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Synergies and tradeoffs among yield, resource use efficiency, and environmental footprint indicators in rice systems

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ABSTRACT

A major question facing global rice systems is the extent to which yield and resource use efficiency indicators can be simultaneously optimized to sustainably meet future food demand. However, research approaches for evaluating synergies and tradeoffs among multiple indicators have been limited to date. Using the case study of rice production in Uruguay, we quantified five cropping system performance indicators at the farm-level from 2012 to 2017, covering approximately 40% of national rice area. Results suggest that maximizing performance in one indicator is associated with tradeoffs for other indicators, with no farm simultaneously ranking as a top-performer (defined as top 10% of farms) across all indicators. The gaps between the average and top-performing farms were largest for agrochemical contamination risk (33%) and smallest for yield (11%). Comparing the groups of top-performing farms within each indicator revealed opportunities for improving system-level performance via synergistic effects between yield and resource use efficiencies, but not between carbon footprint, agrochemical contamination risk, and other indicators. Importantly, synergistic effects were more pronounced for farms at lower compared to higher productivity levels, suggesting less room for sustainability improvements at higher yield levels, unless yields can be further increased without elevated inputs. Important factors to improve the aggregated sustainability index included N fertilizer rate and seeding date. With potential application to rice production systems worldwide, this study highlights an integrated research approach for quantifying synergies and tradeoffs among multiple indicators to understand opportunities for increasing crop yields without negatively impacting resource use efficiency and environmental footprint.

1. Introduction

Rice is one of the most important crops for world food supply, responsible for around 19% of human caloric intake globally and 27% in low and middle-income countries (Lomax, 2017). It is estimated that rice yields need to double by 2050 to maintain food security (Ray et al., 2013; USDA-ERS (United States Department of Agriculture, Economic Research Service), 2019), thus improving productivity should remain a top research priority in future decades. Although intensification of existing rice cropland has led to higher yields (Hazell, 2009), significant concerns have been raised about the environmental footprint of rice production.

Suboptimal nitrogen (N) management in paddy fields causes environmental pollution (Choudhury and Kennedy, 2005; Zhao et al., 2009; Linquist et al., 2012a; Linquist et al., 2012b). Large amounts of energy are consumed during cultivation, specifically associated with fuel use during land preparation and embodied energy in agricultural inputs (Quilty et al., 2014). In addition to energy inputs, elevated soil greenhouse gas (GHG) emissions are closely linked to carbon footprint (Zhang et al., 2017), making rice systems an important contributor to climate change. Indeed, rice has a higher global warming potential per unit production compared to the other staple cereal crops wheat and maize (Linquist et al., 2012b) due to methane emissions occurring under flooded soil conditions (Le Mer and Roger, 2001). Other agrochemicals used in crop production, such as herbicides, insecticides, and fungicides also pose an environmental risk, negatively impacting surrounding

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ecosystems (Abdullah et al., 1997). Rice systems also consume large amounts of water, a key sustainability issue. Given the importance of rice in maintaining global food security, there is a pressing need to develop new research strategies for simultaneously increasing rice production while addressing these and other environmental concerns. Importantly, such research approaches have to occur at the field-level where crop management decisions are made, which can be difficult because there is often a focus on enhancing economic profitability and farmer livelihoods.

Attempting to optimize agricultural systems for multiple goals can have inherent challenges, particularly given the tension between managing for agronomic productivity vs. environmental quality (Robertson and Swinton, 2005; Kanter et al., 2018; Klapwijk et al., 2014). An important aspect in improving agricultural sustainability is to quantify the performance of key indicators, allowing scientists and policy-makers to monitor and compare outcomes across time or among systems (Sachs et al., 2010; Hayati et al., 2010). For example, specific indicators for rice systems corresponding to the environmental challenges described above include, but are not limited to: N use efficiency, energy use efficiency, C footprint, and agrochemical contamination risk. Yet, the majority of previous research has focused on one or two of these variables at a time, meaning important tradeoffs may be occurring between indicators that have not been previously quantified (Kanter et al., 2018). Several recent studies have evaluated sustainable rice production practices or systems across multiple indicators (Stuart et al., 2018; Devkota et al., 2019; Devkota et al., 2020; Okpiaifo et al., 2020). An important finding of these studies is that tradeoffs were identified regardless of the system, indicating that the consequences of efforts to increase crop production in relation to the other resource use efficiency and environmental indicators remain poorly understood.

To provide insights for future management, the implications of optimizing one indicator over another can be assessed by evaluating variability among farms. For studies considering multiple indicators of sustainability in rice, previous work has generally focused on comparing differences between management practices (e.g. Stuart et al., 2018; Devkota et al., 2020). While this approach reveals consequences due to specific changes in management, it does not capture the wide range of potential relationships occurring among multiple indicators at the farm-level. Within a given region, large variation in management practices and biophysical conditions interact to produce different yield and environmental outcomes, providing an opportunity to evaluate whether groups of farms that have optimized one indicator (e.g. yield) are likely to have tradeoffs or synergies across other indicators (e.g. energy use efficiency or agrochemical contamination risk). One study demonstrating this approach was Silva et al. (2018) who evaluated relationships between yield, labor productivity, N use efficiency, and gross margin across a large sample of farms in Central Luzon, Philippines. Results indicated there was an opportunity for agricultural intensification in many fields, but this finding may not apply to other high-yielding rice systems in the world. Cropping systems with low yields and large yield gaps often have considerable scope for improving productivity and input-use efficiencies. In contrast, high-yielding cropping systems are often characterized by higher inputs and less room for yield improvement, which may result in decreased resource use efficiencies. Therefore, in addition to evaluating the extent to which improvements in both sustainability and yield are possible across multiple farm-level performance indicators, comparing among groups of farms at lower yield levels versus farms that have already reached higher yield levels is necessary to understand the relative potential for synergies or tradeoffs.

