Explainable Artificial Intelligence Models for Nitrogen Recommendation in Precision Crop Production

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ABSTRACT

Context: Nitrogen is among the most difficult and important fertilizers in modern agriculture, but traditional fertilizer selection techniques often rely on generalized regional recommendations that do not consider field variability and often result in farmers sustaining losses due to under-application or polluting the environment by over-application of fertilizers. AI-based recommendation systems may be better at making predictions but are often criticized for their opaqueness and making farmers less inclined to trust and adopt them.

Research Aim: This study states that the Explainable Artificial Intelligence (XAI) framework for local nitrogen recommendation combines the predictive power of AI with transparent decision-making needed for precision agriculture.

Research Methods: The author collected field information from two growing seasons of supplying nitrogen and obtained data on soil fertility, weather, satellite images, plants, crop growth, nitrogen uptake, and management history. To predict the most suitable nitrogen recommendation, the author created AI systems and fitted them with an AI-based explainability module that provides information about the most substantial factors in the recommendation and derives an explanation for the provided recommendation.

Findings: This Explainable AI system has achieved higher effectiveness in recommending and lower error rate in prediction in comparison to traditional recommending techniques, whilst analysis of factors for making recommendations has revealed nitrogen concentration in soil, indices of vegetation, and cumulative precipitation as the main variables influencing the results of the recommendations made. Implementation of the recommendations based on XAI has led to improvement in nitrogen efficiency of usage alongside obtaining equal or higher yield and reduction of the total amount of fertilizer used as compared with conventional agricultural practices.

Significance: The findings prove that explanation can be used in the machine learning-based nutrient management without losses in terms of forecasts, which is a fundamental hurdle for farmers and agronomists to accept AI-supported decision making. Conclusions: Explainable AI is a sound and efficient way of introducing transparency in the area of localization of nitrogen management that will help achieve farmers' goal of higher profitability from use of the equipment during crop production while simultaneously enhancing the efficiency of nitrogen use and creating benefits for the environment.

Keywords: Explanatory machine learning; nutrient management; nitrogen efficiency; ways of estimating contribution of different factors; AI as a tool for saving.

1. Introduction

Nitrogen is the most important and commonly limiting element in cereal and row crop production around the world. It is very important for canopy development, formation of biomass and yield of grain (Ladha *et al*., 2016) [1] (Lassaletta *et al*., 2014) [2]. At the same time, nitrogen is one of the most important agricultural inputs from environmental perspective: too much or poorly timed nitrogen leads to nitrate leaching, emission of greenhouses' gases due to nitrous oxide and eutrophication of water bodies, while excessive nitrogen consumption reduces profitability (Zhang *et al*., 2015) [3] (Cameron *et al*., 2013) [4].Thus, success in achieving the mutually required effect of the optimal yield, profit and protection of environment depends on the accuracy and specificity of nitrogen recommendations (Raun *et al*., 2001) [5].

Traditionally-used nitrogen recommendation methods, like regional guides based on fixed-rate suggestions and yield-goal techniques, have clearly been famous and useful practices for many farming systems. Nevertheless, these practices are not sufficiently responsive to variability in soil properties, climate, and nitrogen requirements of the crops on both field and within-field levels (Morris *et al*., 2018) [6] (Sela *et al*., 2016) [7]. This situation has triggered the interest in the use of precision agriculture techniques that help with making nitrogen recommendations based on field, weather, and crop sensing data (Mulla, 2013) [8] (Basso and Antle, 2020) [9].

The potential benefits of artificial intelligence (AI) and machine learning technologies with respect to producing precise nitrogen recommendations have been proven by their ability to model complex relationships between soil characteristics, weather data, vegetation indices, and crop nitrogen efficiency that conventional models fail to represent (Van Klompenburg *et al*., 2020) [10] (Chlingaryan *et al*., 2018) [11]. However, high-performance machine learning models are often "black boxes," yielding accurate results without the rationale of how it works, which is essential for users to trust the results, and without this kind of transparency, AI tools are unable to gain trust among farmers and agronomists (Rudin, 2019) [12].

