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Data-Driven Spatial Targeting for Sustainable Intensification of Rice Systems in the Philippines

Royette Santos
https://orcid.org/0009-0007-8583-6649
Hari Nayak
https://orcid.org/0000-0003-2585-1576
Pompe Sta Cruz
https://orcid.org/0000-0001-5742-9914
Anton Urfels
https://orcid.org/0000-0003-2920-8721
Virender Kumar
virender.kumar@cgiar.org

International Rice Research Institute (IRRI) https://orcid.org/0000-0002-2521-7578

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Abstract

Rice is central to food security in the Philippines, yet persistent yield gaps driven by suboptimal agronomic management continue to hinder progress toward national rice self-sufficiency. Identifying spatially explicit interventions is critical to narrowing these gaps sustainably across diverse production environments. This study assessed the key drivers of rice yield gaps and identified targeted nitrogen (N) management strategies in two major irrigated provinces, Iloilo and Nueva Ecija. We developed a Random Forest yield prediction model using survey data from 514 farmer fields across dry and wet seasons, interpreting variable importance with Shapley Additive Explanations (SHAP), and Individual Conditional Expectance to estimate field -specific N recommendations and closure potential. Average farmer yields reached only ~ 68–71% of attainable levels, leaving significant yield gaps of 29–32%. Nitrogen rate was identified as the dominant yield-limiting factor. We evaluated three management scenarios: (i) local government blanket recommendations, (ii) data-driven blanket recommendations (not spatially targeted), and (iii) spatially targeted N recommendations. Targeted approaches predicted yield gains of approximately 1.11 t ha^{-1} in Iloilo and 1.96 t ha^{-1} in Nueva Ecija. These predicted gains translate into estimated annual production increase of ~ 32,100 – 43,800 tons in Iloilo (60% of farmland) and ~ 108,000-132,100 tons in Nueva Ecija (47% of farmland). Remarkably, this approach achieves 86% of the potential production increase with only 15% of increased in fertilizer use compared to blanket approaches. On-farm validation further confirmed the effectiveness of the recommendations, increasing grain yield by 15.1% (0.69 t ha^{-1}) in Iloilo and 11.7% (0.76 t ha^{-1}) in Nueva Ecija. This study provides the first integrated application of machine learning, spatially targeted N optimization, and on-farm validation to assess yield gap drivers in the Philippines. It provides spatial intelligence to prioritize high-impact interventions and production zones, improve fertilizer subsidy design, and support a scalable pathway toward national rice security.

1. Introduction

Rice is the principal staple crop and the dominant source of dietary energy for more than half of the global population, underscoring its pivotal role in global food and nutritional security (Fukagawa and Ziska, 2019; USDA ERS 2025). In the Philippines, rice plays a critical role in food security, rural livelihoods, and the national political economy. It occupies more than one-third of total cultivated area and provides 30–75% of the daily caloric intake for over 100 million Filipinos (FAO, 2020). With an average per-capita rice consumption of 118.8 kg per year, the Philippines ranks among the world's top rice-consuming nations (FAO, 2021). Continued population growth, projected at around 1.5% annually, is expected to increase national rice demand by a further 13–15% by 2030 (World Bank, 2021).

Meeting this rising demand through sustainable gains in production and productivity is becoming increasingly challenging because of limited scope for cropland expansion, declining soil fertility, increasing climate variability, and inefficiencies in resource management (FAO, 2020). These challenges are further compounded by biotic stresses, including insect pests and diseases (Savary et al., 2019) and weeds (Fahad et al., 2019), which interact with abiotic stresses, exacerbating yield losses and

threatening resilience of rice-based systems (Wassmann et al., 2009). As a result, despite sustained public investment in irrigation infrastructure, varietal improvement, and input subsidies, domestic rice production has not kept pace with demand, necessitating periodic imports to stabilize domestic markets. In 2022 alone, the Philippines imported approximately 3.83 million metric tons of rice, making it the world's largest rice importer (Philippine Statistics Authority, 2023)-a situation likely to persist unless the underlying production constraints are effectively addressed.

Bridging existing attainable rice yield gaps is therefore a national priority and offers a major opportunity to increase rice production without expanding cultivated area, thereby strengthening food security while improving farmers' livelihoods. The attainable yield gap is defined as the difference between the attainable yield (top 10th percentile farmer's yield) and average farmers' yield. Bridging this gap requires identifying spatially explicit productivity drivers and precise targeting of these interventions. This is because rice management practices vary widely across landscapes and their interaction with environmental conditions, planting time, and genotypes leads to significant variations in rice productivity at the landscape scale (Laborte et al., 2012; Stuart et al., 2016). Although extensive on-farm studies in the Philippines and across Asia have examined rice yield variability and constraints, most have relied on frontier-based approaches such as stochastic frontier analysis or data envelopment analysis to quantify technical efficiency and explore yield gaps (Laborte et al., 2012; Stuart et al., 2016). These conventional analytical approaches, while informative, struggle to capture key insights due to their limitations in analyzing the complex interactions between various management practices and their impact on rice yields.

Previous studies have identified large rice yield gaps in these regions, primarily attributed to suboptimal nutrient management practices (Silva et al., 2017; Yuan et al., 2022), limited adoption of improved seed varieties (Silva et al., 2017), and traditional farming techniques (Dawe et al., 2014). These gaps represent valuable opportunities for improvement (Moya et al., 2015) and have prompted government interventions, including Rice Competitiveness Enhancement Program (RCEP), which promotes certified seeds, mechanization, and capacity building through a largely top-down approach to boost productivity in key production regions such as Western Visayas and Central Luzon (Department of Agriculture, 2021). However, insights into the nature, magnitude, and spatial heterogeneity of yield gaps in these regions remain generalized and incompletely understood (PhilRice, 2022a), limiting the effectiveness of blanket policy interventions.

Recent advances in the use of large on-farm data combined with interpretable machine learning (ML) approaches offer new opportunities to overcome these limitations. These methods have shown strong potential to identify field- and seasonal-specific drivers of yield and sustainability gaps, and to inform targeted management intervention for sustainable intensification (Saikai et al., 2020; Kakimoto et al., 2022; Nayak et al., 2024; Coggins et al., 2025). For example, Nayak et al. (2024) applied a bottom-up, data-driven framework integrating interpretable ML, spatial analysis, and ex-ante evaluation to design sustainable intensification pathways in Eastern India, showing that optimized irrigation and nitrogen management could increase average yields by up to 0.68 t ha^{-1}. Despite growing global recognition of

the value of on-farm data and interpretable ML for yield gap analysis (Nayak et al., 2024), and for narrowing sustainability gaps such as nitrogen use-efficiencies (Coggins et al., 2025), comparable data-driven, interpretable ML analysis tailored to Philippine rice systems aimed at guiding sustainable intensification remains limited.

Against this backdrop, the present study employs an interpretable ML framework coupled with ex-ante analysis and spatial intelligence, using extensive on-farm data from Philippine rice production systems. The objectives are to identify field- and season-specific productivity and efficiency constraints, quantify their relative importance across landscape, and generate site-tailored management recommendations. By doing so, the study advances methodological innovations beyond traditional frontier-based models while directly addressing the critical need for actionable, locally adapted strategies to sustainably bridge rice yield gaps in the Philippines. Given the country's diverse agro-ecological conditions and heterogeneous farming practices, such integrated, data-driven approach is essential for designing targeted interventions that enhance productivity and address the complex challenges the Philippine rice sector is facing.

[Insert Fig. 1 here]

Figure 1. Representative rice production fields in surveyed sites in Iloilo and Nueva Ecija, Philippines. Photocredit: Royette C. Santos.

2. Materials and Methods

2.1 Study area and site selection for survey

The study area covered two major rice producing provinces of the Philippines: Iloilo (Region VI) and Nueva Ecija (Region III) (Fig. 1). Each study site represents distinct agro-ecological environments. Iloilo (10.9092° N, 122.5146° E) is located in the Visayas region, while Nueva Ecija (15.7295° N, 120.8729° E) is situated in Central Luzon. Together, these provinces contribute substantially to national rice production. Iloilo produces approximately 1.0 M mt of rice per year, accounting for about 4% of total national production, while Nueva Ecija contributes around 1.8 M mt of paddy rice annually, representing about 9% of national production (PSA, 2024).

Differences in environmental conditions, management practices, and production challenges between the two provinces provide a valuable comparative framework for examining the drivers of rice yield variability under contrasting ecological and management settings. Although both Iloilo and Nueva Ecija fall under Type 1 climate according to the Modified Coronas classification, characterized by clearly defined wet and dry seasons, the weather conditions during the rice growing period differed substantially between provinces and seasons. In Iloilo, the dry season spans from September through December, and wet season from May to October, whereas in Nueva Ecija, the dry season runs from January to April and wet season from June to September. Mean monthly rainfall ranges from 250–300 mm in Iloilo and 550–730 mm in Nueva Ecija, with July and August months wettest in both provinces. Soil types in both provinces

are predominantly clay and clay loam, with pH values between 6.5 and 7.6, indicative of moderate to high inherent fertility.