Evaluating tradeoffs between production and environmental goals is key for optimizing holistic systems-level performance, but this approach often requires complex interpretation before results can be applied to policy or used in decision-making, particularly when multiple indicators are considered. In contrast, research evaluating relationships between one or two outcomes can provide more direct conclusions, but does not reflect potential conflicts between multiple goals. For example, Hafeez et al. (2014) found tradeoffs between yield and energy use, as higher yield was achieved by an increase in irrigation pumping for rice in the Philippines. Zhu et al. (2019) investigated the tradeoff between yield and GHG emission, concluding that N rate is critical for optimizing both indicators. When multiple indicators are assessed, an alternative approach to capture system performance is to create a high-level indicator summarizing changes across individual indicators (Reig-Martínez et al., 2011). In this case, individual indicators undergo a process of normalization, weighting, and aggregation to create a composite indicator (Gómez-Limón and Sanchez-Fernandez, 2010). The advantage of an aggregated sustainability indicator is that it provides a single value for efficient communication, comparison, and decision-making. This approach is frequently used in policymaking, where the scope of application is generally at larger spatial scales (EEA (European Environment Agency), 2005; OECD (Organisation for Economic Cooperation and Development), 2001; Payraudeau and van der Werf, 2005; Reig-Martínez et al., 2011). However, to our knowledge there are limited reports of developing a composite indicator at the farm-level to improve the sustainable management of rice systems.

Uruguay is one of the highest-yielding rice systems in the world (Zorrilla, 2015; FAOSTAT, 2017). Unlike most rice-producing countries where continuous rice or cereal-based rotations are dominant, rice in Uruguay is rotated with pasture and cattle production. Since most rice growers are specifically focused on rice farming and do not own the land, they have engaged in a strong alliance between farmers and millers to create a vertically integrated value chain based on strict grain quality standards and high-value export markets to ensure profitability (Zorrilla, 2015). With continuous improvement in crop management and productivity over the past few decades, research at the national scale has suggested that yield gains did not come at an increased environmental cost (Pittelkow et al., 2016). This research assessed the change in indicators for N fertilizer use, energy use, carbon footprint, and water productivity. At the farm-level, Tseng et al. (2020) found that high-yielding farms were associated with greater NUE and lower carbon footprint per unit of production compared to the regional average, while attempts to further improve yield at high yield levels were likely to decrease environmental performance. However, these studies did not address an important knowledge gap at the field-level: do farms with the highest yield also obtain the highest sustainability performance, and vice versa, can farms with highest performance in certain indicators also maintain high yield?

To achieve the sustainable intensification of rice systems, this is an essential question, yet few studies have demonstrated a framework for evaluating positive and negative relationships between multiple indicators at the farm-level that is applicable to other rice production regions in the world. Thus, the objectives of this research were to: 1) determine the extent to which sustainability indicators can be optimized simultaneously in order to achieve production goals while reducing environmental footprint, 2) assess synergies and tradeoffs associated with maximizing performance of one indicator in relation to others, at both low and high productivity levels, and 3) identify opportunities for improving overall system level performance based on an aggregated index representing all indicators.

2. Methods

2.1. Dataset

Field-level records used in this study were obtained from one of the main commercial rice millers, SAMAN (Sociedad Anónima Molinos Arroceros Nacionales) across 6 cropping seasons (2012–2017 planting year). This database was used by Tseng et al. (2021) to evaluate factors contributing to yield gaps. For a thorough review of rice cropping systems in Uruguay (rotation, tillage practices, inputs, etc.), the reader is referred to Blanco et al. (2010), Pittelkow et al. (2016), Tseng et al. (2020), and Tseng et al. (2021). The dataset contained field

management and input information originally kept for the company to track and arrange the field operation services provided to farmers. The dataset used in this study includes 3937 observations (entries of management records at the field-level over the study period). For clarity purposes, we refer to these entries as "fields" hereafter, with these fields managedby 268 farms. In total, 61 variables associated with yield, management information, and field conditions based on agronomists' records (such as in-season weed pressure) were available in the database. Since this was a field-level dataset, data preprocessing was applied to remove data points containing records with unrealistic values and specialty rice varieties, which do not reflect the majority of rice cultivation in Uruguay.

2.2. Estimation of resource use efficiency and environmental footprint

We evaluated 5 indicators to assess relationships among yield, resource use efficiency, and environmental footprint for rice production: 1) Yield, 2) Nitrogen use efficiency (NUE), 3) Energy use efficiency (EUE), 4) Carbon footprint (CF), and 5) Agrochemical contamination risk (ACR). To increase the relevance and impact of scientific efforts for advancing sustainable agriculture, a set of indicators covering multiple aspects of the crop production system is required, ideally developed with broad support from multiple stakeholders along the value chain. These indicators are closely related to the performance indicators outlined in the Sustainable Rice Platform (SRP) (SRP, 2019). The SRP is a global partnership between multiple public and private sector actors to facilitate the adoption of sustainable rice production practices at the farm- and regional-level (http://www.sustainablerice.org/). The SRP involves a set of indicators covering 12 aspects of sustainability including yields, resource use efficiencies, and socioeconomic dimensions. We are aware that it is important to evaluate multiple aspects of farming systems beyond biophysical outcomes to achieve sustainable intensification goals including food safety, labor productivity, water use and quality, biodiversity, worker health and safety, child labor, and women empowerment (SRP, 2019). However, due to limited data availability in Uruguay at the scale of analysis for this study (around 70,000 ha per year), we were only able to focus on the set of 5 indicators above. Conducting more comprehensive surveys to address all SRP indicators is an important area for future research. Ultimately a broad suite of indicators covering economic, environmental, and social dimensions at field to regional scales should be assessed to develop pathways for sustainable intensification. See the following studies for a recent review of available indicators and recommendations (Musumba et al., 2017; Mahon et al., 2018).

Nitrogen use efficiency was calculated as partial factor productivity of nitrogen (PFP_N), which is determined by dividing yield by the amount of N fertilizer applied at per hectare basis. While we are aware of multiple calculations regarding NUE, we selected PFP_N as it does not require extensive information and is suitable for field-level data where information is often limited to yield and N rate (control plots without fertilizer were not available to calculate the yield response to N fertilizer addition). Similarly, PFP_N is used by SRP as a measurement of NUE (SRP, 2019). It is worth noting here that we only intended to compare NUE among fields of Uruguay rice farmers, which generally apply N well below the global level (70 kg N ha^{-1} compare to 100 kg N ha^{-1} and above for most intensified managed rice fields globally, Castillo et al., 2012). Aside from N fertilizer inputs, there are several other potential sources of N (biological N fixation from legume forages and manure from previous livestock ranging) that should be considered to assess NUE at the cropping systems level in future work.

