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Distinguishing between yield plateaus and yield ceilings: A case study of rice in Uruguay

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A R T I C L E I N F O

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Yield plateau
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A B S T R A C T

Rice yields in Uruguay have increased rapidly (159 kg^{-1} ha^{-1} y^{-1}) between 1990 and 2013. There is evidence, however, of an incipient yield plateau in recent years. The aim of this study was to determine if the recent slowdown in yield gains is because average yield (Ya) has approached the yield potential (Yp) ceiling, which makes it increasingly difficult for farmers to sustain further yield gains. We followed the methodology developed by the Global Yield Gap Atlas to estimate Yp and associated yield gaps for irrigated rice supported by data from high-yield experiments to calibrate the rice simulation model Oryza (v3). Subsequently, the model was used to simulate Yp using long-term daily weather data from seven locations, representing 90 % of total rice area in Uruguay. The exploitable yield gap (Yeg) was calculated as the difference between 80 % of Yp and Ya. Estimated national average Yp was 13.9 Mg ha^{-1}, with relatively small variation across sites, from 13.1 to 15.1 Mg ha^{-1}. Average Ya was 8.3 Mg ha^{-1}, ranging from 7.9 to 8.5 Mg ha^{-1} across sites, and representing 60 % of Yp. Our analysis suggests there is still room to further increase rice yields in Uruguay, because the Yeg is 2.8 Mg ha^{-1}, which means the current yield plateau is not due to Ya approaching Yp, as has occurred in other high-yield irrigated rice systems in China and California, USA. The approach followed here can help determine whether yield plateaus are occurring due to a small Yeg or other factors.

1. Introduction

Uruguay produces 1.4 million metric tons (MMT) of paddy rice per year, ranging from 1.2 to 1.6 MMT during the last 10 years (DIEA, 2021). Uruguay is an export-oriented rice producing country with ca. 90 % of total annual production exported, ranking within the top 10 rice exporting countries worldwide (FAO, 2018; USDA, 2021). The Uruguayan rice sector has undergone major changes in recent decades that supported rapid increases in average rice yield (Ya) of 159 kg ha^{-1} y^{-1} (Fig. 1). This rate of yield gain is the highest among those of major rice producing countries (Grassini et al., 2013).

Drivers of yield increase before the plateau included the adoption of high-yielding cultivars and agronomic improvements such as improved soil management practices, optimal planting date, drill sowing, early weed control using herbicides, improved irrigation management, basal nitrogen and phosphorus fertilization at sowing and N topdressing increased, disease control using fungicides (Blanco et al., 2010). These yield-growth drivers were supported by the strong cooperation between farmers and rice mills within a vertically integrated value chain for technology transfer. This favorable trend has shown a marked slowdown in recent years with an incipient yield plateau apparent since 2013 at a yield averaging 8.2 Mg ha^{-1} (Fig. 1).

Cassman et al. (2003) and Lobell et al. (2009) have argued that Ya starts to plateau when it reaches ca. 80 % of the yield potential (Yp). Further increase in Ya above the 80 % of Yp is difficult and typically not cost-effective due to the diminishing yield gains from investments in additional applied inputs, technologies, and labor. Likewise, it is challenging for a high proportion of farmers to achieve the perfection in crop and soil management that is needed to reach Yp. At issue is whether the incipient rice yield plateau observed in Uruguay can be attributed to a biophysical limit or whether it is associated with current agronomic management practices that limit yields well below the attainable yield. Answering this question requires robust estimation of Yp, which is defined as the yield of a competent crop cultivar when grown with non-limiting water and nutrients and with all biotic stresses effectively controlled (Evans, 1993; van Ittersum and Rabbinge, 1997). The

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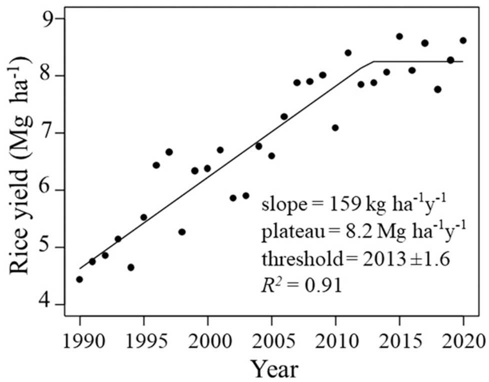

Fig. 1. Rice yield trends in Uruguay from 1990 to 2020 based on data collected by the rice sector commission (CSA) and agricultural statistics (DIEA-MGAP). Solid line indicates the fitted linear-plateau model; all model parameters were statistically significant ($P < 0.001$). Also shown are the parameters (± standard error) and coefficient of determination (R^2).

exploitable yield gap (Yeg) is defined as the difference between 80 % of Yp (hereafter referred to as "attainable yield") and current average farm yields (Cassman et al., 2003; Lobell et al., 2009).