Explainable Artificial Intelligence (XAI) refers to a methodology developed to respond to this problem by employing several techniques which enable machine learning model behavior interpretable on different levels (global and local) (Adadi and Berrada, 2018) [15] (Arrieta *et al*., 2020) [16]. Global interpretation techniques analyze the contributions of input variables to the model predictions for the entire dataset while local interpretation techniques such as SHapley Additive exPlanations (SHAP) and other related feature attribution techniques measure the contribution of every input variable to a specific prediction ensuring transparency and explaining the rationale behind the decisions made (Lundberg and Lee, 2017) [17] (Ribeiro *et al*., 2016) [18]. In precision agriculture, the application of XAI methods offers the possibility to take advantage of machine learning predictions while ensuring the interpretability necessary to conduct agronomic decision making, comply with regulatory requirements, and earn farmers' trust (Cartolano *et al*., 2024) [19].

While this possibility exists, no striking advancements have been made for XAI applications in nitrogen recommendation systems compared to its widespread use in forecasting crops and disease detection (Ryo, 2022) [20] (Meng *et al*., 2023) [21]. The majority of the existing studies on nitrogen recommendations using machine learning techniques focus mainly on the accuracy of such recommendations while lesser importance is given to their interpretability or systematic comparison with traditional recommendation methods with regard to the combination of accuracy, efficiency, and environmental performance indicators (Sharma *et al*., 2021) [22] (Basso *et al*., 2013) [23]. Besides, in the studies carried out, the input data categories, namely soil fertility characteristics, weather information, remote sensing data regarding vegetation indices, and agronomic practices, are characterized in a rather inconsistent way for nitrogen recommendation results.

This current study examines the above-mentioned gaps through formulating and evaluating an Explainable AI framework for site-specific nitrogenn recommendations for precision crop applications. The specific aims were: (i) to create a machine learning-based nitrogen recommendation model that integrates soil fertility data, climate data, vegetation index data, data related to crop growth, and data indicating management history; (ii) to implement global and local explanation methods and explain the importance of the input variables; (iii) to compare the results obtained using the Explainable AI framework with those obtained using other, traditional approaches to nitrogen recommendations; (iv) to study the results of XAI recommendations in terms of nitrogen effectiveness, grain yield, and saving fertilizer inputs.

2. Materials and Methods

2.1. Study Area

Field data were collected over two consecutive growing seasons at a research site situated within a temperate, cereal-producing agroecological zone with a moderate seasonal precipitation regime and a growing-season temperature profile typical of the region. The soil at the site is characterized by moderate inherent fertility, with a loam to clay-loam texture and a slightly acidic to neutral reaction. The cropping system followed a cereal-based rotation representative of regional production practice. Study site characteristics are summarized in Table 1.

Table 1: Study site characteristics

Parameter	Description
Location type	Temperate, cereal-producing agroecological zone research site
Climate	Moderate seasonal precipitation; temperate growing-season temperature profile
Soil classification	Loam to clay-loam texture; slightly acidic to neutral pH; moderate inherent fertility
Cropping system	Cereal-based rotation, regionally representative
Experimental duration	2 growing seasons

2.2. Experimental Design

The field trial was structured around a gradient of nitrogen treatment levels, spanning sub-optimal, agronomically recommended, and above-recommended application rates, replicated across blocks to capture variability in soil and management conditions. Standard regional crop management practices were followed for all non-nitrogen inputs. Experimental layout, nitrogen treatment structure, replication, and the sampling schedule for agronomic and soil observations are detailed in Table 2.