Similar to NUE, energy use efficiency was determined by partial factor productivity of energy input, expressed as kg rice MJ input $energy^{-1}$. See Tseng et al. (2020) and Pittelkow et al. (2016) for full details. Energy input was determined separately in each field based on the management records of NPK fertilizer, seed, amount of diesel used in recorded field operations (land preparation and tillage, planting, machine use for pesticide and fertilizer applications, and harvest) but not irrigation, agrochemical inputs, or human labor due to lack of data. The conversion factors used to convert different categories of inputs to energy values were similar to Pittelkow et al. (2016) (Table S1).

The C footprint of each field was estimated by considering the parameters of IPCC-based field methane and nitrous oxide emissions during the rice growing season, as well as the estimated CO_2 emissions associated with NPK fertilizer, seed, and diesel fuel use in recorded field operations. For detailed conversion factors, refer to Table S1. All parameters were converted to CO_2 equivalents as global warming potential, then summarized to the scale of kg CO_2 ha^{-1} to allow between-field comparisons. Field emission of methane (CH_4) was estimated using IPCC tier 2 method (IPCC, 2006) with field-specific scaling factors considering length of flooding and remaining organic matter from previous crop as explained in Supplementary methods. The field-level N_2O emission was estimated by IPCC tier 1 methods accounting for only the rate of synthetic N applied and the emission factors for flooded rice fields (EF_{1FR}) (IPCC, 2006).

To estimate the environmental impact of herbicide, fungicide, and insecticide applications, we calculated agrochemical contamination risk (ACR) using freshwater ecotoxicity effect factors from USEtox model 2.0 (available at www.usetox.org; Henderson et al., 2011). The USEtox model is commonly used for evaluating agrochemical impacts within agricultural production during life cycle assessment (i.e. Berthoud et al., 2011; Nordborg et al., 2017). This model provides a relative ecotoxicity measure which is expressed as the potentially affected fraction of species (PAF) per volume of fresh water. In short, the ecotoxicity effect is the sum of the amount of each active ingredient multiplied by the characterization factor supplied in USEtox:

$$EF_i = \sum_j CF_j \times M_{ij}$$

where

EF_i is the total ecotoxicity effect of field i associated with its agrochemical input represented as potentially affected fraction of species (PAF) per volume of fresh water.

CF_j is the characterization factor of agrochemical substance j, which is the result of the modeling from environmental fate, exposure potential, and toxicity effect of a given substance.

$M_{ij}$is the amount of agrochemical substance j applied in field i.

In each field, the active ingredients of agrochemical were obtained from the management records, then the total amount of ecotoxicity was calculated by summing the total effects of individual agrochemicals, assuming the recommended rate was used (Pesticide handbook of Uruguay is available at: https://www.laguiasata.com/). In the case of missing active ingredients in the USEtox database, the characterization factors of similar molecules were used. In cases where recommended rate or characterization factors were missing, the value was imputed using the average across other agrochemicals used in management records for this study. The characterization factors of active ingredients were log transformed as the range of PAF across active ingredients verified by more than 15 orders of magnitude (USEtox 2.0 documentation, Available at: DOI: 10.11581/DTU:00000011).

2.3. Synergy and tradeoff analysis

Synergy and tradeoff analysis was employed by using the procedure described by Silva et al. (2018) with slight modifications. To identify top-performing farms in each indicator, indicators for individual fields were first aggregated at the farm-level. From a total of 265 farms, we selected a subset of 124 farms that produced rice every year and were therefore considered to represent mainstream production practices for this region. Thus, only farms with at least 1 field record in every season were kept for the following analysis. This approach also helped to avoid bias due to small sample size for some farms (e.g. insufficient fields

within a farm). the final database included a total of 124 farms, representing 73% (2753 out of 3768) of initial field-level records. Each these farms included 22 fields on average during the study period, hence they still represented the majority of observations. To assess the consequences of this decision, data analysis was also performed on the full dataset (i.e. all 3768 field-level records) and results and conclusions were not different. For each indicator, the top-performing farms were defined as the top 10% (representing 13 farms or around 286 fields) that had the highest values of Yield, NUE and EUE, or the lowest values of CF and ACR, respectively. A Venn diagram was created in R (R Core Team, 2013) using *limma* package (Smyth, 2005) to visualize the degree of overlap among the top-performing farms for each indicator (multiple overlapping sections of the diagram indicates that top-performance in different indicators can be achieved simultaneously).

To compare the groups of top performing farms against each other, Mood's median test was used to test the difference in median values among the 5 groups for each indicator. This was performed with the *RVAideMemoire* (Hervé and Hervé, 2020) package in R, followed by a post-hoc pairwise median test using *rcompanion* package (Fox and Weisberg, 2018) in R 3.6.1 (R Core Team, 2013) if significance among groups was found. To identify synergies or tradeoffs in relation to the other indicators when farms maximized the performance in one indicator, the median value of each top performing group was also compared against the grand mean of all farms using the Wilcoxon rank-sum test (R build-in function *wilcox.test()*). Results were expressed for each indicator as the relative change of top-performing farms compared to all farms.

To further understand tradeoffs among indicators at different productivity levels, the 124 farms were divided into top-yielding (average yield >8.5 Mg ha^{-1}) and bottom-yielding (average yield <8.5 Mg ha^{-1}) groups. This consisted of 62 farms in each group, and the data analysis procedures described above were repeated for both groups.

2.4. Analysis of aggregated sustainability index

To assess overall farm performance, we calculated an aggregated index by using the average of standardized values (*Z*-scores) for the 5 indicators. The reason for using standardized values is to avoid the analysis being driven by indicators that have greater values and to stabilize the effects of high variability in outcomes across farms. The Z-score normalization method is commonly used in sustainability assessment and provides a simple yet effective normalization without a predefined baseline or targeted values (Pollesch and Dale, 2016). To identify influential field-level factors that were important for increasing this sustainability index and could be prioritized in future research and management efforts, a linear model using the lm() function in R was fit to the aggregated sustainability index using predictor variables that were previously identified as factors explaining yield gap in these systems (Tseng et al., 2021). The coefficients of the predictors variables quantified the effect of the predictors on the aggregated index, while the importance of the predictors was expressed as type III (partial) sum of squares (the sum of square for each variable when it was introduced last into the model).