Site selection for this survey study focused on irrigated rice systems. In each province, the five largest irrigated rice producing municipalities were identified in consultation with the Provincial Agriculture Offices. Within each municipality, the five highest rice producing *barangays/villages* (the smallest local administrative unit) were selected through close coordination with the Municipal or City Agriculture Offices, resulting in a total of 50 irrigated rice producing barangays/villages across both provinces. Within each barangay, farmers were randomly selected using a fish-bowl technique from the list provided through the Registry System for Basic Sectors in Agriculture (RSBSA).

2.2 Survey data collection methodology and curation

A purposive stratified random sampling technique was used to select farmers directly involved in irrigated rice production (excluding rainfed and upland farmers) for this survey. This sampling approach was employed to capture variability in agricultural practices and yield outcomes within each study site by ensuring representation from important subgroups, thereby enhancing the reliability and generalizability of the findings. A total of 538 farmers registered with RSBSA were surveyed after the harvest in each season, with support from local government units in selected municipalities.

Data on crop management practices including variety selection, land preparation, water management, nutrient management, weed management, and insect pest and disease management, along with other basic information about field and farmer profiling and yield outcomes, were collected using a structured questionnaire. Surveys were implemented digitally using an Open Data Kit (ODK)-based platform (Kobo Toolbox), which enabled efficient data collection, and real-time monitoring from farmer's field through a web-based portal.

Data entries with errors and extreme observations were identified using boxplots. Bivariate and multivariate outliers were identified using Robust Mahalanobis Distance (RMD, Gnanadesikan and Kettenring, 1972). Datapoints with such outliers were excluded from the whole dataset, whereas error entries were revalidated by follow-up interviews and focus group discussions. Common errors encountered were mainly in varietal spellings, numerical inputs, duplication of entries, and unit misinterpretation. These were then corrected using expert knowledge and available literature. The final curated dataset comprised 514 field observations (258 from Iloilo and 256 from Nueva Ecija) and eight key management-related yield-determinants.

2.3 Sustainable intensification strategy

The study adopted a bottom-up approach that builds from detailed on-farm data observations from the ground, rather than imposing a generalized top-level recommendation. The objective was to design a sustainable intensification (SI) strategy aimed at closing the rice yield gaps through more efficient use of existing resources. The approach sought to minimize on-farm yield variation by identifying management practices that can be optimized to enhance rice productivity with cost-effective use of external inputs

and minimizing environmental impacts. The analysis consisted of two main components. First, an interpretable ML framework was applied (Nayak et al., 2024) to identify key productivity drivers and spatial intelligence was leveraged to bridge the rice yield gap. Second, we focused on optimizing the most critical management drivers through an ex-ante scenario analysis.

2.3.1. Yield gap estimation and identification of productivity drivers

For each site (Iloilo and Nueva Ecija) and season (dry-season, DS and wet-season, WS), farms were classified into three groups: high-yielding (top 10%), moderate-yielding (middle 80%), and low-yielding (bottom 10%). The yield from high-yielding farms was designated as the attainable yield and used to estimate the yield gap, which was calculated as the difference between the attainable yield and the actual yield achieved by farmers (Stuart et al., 2016). Furthermore, to identify key drivers of productivity, we developed a rice yield prediction model using management practices and self-reported yields from farmers. We interpreted the model using SHAP (SHapley Additive explanations) scores and other interpretable machine learning frameworks, as described below. The performance of each model was evaluated using Out-of-Bag (OOB) R^2 and Root Mean Square Error (RMSE).

2.3.2. Productivity drivers and optimization

To check if rice yields differ significantly across season, t-test was conducted. Preliminary statistical analyses indicated wide differences in grain yield between dry and wet seasons. Therefore, separate ML models were fitted for dry and wet seasons to enhance our understanding of the rice yield variability among growing seasons. For both seasons, province-specific Random Forest (RF) models (Breiman, 2001) were fitted to account for differences in management practices between Iloilo and Nueva Ecija. The Random Forest model was selected due to its high predictive accuracy in agronomic data analysis (Nayak et al., 2022), nonparametric nature (Boulesteix et al., 2012), and ability to capture nonlinear association between predictors and output (Strobl et al., 2009). RF models were built using the ranger package (Liaw and Wiener, 2002) in R studio v12.4.1.

Key productivity drivers were identified using a random forest model interpreted with SHAP values. SHAP values were generated using the *fastshap* package (Greenwell, 2023) to explain individual farm-level yield predictions. As a post-hoc method, SHAP quantifies the contribution of individual management practice to yield prediction and provides insight into the contextual value of different management practices for productivity improvement, thereby enabling site-specific interventions. For finding global importance, the absolute SHAP values for any feature were averaged across the farm fields and ranked.

A partial dependence plot (PDP) was generated using the *pdp* package (Greenwell, 2017) to examine the relationship between N application (the most influential management variable) and yield outcomes (Friedman and Meulman, 2003). This analysis was conducted season-wise to identify opportunities for optimizing N use to bridge yield gaps in a cost-effective and environmentally sustainable manner. To estimate field-specific yield improvement potential from adjustments in N rates, individual conditional

expectation (ICE) analysis was performed. ICE curves were generated across a vector of N application rates to quantify the expected yield gains associated with changes in N input. The analysis was conducted separately for each variety type and province using their respective yield models. From these ICE plots, the minimum N rates achieving near-maximum yield were identified. This is referred to as the “data-driven optimum N rate” in this study.

The interpretable ML package was used for ICE analysis in the R environment. The anticipated economic, yield, and environmental benefits of spatially targeted optimal N-rate versus blanket N recommendations were assessed through a scenario analysis involving different N recommendations. In the targeted approach, optimal N rates were adjusted only in N-limiting fields, whereas blanket interventions involved applying the same N rates (either LGU recommendation or optimal N rate estimated based on a data-driven approach) across all farms. For Scenario 1 (blanket intervention), N rate was applied as per LGU blanket recommendation based on soil fertility map (90 and 100 kg ha^{-1} during the wet and dry seasons, respectively in Iloilo, and 110 and 120 kg ha^{-1} during the wet and dry seasons, respectively, in Nueva Ecija). For Scenario 2 (data-driven blanket), all fields received economically and environmentally optimal N rate derived from ICE analysis, while for Scenario 3 (targeted intervention), province and season specific optimal N-rate was applied only to N-limited fields identified by negative SHAP value for N. This was designed to delineate the importance of targeted interventions in N use, investments, and savings over blanket recommendations. The predicted yield gains, economic benefits, and changes in N investments for each scenario were aggregated across regions.

2.4 Mapping regional variability in yield gap closure potential

Field-specific yield improvement resulting from adjustments in N rate was estimated from ICE plots and subsequently aggregated spatially to identify locations with the highest anticipated yield gains based on the ex-ante scenario analysis. Spatial analyses were carried out in the QGIS environment. Classified maps depicting low, moderate, and high yield gain potential were generated for policy planners, highlighting areas with varying levels of responsiveness to targeted productivity interventions.

2.5 Establishment of on-farm validation trials

To validate the practical applicability of the data-driven N recommendations derived from interpretable ML framework, on-farm validation trials were established under farmer field conditions in Nueva Ecija (n = 5) during DS 2024 and Iloilo (n = 6) during DS 2025. Side-by-side comparisons of farmer’s practice (FP) and data-driven N recommendations (Demo) were established using two adjacent plots of comparable size to minimize variation arising from soil properties, irrigation conditions, and topography. The FP plots followed the conventional fertilizer management of farmers, whereas Demo plots used the data-driven N recommendations identified through ICE. All other crop management practices such as variety, crop establishment method, crop establishment date, water management, pest and disease management,

and harvesting were maintained the same for both plots to isolate the effect of improved N recommendation.

Actual grain yield was collected and recorded at harvest from both the FP and Demo plots based on farmers' harvested production area and subsequently adjusted to 14% MC. The validation data were analyzed using paired t-test with each farmer considered as a paired experimental unit. Mean grain yield and absolute yield gain were calculated for each province. This validation was conducted to determine whether machine-learning derived recommendations consistently improved rice productivity under farmer-managed conditions and to assess its potential for broader implementation.

3. Results and Discussion

3.1 Baseline production practices in irrigated rice production system of the Philippines

Socio-economic characteristics, production practices, input-use and productivity varied across provinces and seasons (Figure 2). The average age of farmers was 56 and 59 in Iloilo and Nueva Ecija, respectively. Of the total respondents, 61% were male and 39% female in Iloilo, while 80% were male and 20% female in Nueva Ecija. The average land holding size was smaller in Iloilo (1.25 ha.) compared to Nueva Ecija (1.65 ha.), reflecting smaller farm sizes in Western Visayas than in Central Luzon. Farmers had extensive rice farming experience of 30 and 32 years in Iloilo and Nueva Ecija, respectively. Basic land preparation comprising plowing, harrowing, and levelling was widely practiced in both provinces across wet (WS) and dry seasons (DS).