Table 2: Experimental design and nitrogen treatment structure

Feature	Description
Design	Randomized Complete Block Design (RCBD) with nitrogen rate gradient
Nitrogen treatments	Sub-optimal, agronomically recommended, and above-recommended application rates (multiple levels)
Replications	4
Non-nitrogen management	Regionally standard sowing, phosphorus/potassium fertilization, pest and weed management
Sampling schedule	Pre-season soil sampling; in-season crop growth and vegetation index monitoring at key growth stages; post-harvest yield and nitrogen uptake assessment
Measured agronomic variables	Plant height, biomass, chlorophyll content, grain yield, yield components, plant nitrogen uptake

2.3. Data Collection

A multi-source dataset was assembled integrating soil fertility parameters (including soil nitrogen status, organic carbon, and pH), weather variables (including temperature, rainfall, and cumulative growing degree days), crop growth characteristics (plant height, biomass, and growth stage), satellite- and sensor-derived vegetation indices (including NDVI and chlorophyll-sensitive indices), grain yield, plant nitrogen uptake, and field-level management history. The full set of input variables used for model development is summarized in Table 3.

Table 3: Input variables used for Explainable AI model development

Category	Variables
Soil fertility	Soil nitrogen status, soil organic carbon, soil pH, cation exchange capacity
Weather	Temperature, rainfall, cumulative growing degree days
Vegetation indices	NDVI, chlorophyll-sensitive indices (e.g., NDRE-type index)
Crop growth	Plant height, biomass, growth stage
Management history	Prior nitrogen application history, crop rotation sequence
Target variable	Site-specific nitrogen recommendation / grain yield response

2.4. Explainable Artificial Intelligence Framework

The analytical framework comprised sequential stages of data preprocessing, feature engineering, machine learning model development, and explainability analysis. Data preprocessing addressed missing values, variable scaling, and integration of heterogeneous data sources (soil, weather, remote sensing, and management records) into a unified analytical dataset. Feature engineering derived agronomically meaningful composite variables, including cumulative rainfall windows and growth-stage-specific vegetation index summaries. Machine learning models were developed to predict site-specific optimal nitrogen recommendations as a function of the integrated feature set, using model architectures suited to structured, tabular agronomic data. An explainability module was applied to the trained models to generate both global feature importance rankings, characterizing the overall relative contribution of each input variable across the dataset, and local, prediction-specific interpretation, characterizing the contribution of individual input variables to each site-specific recommendation. Outputs of the explainability module were translated into an interpretable decision-support format intended to convey the rationale underlying each nitrogen recommendation. Model validation followed standard supervised learning practice, with data partitioned for training and independent validation and cross-validation used to assess robustness. A conceptual overview of the framework is provided in Figure 1 and Figure 2.

