sectors vital to reducing the country's dependence on food imports and revitalizing domestic agricultural production (UNIDO 2019). Historically, rice represented a key component of Venezuela's agricultural output, with production reaching 1.15 million tons in 2014 (FAOSTAT 2024; USDA 2016). However, this progress was undermined by the onset of economic stagnation in 2013, which gradually eroded the country's productive capacity and destabilized the food supply chain (Zerpa & Soto 2017; FAO 2018). By 2016, as hyperinflation accelerated and institutional support weakened, rice production had fallen sharply to 500,000 tons, driven by both a reduction in cultivated area and a decline in yield, reflecting the broader structural and financial challenges faced by the agricultural sector (USDA 2016; IMF 2018).

According to the World Food Programme (WFP 2025), around 40% of the Venezuelan population is currently facing moderate to severe food insecurity. Furthermore, this unfavorable scenario caused a shortage of inputs for agricultural production (low quality and minimum quantity availability), which, combined with the lack of government support, the lack of public investment in productive infrastructure, and limited bank credit, led to a technological "lag" and a reduction in rice cultivation areas. From 2014 to 2022, there was a significant decline in rice production and harvested area in Venezuela, which was insufficient to meet the Venezuelan population's food needs (Supplementary Fig. 1). On average, over the last 10 years (except 2020, a year of low imports due to restrictions caused by the COVID-19 pandemic), rice production has been in sharp decline and around 45% of the country's rice needs have had to be met by imports, leaving the country hostage to fluctuations and sanctions in the international market (FAOSTAT 2024). It is therefore imperative to develop strategies that maximize agricultural yields and support consultants and producers in decision-making regarding the country's self-sufficiency, e.g., by developing strategies to close the yield gap.

Yield potential (Yp) is the maximum that a plant can produce in the absence of biotic or abiotic stress and is determined by solar radiation, temperature, atmospheric CO_2, and genetics (Evans and Fisher 1999; Van Ittersun and Rabbinge, 1997). The yield gap (Yg) is determined by the difference between the Yp and the actual yield (Ya) in the field (Lobell et al. 2009). It is also known that the economically exploitable potential is about 80% of Yp (Cassman 1999; Cassman et al. 2003). Studies on Yp and causes of Yg have already been conducted in several countries around the world, such as rice in the USA (Espe et al. 2016), rice and maize in Indonesia (Agustiani et al. 2018), wheat in Australia (Hochman et al. 2016), and irrigated rice and soybeans in Brazil and Argentina (Duarte Junior et al. 2021; Ribas et al. 2021a, b; Tagliapietra et al. 2021; Winck et al. 2023; Meus et al. 2024). However, there are no reports of studies on the yield gap and factors leading to the yield gap in rice for Venezuela, which are essential to achieve food self-sufficiency in this country.

By analyzing yield data, crop management practices, and environmental characteristics, it is possible to obtain an estimate of Yp and to identify and evaluate the factors that lead to Yg (Edreira et al. 2017; Andrade et al. 2022). Thus, by diagnosing these factors, it is possible to recommend management decisions, such as the ideal sowing date, fertilizer rate, seed treatment, crop rotation, planting density, and others (Silva et al. 2022; Winck et al. 2023; Rizzo et al. 2023). Identifying the factors limiting higher yields through on-farm research experiments is laborious, expensive, and time-consuming, often requiring multiple years and locations to correlate with environmental interactions over time and area in a given region.

A farmer data-based approach can be used to identify the main yield constraints for individual crops in specific regions (Stuart et al. 2016; Edreira et al. 2017, 2020). This approach can also guide the subsequent development of field experiments aimed at specifically working on each factor identified as a cause of Yg and evaluating management practices to overcome them and ultimately make investments more efficient (Andrade et al. 2022; Rizzo et al. 2023). To this end, we used a robust set of data reported by farmers from 401 fields to identify the main factors causing Yg in the states of Portuguesa, Cojedes, and Guárico, which together account for more than 90% of irrigated rice production in Venezuela (Fig. 1). The objectives in this study were threefold: (i) to determine the rice Yp and Yg for the wet and dry seasons, (ii) to identify the biophysical and management factors causing the Yg, and (iii) to estimate whether it is possible to achieve rice self-sufficiency by closing the Yg in Venezuela.

2 Material and methods

2.1 Study sites and meteorological data

Between the 2018 and 2024 growing seasons, a total of 464 irrigated rice fields (on average, 66 fields per year) were monitored across three main producing states in Venezuela: Portuguesa, Cojedes, and Guárico (Fig. 2). Of these, 317 fields were cultivated during the dry season (DS) and 147 during the wet season (WS). According to the Köppen-Geiger climate classification, these regions have a tropical

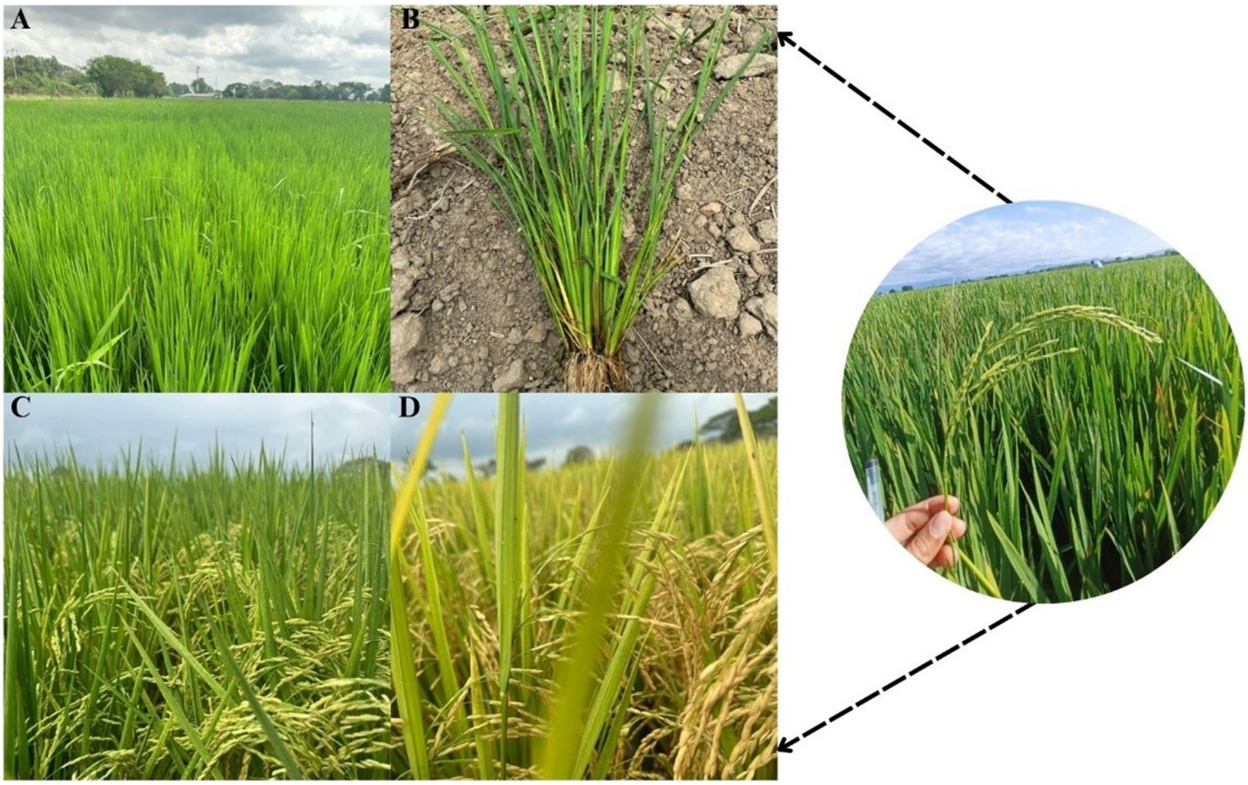

Fig. 1 Field visits for monitoring and data collection in irrigated rice farms in Venezuela under the Pilot Project ST 52 of the United Nations Industrial Development Organization (UNIDO). **A**, **B** Crop and plants during the vegetative phase. **C**, **D** Crop and plants during the reproductive phase. Photos credits: Tarmar Lopez.