3. Results and discussion

3.1. Insights from top-performing farms

Across this dataset, no single farm was categorized as a top-performer for more than 3 indicators covering aspects of food production and resource use efficiency (Table S2 and Fig. 1). These results indicate that maximizing performance across multiple indicators is a challenge, which has implications for global sustainable intensification efforts in rice systems. Holistic improvements across different economic and environmental dimensions are required now more than ever (SRP, 2019), highlighting the need for similar investigations in other rice systems. When considering fewer indicators to be maximized, 5 farms (4%) achieved the top performance in 3 indicators (2 farms for Yield, NUE and EUE; 2 farms for EUE NUE and CF; 1 farm for Yield, EUE and ACR). Meanwhile, 13 farms (10%) achieved the top performance in at least 2 indicators. Lastly, there were 47 farms (38%) that achieved the top performance in at least 1 indicator. Overall, these results suggest that optimizing performance (i.e. achieving top 10% relative to other farms) might be possible for a small group of indicators, but not across all 5 indicators evaluated here. As mentioned above, food system transformation to address economic, environmental, and social dimensions of sustainability should include a broader set of indicators (Musumba et al., 2017; Mahon et al., 2018).

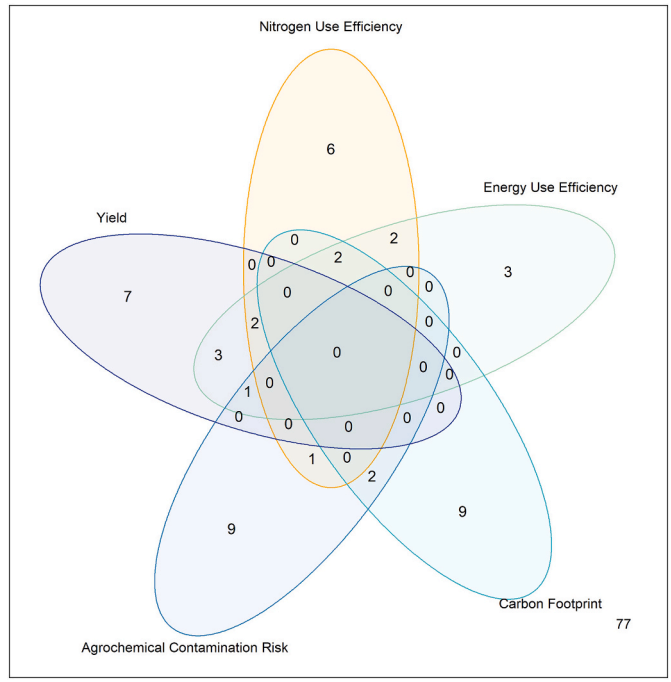

Fig. 1. Venn diagram for visualizing the intersection of top-performing farms for each indicator, defined as the top 10% of all 124 farms. The number in colored shades represents the number of farms categorized as the corresponding top-performing groups in overlapping circles. The number (77) at the bottom-right indicates the farms that do not belong to any of the top-performing groups.

The standardization and quantification of agricultural indicators is necessary to address system-levels performance (Kanter et al., 2018). Recently, new frameworks covering multiple aspects of sustainability have been adopted by the international rice community to track and promote management practices that simultaneously reduce environmental impacts and improve human livelihoods at the farm-level (SRP, 2019). However, our results question the assumption that multiple indicators can be maximized at the same time. We found no evidence that farms could maximize performance across more than 3 of 5 indicators investigated, raising doubts about the potential for increasing crop production to the level of top-yielding farmers without negatively influencing environmental quality. These results highlight the need for not only quantifying multiple indicators, but analyzing tradeoffs between indicators, as done recently for rice production regions of Asia (Stuart et al., 2018; Devkota et al., 2019; Devkota et al., 2020). Given the importance of rice as a staple food crop, we note that win-win outcomes are not necessarily likely or feasible given current market conditions. Thus, we encourage governments, research organizations, businesses, and policy-makers to explicitly quantify tradeoffs when attempting to address the dual goals of enhancing food security while decreasing environmental footprint, particularly in high-yielding rice environments.

Another important finding is that the gap between the average and top-performing farmers differed among indicators (Table 1). Understanding the relative opportunity for improvement among farms could help identify areas to prioritize in research and crop management. For example, top-performing farms for yield only had 11% higher yield compared to all farms ($n = 124$), while there was a 33% gap between top-performing farms for ACR, representing the greatest opportunity improvement relative to other indicators. Similarly, NUE had the second largest gap, with the top-performing farms for NUE displaying a 30% increase compared to all farms. Other indicators had smaller gaps suggesting less room for improvement (EUE and CF gaps were 12% and 14%, respectively). This implies that, in addition to the difficulty of maximizing farm performance across indicators, the potential for improvement within indicators could be more limited for some indicators having smaller gaps.

In recent decades, a main research effort in Uruguay has been improving yield via improved crop management practices and high-yielding locally developed varieties, resulting in a yield gain of around 38% (Pittelkow et al., 2016). This could help explain why gaps were larger between top-performing and all farms for performance indicators other than yield. At the global level, closing yield gaps in rice systems should remain a key research goal, as many regions have the potential to further improve productivity (Neumann et al., 2010; Stuart et al., 2016). However, this does not mean that other performance indicators should be left unattended, particularly if they conflict with food security goals. Similar to our study, Devkota et al. (2019) simultaneously quantified yield gaps and differences in sustainability outcomes for rice systems in 6 Asian countries. While these authors found that there were relatively large differences in top-performing compared to average farmers (multiple indicators >20%, with NUE gap being the lowest at 11–20%), here we found differences in yield and EUE were relatively narrow, suggesting lower variability among management practices and yields for rice farms in Uruguay.

Future research could focus on reducing N fertilizer and pesticide use while maintaining yield to improve resource use efficiencies for average farms in Uruguay. Although average NUE in this study (128 kg kg^{-1}) was more than twice that of the global average reported by Dobermann (2007) of 62 kg kg^{-1}, this indicator still showed the highest difference for top-performing compared to average farms. This can be attributed to the fact most rice fields are rotated with pasture and cattle ranging activities in Uruguay. The soil carryover of N from these activities has been shown to be a major source of N for the subsequent rice crop (Castillo et al., 2012). Crop rotation with improved pasture containing legume mixtures helps support biological N fixation, meaning these farmers can apply less N fertilizer compared to fields without such rotation (Terra et al., 2020), which might be one reason for the high variability of NUE across farms when some of the farms did not implement such rotation. Past studies suggest that up to 100 kg N ha^{-1} can be fixed by legume species (Labandera et al., 1988; Danso and Curbelo, 1991), most of which is consumed by cattle during the pasture phase of the rotation, but this organic N further cycled by livestock (consumption and deposition) may still represent a source of N to complement current N fertilizer inputs for rice production of ~70 kg N ha^{-1} (Castillo et al., 2012).