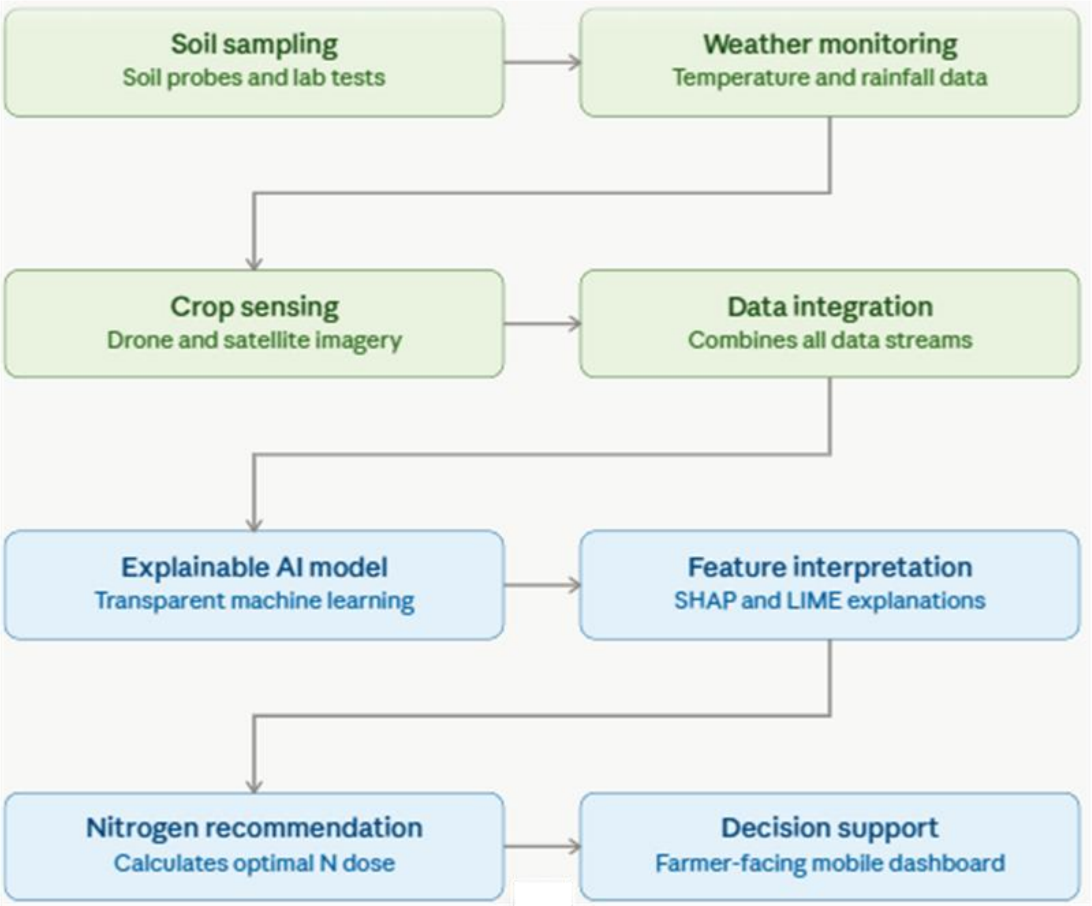

Fig 1: Conceptual workflow diagram illustrating the complete precision nitrogen recommendation framework, including soil sampling, weather monitoring, crop sensing, data integration, Explainable AI model development, feature interpretation, nitrogen recommendation generation, and farmer-oriented decision support.