Transplanting was the main crop establishment method in Nueva Ecija as reported by 80-86% of surveyed farmers, whereas wet-DSR predominated in Iloilo (61-85%) (Figure 2). Varietal preferences also differed markedly between provinces and seasons. In Iloilo, farmers predominantly used inbred varieties, primarily NSIC Rc 222 and Rc 216 in both seasons, while hybrid rice varieties were used by only 13% of surveyed farmers mainly during DS. In contrast, hybrid rice varieties dominated the DS in Nueva Ecija, with around 70% of farmers cultivating hybrids, whereas inbred varieties, again led by NSIC Rc 222 and NSIC Rc 216, remained more common during the WS. These results showed that the farmers preferred hybrid rice in transplanted rather than direct-seeded areas and during the DS over WS (e.g. in Nueva Ecija). This could be because hybrid cultivars (SL8H and Longpin) generally showed superior yield performance during the DS but were less consistent during the WS in both provinces.

In-season water management practices varied by site. In Iloilo, continuous flooding was practiced by only 10-12% of surveyed farmers, while the majority (77 to 80%) adopted multiple drainage water management in their rice fields (Figure 2). In contrast, the prevalence of continuous flooding was higher in Nueva Ecija than Iloilo, where 27 to 36% of farmers practiced this method. Nevertheless, multiple drainage remained the most dominant method of water management in Nueva Ecija as well, with 59-62% of surveyed farmers applying this method.

Nitrogen application rates were consistently higher in Nueva Ecija, averaging 122 kg N ha^{-1} in DS and 100 kg N ha^{-1} in WS, compared with 72 kg N ha^{-1} in both seasons in Iloilo (Figure 2). Phosphorus (average ~ 20 kg ha^{-1}) and potassium (25 kg ha^{-1}) application rates were broadly similar across provinces, while the use of organic amendments was limited in both systems. Weed, insect, and disease control ratings ranged from good to excellent across sites.

Rice straw removal was not a common practice across surveyed fields, with most farmers incorporated (>70% in Iloilo and 60% in Nueva Ecija) rice straw in the soil (Figure 2). However, rice straw burning remained prevalent, with 26 to 38% of surveyed farmers burning straw across sites. Average grain yield in Nueva Ecija was significantly higher than in Iloilo, with 5.20 t ha^{-1} and 7.47 t ha^{-1} in WS and DS, respectively. In contrast, average yield in Iloilo was around 4.2 t ha^{-1} across seasons.

Figure 2. Characteristics of Rice Production Sites

[Insert Figure 2 here]

Control Rating : Excellent = very effective control, almost no visible weeds or diseases; rice field is clean and vigorous;Good = few weeds or diseases present, minimal impact on rice crop; control is highly effective

Abbreviations: Wet-DSR: Wet direct-seeded rice - seeds sown directly into puddled/wet soil; Dry-DSR: Dry direct-seeded rice - seeds sown directly into dry soil before flooding; TPR: Transplanted rice - seedlings raised in a nursery and later transplanted into the field; SD: single drainage – Fields were drained once (usually mid-season) to improve growth; MD: Multiple drainage - Fields were drained several times to save water and improve aeration; CF: continuously flooded - Fields remained submerged for most of the season

3.2 Seasonal and spatial variation in rice yields and rice yield gaps

Rice yield varied significantly across seasons and provinces (Figure 3). Yields were substantially higher during the DS than the WS in Nueva Ecija, while only marginal seasonal differences were observed in Iloilo. This pattern is consistent with global observations that the DS often benefits from higher solar radiation and reduced cloud cover, leading to improved crop growth, grain filling, and higher yield (Devkota et al., 2019; van Oort and Zwart, 2018). For example, in Iloilo, farmers' average and attainable yields were 4.1 to 4.2 t ha^{-1} and 5.8 to 5.9 t ha^{-1}, respectively across DS and WS with minimal seasonal variation, resulting in a consistent yield gap of approximately 1.7 t ha^{-1} (Figure 3). In contrast, Nueva Ecija showed marked seasonality, with average yields of 7.5 t ha^{-1} in the DS and 5.2 t ha^{-1} in the WS. Corresponding attainable yields were 10.6 and 7.7 t ha^{-1}, resulting in actual yield gap of 3.1and 2.5 t ha^{-1} during the DS and WS, respectively. Across provinces and seasons, farmers' average yields achieved only ~68–71% of the attainable yield, leaving a persistent yield gap of 29–32%.

The seasonal yield variability and average yields observed in this study are well aligned with national datasets. For example, the Philippine Rice Information System (PRiSM) consistently reports higher DS yields in Central Luzon and smaller seasonal differences in Western Visayas. This is consistent with broader evidence showing that DS rice production often benefits from higher solar radiation and reduced cloud cover, which enhance crop growth and grain filling (Devkota et al. 2019; van Oort and Zwart 2018). PhilRice's Ricelytics platform likewise shows average yields of 5.47 and 6.53 t ha^{-1} during the wet and dry seasons, respectively in Nueva Ecija, and 3.30 and 3.20 t ha^{-1} during the wet and dry seasons, respectively, in Iloilo (PSA, 2024), closely matching our findings.

In Nueva Ecija, higher DS yields can be attributed to a combination of favorable climatic conditions (e.g., higher solar radiation, lower risks of climatic shocks such as typhoon, and floods) and more intensive management, including higher N application rates (120 kg N ha^{-1} in the DS versus 100 kg N ha^{-1} in the WS) and greater adoption of hybrid rice (72% in the DS compared with 12% in WS; Figure 3). In contrast, the limited seasonal variability observed in Iloilo may be due to relatively comparable climatic conditions across seasons at this site, combined with management practices that buffer seasonal effects. For example, key input use and management practices were similar across seasons, including N application which was on an average 72 kg ha^{-1} in both seasons (Figure 2). Moreover, adoption of dry-DSR was higher in the DS than in the WS (27% versus 3%) (Figure 2). Based on our survey data, the dry-DSR yields were lower than wet-DSR (data not shown), higher dry-DSR in DS might have compensated any climatic yield advantage that the DS might otherwise have offered.

Previous studies have also reported large rice yield gaps in the Philippines, consistent with the findings of this study. Silva et al. (2017) estimated potential yield gaps of ~ 3.2 t ha^{-1} in the WS and ~ 4.8 t ha^{-1} in the DS in Central Luzon (Nueva Ecija), with efficiency and technology gaps contributing substantially. Silva et al. (2017) further highlighted farm-level and regional constraints to intensification in the same region, emphasizing the role of nutrient management, irrigation, and labor dynamics. Similarly, the Global Yield Gap Atlas (GYGA) places Philippine rice yield gaps in the range of 25–35%, broadly consistent with our findings (GYGA, 2023). More broadly, Laborte et al. (2012) reported that the Philippines, as a rice-importing country, tends to exhibit larger gaps between average and best farmers' yields than exporting countries like Vietnam and Thailand, due to management and input constraints.

It is important to note that the yield gaps reported here primarily reflect management heterogeneity within provinces, as attainable yields were defined using top-performing farms rather than simulated climatic potential yields. While this approach does not fully capture environmental variability within provinces, it provides realistic, context-specific benchmarks for improvement. Consistent with the assessment of Silva et al. (2022), our results underscore substantial scope to increase rice production in the Philippines through targeted closing of management-related yield gaps, especially nutrient management, and strengthened extension and service delivery systems.

[Insert Figure 3 here]

Figure 3. Average grain yield, attainable yield, and attainable yield gaps in Iloilo and Nueva Ecija, Philippines during the dry season and wet season of 2021.

3.3 Main drivers of rice yield identified by interpretable ML and estimation of data-driven economic and environmental N optimization

Yield variability was analyzed using province- and season-specific machine learning models to identify key management drivers and assess their potential contribution to yield gap closure. Overall, the models demonstrated moderate predictive accuracy, reflecting inherent variability in farmer-managed systems. During the WS, the mean OOB R^2 was 0.35 in Iloilo and **0.62 in Nueva Ecija**, with an RMSE of **0.75 and 0.81 t ha^{-1}**. In the DS, model performance fitted for Nueva Ecija achieved an R^2 of **0.70** with an RMSE of **1.21 t ha^{-1}**, whereas Iloilo model showed lower explanatory power (R^2 = **0.33**; RMSE = **0.69 t ha^{-1})**. Despite moderate R^2 values, the models captured meaningful variation in yield and were sufficient for identifying key management drivers and assessing scenario-based improvement. The spread of SHAP values (Figure 4) was summarized. Individual points represent single observations with colored feature value representing its magnitude and direction of influence on the predicted outcome. Features were ranked according to mean absolute SHAP values to assess overall importance. Across seasons, nutrient management, particularly nitrogen (N) application consistently emerged as the dominant driver of rice yield variability (Figure 4). In Nueva Ecija during the DS, total N rate was the most influential factor, followed by varietal selection, and total P, whereas in the WS, total N rate was followed by phosphorus (P) and potassium (K) application rates (Figure 4, B). In Iloilo, nutrient variables similarly dominated yield determination, although their relative importance was lower than in Nueva Ecija. During the DS, total N is followed by total K and total P, while during the WS, total N is followed by total K and weed management control (Figure 4). Given the consistent importance of N across seasons and provinces, subsequent analysis focused on quantifying its yield response, estimating data-driven N optimization, and implication for spatial targeting.