Table 1
Comparison of mean indicator values for all farms and top-performing farms. For top-performing farms, median values were used instead of means to avoid the influence of outliers with a smaller sample size.

	All Farms		Top Farms		% of Change
	Mean	SD	Mean	SD	
Yield (kg ha^{-1})	8457	655	9421	274	11%
NUE (kg kg^{-1})	128	20.7	167	13.	30%
EUE (kg MJ^{-1})	0.64	0.05	0.72	0.01	12%
CF (kg CO_2 eq ha^{-1})	4614	445	3957	182	−14%
ACR (log PAF m^3 ha^{-1})	25.9	5.6	17.3	2.1	−33%

NUE = Nitrogen use efficiency; EUE = Energy use efficiency; CF = Carbon footprint; ACR = Agrochemical contamination risk.

Although pesticide use in Uruguay rice production is low compared to other rice systems due its unique rice-pasture rotation (Deambrosi, 2003), the large difference in top-performing and average farms for ACR suggests that pesticide use can be further reduced without penalizing yield. As the gap of ACR is roughly triple the size of the yield gap (Table 1), future investigations could focus on technologies to reduce agrochemical inputs or selection of pesticides with lower agrochemical contamination risk including integrated pest management, disease-resistant cultivars, or precision applications to achieve higher efficacy. For example, a recent study on implementation of integrated pest management showed yield was maintained with 50% of reduction of pesticide usage in Southeast Asia (Babendreier et al., 2019).

3.2. Synergies and tradeoffs among indicators

Next, the top-performing farms in each indicator were grouped together and their performance compared against each other (Fig. 2). Generally, groups were not significantly different except for the top-performing farm within that given indicator (e.g. only the farms with lowest CF were different than the other groups for the comparison of CF, Fig. 2D). Moreover, the top-performing farms that maximized yield and EUE were not different within Yield and EUE, indicating a synergistic relationship (Fig. 2A and C). Also, farms that minimized ACR had lower values than several other groups for the indicators of NUE and EUE. Regardless of indicator, the top-performing farms achieved values better or close to the average across all farms. This finding corresponds to Devkota et al. (2021) where top yielding farms can also have improved resource use efficiencies. Despite this possibility, our results underscore the difficulty in farms maximizing performance across indicators as suggested in Fig. 1 and Table S2. Yet, when selecting a single indicator to target for improvement, they also show the potential of improving multiple performance indicators compared to the average of all farms.

Following this logic, we next quantified the difference between the top-performing farms in each indicator and the mean of all 124 farms to determine how optimizing one indicator could improve other indicators (Fig. 3). Contrary to results above, where farms had to achieve maximum performance (top 10%) for different indicators or when the groups of top-performing farms were compared against each other, we found more synergies than tradeoffs across indicators when top-performing farms were compared to the mean of all farms (Fig. 3). This finding highlights the potential for synergistic effects among indicators and is perhaps a more realistic scenario because the threshold for comparison is average farm performance for a specific indicator. For example, in top-performing farms for yield, there was a significant 10% increase in EUE and positive improvements in NUE and CF compared to the mean (Fig. 3a). In top-performing farms for NUE, synergies were also found with EUE (Fig. 3b). In top-performing farms for EUE, all other indicators showed positive improvements (2–17%) compared to the average of all farms, with significant synergies for Yield and NUE (Fig. 3c). Synergistic effects in maximizing Yield, NUE, and EUE resulted from both improving productivity and resource use efficiencies at the farm-level (i.e. top-performing farms for EUE also increased yield by 5%, Fig. 3c).

These results demonstrate the potential for simultaneously achieving higher yield and energy use efficiency, consistent with past investigations for rice production in the Philippines (Quilty et al., 2014). In addition, they align with findings from cereal production systems in China supporting the concept of "double high" (e.g. high yield and high resource use efficiency) (Shen et al., 2013). While neither Shen et al. (2013) nor Quilty et al. (2014) reported agrochemical footprint, we found that higher agrochemical inputs might become a concern when high yield and EUE is the primary goal (ACR increased by 17%, not significant, $p < 0.25$) (Fig. 3a). Our results also agree with previous findings at the national level in Uruguay where ACR increased due to