Understanding whether the yield plateau is related to a biophysical limit is relevant for several reasons. First, it is critical for understanding the available room to increase production on existing cropland (e.g., Grassini et al., 2011; Aramburu-Merlos et al., 2015), which is relevant in the case of Uruguay as rice harvested area has declined by ca. 20 % over the last 10 years (DIEA, 2021). Second, if farmers have already closed the Yeg, it is important to avoid excessive application of agricultural inputs, with associated high costs and negative environmental impact (Gibson et al., 2019; Tenorio et al., 2020). Finally, robust estimates of Yp and Yeg can help orient investments in agricultural research & development and policy (van Oort et al., 2017). For example, a very small Yeg may not justify a high level of investment in technologies that can help break the yield barrier rather than a focus on management practices to increase producer profit via greater input-use efficiency. It may also be possible to identify regions within a country where Yeg is still large and, therefore, where room exists for yield increase via improved agronomic management. Another potential cause of the current yield plateau could be climate change. For example, several studies have reported that climate change trends could negatively affect rice yields in Uruguay (Nagy et al., 2014; Tiscornia et al., 2016), Asia (Wassmann et al., 2009; Desai et al., 2021) and worldwide (Ortiz-Bobea et al., 2021). Therefore, understanding whether Yp has changed over time due to climate change is also important to identify the drivers of the current yield plateau in Uruguay.

Previous attempts to estimate Yp and Yeg in Uruguay have relied on measured yields in experimental trials (Pérez de Vida and Macedo, 2013) or high-yielding farmer fields (Blanco et al., 2010; Tseng et al., 2021). While this approach has some advantages, it also has major limitations (van Ittersum et al., 2013). For example, if none of the field experiments or surveyed farmers achieved full Yp due to sub-optimal crop and soil management, then estimates of Yp will be underestimated. Likewise, highest measured yields in specific years and/or sites may not be representative of the Yp based on the dominant climate and soil types across the rice producing area in Uruguay.

The goal of this study was to determine if the current yield plateau in Uruguay is caused by a biophysical yield limit. Hence, we calculated Yp and Yeg for Uruguay following a methodology that accounts for variation in weather across major rice producing regions in the country using a well-validated crop simulation model to estimate Yp. Trends in Yp and weather parameters influencing Yp (Tmax, Tmin, and solar radiation) were also evaluated to identify changes in Yp driven by climate. We also compared our Yeg values with those reported in previous studies that followed a different approach for estimating Yeg. Finally, we compared the Yeg for rice in Uruguay with values reported for other high-yield irrigated rice systems in other major rice-producing countries.

2. Methods

2.1. Harvested area, reference weather stations (RWS) and weather data

Irrigated rice in Uruguay is grown in ca. 180,000 ha (Fig. 2**a**). For research and extension purposes, the rice area in Uruguay is divided in three regions: north, central, and east. These regions account for a respective 22 %, 13 %, and 65 % of national rice harvested area. We followed the protocols developed by the Global Yield Gap Atlas (GYGA; www.yieldgap.org) to select representative sites (van Bussel et al., 2015; Grassini et al., 2015). Briefly, digital maps of rice harvested area were retrieved from the MGAP Census 2011 data, Ministry of Livestock, Agriculture and Fisheries (DIEA, 2011). The agricultural district represents the smallest administrative territorial division within Uruguay, which are used for census and statistical purposes. Following the GYGA protocols, four climate zones were identified, covering 98 % of national rice harvested area (Fig. 2**b**). Each climate zone corresponds to a specific combination of growing degree-days, temperature seasonality, and aridity index (Van Wart et al., 2013). Within selected climate zones, seven reference weather stations and associated buffer zones were selected, covering 90 % of national rice harvested area (Table S1). Buffer zones were created based on an area of 100-km radius around each selected reference weather station. Borders of the buffers were

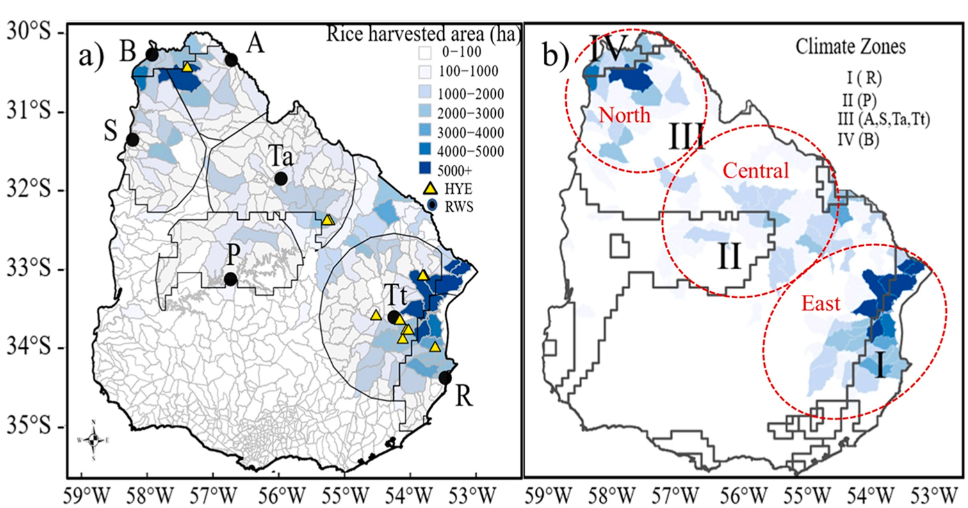

Fig. 2. (a) Selected reference weather stations (RWS, black dots) with associated buffer zones, and location of the high yielding experiments used for model calibration and evaluation (HYE, yellow triangles). (b) Selected climate zones (I–IV) and rice producing areas (north, central, and east; red dashed circles). Also shown in blue color is the rice harvested area by agricultural administrative district. Ta: Tacuarembó, P: Paso de los Toros, R: Rocha, Tt: Treinta y Tres, A: Artigas, S: Salto Grande, B: Bella Unión.