savannah climate (Aw), which allows for two irrigated rice harvests per calendar year, one in each season. Data collection was carried out by field technicians from the National Foundation for Irrigated Rice in Venezuela (FUNDARROZ), using a structured survey methodology. To ensure consistency and data reliability, biweekly meetings were held to provide technical training and ongoing support to the survey teams. The recorded data included key agronomic practices such as cultivar selection, sowing date, fertilization, irrigation method, soil preparation, crop protection, production system, and other farm-level management strategies. A rigorous data quality control process was used by excluding fields with missing essential information such as yield, fertilization, or sowing date, or those using outdated cultivars. After the quality control, 401 fields with complete and reliable records (275 in DS and 126 in WS) were retained for analysis, representing 86.4% of the original dataset.

Daily meteorological data from 2018 to 2022 were collected at meteorological stations provided by the United Nations Industrial Development Organization (UNIDO) and the Association of Agricultural Producers of Portuguesa (ASOPORTUGUESA). To estimate the Yp of an irrigated crop, at least 10 years of meteorological data are required (Grassini et al. 2015). Therefore, NASA POWER radiation and temperature data from 2012 to 2017 were retrieved and calibrated according to the relationship between measured (station) and estimated (NASA POWER) data from 2018 to 2022 (Supplementary Fig. 2) (Van Wart et al. 2013). Furthermore, NASA POWER was used to supplement/correct missing meteorological data at stations 3, 5, 4, and 7% for buffer zones I, II, III, and IV, respectively (Fig. 3). Further details on the correction and adjustment of the meteorological data can be found on the Global Yield Gap Atlas Platform (http://www.yieldgap.org).

Sites were selected using (i) a climate zone (CZ) scheme that delineates geographic areas based on spatial variations in growing degree days, temperature seasonality, and aridity index (Van Wart et al. 2013) and (ii) the distribution of irrigated rice area in 2010 (SPAM2010; http://www.mapspam.info). First, CZs that accounted for > 5% of the total national rice area were selected. Then, within each selected CZ, polygons with a radius of 100 km (referred to as "buffer zones") were created around existing weather stations. The buffer zones were cut off from the CZ edges to minimize climatic variability within the buffer zones. A total of four buffer zones were created according to the availability of weather stations and climate zones in each region, covering 54% of the irrigated rice area in Venezuela (Yu et al.

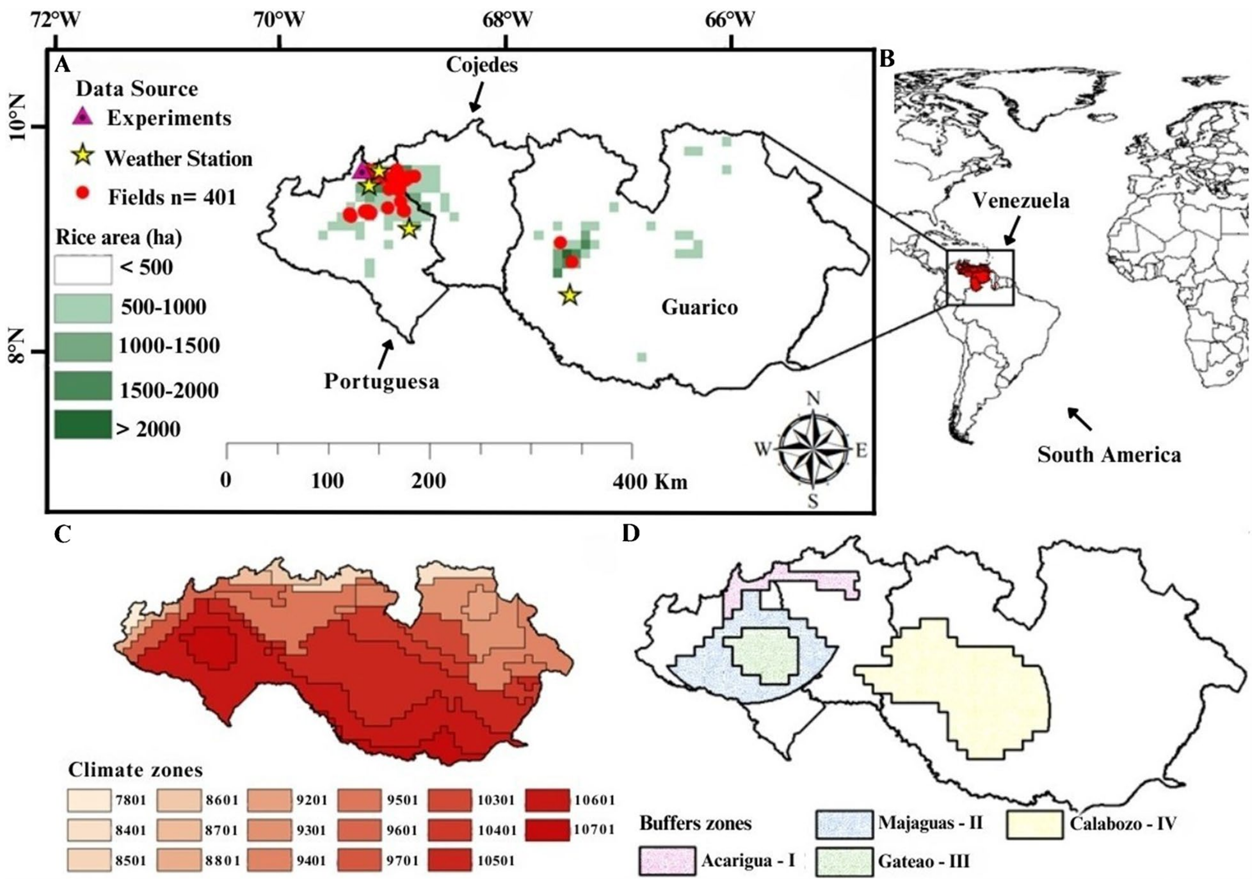

Fig. 2 **A** Location of the states of Portuguesa, Cojedes, and Guárico in Venezuela, including irrigated rice experiments, meteorological stations, and survey fields. (B) Location of Venezuela in South America. **C** Climate zones and **D** identification of the four buffer zones used in the study.