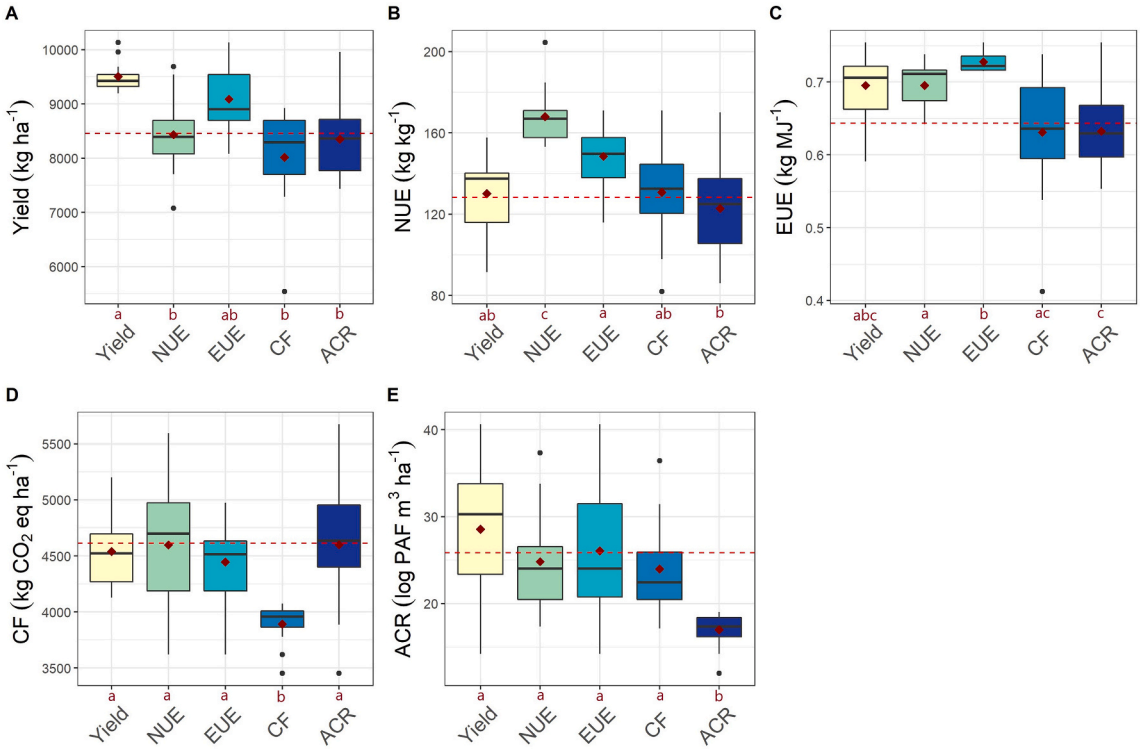

Fig. 2. Boxplots of top-performing farms for each indicator (x-axis) and their corresponding distribution of A) Yield, B) Nitrogen use efficiency C) Energy use efficiency D) Carbon footprint and E) Agrochemical contamination risk. Each color represents an indicator being maximized (e.g. yellow represents the top-performing farms for yield). The red dashed line represents the mean of all 124 farms. Solid lines within each box represent the median of top-performing farms and the diamond represents the mean. Please note that some variable observations caused the deviation of mean from median. Therefore, median was used as the average performance measure in top-performing farms. Similar letters indicate non-significance on the paired comparison. NUE = Nitrogen use efficiency; EUE = Energy use efficiency; CF = Carbon footprint; ACR = Agrochemical contamination risk. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

recent intensification efforts including increasing usage of insecticide in some specific years and fields (Pittelkow et al., 2016).

An alternative scenario is to evaluate the response of yield and resource use efficiency indicators when farms minimize environmental footprint to see if productivity goals are sacrificed (Fig. 3d and e). Generally, no significant tradeoffs in other indicators were found when farms optimized CF and ACR, except several yield tradeoffs or synergies with ACR (Fig. 3 d-e). Despite no strong relationships between environmental footprint and resource use efficiency indicators (Fig. 3 d-e), top-performing farms for NUE were associated with a reduction in ACR by 7% (positive trend, non-significant) (Fig. 3b). One possible explanation is, when N fertilizer is properly managed to meet crop demand without excessive inputs, the susceptibility to diseases such as rice blast can be minimized (Long et al., 2000), consequently reducing the use of fungicide. Therefore, when considering a single indicator to improve among all indicators studied here, one strategy could be improving agricultural productivity to help mitigate environmental impacts, as documented in other work (Burney et al., 2010; Tilman et al., 2011). However, our current data do not indicate benefits associated with higher yields across all indicators, as some level of tradeoffs still occurred for ACR when yield was optimized (Fig. 3a).

To meet sustainable development goals, it is important to set realistic targets for improvement. However, given the large variability among farms studied here, it is unlikely that lower yielding farms could reach the top 10% in the short-term. Therefore, we further tested if the relationships among indicators were consistent across productivity levels by splitting the full dataset into low-yielding and high-yielding farms and repeating the analysis. Generally, the direction of these relationships was consistent for yield and resource use efficiency indicators (Fig. 4, a-c), yet the magnitude changed for the different productivity levels. The synergistic effects between yield and EUE were stronger at the lower productivity level than at the higher productivity level (Fig. 4a and c). This is not surprising, as improving yield is commonly found to also increase resource use efficiency in systems with a large yield gap. Yet, one interesting finding is that improving yield at the lower productivity level could be linked with greater cost of ACR compared to the higher productivity level (Fig. 4a). This is possibly because lower yielding farms could also have lower yield potential, making them more susceptible to biotic or abiotic stressors such as pest pressure. For environmental indicators (Fig. 4d-e), no significant tradeoffs or synergies were present among CF or ACR regardless of productivity level (Fig. 4, d-e). However, the direction of change was different between the low and high productivity levels. This indicates that the strategy of managing CF and ACR might need to be modified depending on the level of productivity.

3.3. Research frameworks for improving holistic performance

In the previous sections, we discussed two strategies for improving systems-level sustainability, first focusing on indicators with the most potential for improvement, and second focusing on indicators that displayed synergistic relationships. However, this analysis was unable to capture the integrated performance of multiple indicators, in which positive and negative relationships were observed. Hence, we created a composite sustainability index to reflect the inherent dynamics among all indicators (Gan et al., 2017) with the goal of identifying important factors and management practices for increasing holistic cropping system performance.

Nitrogen rate was the most influential factor explaining variability in our composite index across farms (partial sum of squares of 10.7,