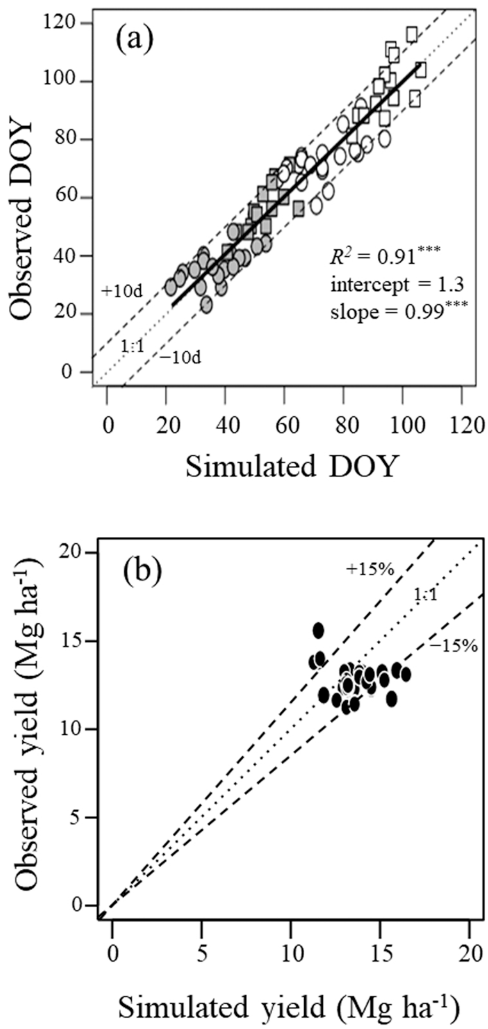

Fig. 3. (a) Comparison between observed and simulated flowering and maturity dates (solid and empty symbols, respectively). Symbol types indicate early (circles) and late sowing dates (squares). (b) Measured versus simulated grain yield based on data from well-managed experiments. DOY: day of year (Julian day). Asterisks indicate significance at $p < 0.001$***. R^2: coefficient of determination. Maturity date corresponds to R9 stage (Counce et al., 2000).

clipped by the borders of the climate zone where the reference weather station was located **(**Fig. 2**a)**.

Measured daily weather data from 1997 to 2020 were retrieved from different sources, including INIA (National Institute of Agricultural Research), INUMET (Uruguayan Institute of Meteorology), ALUR (Alcohols of Uruguay), and Agridiamond S.A. (private company) (INIA-GRAS, 2015; GYGA, 2021). Variables needed for simulation of Yp include daily minimum and maximum temperatures (Tmin and Tmax, respectively) and incident solar radiation. Missing data were filled following the methods of Van Wart et al. (2015). Briefly, gaps of radiation and temperature of no more than 5 consecutive days were filled using linear interpolation. For gaps in temperature larger than five consecutive days, we used daily NASA-POWER data, after correcting for local bias in the NASA temperature data using the measured weather data from reference weather stations. In the case of solar radiation, gaps larger than five consecutive days were filled with raw NASA-POWER data because it has been shown that NASA-POWER solar radiation has good agreement with measured values (Bai et al., 2010; White et al., 2011). These procedures provided complete daily weather records of all variables required for simulating Yp over the 1997–2020 period.

Table 1
Rice yield potential estimated for the twenty-three-year period (Yp: 1997–2020). Average yield (Ya), exploitable yield gap (Yeg), and relative yield (RY) registered from 2016 to 2020 for each reference weather stations (RWS), climate zones (CZ) and rice regions of Uruguay. The RWS, CZs and regions are sorted from highest to lowest RY. Also shown are the national averages.

Site	Yp (Mg ha^{-1})	Ya (Mg ha^{-1})	Yeg (Mg ha^{-1})	RY (%)
RWS				
B	13.1^{d}	8.5^{a}	1.6^{b}	67^{c}
S	13.1^{d}	8.3^{a}	1.8^{b}	66^{c}
A	13.4^{cd}	8.3^{a}	2.3^{b}	62^{c}
Tt	13.9^{c}	8.3^{a}	2.8^{b}	60^{bc}
P	13.7^{c}	8.0^{a}	2.9^{b}	59^{bc}
Ta	14.5^{b}	8.2^{a}	3.1^{ab}	58^{bc}
R	15.1^{a}	7.9^{a}	4.5^{a}	51^{a}
RWS effect	***		***	***
CZ				
IV	13.1^{c}	8.5^{a}	1.6^{b}	67^{b}
III	13.7^{b}	8.3^{a}	2.5^{b}	62^{b}
II	13.7^{b}	8.0^{a}	2.9^{b}	59^{ab}
I	15.1^{a}	7.9^{b}	4.5^{a}	51^{a}
CZ effect	***		***	***
Regions				
North	13.2^{b}	8.4^{a}	1.9^{b}	65^{b}
Central	14.1^{a}	8.1^{a}	3.0^{a}	59^{a}
East	14.5^{a}	8.1^{a}	3.7^{a}	56^{a}
Region effect	***		***	***
Country mean	13.9	8.3	2.8	60