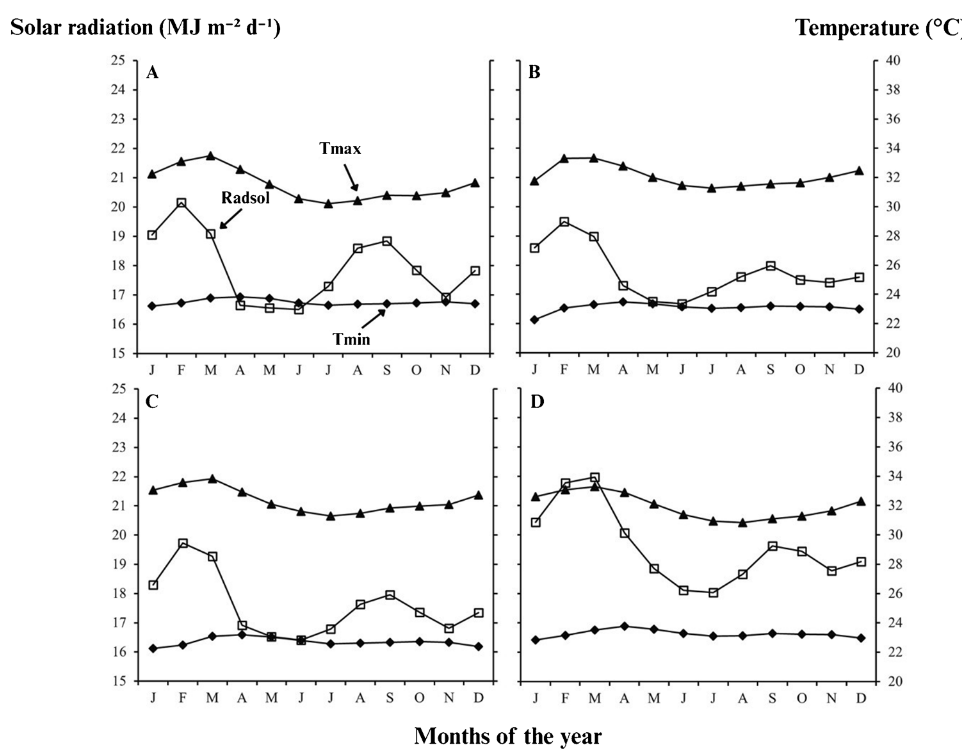

Fig. 3 Ten-year average of monthly incoming solar radiation (Radsol), and maximum (Tmax) and minimum (Tmin) air temperature in the four buffer zones: **A** Acarigua, **B** Las Majaguas, **C** Gateao, and **D** Calabozo, which represent the irrigated rice production regions in the states of Portuguesa, Cojedes, and Guarico of Venezuela. Source: UNIDO and ASOPORTUGUESA meteorological stations, and NASA POWER.

2020; http://www.yieldgap.org). The four buffer zones are located in the three main irrigated rice-producing states of the country, so we focused on collecting data from crops within these boundaries.

2.2 Estimation of yield potential: validating the Oryza v3 simulation model

The Yp of irrigated rice was estimated using the Oryza v3 model (Li et al. 2017), a well-known and widely used process-based model that allows the simulation of plant development and growth processes of a rice crop on a daily time step under field conditions, assuming that biotic factors (diseases, insects, and weeds) and abiotic factors (water and nutrients) are not limiting. The calibration used to evaluate the model was the one that used data and genetic coefficients from the cultivar FEDEARROZ 2000 developed for Colombia (Barrios-Perez et al. 2021). This rice cultivar is similar in developmental cycle to the cultivar ASP18, the most widely grown rice cultivar in Venezuela in five sowing periods (May, June, November, December, and January). Therefore, the genetic coefficients of the cultivar FEDEARROZ 2000 were assumed to be the same for the cultivar ASP18 in the model.

Evaluation of the Oryza v3 model in Venezuela with the cultivar ASP18 was conducted using independent data on rice development and yield in farm fields collected by FUNDARROZ technicians and extension agents. The trials were established under potential conditions, ensuring the absence of biotic and abiotic stresses such as nutrient deficiencies or weed competition. All experiments were managed using optimal agronomic management practices, including timely irrigation, pest control, and full nutrient supply based on crop demand. Each plot had 25 m^2, with four replications, and plant development monitoring was performed every 3 days. The variables evaluated were the dates of developmental stages R1 (beginning of flowering), R4 (milky grain), and R8 (physiological maturity), following the developmental scale by Counce et al. (2000), and grain yield adjusted to 13% moisture content. The statistics root mean square error (RMSE) and normalized root mean square error (NRMSE) were used to evaluate model performance and prediction accuracy (Janssen and Heuberger 1995) (Fig. 4). The statistics used showed a good performance of the Oryza v3 model for both development (RMSE of 5.6 days and NRMSE 6.4%) and yield (RMSE 0.8 Mg ha^{-1} and NRMSE 9.9%) (Van Oort et al. 2011; Mongiano et al. 2019; Ribas et al. 2020).

2.3 Yield potential simulation and yield gap determination

The Yp was simulated for the agricultural years 2012 to 2022 (10 agricultural years in total). The cultivar used was ASP18 (the most commonly grown cultivar in the country), in both seasons based on measured and estimated meteorological data. The sowing date, cycle, and planting density were determined according to the practice of more than 50% of the farmers. This information was obtained through discussions with farmers and extension agents (Supplementary Fig. 3). The average Yp was estimated following the protocol established by the Global Yield Gap Atlas (GYGA) (Van Ittersum et al. 2013; Grassini et al. 2015). Yp was initially simulated for each buffer zone, which represents spatial units centered around weather stations and delineated within a radius of 100 km to capture areas with relatively homogeneous climatic conditions and a high concentration of irrigated rice production. These buffer zones were adapted to the Venezuelan context and validated previously by Martinez et al. (2024). Seasonal Yp values were aggregated using a weighted average, with weights corresponding to the harvested area of irrigated rice within each buffer. Finally, an overall mean Yp was calculated by combining seasonal estimates, also weighted by their respective harvested areas.

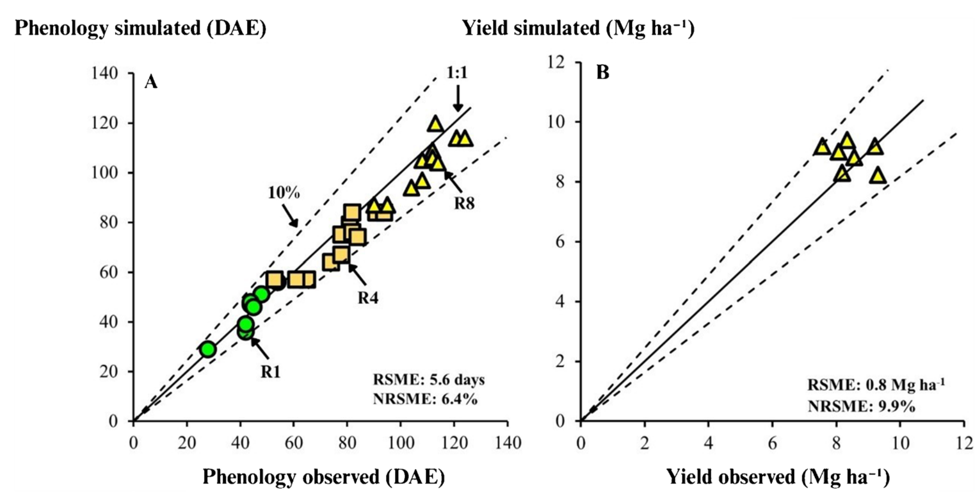

Fig. 4 Simulated and observed data of **A** developmental stages R1, R4, and R8 (phenology) in days after emergence and **B** grain yield in the evaluating of the Oryza v3 model for irrigated rice in Venezuela. The solid black diagonal is the 1:1 line. The dotted black diagonal represents the 10% deviation.