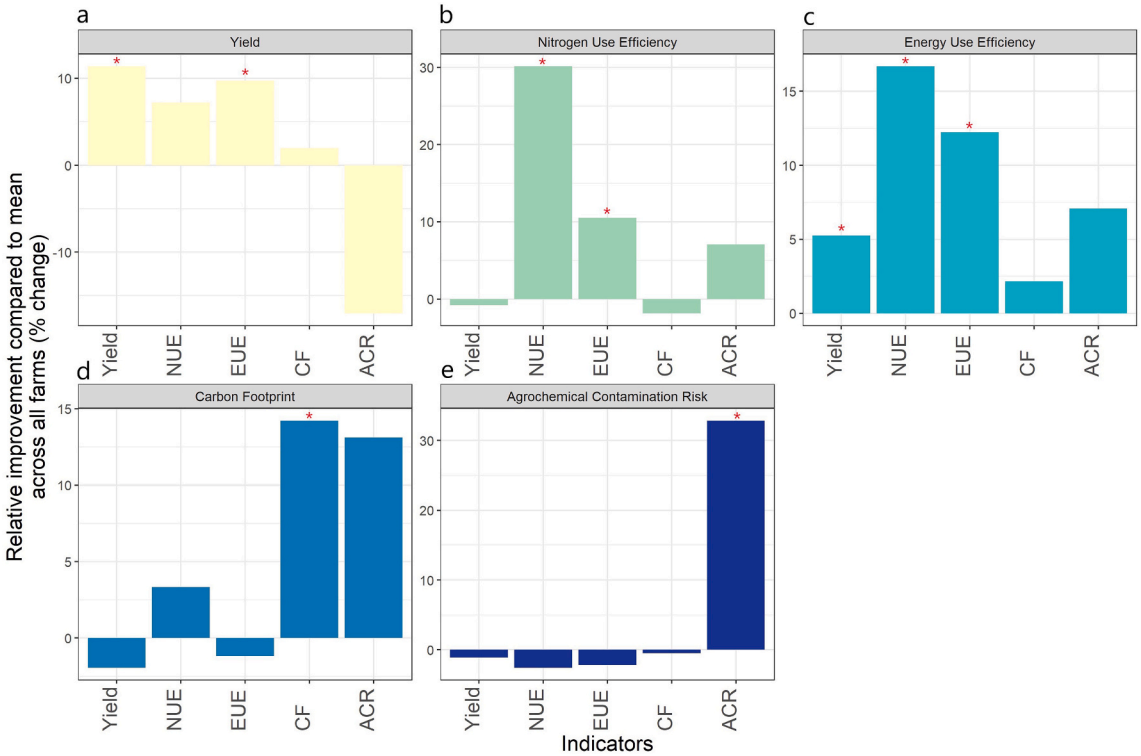

Fig. 3. The relative improvement of top-performing farms compared to the mean across all 124 farms (% change) for the individual indicators of a) Yield, b) Nitrogen use efficiency, c) Energy use efficiency, d) Carbon footprint, and e) Agrochemical contamination risk. Each panel is labeled according to the indicator optimized (e.g. panel A represents the top-performing farms for yield) and bars show the corresponding performance of these farms across the full set of indicators. Positive values indicate improved performance (higher yield and resource use efficiency and lower environmental footprint). "*" sign suggests significant change from Wilcoxon rank test. NUE = Nitrogen use efficiency; EUE = Energy use efficiency; CF = Carbon footprint; ACR = agrochemical contamination risk.

Table 2) followed by Seeding rate, Seeding date, and percentage of high Potential fields. Interestingly, these are the same factors associated with closing yield gaps in Uruguay (discussed in Tseng et al., 2021), but the direction of effects changed in some cases for their contributions to the aggregated sustainability index. For example, N rate was positively associated with closing yield gaps in Tseng et al. (2021), but negatively associated with the composite index in this study. This finding is aligned with current understanding of the costs and benefits of N fertilizer inputs in global cereal production systems, where the dual goals of increasing crop production and decreasing environmental impacts are often conflicting (Tilman et al., 2011). Similar to management practices associated with increasing the composite index here (Seeding date, N fertilizer and Seeding density), other studies have also found reduced N fertilizer and seed inputs contribute positively to the sustainable intensification of rice systems in the Mekong Delta, Vietnam (Huelgas and Templeton, 2010; Rejesus et al., 2014; Stuart et al., 2018).

Farmers are currently only compensated for yield (by selling high-quality rice to millers) but not overall performance on sustainability, thus optimizing rice productivity is understandably the focus of management efforts at the farm-level. In light of the complex relationships among indicators presented above, managing rice systems to promote synergies while minimizing tradeoffs will remain a significant challenge for researchers, farmers, and policy-makers. However, the approach used in this study demonstrates the potential benefits of establishing a composite indicator as the management goal instead of yield, specifically through government support or incentive programs. Instead of focusing on economics, management factors can be identified that simultaneously balance food production and sustainability goals. However, given food security and economic livelihood concerns in smallholder rice production, combined with current market conditions, this is unlikely without significant changes in policy and financing. For example, mechanisms such as payments for ecosystem services would help financially reward farmers for reducing environmental impacts. While our study represents a first step in creating a composite index for more holistic cropping system performance, additional field experiments would be needed to determine the optimum reduction level for each input.

3.4. Limitations and prospects

This study was based on data from actual farms, which has more relevancy for farmers and the rice sector compared to field experiments, but there are several limitations that need to be considered. For example, the dataset only allowed us to investigate farms under the operation of SAMAN, which represents a large portion of rice production in Uruguay but does not include all possible combinations of farming practices. In addition, multiple indicators were calculated using conversion factors and coefficients from available management records instead of direct measurement (e.g. energy inputs, field GHG emissions, USEtox characterization factors). While this is standard practice in the literature, this could lead to reduced variability and bias. For example, in the energy estimates we did not consider human labor which has been included in other comparable studies such as AghaAlikhani et al. (2013). Also, we did not account for organic N inputs from legumes in pasture or previous animal production activities such as manure when calculating NUE due to lack of data. In contrast, the NUE indicators for SRP suggest including both organic and inorganic N sources. Thus, we suggest comparison of NUE values should be confined within Uruguay rice systems, as direct comparison of NUE between systems in other parts of the world that use different data sources and inputs could lead to inappropriate conclusions.

We were unable to include all necessary indicators of sustainability due to data limitations. For example, socioeconomic indicators are missing in this study, which is not uncommon as they have been