Means followed by different letters are significantly different. Asterisks indícate statistical significance at $p < 0.001$***. Ta: Tacuarembó, P: Paso de los Toros, R: Rocha, Tt: Treinta y Tres, A: Artigas, S: Salto Grande, B: Bella Unión.

Table 2
Comparison of attainable yield (AY), actual yield (Ya), exploitable yield gap (Yeg) and relative yield (RY) estimated for rice in Uruguay in our study with those reported in the literature. Approaches used for estimating AY in each study are shown. In our study, AY was estimated as 80 % of the simulated Yp. Further detailed information is presented in Table S3.

Study	Approach	AY (Mg ha^{-1})	Ya (Mg ha^{-1})	Yeg (Mg ha^{-1})	RY (%)
Blanco et al. (2010)	Highest farmer yield	11.1	5.6	5.5	40
Pérez de Vida and Macedo (2013)	Average from variety trials	8.1	6.7	1.3	67
Tseng et al. (2021)	Top 10 % farmer yield	10.3	8.4	1.9	65
Tseng et al. (2021)	Highest farmer yield	11.2	8.3	2.9	60
Our study	Crop model	11.1	8.3	2.8	60

Table 3
Comparison of average yield potential (Yp), yield (Ya), exploitable yield gap (Yeg) and relative yield (RY) for high-yield irrigated rice systems located in non-tropical regions included in the Global Yield Gap Atlas (www.yieldgap.org). Countries were sorted from highest to lowest RY.

Country (or región)	Yp (Mg ha^{-1})	Ya (Mg ha^{-1})	Yeg (Mg ha^{-1})	RY (%)
Egypt	11.9	9.6	nil	81
California, USA	13.2	9.3	1.3	71
China	9.5	6.5	1.1	68
South-central USA	12.2	7.9	1.9	65
Uruguay (current study)	13.9	8.3	2.8	60
Southern Brazil	14.8	7.6	4.3	51
Argentina	14.1	6.7	4.6	48

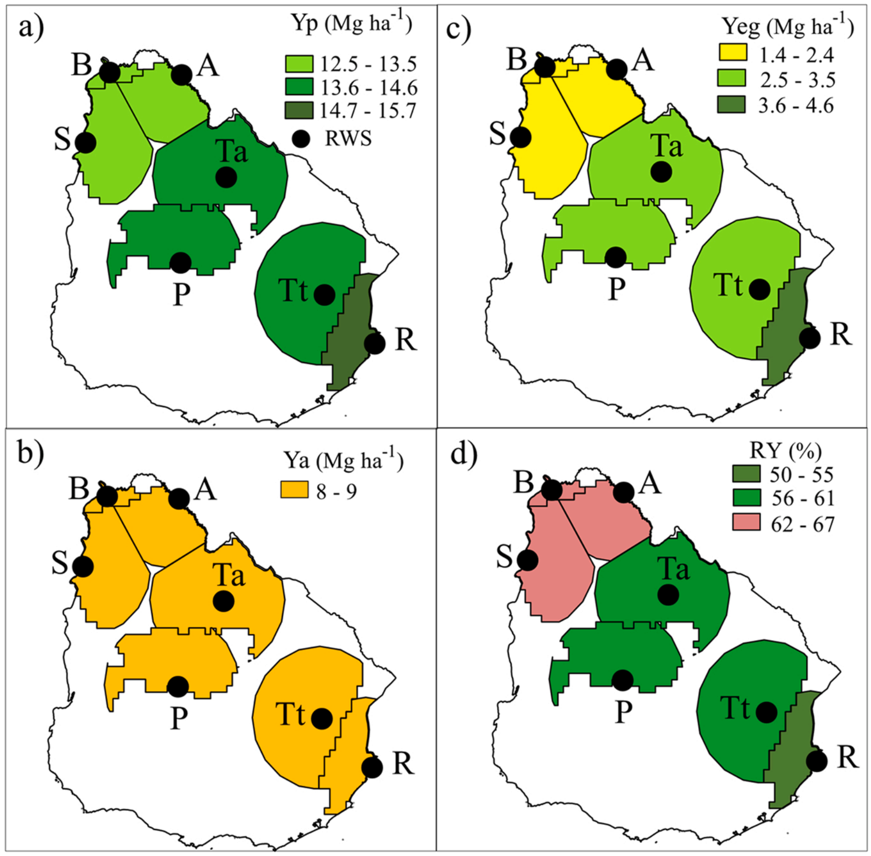

Fig. 4. (a) Average yield potential (Yp), (b) actual yield (Ya), (c) exploitable yield gap (Yeg), and (d) relative yield (RY) for each reference weather station (RWS) (2016–2020). Ta: Tacuarembó, P: Paso de los Toros, R: Rocha, Tt: Treinta y Tres, A: Artigas, S: Salto Grande, B: Bella Unión.