The SHAP and ICE based methodology enabled quantification of field-specific limitations and yield improvement potential, providing actionable insights for site-specific interventions. Population-level response (as revealed from PDP) showed significant yield improvements till N rates of 105 kg ha^{-1} in Iloilo and 140 kg ha^{-1} in Nueva Ecija during the DS and 103 kg ha^{-1} in Iloilo and 131 kg ha^{-1} in Nueva Ecija during the WS, before it starts to plateau (Figure 5). These findings are consistent with Buresh et al. (2019), who reported that the most effective responses to N fertilizer typically occur during the dry season when disease pressure is lower compared to the wet season. Importantly, approximately 98% of surveyed fields in Iloilo and 68% in Nueva Ecija applied N rates below these thresholds during the DS, while 90% and 95% applied below during the WS in Iloilo and Nueva Ecija, respectively, suggesting considerable potential for yield improvement through optimized N management. However, only a small fraction (5-21%) of the field applied a higher dose of N, which could benefit from N saving, if N is managed precisely.

The findings of this study are consistent with previous work in the Philippines and Southeast Asia. Silva et al. (2017) reported that nutrient management, particularly N application, explained a large share of yield gaps in irrigated rice in Central Luzon, with suboptimal N use contributing to efficiency gaps of 20–30%. Similarly, Laborte et al. (2012) and the Global Yield Gap Atlas (GYGA, 2023) identified fertilizer management as a dominant explanatory factor for gaps between average and potential yields across major rice-growing provinces. These studies converge with our findings that N management is a key lever for bridging the gap. In contrast, our results suggest that within the specific sites of Iloilo and Nueva Ecija, N fertilizer accounted for the largest share of yield variation relative to other inputs. Thus, while our findings reinforce the importance of N, and also point to a need for spatial targeting to improve yield and N use efficiency: targeting N management in areas where it is most limiting. Despite clear role of N in closing yield gaps, the increasing cost of N-based fertilizers in the Philippines poses a challenge to achieving these improvements. According to Briones (2016), rising fertilizer prices remains a significant barrier to achieving optimal N use in the Philippines. Hence, the role of government in providing smart subsidy programs is critical to enhance fertilizer affordability and promote optimal N use while ensuring no unintended consequences. Current government investments focus largely on variety improvement, seed distribution, and mechanization, but constraints such as insufficient N fertilizer applications and limited fertilizer subsidies remain un-addressed (Briones, 2016; PhilRice, 2022b).

[Insert Figure 4 here]

Figure 4. SHAP summary plots (left) and global feature importance rankings based on mean absolute SHAP values (right) for rice yield prediction models in Iloilo during the wet season (A) and dry season (B), and Nueva Ecija during the wet season (C) and dry season (D). Each point in the SHAP summary plots represents an individual field observation and is colored according to the feature value. Positive SHAP values indicate a positive contribution to predicted yield, whereas negative values indicate a negative contribution. Bar plots show the overall importance of each predictor based on its mean absolute SHAP value.

[Insert Figure 5 here]

Figure 5. Rice yield response curves to nitrogen in Iloilo and Nueva Ecija, Philippines, showing the data-driven optimum nitrogen application rates during the dry and wet seasons.

3.4 Ex-ante scenario analysis for yield gain prediction with N management

The result of ex-ante scenario analysis with ICE predicted potential productivity gains, economic, and N investment across provinces and seasons (Table 1). Blanket use of the LGU-based recommendation in Iloilo (Scenario 1) where all fields received a N rate of 90 and 100 kg ha^{-1} during the wet (WS) and dry seasons (DS), respectively, was predicted to produce a yield gain of 0.42 t ha^{-1} (WS) and 0.74 t ha^{-1} (DS). This corresponds to an additional ~30,000 to ~33, 000 tons of annual rice supply across a total rice area of 115,745 ha. with an additional ~3,200 tons of N required compared to current farmer practices. The relatively larger predicted yield gain in this region implies that the current N rate (72 kg ha^{-1}) is

insufficient to meet the crop's N demand which may be compounded by reduced mobility during the DS. In Nueva Ecija, the blanket LGU intervention (110 kg ha^{-1} in WS and 120 kg ha^{-1} in DS) can result in yield increases of 0.41 t ha^{-1} (WS) and 0.46 t ha^{-1} (DS), translating into ~54, 000 to ~70,600 tons of additional rice across a total rice area of 287,415 ha. Interestingly, this approach led to a slight decrease in N use by 313 tons during the DS relative to the current rate of 122 kg ha^{-1}, but an additional 2,412 tons during the WS compared to current practices in Nueva Ecija (100 kg ha^{-1}). While simple to implement, we observed that this uniform recommendation could lead to significant variability in yield outcomes with some areas anticipated to have significant yield losses, particularly in areas where the current N application rates are higher.

Blanket recommendation based on the maximum vector of N emerging from ICE (Scenario 2), demonstrated higher yield gains compared to Scenario 1. In Iloilo, yield gains of 0.90 t ha^{-1} and 0.72 t ha^{-1} were predicted for both the DS and WS, respectively, resulting in ~40,800 to ~51,200 tons of additional rice production. In Nueva Ecija, this scenario produced gains of 1.04 t ha^{-1} and 1.02 t ha^{-1} during the DS and WS, respectively, equivalent to ~136,400 to ~160,000 tons of additional rice. However, this approach required a substantial increase in N inputs, with ~4,555 tons of additional N investment required in Iloilo and ~8,599 tons in Nueva Ecija. Scenario 2 demonstrates the power of an approach based on an analytics-based blanket N rate rather than recommendations from experimental scenarios.

Scenario 3, which utilized a targeted N management approach based on SHAP analysis, achieved the most efficient N use among all scenarios. In Iloilo, we observed yield gains of 1.18 t ha^{-1} (from only 60% of the fields) and 1.04 t ha^{-1} (from intervening 60% of fields) during the DS and WS, respectively. This resulted in ~32,100 to ~43,800 tons of additional volume of production, with significantly lower N inputs of ~691 tons. In Nueva Ecija, targeted intervention can lead to yield increase of 2.19 t ha^{-1} (with N rate changing in only 39% of the fields) and 1.73 t ha^{-1} (N rate changing in 47% of fields), translating into ~108,300 to ~132,100 tons of potential increase in production with reduction in N use of ~14,800 tons. Compared to blanket recommendations, this scenario demonstrated substantial benefits for resource use efficiency and reduction in fertilizer investments. The optimal N rate appears to be context-dependent underscoring the need for region-specific and season-adjusted N management strategies targeting areas with lower N application rates. Previous efforts such as the Rice Crop Manager (RCM) have pioneered nutrient management decision-support tools for rice farmers. This study builds on the same principle with RCM following precision nutrient management and advances it by applying scenario analysis with machine learning to simulate yield outcomes under different N management strategies using recent agronomic data.

The power of solution targeting is very evident in Scenario 3 by providing higher yield gains and lower fertilizer investments than blanket recommendations. Although spatial targeting would not result in more total rice production than the blanket recommendations of Scenarios 1 and 2, and opportunities for productivity gains more clearly identified, targeting allows scarce resources like N fertilizers to be focused on areas where the returns on investments will likely be substantial. Such identification can be achieved through tools like remote sensing and other yield monitoring systems of LGUs that help identify

low-yielding areas or nutrient-deficient fields. While blanket recommendations may offer higher overall production gains, targeted approaches offer significant advantages in optimizing resource use and environmental outcomes. In the Philippines, where fertilizer subsidies are limited and prices of fertilizers are increasing, it is crucial to focus on strategies that maximize NUE while minimizing input costs. Targeted approaches such as those demonstrated in Scenario 3 provide an opportunity for the government to maximize the impact of public investments in fertilizers, optimize fertilizer allocation, and ensure that scarce resources are directed to areas where the benefits are most substantial. This not only improves equity in resource allocation but also ensures that public investments translate into tangible benefits in terms of increased rice production and national food security.

Table 1: Predicted yield and profitability gains across N recommendation scenarios

[Insert Table 1 here]

3.5 Spatial benefit estimation

The extent of yield benefits (Figure 6) was visualized spatially to assist policymakers and planners in identifying specific areas where interventions would yield the greatest return, thus ensuring efficient resource allocation. For instance, in Iloilo, over 60% of the area could benefit from improved N management during the DS and WS, particularly in municipalities where negative SHAP values have been observed. In Nueva Ecija, around 39% and 47% of the area during the DS and WS, respectively, show similar potential with some clusters concentrated in specific municipalities identified as priority targets. Areas with consistently high yield gain potential across both seasons emerge as high-impact zones ideal for year-round interventions. In contrast, areas with high yield potential during the WS but limited gains in the DS may indicate effective N management practices in the DS, highlighting opportunities for improvement during the WS and need a temporal effective resource allocation. These insights provide critical guidance for enhancing productivity through precise targeting of N management interventions. Given the rising fertilizer prices, the study recommends prioritizing high-impact zones and aligning strategies to account for spatial and seasonal variability to ensure efficient use of resources and promote sustainability. Overall, we emphasize the value of targeting interventions, focusing resources on areas where returns on investment are likely to be significant. Blanket N recommendations risk exacerbating GHG emissions without addressing site-specific needs.