The Yg was calculated by the difference between Yp and the average farm yield (Ya) provided by the Venezuelan Federation of Rice Producers Organization (FEVEARROZ), as the data showed a statistical agreement (RMSE 0.6 and NRSME 16.1%) with the FAO data (Supplementary Fig. 4). The yields of the last five agricultural years (2018 to 2022) were used to define the average yield of farmers, as using a longer period would have affected the estimation of Ya due to the inclusion of technological bias (Van Ittersum et al. 2013). Due to the instability and lack of information at the spatial and temporal level, the annual average yield was used to calculate Yg at the sowing season and buffer zone level (Eq. 1).

$$Yield\ gap\ (Yg) = Yp - Ya \tag{1}$$

2.4 Statistical analysis

2.4.1 Yield-based stratification for contrasting group analysis

To analyze the data from the full set of 401 irrigated rice fields, we categorized the observations into two contrasting yield groups: high-yielding (HY) and low-yielding (LY). This classification was based on the yield distribution within each sowing season, defining the upper tercile of fields as HY and the lowest tercile as LY. The intermediate tercile was excluded from the comparison to enhance the contrast between groups and better capture the most relevant differences in agronomic practices and environmental conditions a procedure commonly adopted in this type of analysis. In the wet season, from 126 fields, yields above 6.2 Mg ha^{-1} (HY) and below 4.9 Mg ha^{-1} (LY) were selected, totaling 88 fields. For the dry season, among 275 fields, those with yields above 8.0 Mg ha^{-1} and below 5.9 Mg ha^{-1} were selected, resulting in 187 fields. Differences in agronomic and environmental variables between HY and LY groups were evaluated using the Student *t*-test or the Wilcoxon rank-sum test for non-parametric data, with significance thresholds of 1%, 5%, and 10%, and all analyses were conducted using InfoStat software (Rizzo et al. 2023).

2.4.2 Identification of yield-limiting factors through decision tree modeling

We used a conditional inference tree analysis based on the entire dataset (n = 401 fields) to identify the agronomic causes of the Yg for rice, considering both cropping seasons in Venezuela, the wet and dry seasons (Tenorio et al. 2021; Rizzo et al. 2023; Merlos et al. 2024). The analysis was conducted in R using the partykit package (Hothorn & Zeileis 2015) and tested the independence between yield and field and management variables. The algorithm selects the variable with the highest association to yield (lowest *p*-value), generating successive binary splits to form a tree structure. The terminal nodes represent the final subsets of fields, while the node sizes are defined by predefined criteria. We used a significance level of 5% for the independence test and considered all collected agronomic variables as predictors of farmer yields (Mg ha^{-1}).

To complement the identification of limiting factors, we also analyzed the individual relationships between yield and key agronomic variables, including total N, P_2O_5, and K_2O application rates. The boundary function method proposed by French and Schultz (1984) was used to determine the point of maximum technical efficiency (PMTE), defined as the input level beyond which yield increases are less than 0.05 Mg ha^{-1} (Zanon et al. 2016). Yield responses to previous crop and crop establishment methods were further examined using boxplots, and the differences between groups were tested using the non-parametric Kruskal–Wallis test at 5%. The previous crop included rice, maize, fallow, and notably mung bean (*Vigna radiata*), which was grown exclusively during the dry season and followed by rice in the following wet season, characterizing systems such as rice–rice, maize–rice, fallow–rice, and mung bean–rice. The crop establishment methods assessed were tillage (with plowing and harrowing), pre-germinated seeding (broadcasting soaked seeds into flooded fields), and no-tillage (direct seeding into moist, undisturbed soil). Each of these systems involves distinct technical requirements: no-tillage requires specialized seeders, proper crop residue management, and improved weed control, while maize-based rotations demand adapted harvesters, drying facilities, and greater on-farm storage capacity.

2.4.3 Scenario-based projections to assess rice production potential and national self-sufficiency in rice

Finally, linear models were fitted to derive the annual rate of yield improvement and harvested area for rice in Venezuela until 2040 (Marin et al. 2022). Three scenarios were created for the analysis: (i) normal production trends (NPT), using the average production and area trend of the last 15 years (2009–2023) (Supplementary Fig. 5), (ii) normal yield and area increase trends (NIA), which follow the average normal yield trend but use the historical maximum area ever planted to rice in Venezuela (from 95,000 to 230,000 hectares; see Supplementary Fig. 1), and (iii) the intensification of the system through Yg reduction (INT) assumes substantial investments in agricultural research and development programs aimed at closing the average annual Yg, including the technical training of agronomists and extension consultants, the organization of field days to disseminate best practices to farmers, and the strategic orientation of scientific research toward the key biophysical and management factors that cause the Yg (Marin et al. 2022). In this scenario, assuming an exploitable yield equivalent to 80% of the Yp, rice yields could increase from 4.8 to 7.8 Mg ha^{-1} and the cultivated area would also be fully utilized, as assumed in the NIA scenario. Both scenarios were evaluated by comparing their ability to meet the demand for rice in Venezuela. The average demand from 2009 to 2023 was estimated at 1.2 million tons per year, based on the sum of domestic rice production and annual rice imports (FAOSTAT 2024).

3 Results and discussion

3.1 Yield potential and yield gaps across buffer zones and crop cycles

The estimated Yp ranged from 8.6 to 9.8 Mg ha^{-1} in the wet season (WS) and from 10.4 to 10.9 Mg ha^{-1} in the dry season (DS) across buffers I, II, III, and IV (Fig. 5). The Yg, expressed as a percentage of Yp, varied from 48% to 56% in the WS and from 58% to 61% in the DS. At the national level, Yp in the WS was 9.2 Mg ha^{-1}, with a Yg of 53%, while in the DS Yp reached 10.5 Mg ha^{-1}, and Yg was 59%. These results correspond to an average Yp of 9.8 Mg ha^{-1} across both seasons. An alternative way to estimate the potential of a crop would be to use a large number of yield data from commercial fields, evaluating the 95% percentile of the data distribution, provided there is no genetic lag in the country (Van Ittersum et al. 2013). In Supplementary Fig. 6, it can be seen that the difference between the potential simulated by the Oryza v3 model (9.2 and 10.5 Mg ha^{-1}) and the potential observed in farmers' fields (8.7 and 9.9 Mg ha^{-1}) for WS and DS, respectively, is very close, demonstrating the robustness of the model and its excellent performance in simulating the Yp of rice in Venezuela.

The higher Yp for buffer zone IV in WS is directly associated with higher incident solar radiation, as well as with a slightly later sowing than in the other buffers, with the critical period for rice (reproductive phase) coinciding with the period of greatest availability of solar radiation (Meus et al. 2020, 2021). The greater Yp in the DS compared to the WS is related to the greater availability of solar radiation in January and February and the lower amount of rainfall in all buffer zones (Fig. 2). Excessive rainfall can reduce the leaf area index and increase susceptibility to diseases, and low availability of solar radiation can result in a lower number of spikelets and thousand-grain weight (Deng et al. 2019; Yin et al. 2023).

The largest Yg was observed during the dry season (DS) across all regions, ranging from 58 to 61% of the Yp. When considering the entire agricultural year, Venezuela shows an average Yg of 56%, equivalent to 5.5 Mg ha^{-1} (Supplementary Fig. 7). Compared to other major rice-producing countries, Yg in Venezuela is considerably larger compared to 27% in the USA, 33% in China, 47% in Brazil, and 54% in Argentina and is close to the levels reported for sub-Saharan Africa (60%) (Espe et al. 2016; Deng et al. 2019; GYGA, 2024). Importantly, this large gap is primarily associated with low average on-farm yields (Ya) rather than exceptionally high Yp, as demonstrated in Supplementary Fig. 7. While the estimated Yp values (9.2 Mg ha^{-1} in WS and 10.5 Mg ha^{-1} in DS) are consistent with those observed in other irrigated rice systems, farmers in Venezuela currently achieve only 47% and 41% of Yp in WS and DS, respectively. This indicates significant inefficiencies in crop management and highlights the potential to close the gap through improved practices, such as optimizing sowing dates and introducing crop rotations with rice (Ribas et al.