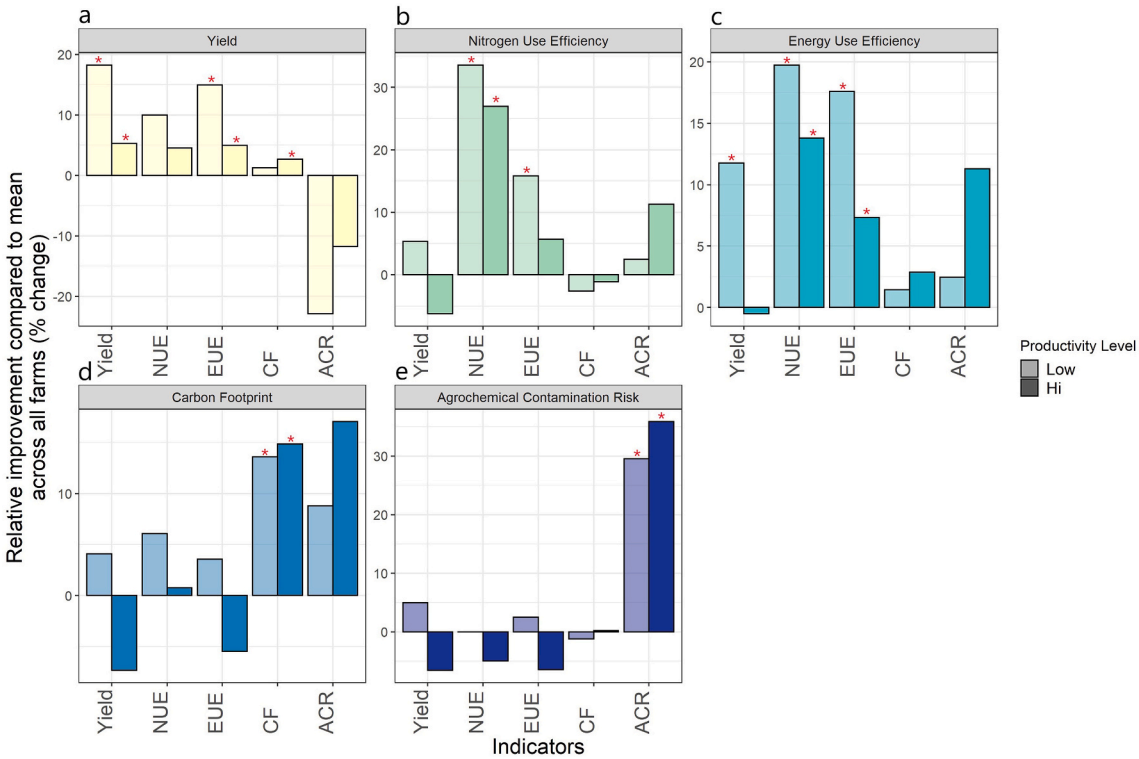

Fig. 4. The average improvement of top-performing farms in a) Yield, b) Nitrogen use efficiency, c) Energy use efficiency, d) Carbon footprint, and e) Agrochemical contamination risk relative to the average performance of 62 farms within either low or high intensification levels. The lighter color presents the farms at the lower half of yield (low intensification level) while the darker color bar represents farms at the higher half of yield distribution (high intensification level). The positive value suggests the improvement of performance (higher yield and resource use efficiency and lower environmental footprint). "*" sign suggests significant change from Wilcoxon rank test. NUE = Nitrogen use efficiency; EUE = Energy use efficiency; CF = Carbon footprint; ACR = agrochemical contamination risk.

Table 2
Parameter estimates of field-level factors and their influence on the aggregated index representing all 5 indicators. The type III partial sum of squares (Partial SS) represents the proportion of variability explained by each factor in the model.

Variables	Estimate	Partial SS
(Intercept)	2.783	4.27
Seedling Rate	−0.010***	4.05
N Rate	−0.032***	7.82
Seeding date (deviation from Nov1st)	−0.014*	1.008
% of improved pasture fields	0.001	0.04
% of high potential fields	0.003.	0.753
% of uniform germination fields	0.003	0.255
% of low weed infestation fields	0.005	0.504
R^2	0.422	
Adjusted R^2	0.365	

SS = sum of squares. Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1.

neglected under sustainable intensification frameworks (Petersen and Snapp, 2015). This is a key area for future improvement. Generally, building adequate indicators requires collaborative efforts among multiple stakeholders, and collecting farm-level data can be time-consuming and costly. In this study, the data was already collected by commercial mills for accounting and crop management purposes, which limited the indicators that could be calculated. For example, water use was not monitored by farmers or mills and therefore water productivity or water use efficiency was not included as an indicator. While irrigation efficiency has been researched extensively in other regions, adoption of these practices is not common in Uruguay, and general water management infrastructure and decisions (i.e. types or irrigation systems used) tend to be similar across farms. Nonetheless, not including a water footprint indicator is a drawback of this study, given the importance of freshwater consumption by rice systems globally. For improvement in future research, SRP has provided a set of performance indicators developed in collaboration between multiple actors in the rice value chain (SRP, 2019), which can serve as a starting point to improve coverage of this analysis.

4. Conclusion

Rice systems worldwide have to balance the competing demands of increasing yield while reducing environmental costs. Yet, relatively few studies have used field-level data to examine the effects of farmers managing for high yields versus maximum resource use efficiencies and sustainability outcomes. In this study we evaluated synergies and tradeoffs among yields, resource use efficiencies, and environmental footprint indicators for rice production in Uruguay. Results suggest it is challenging to simultaneously maximize yield and multiple sustainability indicators (i.e. top 10%) at the farm-level. However, when top-performing farms for each indicator were compared to the average of all farms, there were opportunities to improve multiple indicators due to synergistic effects, specifically related to yield, EUE, and NUE. These relationships were indicator-specific and tradeoffs still occurred, particularly for the environmental indicators CF and ACR. While analysis frameworks for addressing tradeoffs have been proposed previously (Klapwijk et al., 2014), our results show that greater efforts are needed to quantify cropping system outcomes across a range of indicators in rice systems to understand relative gaps in performance and determine which relationships are likely to result in tradeoffs rather than synergies. When results were divided into low-yielding and high-yielding farms, the degree of synergies decreased at high yield levels. These results have implications for any high-yielding rice system, and this tension should be acknowledged as an inherent challenge in efforts to simultaneously improve crop productivity and environmental quality. Finally, a

composite index was calculated to identify management factors that simultaneously balanced food production and sustainability goals. Both N and seeding rate significantly influenced holistic farm performance, suggesting the potential of optimizing input use as a means of improving outcomes across an integrated set of indicators.

Our analysis was based on farm-level management records covering a large area in Uruguay (~70,000 ha). However, the research framework developed in this study can be applied to any rice system to support evidence-based decision-making at both the scientific and policy level before proposing possible changes to current management practices for improved sustainability. Looking to the future, in this study we mainly discussed the potential of promoting synergies and avoiding tradeoffs, yet the progression of sustainable intensification often requires more transformative changes such as the implementation of systems redesign or incorporating novel crop rotation patterns to increase diversity (Davis et al., 2012; Pretty et al., 2018; Hunt et al., 2019). While this is beyond the scope of this study, we acknowledge the need for systematic changes in cropping systems, including enabling policies and markets, which can benefit sustainability but also help increase yield potential. To achieve such a vision, joint research across all stakeholders is necessary to develop new cropping systems that are economically profitable and environmentally sound, as well as the necessary indicators to monitor and report for the rice sector. Tracking such performance is a critical step in measuring progress towards agreed upon targets for sustainable intensification.

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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.crsust.2021.100070.

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