[Insert Figure 6 here]

Figure 6. Spatial distribution of yield gain potential due to improved N showcasing high-priority areas for yield optimization in a) Iloilo DS b) Iloilo WS c) Nueva Ecija DS d) Nueva Ecija WS, Philippines.

3.6 On-farm validation of data-driven nitrogen recommendations

The on-farm validation trials confirmed that the machine learning-derived N recommendations effectively improved rice productivity in both sites (Figure 7). In Iloilo, Demo plots where improved N recommendations were implemented obtained a mean grain yield of 5.23 t ha^{-1}, significantly higher (P

<0.005) than the 4.55 t ha^{-1} achieved under the FP, representing an average yield gain of 0.69 t ha^{-1} (15%). Likewise, in Nueva Ecija, the Demo plots produced an average of 7.29 t ha⁻¹ which is significantly higher than the grain yield obtained under FP (6.53 t ha^{-1}). This translates to an average production gain of 0.76 t ha^{-1} (12%) (P<0.005). These results validate the prediction of the interpretable ML framework that N management was the primary yield-limiting management factor in both provinces. These findings confirm that current N management practices remain suboptimal in many farmer fields and that optimizing N management alone can substantially improve rice productivity and can contribute to narrowing existing yield gaps. This field validation trial provides independent evidence that the machine learning-derived recommendations successfully identified N-limited production systems and generated practical recommendations that translated into measurable yield improvements under farmer-managed conditions.

[Insert Figure 7 here]

Figure 7. On-farm validation of data-driven nitrogen (N) recommendations in Iloilo and Nueva Ecija, Philippines. Grain yield under farmers' practice (FP) and the data-driven N recommendation (Demo) from side-by-side on-farm validation trials. Boxes represent the interquartile range, the horizontal line indicates the median, black diamonds denote the mean grain yield, and points represent individual farmer fields. Blue text indicates the mean yield advantage of the data-driven recommendation over the farmers' practice. Paired t-tests showed that the data-driven N recommendation significantly increased grain yield in both provinces (P < 0.005) represented by ***.

3.7 Policy Implications

The findings of the study provide strong empirical evidence to support a shift from conventional blanket input policies to data-driven, spatially targeted agricultural interventions in the Philippines. Several key implications emerge. First, the consistent main driver of rice yield variability (N management) identified through ML, highlights the need to reorient fertilizer policies toward spatially targeted nutrient management. Current blanket recommendations and subsidy programs do not adequately account for management and production heterogeneity resulting in suboptimal N application. The results demonstrate that targeted N application (Scenario 3) can deliver higher yield gains (up to 1.11 t ha^{-1} in Iloilo and 1.97 t ha^{-1} in Nueva Ecija) while reducing total fertilizer investments. This suggests that fertilizer subsidy programs (e.g., under RCEP or LGU distribution schemes) would benefit from transitioning toward policy support mechanisms that incentivize more site-specific nutrient management together with tailored recommendations. This has direct implications for achieving national rice self-sufficiency. In 2023, the Philippines imported around 3.48M MT of rice and spent approximately USD 511 per MT for a total of more than 1.8 billion USD (Bureau of Plant Industry, 2024; Philippine Statistics Authority, 2024). These imports could be substantially reduced with small changes towards data-driven fertilizer recommendations that help close yield gaps and reduce import dependence. Importantly, evidence from this study suggests that simply increasing fertilizer subsidies without targeting would be inefficient. Experiences from heavily subsidized systems such as India (85-90% of market price) show

that uniform subsidies have often led to excessive N application, inefficient N use, and environmental risks (Coggins et al., 2025). In contrast, the results here demonstrate that targeting N-limited fields and clusters identified through SHAP-based analysis maximizes yield gains while minimizing input use, thereby improving return on public investment.

Currently, fertilizer subsidies in the Philippines remain modest, with government allocation at 72-109 M USD (4-6 billion PhP) (Department of Agriculture, 2021). These were mainly implemented through the RCEP and National Rice Program using fertilizer discount vouchers targeting registered farmers with no fixed subsidized price, limited coverage per hectare (1 bag per ha. based on interview), and weak linkage to site-specific recommendations (Department of Agriculture, 2021). Scaling up subsidy support would increase their cost efficiency and impact if coupled with spatial and data-driven targeting mechanisms. Strengthening such programs requires not only increased investment but also integration with decision-support tools and governmental decision-making processes. For example, the RCM, developed by IRRI and PhilRice and institutionalized by the DA through Memorandum Order No. 20 (2019). Such policies provide a strong reference for further strengthening and improving targeted fertilizer policies.

Second, the observed spatial heterogeneity in yield gap closure potential underscores the importance of geographically differentiated policy targeting. The identification of high impact zones, where yield gains from improved practices are higher, provides a basis for prioritizing public investments rather than distributing resources uniformly. In these areas, interventions can be designed to address not only the major key drivers but also relevant secondary constraints – such as pests, disease, seed rate, and planting dates – aligned with government priority areas, thereby enabling a more integrated approach to productivity improvement. This approach allows policy makers to strategically position inputs, extension services, and capacity-building efforts in areas with the highest marginal returns. This enhances both the economic efficiency and equity to ensure that limited public resources generate the maximum return on investments.

Third, the study highlights the growing importance of data and digital agriculture in policy implementation. The demonstrated effectiveness of interpretable ML approaches suggests that integrating farm-level data, remote sensing, and digital tools (e.g., LCAS, RCM, PRiSM) can enable real-time advisories and adaptive recommendations for farmers. Strengthening national data infrastructure and building LGU-level capabilities to utilize these tools will be critical for scaling spatially targeted interventions.

Overall, this study provides a strong case for transitioning from uniform, input-intensive policies toward evidence-based, spatially explicit, and efficiency-oriented agricultural strategies. Embedding such approaches within national programs will be critical for achieving rice self-sufficiency while ensuring sustainable resource use in the Philippines.

3.8 Limitations of the study and future directions

This study has several limitations. The yield models developed did not fully capture observed variability, underscoring the need for larger datasets to improve predictive accuracy. Socioeconomic and environmental factors, such as land tenure, irrigation infrastructure, market access, and climate variability, were not included due to data limitations. Incorporating these dimensions in future studies could provide deeper insights into the root causes of yield variability and inform more holistic solutions. Although the machine learning-derived N recommendations were successfully validated under farmer-managed conditions, additional on-farm validation across a wider range of environments, seasons, and production systems is needed to assess their robustness and scalability. The integration of interpretable ML with multi-location field validation provides a promising framework for developing practical, data-driven nutrient management strategies that support sustainable rice intensification.

4. Conclusion

This study provides the first integrated application in Philippine irrigated rice systems of interpretable ML to diagnose yield gaps across wet and dry seasons, translate field-specific constraints into spatially targeted N recommendations, and subsequently validate those recommendations under farmer-managed conditions. Nitrogen management and variety selection emerged as the major drivers of rice productivity, with N identified as key management constraint across seasons and provinces. Therefore, tailored intervention to improve N management practice can help narrow the gap especially those priority areas identified through SHAP analysis. Larger yield gaps were observed during the dry season, but this season also showed the greatest potential for yield improvement through optimized N management. Scenario analyses further showed that substantial productivity gains could be achieved through targeted N management while requiring substantially lower fertilizer inputs than blanket approaches. These findings demonstrate the value of directing interventions toward high-impact zones where improvements are likely to generate the greatest returns, thereby enhancing resource-use efficiency and supporting more sustainable rice intensification. Importantly, on-farm validation confirmed that the machine learning-derived N recommendations translated into significant yield improvements under farmer-managed conditions, demonstrating the practical applicability of the proposed framework. These findings highlight the potential of integrating interpretable ML with field validation to support spatially-explicit recommendations and guide more effective fertilizer recommendation strategies. Future research should expand the framework across a wider range of production environments, sample sizes, incorporate socioeconomic and policy-related factors, and evaluate long-term agronomic, economic, and environmental outcomes to further strengthen its applicability for sustainable rice intensification.

Declarations

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Declarations:

Ethics approval: The research obtained ethics approval from IRRI's Institutional Research Ethics Committee (2022-0017-A-2017-154).

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

Consent for publication: The authors affirm that research participants provided informed consent for publication.

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.

Availability of data and material: Data from this study are available from the corresponding author upon reasonable request.

Code availability

The code generated for analysis in this study is available from the corresponding author upon reasonable request.