2.2. Crop system and management data

A single rice crop is produced annually in Uruguay. The rice crop season extends from late Sept–Oct (establishment) to Mar–April (maturity). Sowing occurs in early October, with ca. 70 % of all rice area planted in that month. Rice production is highly mechanized, with most crops direct seeded (90 %). Fields are flooded 15–35 days after emergence. The most common crop sequence consists of two years of rice followed by three years of pasture (INIA, 2021; DIEA, 2021). Management practices for each buffer were retrieved from databases provided by private companies (Casarone, Coopar and Saman), covering ca. 75–80 % of national rice area. The private industry database used in this study contained field records, including yield and management practices, collected by their field agronomists across all agricultural districts and regions of Uruguay. This information included dominant crop sequence, average planting date, dominant cultivar, and plant population density (Table S2). Data were verified using other published information and expert opinion from local agronomists. Long-grain varieties are predominant, and, for our simulations, we used INIA Olimar (north and central regions) and El Paso 144 (east region) based on the harvested area planted with each of these varieties according to the rice industry database. Both cultivars (INIA Olimar and El Paso 144) are *Indica* ecotypes; for this reason, variation in Yp across reference weather stations is expected to be mostly driven by weather rather than cultivar differences.

2.3. Calibration and evaluation of the rice simulation model

We used the crop simulation model Oryza (v3) to estimate Yp for irrigated rice in Uruguay (Li et al., 2009, 2017). This model has been widely used for Yeg analysis of rice across a wide range of environments, including Asia (Timsina et al., 2016; Silva et al., 2017), Africa (van Oort et al., 2015b), and the USA (Espe et al., 2016a, 2016b). In a first step, model coefficients that determine rate of crop phenological development were calibrated for the two selected *Indica* cultivars (El Paso 144 and INIA Olimar) using data from field experiments conducted in the east region during 2005–2014. Crops in these experiments received sufficient nutrients and irrigation to avoid nutrient and water limitations, and regular applications of pesticides to kept them free of weeds, diseases, and insect pests. This dataset (hereafter referred to as the “calibration dataset”) included emergence, flowering, and maturity dates recorded over 10 years for two (late and early) sowing dates (INASE-INIA, 2005–2014). Maturity was visually identified when the grains in the lower portion of panicles harden and lose their green color. This period corresponds to R9 stage when grains have begun to dry and all grains have brown hulls (Counce et al., 2000). Calibration was performed using weather data from the reference weather station Treinta y Tres as the field experiments used for phenology calibration were located within the same climate zone.

We calibrated two of the four development coefficients in Oryza (v3): developmental rate in the juvenile phase (DVRJ) and developmental rate in the reproductive phase (DVRR). Following Bouman et al. (2001), we used generic values for the other two development coefficients: developmental rate in the photoperiod-sensitive phase (DVRI) and developmental rate in the panicle formation phase (DVRP), which were retrieved from the standard crop file available in Oryza (v3) for an *Indica* variety. Calibration was performed with the DRATESv2 program included within Oryza (v3). To assess the quality of calibration, dates of simulated flowering and maturity were compared against observed dates. Other coefficients that determine leaf growth, leaf area, and assimilate partitioning factors were not calibrated in this study as these data were not available. Generic values from the Oryza model (ORYZA