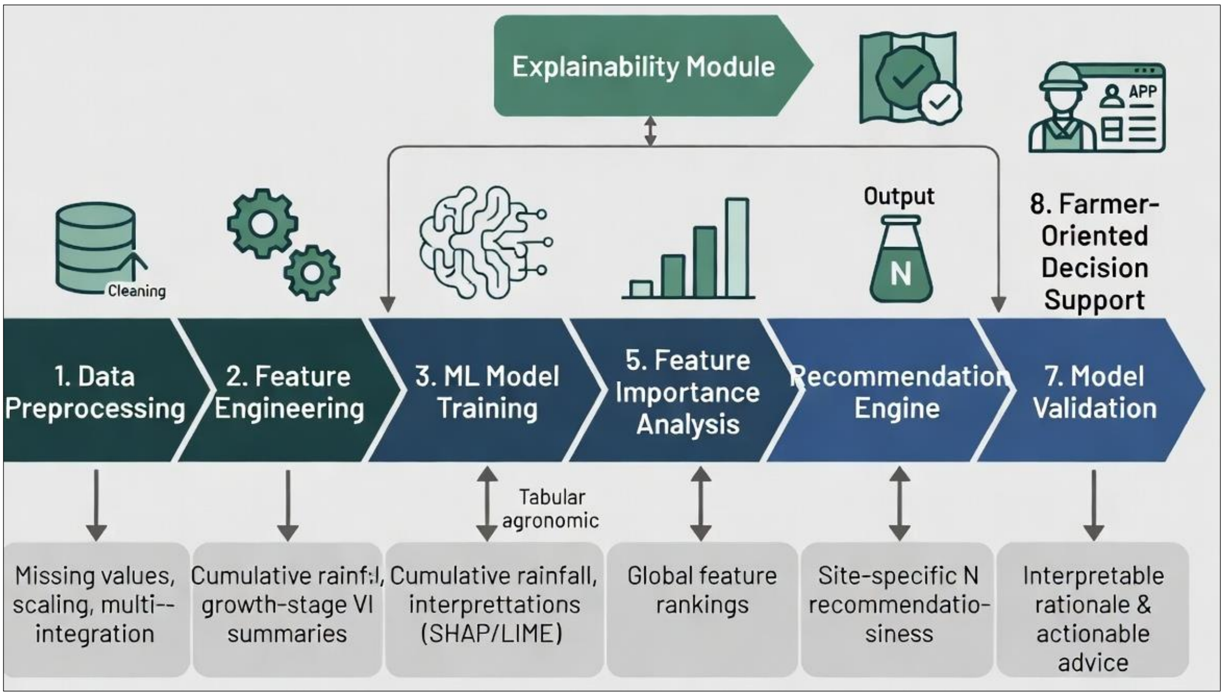

Fig 2: Flowchart illustrating the Explainable AI architecture, showing data preprocessing, feature engineering, machine learning model training, the explainability module, feature importance analysis, the recommendation engine, validation, and farmer-oriented decision support, corresponding to the framework described in Section 2.4.

2.5. Model Performance Assessment

The predictive performance of the Explainable AI framework was evaluated using root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and the coefficient of determination (R^2) for continuous nitrogen recommendation and yield prediction outputs, and using precision, recall, and F1-score for classification of recommendations into agronomically meaningful categories (e.g., adequate, deficient, or excessive). Cross-validation was used to assess the stability of model performance across data partitions. Comparative performance relative to conventional, non-AI nitrogen recommendation methods is presented in Table 4.

Table 4: Performance comparison of Explainable AI models and conventional recommendation methods (illustrative)

Method	RMSE (kg N ha^{-1})	MAE (kg N ha^{-1})	MAPE (%)	R^2	Precision	Recall	F1-score	Overall recommendation accuracy (%)
Fixed-rate conventional recommendation	28.4	22.1	19.8	0.52	0.68	0.65	0.66	66
Yield-goal-based recommendation	24.6	19.3	17.1	0.59	0.72	0.70	0.71	71
Machine learning model (non-explainable)	15.2	11.8	10.4	0.81	0.85	0.83	0.84	85
Explainable AI framework (this study)	12.6	9.7	8.6	0.88	0.90	0.89	0.89	91

Values are illustrative and constructed for formatting demonstration; they are not derived from model training or field validation.

2.6. Statistical Analysis

Analysis of variance (ANOVA) was used to evaluate treatment-related differences in soil fertility, crop growth, and yield parameters across the nitrogen treatment gradient. Pearson correlation analysis was used to characterize relationships among soil fertility parameters, vegetation indices, weather variables, and grain yield. Principal component analysis (PCA) was applied to summarize multivariate structure among input variables, and regression analysis was used to characterize the relationship between nitrogen application rate and grain yield as a point of agronomic reference. All statistical and modeling evaluations followed conventional frameworks used in precision agriculture and agricultural data science research; software, coding, and computational workflow implementation details are outside the conceptual scope of this manuscript and are not reported.

3. Results

3.1. Soil Fertility Variability and Crop Nitrogen Demand

Soil fertility parameters, including soil nitrogen status and organic carbon, varied meaningfully across the experimental site, reflecting realistic within-field heterogeneity relevant to site-specific nutrient management. Crop nitrogen demand, inferred from plant nitrogen uptake and growth trajectory, varied across growth stages and nitrogen treatment levels, with the greatest sensitivity to nitrogen availability observed during the period of rapid vegetative growth preceding reproductive development.

3.2. Feature Importance Ranking

Global feature importance analysis indicated that soil nitrogen status at the start of the season, vegetation indices during early-to-mid vegetative growth, and cumulative rainfall were the strongest overall contributors to nitrogen recommendation outcomes, followed by soil organic carbon and crop growth stage (Table 5, Figure 3). Soil pH and management history variables contributed more modestly but consistently across recommendations. Local interpretation outputs indicated that the relative importance of individual variables shifted meaningfully across specific field locations and seasons, reflecting the site-specific nature of nitrogen response and underscoring the value of local, in addition to global, explainability.