Authors' contributions

Royette C. Santos: Writing-original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Hari S. Nayak:** Writing- review & editing; analysis. **Pompe C. Sta Cruz:** Writing-review & editing. **Anton Urfels:** Writing-review & editing. **Virender Kumar:** Writing-review & editing, Supervision, Funding acquisition, Conceptualization.

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Figures

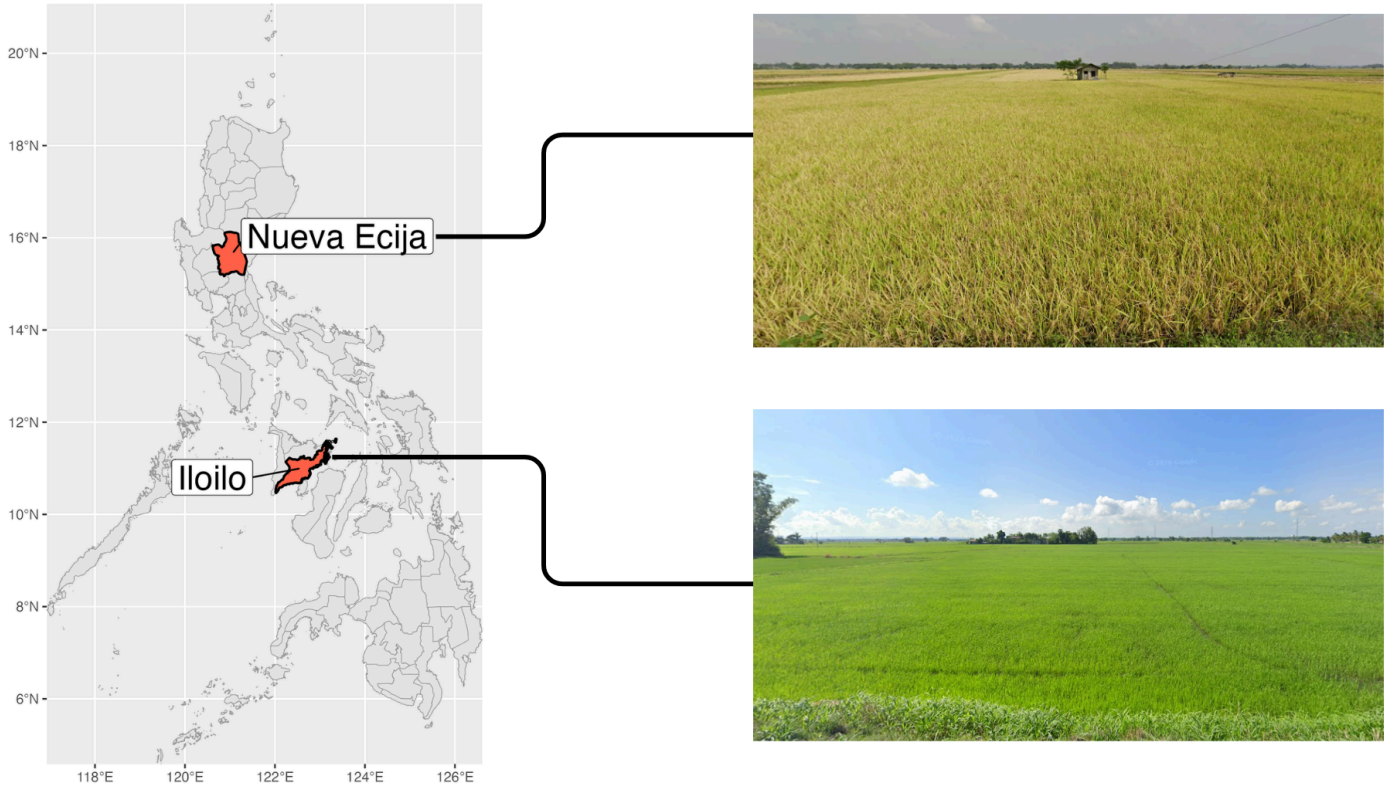


Figure 1

Representative rice production fields in surveyed sites in Iloilo and Nueva Ecija, Philippines. Photocredit: Royette C. Santos.

Demographic Profile and Management Practices		
	Iloilo	**Nueva Ecija**
Demographic Profile		
Age	56	59
Gender	61% M 39% F	80% M 20% F
Average farm size	1.25	1.65
Farming experience (years)	30	32
Management Practice		
Land Preparation	Basic tillage operation (Plowing, harrowing, puddling, and levelling)	Basic tillage operation
Commonly used varieties	DS: NSIC Rc 222 (27%) NSIC Rc 216 (24%) Hybrid (13%) WS: NSIC Rc 216 (30%) NSIC Rc 222 (23%) NSIC Rc 480 (11%)	DS: Hybrid (70%) NSIC Rc 222 (14%) NSIC Rc 480 (3%) WS: NSIC Rc 222 (47%) Hybrid (12%) NSIC Rc 216 (12%)
Predominant crop establishment method	DS: 61% Wet-DSR 27% Dry-DSR 13% TPR WS: 85% Wet-DSR 12% TPR 3% Dry-DSR	DS: 80% TPR 13% Dry-DSR 7% Wet-DSR WS: 86% TPR 7% Dry-DSR 7% Wet-DSR
Pre-season water regime (during fallow)	Non-flooded	Non-flooded
Within-season water regime	DS: 80% MD 11% SD 10% CF WS: 77% MD 11% SD 12% CF	DS: 62% MD 12% SD 27% CF WS: 59% MD 5% SD 36% CF
Nitrogen Rate (kg ha^{-1})	DS: 72 (average) 31 (minimum) 157 (maximum) WS: 72 (average) 25 (minimum) 135 (maximum)	DS: 122 (average) 40 (minimum) 189 (maximum) WS: 100 (average) 23 (minimum) 162 (maximum)
Phosphorus Rate (kg ha^{-1})	19.6 (average)	20.4 (average)
Potassium Rate (kg ha^{-1})	25.0 (average)	25.0 (average)
Use of other organic amendments	Limited	Limited
Weed management control rating	Good to excellent	Good to excellent
Insect and diseases control rating	Good to excellent	Good to excellent
Residue Management		
Straw burning (% farmers)	WS: 22 DS: 26	WS: 24 DS: 38
Timing of residue incorporation before planting	Short straw incorporation period (<30 days)	Short straw incorporation period (<30 days)
Straw removal	Limited	Limited
Output		
Average yield (t ha^{-1})	DS: 4.20 WS: 4.13	DS: 7.47 WS: 5.20