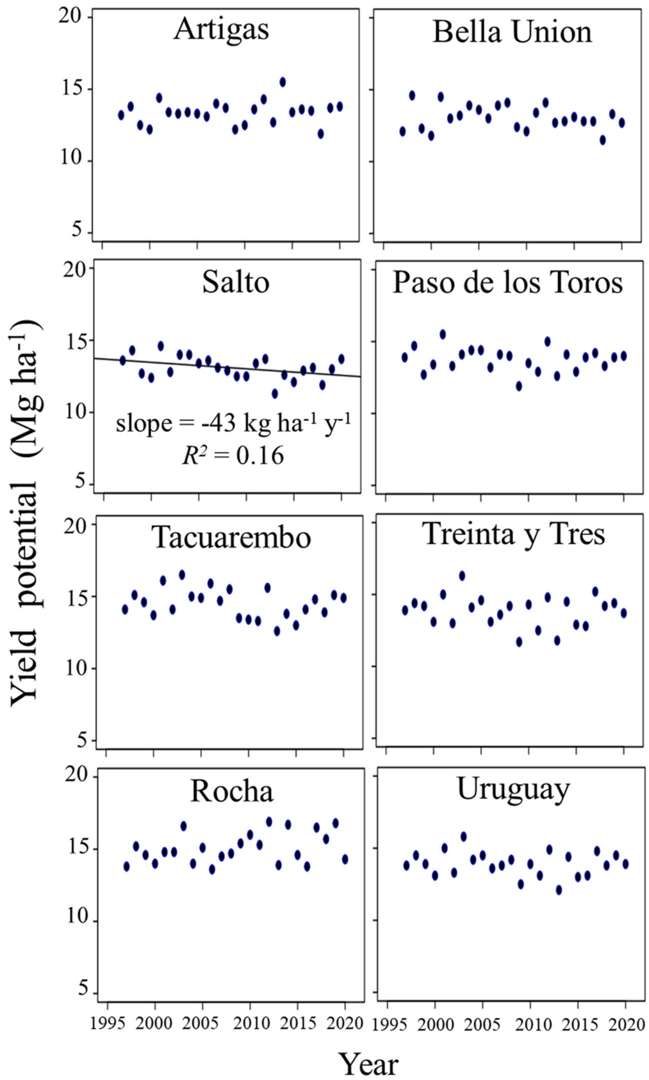

Fig. 5. Trends in rice yield potential based on daily weather records at seven reference weather stations and for Uruguay (1997–2020). Linear regression models are shown only when associated parameters were statistically significant ($p < 0.05$). Also shown are coefficients of determination (R^2) and slopes of the fitted models.

(v3)) were used for these parameters. Our approach can be considered robust because the phenological development rates are the most sensitive parameters governing Yp and its variation across environments (van Oort et al., 2011, 2015a).

In a second step, the calibrated model was evaluated for its ability to estimate Yp. This evaluation was performed using a second independent dataset (hereafter referred to as the "evaluation dataset"), with data collected from high yielding experiments implemented by INIA researchers and from variety trials (INASE-INIA, 2005–2014) located within the seven selected reference weather stations buffer zones and conducted during the 2005–2017 seasons (Fig. 2**a**). Field trials were conducted on experimental stations belonging to the National Research Institute (INIA) and in farmer fields located in the north, central, and east producing regions. El Paso 144 and INIA Olimar were grown in all experiments. The database included 36 high-yielding experiments, where crops received optimal management to ensure non-limiting water and nutrients supply and effective pest control. As a result, average yield was high (12.7 Mg ha^{-1}), ranging from 11.2 to 15.6 Mg ha^{-1}. Oryza (v3) was run under the yield potential mode (i.e., assuming no water and nutrient limitations and no incidence of biotic stresses), with weather data from nearby reference weather station, and simulated Yp were compared to the experimental yields. In this study, rice yields are expressed at 14 % grain moisture content.

2.4. *Simulation of yield potential and determination of yield gap*

After calibration, we used Oryza (v3) model to simulate Yp for the seven reference weather stations buffers based on 23 years of measured weather data (1997–2020) coupled with the reported management information on sowing date and plant density. Simulations assumed no water and nutrient limitations and no biotic stresses. Plant density used for simulations was 260 plants m^{-2} for all reference weather stations. Estimated Yp for the seven buffers was upscaled to climate zone level based on the rice harvested area in each reference weather station buffer zone relative to the total rice harvested area within the climate zone following van Bussel et al. (2015). A similar approach was followed to upscale results from climate zones to national scale.

Annual georeferenced data on Ya were provided by private rice industry companies (Casarone, Coopar, and Saman) for all rice administrative districts. These companies account for 77 % of rice area. We only considered the last five years (2016–2020) of Ya data to avoid the confounding effect of technological trends. The main cultivated varieties were *Indica* ecotype: INIA Olimar and El Paso 144. Each reference weather station buffer zone included several agricultural districts. Average Ya was calculated by weighting the Ya reported for each agricultural district based on its associated rice harvested area. At each spatial scale (buffer, climate zone, country), Yeg was calculated as the difference between attainable yield and Ya. Following Lobell et al. (2009), attainable yield was estimated as Yp × 0.8. We expressed the degree of yield gap closure by computing the ratio between Ya and Yp, hereafter referred to as 'relative yield' (RY).

2.5. *Comparison of yield potential and yield gap with previous studies in Uruguay and other non-tropical high-yield rice systems*

Values of attainable yield and Yeg derived from our study were compared with those reported in previous studies conducted in Uruguay (Blanco et al., 2010; Pérez de Vida and Macedo, 2013; Tseng et al., 2021). In these studies, attainable yield was estimated from maximum or top 10 % farmer yields (Blanco et al., 2010; Tseng et al., 2021) or average yields measured in experimental variety trials (Pérez de Vida and Macedo, 2013). Methods and assumptions used for each study are shown in Table S3.

Finally, we compared Yp, Ya, Yeg and RY in Uruguay versus results reported for other high-yield irrigated rice systems (> 6 t ha^{-1} crop^{-1}) located in non-tropical regions as reported in the Global Yield Gap Atlas (www.yieldgap.org). Our analysis included the following countries or regions: Argentina, southern Brazil, California (US), Southern US, China, and Egypt. The goal of this analysis was to assess the degree of Yeg closure across countries with high Ya and provide insight about remaining room for increasing Ya in Uruguay.