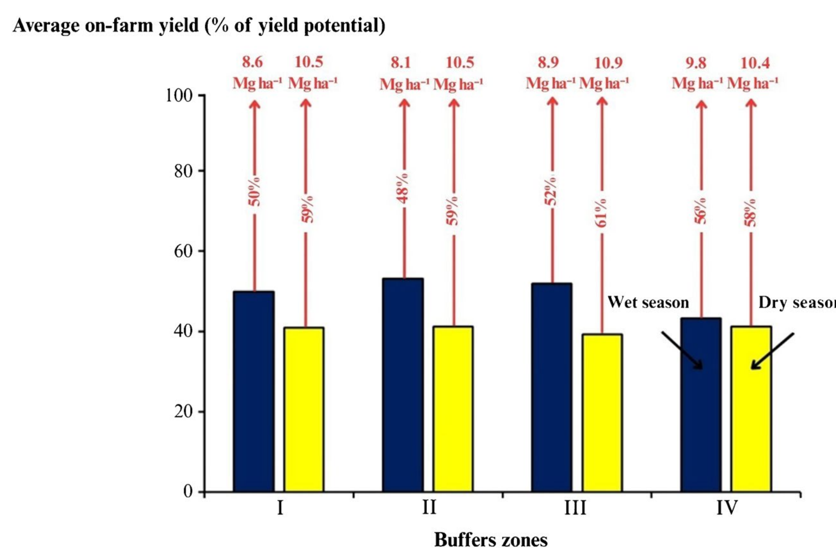

Fig. 5 Yield potential and yield gap as a percentage of yield potential relative to average yield in the four buffer zones of the main irrigated rice areas in Venezuela. The red arrows represent the current yield gap (Yg) with the percentage indicated in the arrows, while the values at the top of each arrow indicate the yield potential in Mg ha^{-1}. The bars represent the average observed yield in farmers' fields for each buffer zone and growing season. The Yg was calculated taking into account the average yield over 5 years (2018–2022).

2021a, b; Theisen et al. 2017) factors that were also identified in this study.

3.2 Agronomic causes of yield variation for different seasons

High-yield fields produced 3.0 to 4.0 Mg ha^{-1} more compared to low-yield fields, with a high level of statistical significance (< 1%) in WS and DS, respectively (Table 1). In WS, high-yield fields stood out for advancing the sowing date, applying greater rates of nitrogen and K_2O, using more herbicides in pre-sowing and fewer herbicides in post-emergence, in addition to using a greater number of pesticide applications. It is noteworthy that the variables related to sowing season, nitrogen, and fungicide and insecticide application presented the highest levels of significance (< 1%) for this season. On the other hand, in DS, for high-yield fields, farmers adopted a lower seeding rate and applied higher doses of nitrogen, P_2O_5 and K_2O, in addition to using more herbicides in pre-emergence. Among these practices, seeding rate and plant nutrition presented the highest levels of significance (< 1%). In both seasons, high-yield fields stand out for the greater amount of nitrogen and K_2O fertilization, showing a high level of significance (≤ 5%).

The conditional inference tree analyses for rice during the wet season (WS) and dry season (DS) were employed to illustrate the effects of specific factors and their interactions (Fig. 6). The crop establishment methods and the preceding crop were identified as the primary management factors explaining the variation in the Yg in Venezuela during the WS and DS, respectively. In the WS, the conditional inference tree selected crop establishment methods, nitrogen (N) application rate, and pre-sowing herbicide application as key explanatory variables, where fields implementing direct seeding and applying > 162 kg ha^{-1} of N exhibited, on average, a yield increase of 1.2 Mg ha^{-1} compared to those not adopting this practice. Furthermore, fields under conventional tillage that applied pre-sowing herbicide achieved an average yield gain of 0.5 Mg ha^{-1} relative to fields that did not apply it. Similarly, in the DS, fields that underwent fallow or maize cultivation prior to rice sowing, adjusted the seeding rate to ≤ 95 kg ha^{-1}, and applied K_2O at rates > 70 kg ha^{-1} demonstrated an average yield increase of 2.0 Mg ha^{-1} compared to those not implementing these practices. Moreover, monoculture fields applying P_2O_5 at rates > 40 kg ha^{-1} and N at rates > 191 kg ha^{-1} achieved, on average, 1.9 Mg ha^{-1} higher yields than those managed with lower input levels. These findings highlight the importance of site-specific management strategies, where optimizing crop establishment methods, fertilization regimes, and rotational practices can significantly reduce the Yg and enhance rice yield under varying seasonal conditions.

The fact that the HY fields in WS anticipate sowing (–19.5 days) and have a higher intensity of plant protection management (64%) is related to the accumulated rainfall mainly in June–July and the higher disease pressure (Table 1; Supplementary Fig. 8). Excessive rainfall hinders sowing and reduces the plant population per unit area. In addition, high relative humidity, prolonged leaf wetness, and moderate temperatures create favorable conditions for the proliferation of pests and diseases (Duarte Junior et al. 2021; Kirtphaiboon et al. 2021). For DS, the lower seeding rate in HY fields (–5.3%) could be related to the higher biomass production, which requires a lower density to avoid shading

Table 1 Comparison of management and inputs between the high yield (HY) fields and the low yield (LY) fields for 274 irrigated rice fields in Venezuela. The values indicate the mean differences (HY-LY) between the highest and lowest terciles of yield. Sowing dates are expressed as day of year (DOY), with values calculated as the number of days after May 1 st for the wet season and after November 1 st for the dry season. N: nitrogen fertilization; P_2O_5: phosphate fertilization; K_2O: potassium fertilization; *n*: number of applications; HY: high yield fields; LY: low yield fields; Significance levels: *** = 1%; ** = 5%; * = 10%; *ns* not significant.

Variables	Wet season				Dry season			
	HY	LY	HY-LY	*p*-value	HY	LY	HY-LY	*p*-value
Yield (Mg ha^{-1})	7.2	4.2	3.0***	<0.0001	9.0	5.0	4.0***	<0.0001
Sowing date (DOY)	16.4	35.9	−19.0***	0.0075	36.2	35.8	0.5^{ns}	0.8659
Seeding rate (kg ha^{-1})	102.7	104.6	−1.9^{ns}	0.6008	93.5	98.7	−5.2***	<0.0001
N fertilizer (kg ha^{-1})	178.0	151.6	26.4***	<0.0001	202.3	180.4	21.9***	0.0002
P_2O_5 fertilizer (kg ha^{-1})	31.8	38.4	−6.6^{ns}	0.6478	59.2	41.6	17.6***	<0.0001
K_2O fertilizer (kg ha^{-1})	81.8	63.2	18.6**	0.0422	114.6	93.5	21.1***	0.0055
Pre-sowing herbicide (*n*)	2.2	1.1	1.1**	0.0131	1.6	1.4	0.2^{ns}	0.5973
Pre-emergent herbicide (*n*)	2.1	1.7	0.4^{ns}	0.4743	1.9	1.2	0.7*	0.0912
Post-emergent herbicide (*n*)	1.8	2.9	−1.0**	0.0341	1.0	1.6	−0.6^{ns}	0.1085
Fungicide (*n*)	1.9	0.5	1.4***	<0.0001	1.2	0.8	0.4^{ns}	0.1520
Insecticide (*n*)	2.6	1.1	1.5***	<0.0001	1.6	1.8	−0.2^{ns}	0.3187