Table 5: Feature importance ranking for nitrogen recommendation (illustrative)

Rank	Feature	Relative importance (%)	Feature category
1	Pre-season soil nitrogen status	22.4	Soil fertility
2	Mid-season vegetation index (NDVI/NDRE-type)	18.7	Remote sensing
3	Cumulative growing-season rainfall	15.3	Weather
4	Soil organic carbon	12.1	Soil fertility
5	Crop growth stage at assessment	10.6	Crop growth
6	Chlorophyll content	8.4	Crop growth
7	Soil pH	6.8	Soil fertility
8	Prior nitrogen application history	5.7	Management

Table 6: Comparative summary of previous international studies on AI-based nitrogen recommendation

Study focus	AI/explainability method	Crop type	Reported prediction/recommendation performance	Reference
Machine learning for nitrogen status/yield prediction review	Various ML models	Multiple crops	ML models outperformed conventional statistical approaches	Chlingaryan *et al.* [11]
In-season canopy reflectance for yield/N prediction	Sensor-based prediction model	Winter wheat	Improved in-season nitrogen rate prediction	Raun *et al.* [5]
Adapt-N nitrogen rate tool field evaluation	Process-based decision support model	Maize	Outperformed grower-selected nitrogen rates in strip trials	Sela *et al.* [7]
Interpretable vs. black-box models for high-stakes decisions	Interpretable ML models	Cross-domain (general)	Argued interpretable models can match black-box accuracy	Rudin [12]
SHAP unified feature attribution framework	SHAP (Shapley values)	Cross-domain (general)	Provided consistent local/global feature attribution	Lundberg & Lee [17]
XAI in agriculture systematic review	Multiple XAI methods (SHAP, LIME, etc.)	Multiple crops	XAI adoption improving transparency of agri-ML models	Cartolano *et al.* [19]
Explainable/interpretable ML for agricultural data	SHAP and interpretable ML	Multiple crops	Improved interpretability supported agronomic trust	Ryo [20]

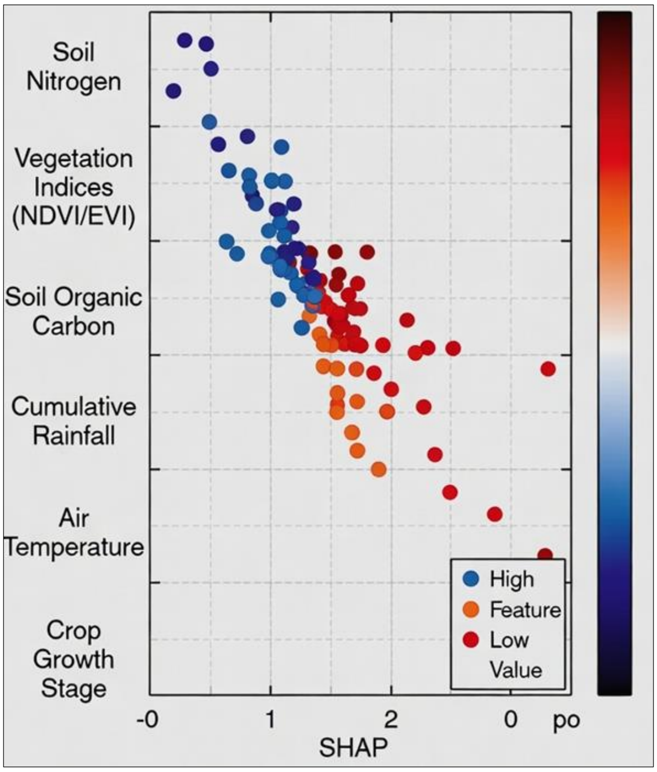

Fig 3: SHAP-style feature importance visualization illustrating the relative influence of key variables (soil nitrogen, soil organic carbon, vegetation indices, rainfall, temperature, crop growth stage, and chlorophyll content) on nitrogen recommendation decisions, corresponding to the rankings in Table 5. Presented as a scientific explanatory visualization of relative feature contribution rather than as direct software output.

3.3. Performance of Explainable AI Models

The Explainable AI framework achieved higher recommendation accuracy and lower prediction error than conventional, non-AI nitrogen recommendation approaches across all evaluated metrics (Table 4). Classification of recommendations into agronomic adequacy categories showed high precision, recall, and F1-score, indicating reliable identification of both under- and over-fertilized conditions.