2.6. *Data analysis*

Statistical analysis was performed using the R software (R Core Team, 2022). Linear regression models were used to analyze trends in Ya and Yp over time. Following Grassini et al. (2013), different models were tested to describe the observed trends: (i) linear, (ii) linear-plateau, (iii) piecewise, and (iv) quadratic plateau. The linear plateau model was fitted using the nls (Bates and Watts, 1988; Bates and Chambers, 1992) function in R, the linear piecewise model was fitted using the R package "segmented" (Muggeo, 2008) and the quadratic plateau model was fitted using the R package "nlraa". The best model was selected based on AIC values. Pseudo R^2 was calculated with the nagelkerke method (Mangiafico Salvatore, 2016), using the nagelkerke function of rcompanion package in R (Nagelkerke, 1991) with a null model defined as the average of yield over years. Trends in Yp and weather parameters (Tmax, Tmin, and solar radiation) over the rice growing season period (sowing to harvest) were assessed for each reference weather station. Pearson correlation analysis was performed using the cor.test function (R Core Team, 2022) while linear regression models were fitted using the lm function in R (Chambers, 1992). Analyses of variance (ANOVA) were performed to evaluate the influence of reference weather stations, climate zones, and rice producing region on Yp, Ya, Yeg, and RY and means were compared using Tukey's tests.

3. Results

3.1. Yield potential, actual yield, and exploitable yield gaps

Comparison of simulated phenological events (flowering and maturity dates) against observed dates across experiments indicated good agreement (RMSE = 0.51 d) and strong correlation between them (R^2 = 0.91) (Fig. 3**a**). Almost all simulated dates fell within ± 10 d of the observed dates while 75 % of simulated values fell within ± 15 % of measured yield (Fig. 3**b**).

Average Yp simulated for Uruguay was 13.9 Mg ha^{-1} **(**Table 1**,** Fig. 4**)**. The Yp varied across regions, climate zones and reference weather stations. Highest Yp was observed at Rocha and Tacuarembo (average: 14.8 Mg ha^{-1}), while Yp in Treinta y Tres and Paso de los Toros was intermediate (average: 13.8 Mg ha^{-1}) and lowest at Salto and Bella Union (average: 13.1 Mg ha^{-1}). Average Yp in the north region was lower than in the central and east regions. Highest Yp corresponded to climate zone I with lower values in climate zones II and III and IV. Spatial variation in Yp was associated with differences in temperature and solar radiation among sites, with lowest Yp at sites with higher temperatures (Artigas, Bella Union and Salto) while highest Yp (Rocha and Tacuarembo) was found at sites with lower temperatures (Fig. S1**)**.

Average (2016–2020) Ya was 8.3 Mg ha^{-1}, representing 60 % of Yp **(**Table 1**,** Fig. 4**)**. Differences in Ya among reference weather stations, climate zones, and rice regions of Uruguay were relatively small, with average yield ranging from 7.9 to 8.5 Mg ha^{-1} across reference weather stations. Average attainable yield, calculated as 80 % of Yp, was 11.1 Mg ha^{-1}. Hence, at national level, Yeg averaged 2.8 Mg ha^{-1}. Yeg was lower in Bella Union, Salto Grande and Artigas (average Yeg: 1.9 Mg ha^{-1}) followed by Treinta y Tres, Paso de los Toros and Tacuarembo (average Yeg: 3 Mg ha^{-1}) and higher in Rocha (4.5 Mg ha^{-1}). Climate zone I exhibited the largest Yeg in comparison with other climate zones II,III and IV. Variations in Yeg among reference weather stations, climate zones and regions, were mainly due to variations in Yp.

3.2. Trends in Yp across rice producing regions in Uruguay

The yield stagnation after year 2013 was not associated with changes in climate over time as we could not detect any trend in Yp at national level and also across regions ($p > 0.39$). An exception was a statistically significant downward trend in Yp at Salto (− 43 kg ha^{-1} y^{-1}; $p < 0.05$) associated with an upward trend in Tmax over time **(**Fig. 5**;** Fig. S1**)**.

3.3. Comparison with previous studies and other high-yield rice cropping systems

A comparison of the attainable yield and Yeg derived from our study with those reported for Uruguay by previous studies is shown in Table 2. Our national attainable yield is similar to two previous studies in which attainable yield was estimated based on highest farmer yields (Blanco et al., 2010; Tseng et al., 2021). In contrast, our attainable yield was greater than those reported in previous studies based on average yield from the 10 % highest farmer yields or average yield from variety trials (Pérez de Vida and Macedo, 2013; Tseng et al., 2021). For Yeg and RY, our estimates were remarkably similar to those estimated by Tseng et al. (2021) based on the highest farmer yields. In contrast, our RY estimates were (i) higher than estimates reported by Blanco et al. (2010) because the latter study was based on Ya from late 2000s (which are lower), and (ii) lower than estimates reported by Pérez de Vida and Macedo (2013) and Tseng et al. (2021) based on the highest 10 % farmer yields, due to lower attainable yield.