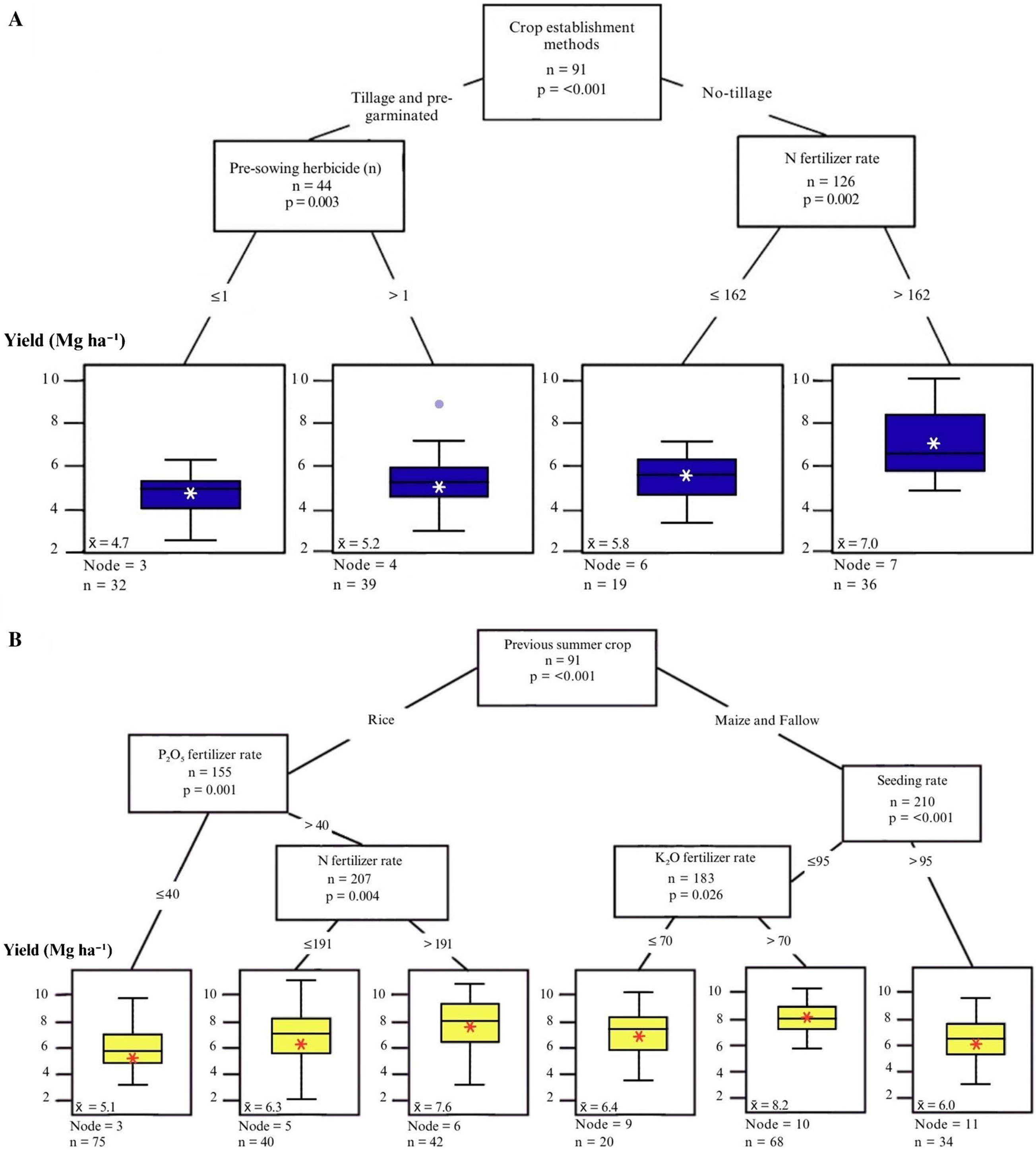

Fig. 6 Conditional inference tree for rice in the wet season (**A**) and dry season (**B**) based on aggregated survey data from Venezuela (n = 126 and 275 for the wet and dry seasons, respectively). In each boxplot, the box delineates the first and third quartiles of yield, while the horizontal line represents the median. The upper and lower whiskers correspond to the 90th and 10th percentiles, respectively. Terminal node means are shown below each boxplot and are expressed in Mg ha^{-1}, and an asterisk marks the mean within the boxplot. The variables included in the conditional inference trees (along with their abbreviations and units) were crop establishment methods and previous summer crops (categorical), pre-sowing herbicide application (n) (number of applications), N fertilizer rate (kg ha^{-1}), P_2O_5 fertilizer rate (kg ha^{-1}), K_2O fertilizer rate (kg ha^{-1}), and seeding rate (kg ha^{-1}).

or lodging by excess of plants. In addition, HY fields have a higher P_2O_5 requirement (36%), which promotes better plant structure and increases grain fixation and weight (Ye et al. 2019; Jiang et al. 2021; Ribas et al. 2021a, b). In both seasons, pre-emergence herbicide management is intensified in HY fields. This strategy allows the use of active ingredients to control grasses such as red rice, as the lack of selective herbicides to control these weeds in post-emergence makes management difficult (Fruet et al. 2020; Ribas et al. 2021a, b). In addition, on average, 12.8% more N and 20.5% more K_2O are applied to HY fields in both seasons. These results show a possible nutrient limitation of the most important macronutrients in LY fields, which reduces yield (Ye et al. 2019; Wang et al. 2021).

Our conditional inference tree analysis identified that, during the wet season (WS), the crop establishment methods were the primary factor explaining yield variation, with farmers who adopted no-tillage (NT) achieving, on average, 22.6% higher yields than those using tilled (Ti) or pre-germinated (PG) sowing. This finding aligns with previous studies indicating that no-tillage reduces weed density and diversity while preserving soil structure, thereby protecting it from the impact of heavy rainfall and promoting plant establishment (Kumar & Ladha 2011; Bhat and Kukal 2015). During the dry season (DS), the conditional inference tree identified the preceding crop as the main factor influencing yield variation. Fields previously cultivated with maize or left fallow produced, on average, 7.7% higher yields than those under continuous rice monoculture (MO). This result can be attributed to the long-term negative effects of monoculture, such as increased pest, disease, and weed pressure, soil degradation, and reduced system-level nutrient use efficiency (Liu et al. 2016; Ribas et al. 2021a, b; Meus et al. 2024).