Figure 2

Characteristics of Rice Production Sites

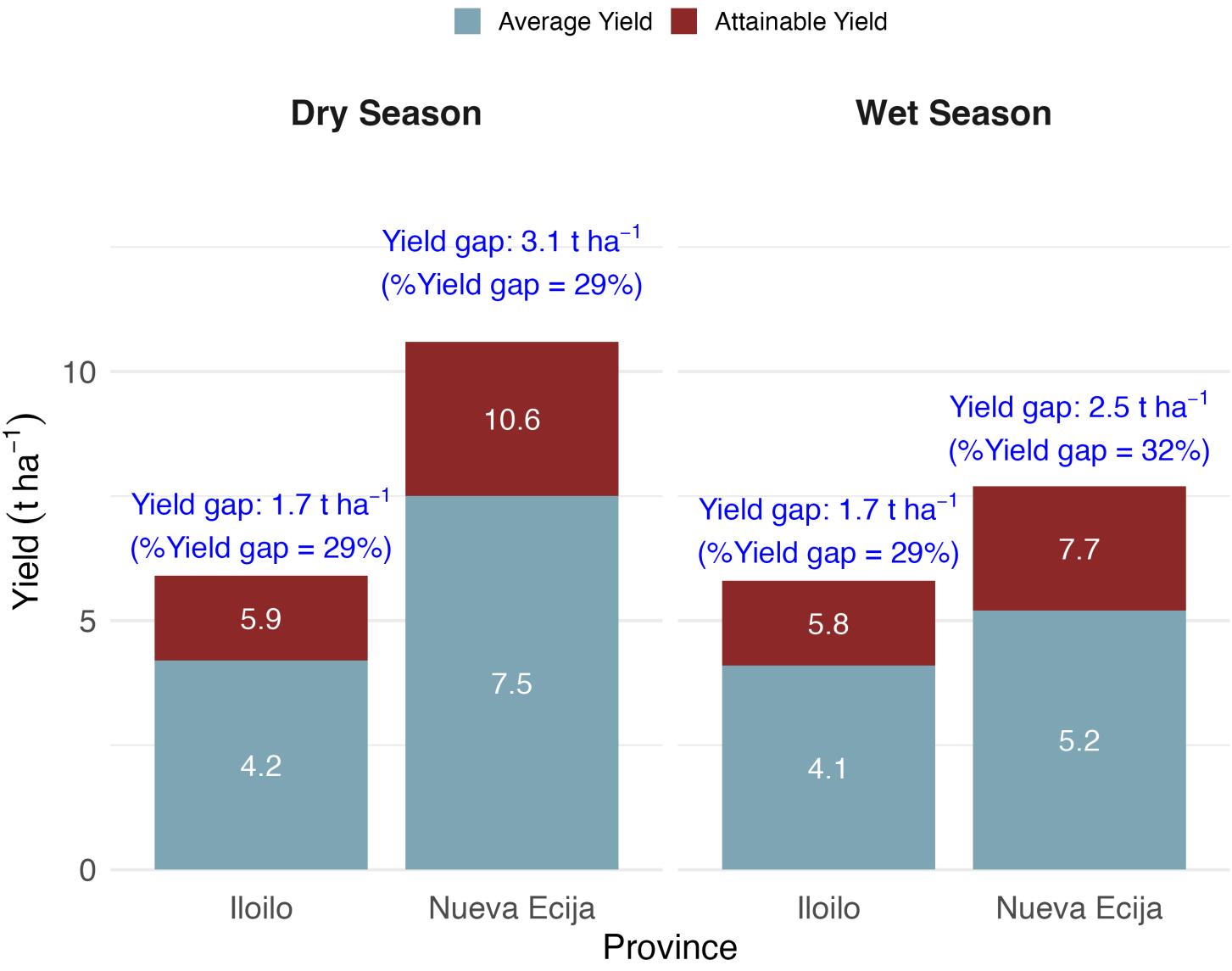


Figure 3

Average grain yield, attainable yield, and attainable yield gaps in Iloilo and Nueva Ecija, Philippines during the dry season and wet season of 2021.

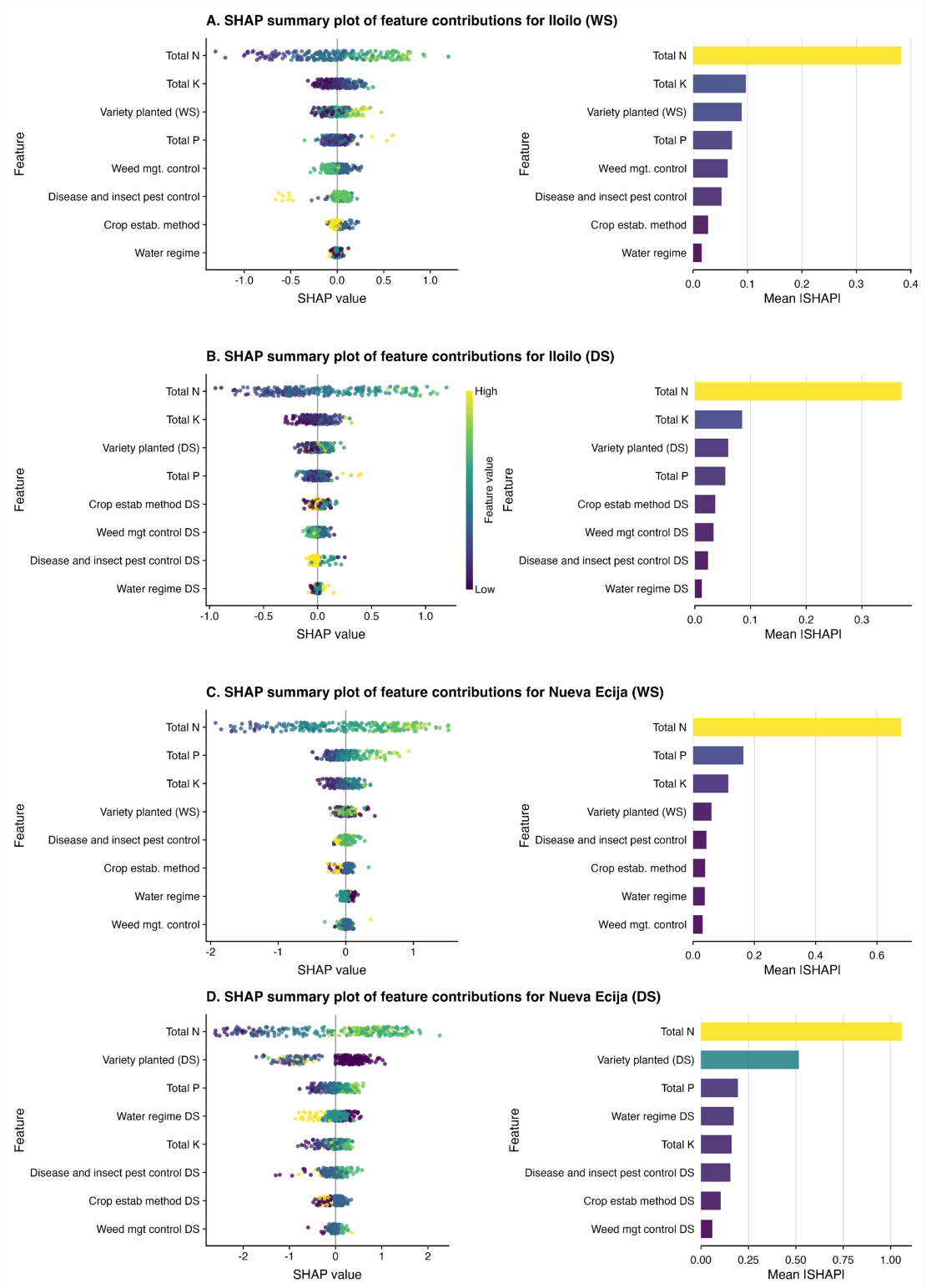


Figure 4

SHAP summary plots (left) and global feature importance rankings based on mean absolute SHAP values (right) for rice yield prediction models in Iloilo during the wet season (A) and dry season (B), and Nueva Ecija during the wet season (C) and dry season (D). Each point in the SHAP summary plots represents an individual field observation and is colored according to the feature value. Positive SHAP values indicate a positive contribution to predicted yield, whereas negative values indicate a negative

contribution. Bar plots show the overall importance of each predictor based on its mean absolute SHAP value.

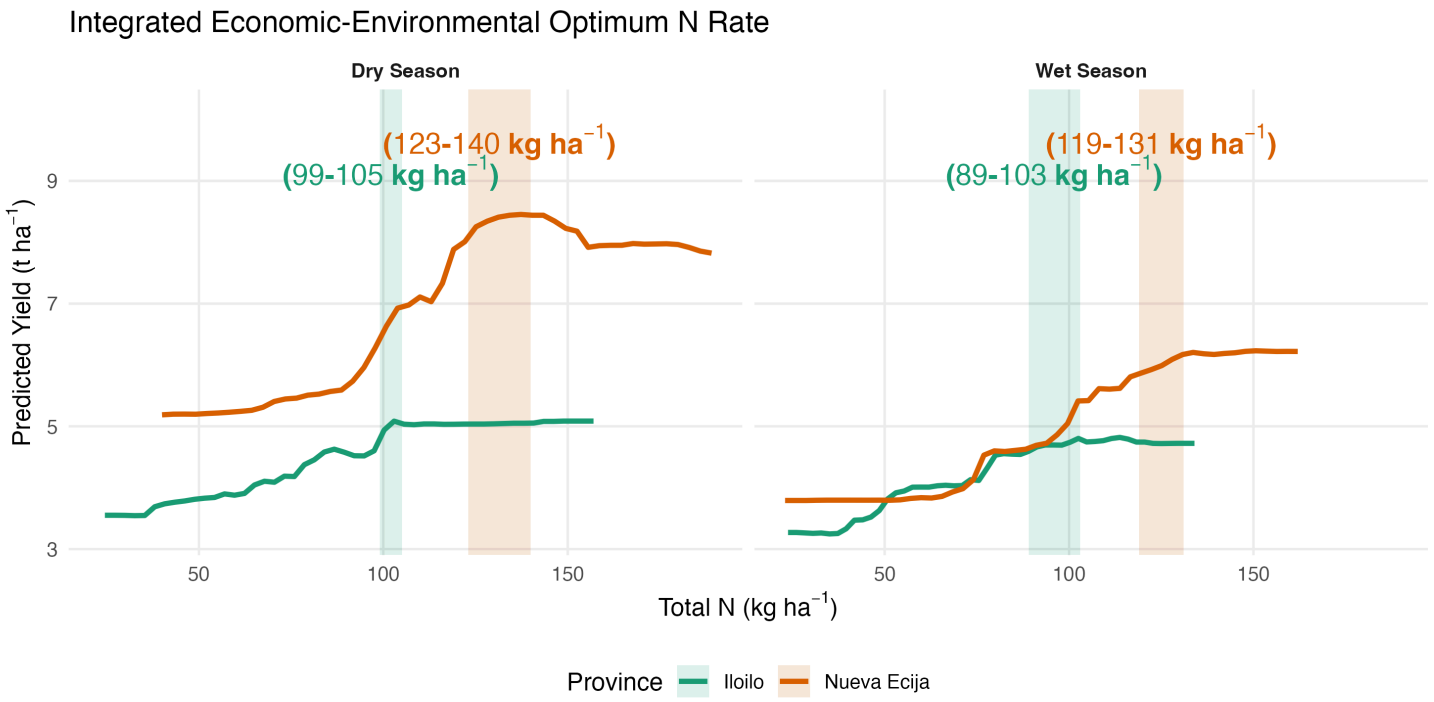


Figure 5

Rice yield response curves to nitrogen in Iloilo and Nueva Ecija, Philippines, showing the data-driven optimum nitrogen application rates during the dry and wet seasons.