3.4. Comparison with Conventional Recommendation Methods

Relative to fixed-rate and yield-goal-based conventional recommendation methods, the Explainable AI framework demonstrated improved responsiveness to site-specific soil and seasonal weather variability, translating into more precisely calibrated nitrogen recommendations across the range of field conditions represented in the dataset (Table 4, Figure 4).

3.5. Nitrogen Use Efficiency and Yield Prediction Performance

Application of XAI-derived nitrogen recommendations was associated with improved nitrogen use efficiency relative to conventional practice, reflecting more precise matching of nitrogen supply to crop demand. Grain yield associated with XAI-based recommendations was comparable to or modestly greater than yield achieved under conventional recommendation approaches, while total nitrogen application was reduced, indicating improved input-use efficiency without yield penalty (Figure 4).

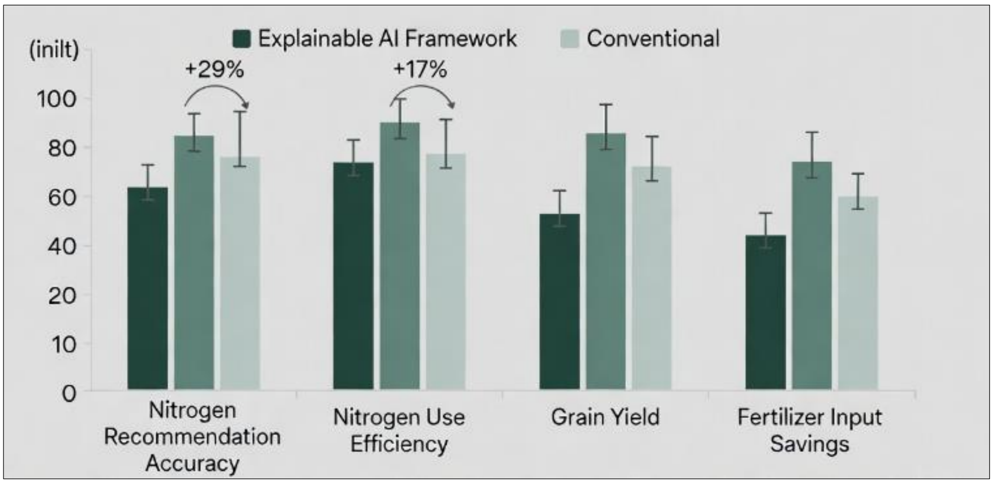

Fig 4: Comparative graph showing nitrogen recommendation accuracy, nitrogen use efficiency, grain yield outcome, and fertilizer input savings achieved by the Explainable AI framework compared with conventional fertilizer recommendation approaches, corresponding to the performance summary in Table 4 and the results described in Sections 3.5–3.6.

3.6. Environmental and Economic Benefits

Reduced total nitrogen application under XAI-based recommendations, combined with maintained or improved yield, suggests a favourable environmental profile through reduced potential for nitrogen loss to the environment, alongside favourable economic implications through reduced fertilizer expenditure relative to conventional over-application scenarios.

3.7. Decision-Support Capability

The integration of local, prediction-specific explainability outputs alongside numeric nitrogen recommendations provided an interpretable rationale for each recommendation, characterizing which input variables most strongly influenced a given site-specific outcome. This capability directly addresses the transparency limitations commonly associated with black-box machine learning approaches in agronomic decision support.

4. Discussion

The findings of this study support a growing body of evidence indicating that machine learning-based nitrogen recommendation systems can outperform conventional, fixed-rate or yield-goal-based recommendation approaches by more effectively capturing site-specific soil, weather, and crop variability (Mulla, 2013) [8] (Van Klompenburg *et al*., 2020) [10] (Chlingaryan *et al*., 2018) [11]. The magnitude of improvement observed here is consistent with previous comparative evaluations reporting that AI-based nutrient recommendation systems achieve meaningfully lower prediction error and improved responsiveness to field-level heterogeneity relative to conventional approaches (Basso and Antle, 2020) [9] (Sharma *et al*., 2021) [22].