To further explore the relationship between these key factors and yield, we analyzed them individually. In the WS, NT increased yield by 1.8 Mg ha^{-1} compared to Ti and PG (Fig. 7 A). In the DS, Ti led to an average yield increase of 1.4 Mg ha^{-1} compared to PG and NT, while NT yielded 0.6 Mg ha^{-1} more than PG (Fig. 7B). During the wet season, no significant differences were observed among fields previously planted with rice, beans, or left fallow before rice sowing (Fig. 7 C). However, an analysis of 88 fields revealed that introducing maize into the system (maize-rice, M/R) resulted in a 1.8 Mg ha^{-1} yield increase compared

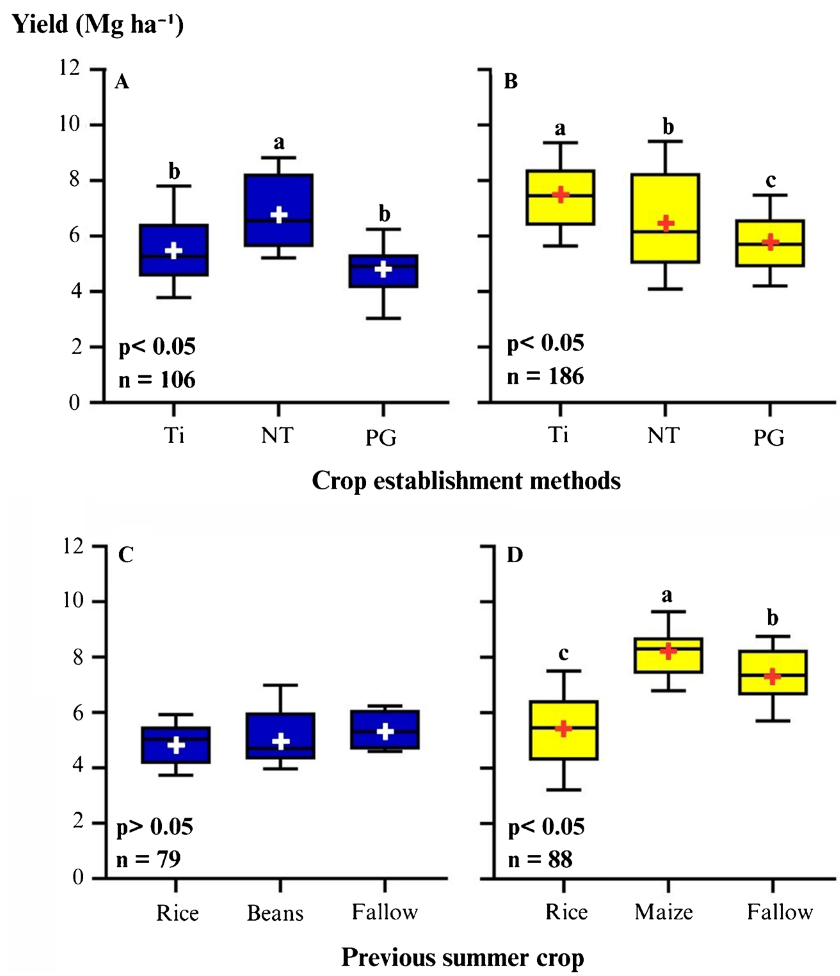

Fig. 7 Boxplots comparing crop establishment methods (**A**, **B**) and the previous crop (**C**, **D**) for rice yield. Blue boxes (wet season) and yellow boxes (dry season). Tillage (Ti), no-tillage (NT), and pre-germinated (PG). The boxes delimit the 25th and 75th percentiles, while the whiskers represent the 90th and 10th percentiles. The number of observations (*n*), the median (horizontal line), and the mean (+) are shown. The statistical significance of the difference in yield (diff.) in all panels was determined using the Kruskal-Wallis test. ns $P > 0.05$.

to fallow-rice (F/R) and rice monoculture (R/R) (Fig. 7D). Furthermore, R/R was the least productive system, reducing yield by 1.9 and 2.8 Mg ha^{-1} relative to F/R and M/R, respectively.

The crop establishment methods exhibited an inverse pattern in both seasons, with no-tillage (NT) increasing yield by 27% and conventional tillage (Ti) by 19% in the wet season (WS) and dry season (DS), respectively. The hypothesis is that adopting no-tillage at the beginning of the dry season is challenging due to rainfall during the preceding harvest period (September–October), when heavy machinery operating on wet soil often disrupts the soil structure, damages field bunds, and creates compaction, thus requiring tillage before the next sowing a pattern corroborated by the high yield variability observed in the boxplot analysis (Fig. 7B; see Supplementary Fig. 8). Similar challenges have been reported in rice-based systems, where soil puddling and machinery traffic under wet conditions lead to subsurface compaction and deterioration of soil physical structure, limiting root development and reducing crop performance (Bhatt & Kukal 2015). The higher yields observed under no-tillage and transplanting, compared to conventional pre-germinated seeding (PG), may be attributed to better plant establishment, since PG systems pose greater challenges for achieving uniform plant distribution and typically require advanced technologies for water management, seed handling, and land leveling (Bouman et al. 2007). Crop distribution is the main management practice affecting grain yield in the dry season, where, on average, continuous irrigated rice cultivation reduces yield by 29.7% (Fig. 7D). In Venezuela, continuous rice cultivation without crop rotation, commonly referred to as rice monoculture, can lead to significant yield reductions due to the higher pressure from weeds (including weedy red rice and *Echinochloa* spp.), pests, and diseases. Similar trends have been observed in Argentina and Brazil, where rice monoculture reduced yields by 5% and 24%, respectively, while rotations with maize or well-managed fallow periods helped disrupt these biological cycles and improve weed control (Liu et al. 2016; Ribas et al. 2021a, b; Meus et al. 2024).

In addition to the key factors identified through the decision tree analysis, other agronomic practices, particularly nutrient management, seeding rate, and pre-sowing herbicide, also play a critical role in determining yield outcomes and offer further opportunities for improvement. To support producer decision-making and inform future research, we examined the relationship between grain yield and the application levels of nitrogen (N), phosphorus (P_2O_5), and potassium (K_2O) across monitored fields (Supplementary Fig. 9). Quadratic regressions were used to estimate the point of maximum technical efficiency (PMTE) for each variable, with optimal values of 192 kg ha^{-1} for N, 67 kg ha^{-1} for P_2O_5, and 123 kg ha^{-1} for K_2O, each associated with yields close to 10 Mg ha^{-1}. While nitrogen application exceeded plant theoretical demand by 30%, this excess, combined with the typically low nitrogen use efficiency in irrigated rice systems, highlights an opportunity to optimize its management through practices such as split application, use of enhanced-efficiency fertilizers, or refined dose adjustments, thereby increasing efficiency and reducing production costs (Xu et al. 2015; Silva et al. 2022; Rizzo et al. 2023). On the other hand, the application rates of phosphorus and potassium were 23% and 32% below crop demand, emphasizing the need for management strategies grounded in site-specific diagnostics such as soil testing and nutrient export balance assessments to prevent long-term nutrient depletion and maintain soil fertility (Römheld & Kirkby 2010; Xu et al. 2015; Zhao et al. 2021; Rizzo et al. 2024).

Moreover, additional agronomic practices, particularly pre-sowing herbicide application and seeding rate, also exert a substantial influence on rice productivity and merit closer attention. Pre-sowing herbicide use is a fundamental practice in irrigated rice systems, as it enables early control of weeds such as weedy red rice (*Oryza sativa f. spontanea*) and barnyardgrass (*Echinochloa crus-galli*) during the crop establishment period, thereby reducing competition for key resources such as light, nutrients, and water (Chauhan & Johnson 2011; Zimdahl 2018). These species, especially weedy red rice, are characterized by their high competitive aggressiveness and rapid spread in South American rice-growing systems, and due to their morphological and genetic similarity to cultivated rice, they exhibit significant tolerance to selective herbicides, rendering post-emergence control ineffective or even unfeasible (Pantone & Baker 1991; Ferrero & Vidotto 1999; Chauhan & Johnson 2011; Zimdahl 2018). Our findings also indicate that seeding rates above 95 kg ha^{-1} are associated with yield reductions, possibly due to increased intraspecific competition, higher lodging risk, and lower canopy light interception efficiency (Feng et al. 2024). These results are consistent with studies conducted in Brazil, also based on data collected from commercial rice fields, which identified optimal seeding rates close to those found in our study, such as 93 kg ha^{-1} (Meus et al. 2020, 2021), and recommended densities between 70 and 90 kg ha^{-1} to achieve high yields (Ribas et al. 2021a, b).