In the case of our cross-country comparison, average Yp was 12.8 Mg ha^{-1} across the selected countries, ranging from 9.5 (China) to 14.8 Mg ha^{-1} (southern Brazil) (Table 3). Yield potential per crop is larger in temperate versus tropical environments due to differences in temperature and crop cycle length. However, the lower Yp per crop cycle is typically compensated by higher crop intensity (Yuan et al., 2021). For example, although its lower Yp, annual potential productivity is greater in China as more than one crop per year can be grown in the central and southern regions of the country. The smallest Yeg corresponded to Egypt (nil Yeg), while southern Brazil and Argentina (4.3 and 4.6 Mg ha^{-1}, respectively) exhibited largest Yeg. The Yeg ranged from 1.1 to 3.0 Mg ha^{-1} across the other cropping systems. Across all the systems, Yeg estimated for South American countries (i.e., Brazil, Argentina, and Uruguay) was comparably larger, with RY ranging from 48 % to 60 % of Yp. Among the South American countries, Uruguay exhibited the smallest Yeg and highest RY.

4. Discussion

Our estimates of attainable yield for Uruguay were almost identical to those reported by two previous studies based on maximum farmer yields (Blanco et al., 2010; Tseng et al., 2021) **(**Table 2**)**. In contrast, our comparison with other studies suggests that attainable yield is underestimated by previous studies that relied on average yields from variety trials or 10 % highest farmer yields (Pérez de Vida and Macedo, 2013; Tseng et al., 2021). Together, these results suggest that leading farmers have closed the rice exploitable yield gap in Uruguay. However, our analysis showed that, on average, actual rice yields in Uruguay have not reached the attainable yield as has occurred in other high-yield irrigated systems located in non-tropical environments such as Egypt, California, and China (Table 3**)**. Hence, although Ya in Uruguay has stagnated over the past eight years until 2020 **(**Fig. 1**),** there appears to be room for further yield improvement. Our study also showed that the Yeg was higher in the central and east regions of Uruguay, especially in Rocha, followed by Tacuarembo, Paso de los Toros and Treinta y Tres (Fig. 4, Table 1**)**. Hence, there is an opportunity for Uruguay to return to steady rates of yield gain by targeting those areas with largest Yeg**.** More broadly, the Yeg approach followed in our study can be used in other countries and cropping systems to discern whether observed yield plateaus are a consequence of a small remaining yield gap as Ya approaches 80 % of Yp.

At issue are the underlying causes for the observed yield plateaus. To some extent, they could be associated with a decline in Yp over time in some locations, although our analysis shows that there is no trend for average Yp at the national level **(**Fig. 5**)**. Another possible explanation is the relatively slow replacement of widely planted varieties resulting in slow progress in genetic improvement (in terms of yield, quality, disease resistance and adaptation to climate). Also, higher costs and lower rice prices (Fernández et al., 2018; Lanfranco et al., 2019) may have imposed constraints to farmer adoption of optimal management practices. Likewise, most rice farmers in Uruguay (70 %) have land and water leasing contracts (Lanfranco et al., 2018), which could affect land access at proper time for field and crop management operations, such as early sowing. Management options to further close Yeg include use of modern cultivars with improved disease resistance, early sowing, and better plant stand uniformity (Tseng et al., 2020; Junior et al., 2021; Ribas et al., 2021; Tseng et al., 2021). Improving the integration and management practices within all ag-systems components in the rotation (e.g. rice pasture-crop), while improving resource use efficiencies (e.g., for nitrogen (Castillo et al., 2021) and pesticides (Lázaro et al., 2021), would contribute to sustain further yield increases (Macedo et al., 2022) with positive impacts on environmental indicators (Pittelkow et al., 2016).

Our assessment indicates that Uruguay could produce an additional 0.4 Mt of rice on existing cropland for a scenario in which average Ya reaches 80 % of Yp throughout Uruguay. This finding is notable because rice harvested area has declined steadily over the past 10 years, from near 195,000 in 2010 to 140,000 ha in 2021 (DIEA, 2021). Hence, narrowing current Yeg would help mitigate the impact of shrinking land resources for rice by maintaining or even increasing national rice production (from current 1.3 Mt up to 1.7 Mt if Yeg is closed). However, narrowing Yeg may be challenging if the upward trends in temperature observed in some regions (**Fig. S1**) persists over time and extends to other rice producing regions, which would lead to a decline in Yp over time. Warming trends reported in our study are consistent with information published in previous studies (Nagy et al., 2014; Tiscornia et al., 2016). It will be important to monitor changes in climate and Yp over coming decades, accounting also for CO_2 concentration, as a basis to inform changes in the agronomic management (e.g., sowing and variety length) that could help mitigate the negative impact of climate change on Yp.

5. Conclusions

Current rice yield represents 60 % of Yp, suggesting that further increase in Ya and total rice grain production is possible in Uruguay. Our analysis identified areas with largest opportunities for yield improvement, with higher Yeg in the central and east regions. Comparison with other high-yield irrigated rice systems in non-tropical region shows that current Yeg in Uruguay rice producing countries is comparably larger, highlighting an opportunity to increase national production and exports.

Declaration of Competing Interest

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

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.2023.108808.

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