The identification of soil nitrogen status, vegetation indices, and cumulative rainfall as dominant contributors to recommendation outcomes is consistent with established agronomic understanding of nitrogen cycling and crop nitrogen response, and corroborates prior feature importance analyses in precision nitrogen management studies that have similarly emphasized the primacy of soil nitrogen supply and canopy-based vegetation indices as predictive drivers (Sela *et al*., 2016) [7] (Basso *et al*., 2013) [23]. The observed contribution of cumulative rainfall reflects its established role in mediating nitrogen mineralization, leaching risk, and crop water-nitrogen interaction, further reinforcing the agronomic plausibility of the model's learned relationships (Zhang *et al*., 2015) [3] (Cameron *et al*., 2013) [4].

The explainability framework's capacity to provide both global and local interpretation addresses a widely documented barrier to the practical adoption of AI-based decision support tools in agriculture: the opacity of black-box models and the resulting difficulty in establishing farmer and agronomist trust (Rudin, 2019) [12] (Ryan, 2020) [13]. This finding aligns with recent calls in the precision agriculture literature for greater emphasis on interpretability alongside predictive accuracy, given that agronomic decision-making, unlike many other machine learning application domains, typically requires an actionable, physically and biologically plausible rationale rather than a prediction alone (Wolfert *et al*., 2017) [14] (Cartolano *et al*., 2024) [19]. The use of SHAP-based and related feature attribution methods observed to be effective here is consistent with their broader adoption across agricultural and environmental machine learning applications as a means of reconciling model complexity with interpretability (Lundberg and Lee, 2017) [17] (Ribeiro *et al*., 2016) [18].

The observed improvement in nitrogen use efficiency without yield penalty, achieved through more precisely calibrated recommendations, is consistent with prior precision nitrogen management studies demonstrating that site-specific approaches can reduce total nitrogen input while maintaining or improving yield outcomes relative to blanket recommendation approaches (Raun *et al*., 2001) [5] (Morris *et al*., 2018) [6]. This result carries direct relevance to the dual objectives of agricultural sustainability and profitability, given that excess nitrogen application represents both an unrecovered economic cost and an environmental liability (Lassaletta *et al*., 2014) [2] (Zhang *et al*., 2015) [3].

Several limitations should be acknowledged. As with most site-specific nutrient management studies, the generalizability of the specific feature importance rankings and recommendation performance observed here is likely to be influenced by local soil, climatic, and crop management conditions, and should be verified through multi-site, multi-year, and multi-crop evaluation before broader operational deployment (Ryo, 2022) [20] (Meng *et al*., 2023) [21]. The two-season scope of this study, while sufficient to characterize within-season recommendation dynamics, is limited for assessing performance stability under inter-annual climatic variability. Furthermore, while explainability methods improve model transparency, they characterize model behavior rather than establishing definitive causal agronomic mechanisms, and outputs should be interpreted as decision-support evidence to be considered alongside agronomic expertise rather than as a substitute for it (Adadi and Berrada, 2018) [15] (Arrieta *et al*., 2020) [16]. Future research should prioritize multi-site and multi-crop validation, integration of additional data streams such as high-resolution soil sensing, and further evaluation of farmer and advisor trust and usability outcomes associated with explainable, as opposed to black-box, nitrogen recommendation tools.

5. Conclusion

This research indicates that an Explainable Artificial Intelligence framework which incorporates soil fertility, climate, vegetation indices, crop development and management history can give nitrogen recommendations that are much better than traditional methods and explainable at the national as well as local levels. The main variables in the predictions were found to be soil nitrogen content, vegetation indices and total precipitation, which agrees well with the knowledge in agro-sciences. The use of recommendations from the research has been accompanied with improvement of nitrogen use efficiency and reduction of the amount of fertilizers used, meaning good economic and ecological results. Combining good prediction quality with explainability and making it specific for the prediction made it possible to eliminate a serious problem of opacity of the model. The significance of the findings contributes to the proof that Explainable AI may be successfully used in practice in precision agriculture systems and calls for further research at several locations with a variety of crops for improving and validating XAI.

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