Our findings for both seasons show that adopting more efficient agricultural practices, such as no-tillage and crop rotation with maize before rice, is crucial for increasing yield in Venezuela. However, implementing these strategies requires greater management and significant investments in infrastructure and technology, which are enablers for crop intensification and yield growth, but currently present a major challenge for farmers in the country (Hajjapoor et al. 2022; Beres et al. 2023; Moss et al. 2025). No-tillage, for example, requires specialized seeders, careful residue management, and more efficient weed control, while including maize in the system demands adapted harvesters, dryers, and increased storage capacity. In addition to the high cost of this equipment, limited access to agricultural credit hinders the modernization of activities, preventing many farmers from adopting these beneficial practices (USDA 2016). This situation is further aggravated by logistical challenges and economic instability, which restrict the import of essential inputs, such as fertilizers and pesticides. Due to tight production margins, many farmers have abandoned rice production or sold their land. Therefore, although the adoption of more sustainable and technologically advanced production systems is essential for reducing the Yg, overcoming these limitations requires expanding access to rural credit, strengthening technical assistance, and implementing public policies that promote sector modernization.

3.3 Self-sufficiency scenario

Following the historical trend in yields and the area under rice production (NPT) (Fig. 8), a decline in rice cultivation is predicted for Venezuela, so that production would be zero in 2033. With the potential area for rice sowing and maintaining the current yield level, an increase of production of 133% would be possible (NIA), but this would not be sufficient to meet the country's demand. Finally, the intensification scenario (INT), in which the Yg are reduced and the potential area under cultivation is utilized, predicts that Venezuela would achieve self-sufficiency in rice by 2034 and double rice production by 2040.

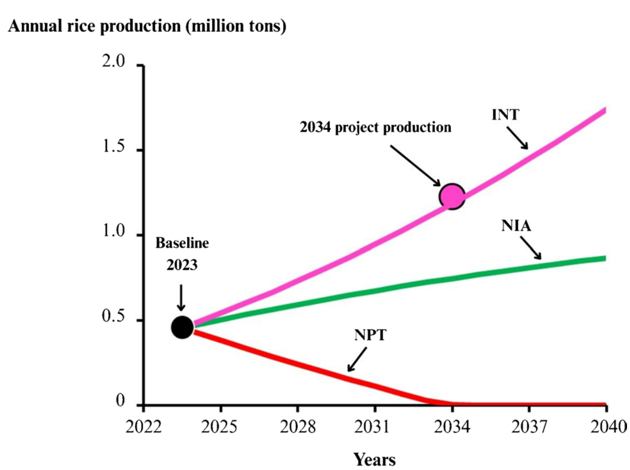

Fig. 8 Changes in rice production under different yield scenarios. Normal production trends (NPT), normal yield and area increase trends (NIA), and intensification of the production system through reduction of the yield gap (INT). The pink dot represents the projected production for 2034 under the INT scenario, which matches the historical average rice demand (1.2 million tons per year) calculated as the sum of domestic production and imports between 2009 and 2023 (FAOSTAT 2024).

These findings reinforce the potential to enhance both productivity and resource-use efficiency through the adoption of more sustainable and tailored agronomic practices, including appropriate crop establishment methods, crop rotation, nutrient management, pre-sowing herbicide application, and optimal seeding rates. Furthermore, in light of the projected scenarios for rice production in Venezuela (Fig. 8), our results underscore that achieving food self-sufficiency will require a strategic shift toward vertical intensification, namely, increasing yield per unit area by narrowing the Yg. Although horizontal expansion remains technically feasible since vast areas suitable for rice cultivation are currently idle due to high production costs and low profitability, simulations under the normal input area scenario (NIA; see Supplementary Fig 1) indicate that increasing cultivated area alone would be insufficient to meet national demand. However, it is observed that in the NIA scenario, even with the full utilization of the potential rice area referring to lands that were previously cultivated but are currently idle, national production would still not be sufficient to meet the national demand for rice. In contrast, the intensification scenario (INT), which combines Yg reduction with full utilization of the potential rice area, projects that Venezuela could achieve rice self-sufficiency by 2034 and double current production levels by 2040. Meeting this goal would require an estimated annual yield gain of 175 kg ha^{-1} yr^{-2}, a realistic and strategic target. In a context of climate change and global geopolitical instability, strengthening domestic food production capacity is essential to ensuring rice self-sufficiency (Brankov et al. 2021; Clapp 2017; Kriewald et al. 2019). Additionally, Venezuela holds significant potential to become a relevant player in the international rice market, exporting to countries lacking suitable production environments. Ultimately, the findings from this study provide practical guidance for researchers, extension agents, and policymakers on where to focus efforts to sustainably improve yield and profitability in the coming decades.

4 Conclusions

This study aimed (i) to quantify the yield potential and yield gaps of irrigated rice in both growing seasons in Venezuela, (ii) to identify the main biophysical and management factors contributing to these gaps, and (iii) to evaluate the country's potential to meet future domestic rice demand. By addressing these objectives, our analysis demonstrates that Venezuela holds significant potential to intensify rice production, particularly by reducing yield gaps, which reach 53% in the wet season and 59% in the dry season. Our findings reinforce the need for concrete and coordinated strategies to overcome these limitations. The adoption of more efficient management practices, especially related to crop establishment methods and preceding crops, combined with investments in infrastructure, is essential to improve yields and enhance the stability of the production system. Under the intensification scenario, national demand of 1.2 million tons would be met by 2034, and by 2040, production could reach 1.8 million tons, generating a surplus of nearly 600 thousand tons available for potential export. The novelty of this study lies in providing the first comprehensive and data-based assessment of rice yield gaps in Venezuela, integrating crop modeling, extensive farm surveys, and future demand scenarios. By offering a broad and strategic perspective on the challenges and opportunities of rice production, this study provides valuable insights to guide the development of public policies, technical assistance actions, and investments in innovation, thereby contributing to national rice self-sufficiency, improved food security, and the sustainable livelihood of rice farmers.

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Authors' contributions All the authors contributed to the study conception and design. Material preparation, data collection, and analysis were performed by João Vitor Santos de Souza, Cintia Piovesan Pegoraro, Camille Flores Soares, Isabela Bulegon Pilecco, Vitória Signor, Lauren Machado Lago, Bruna Pinto Ramos, Marcel Angel Guevara Ordoñez, Maria Carolina Bitencourt, Wilmer Iván Chacón Martinez, Daniel Alejandro Brito Herrera, Tarmar Lopez, Mauricio Fornalski Soares, Eduardo Lago Tagliapietra,Gonzalo Rizzo, Giovana Ghisleni Ribas, and Nereu Augusto Streck; Alencar Junior Zanon spearheaded the writing of the manuscript, actively contributing to its creation and development. All the authors commented on previous versions of the manuscript. All the authors read and approved the final manuscript.

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Data Availability The datasets generated during and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Code Availability Not applicable.

Declarations

Ethics approval Not applicable.

Consent to participate Informed consent was obtained from all individual participants included in the study.

Consent for publication The authors affirm that the human research participants provided informed consent for publication of the images.

Competing interests The authors declare no competing interests.

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