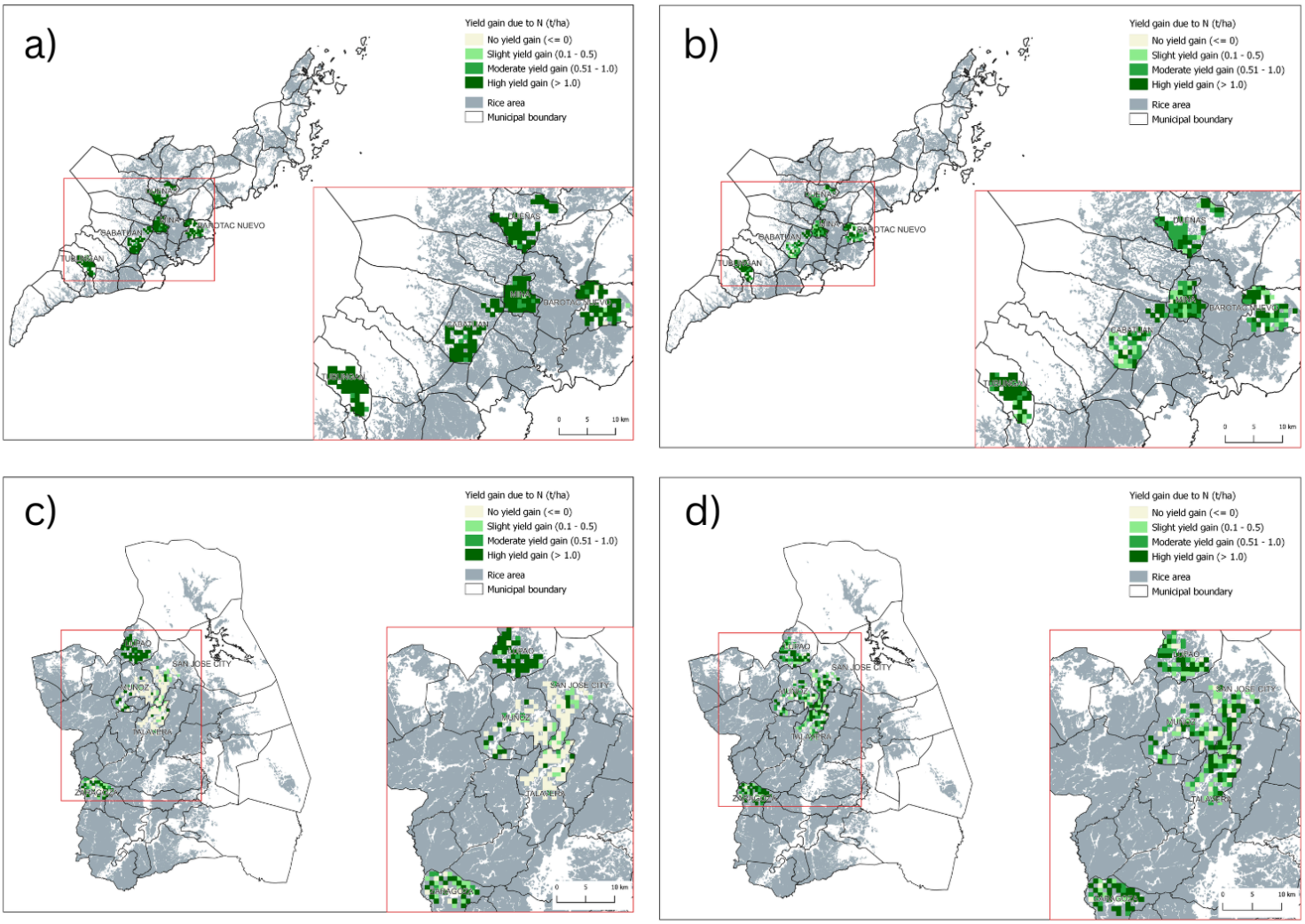


Figure 6

Spatial distribution of yield gain potential due to improved N showcasing high-priority areas for yield optimization in a) Iloilo DS b) Iloilo WS c) Nueva Ecija DS d) Nueva Ecija WS, Philippines.

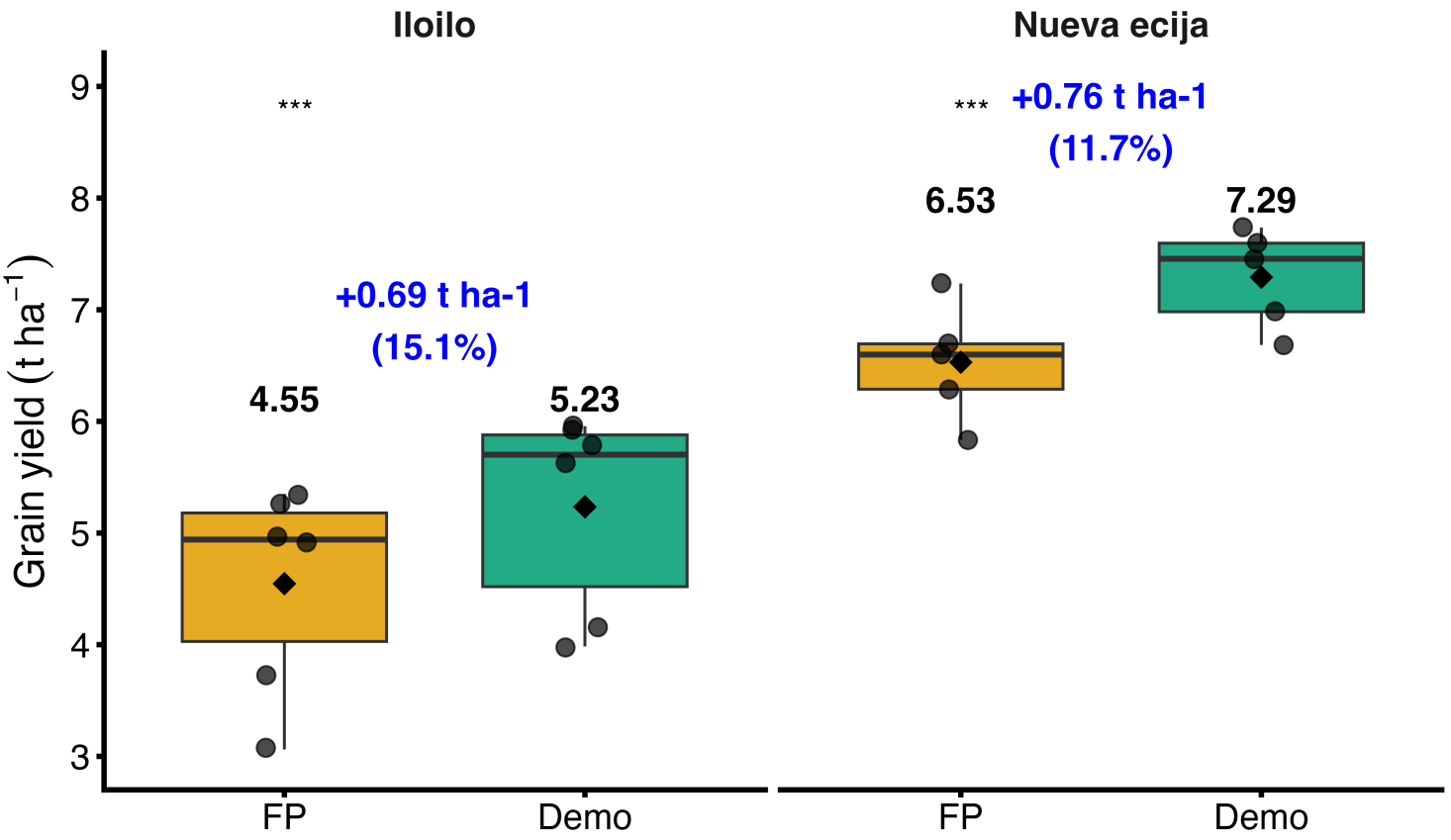


Figure 7

On-farm validation of data-driven nitrogen (N) recommendations in Iloilo and Nueva Ecija, Philippines. Grain yield under farmers' practice (FP) and the data-driven N recommendation (Demo) from side-by-side on-farm validation trials. Boxes represent the interquartile range, the horizontal line indicates the median, black diamonds denote the mean grain yield, and points represent individual farmer fields. Blue text indicates the mean yield advantage of the data-driven recommendation over the farmers' practice. Paired t-tests showed that the data-driven N recommendation significantly increased grain yield in both provinces ($P < 0.005$) represented by ***.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- Table1.docx