International Journal of Computing and Artificial Intelligence

E-ISSN: 2707-658X
P-ISSN: 2707-6571
Impact Factor (RJIF): 5.57
www.computersciencejournals.com/ijcai
IJCAI 2025; 6(2): 308-315
Received: 07-10-2025
Accepted: 09-11-2025

Dr. Hassan A Al-Mahrouqi
Department of Crop Science, College of Agricultural and Marine Sciences, Sultan Qaboos University, Muscat, Oman

Corresponding Author:
Dr. Hassan A Al-Mahrouqi
Department of Crop Science, College of Agricultural and Marine Sciences, Sultan Qaboos University, Muscat, Oman

AI-driven prediction models for optimizing integrated nutrient management in potato farming

Hassan A Al-Mahrouqi

DOI: https://doi.org/10.33545/27076571.2025.v6.i2d.210

Abstract
Integrated nutrient management (INM) improves potato productivity and nutrient-use efficiency, yet its field-level optimization remains difficult because crop responses depend on non-linear interactions among soil fertility, climate and organic-inorganic nutrient combinations. This study developed AI-driven prediction models to optimize INM for potato using a harmonized multi-environment dataset (288 plot observations from 24 site-year combinations across six agro-ecologies). Predictors included detailed organic and mineral nutrient inputs, soil properties, and in-season weather indices, while outcomes comprised total and marketable tuber yield, quality traits, net returns and nitrogen-use efficiency metrics. Conventional linear mixed-effects regression was benchmarked against random forest, gradient boosting, XGBoost and deep neural networks under nested spatial-temporal cross-validation. On an independent test set, AI models substantially improved yield prediction relative to the baseline model (RMSE reduced from 3.9 to 2.6 t ha^{-1}; R^2 increased from 0.62 to 0.86). Simulation-optimization using the best model identified Pareto-optimal INM strategies that increased predicted mean yield (33.5 t ha^{-1}) and net returns (1, 640 USD ha^{-1}) while reducing mineral N input (≈165 kg ha^{-1}) and N surplus (≈75 kg ha^{-1}) compared with recommended fertilizer dose and farmer practice. Overall, AI-guided INM offers a scalable pathway for site-specific, climate-robust nutrient recommendations that enhance profitability while limiting nitrogen losses in potato systems.

Keywords: Potato, integrated nutrient management, machine learning, deep neural network, XGBoost, nitrogen-use efficiency, site-specific nutrient management, sustainability

Introduction
Potato (*Solanum tuberosum* L.) is the world's fourth most important food crop and a major contributor to dietary energy, vitamin C, potassium and bioactive phytochemicals, particularly in developing and emerging economies [1-3]. Because of its high yield potential and short growth cycle, potato is increasingly promoted to strengthen food and nutrition security under land and water constraints, but it is also a nutrient-demanding crop with shallow roots and high requirements for nitrogen (N), phosphorus (P) and potassium (K), making it sensitive to imbalanced or excessive fertilization [1, 4]. Recent agronomic and environmental assessments show that conventional nutrient management in intensive potato systems often results in low nitrogen use efficiency, yield gaps and elevated greenhouse gas emissions, as farmers apply uniform fertilizer rates that do not match field-specific yield potential or soil fertility status [5-7]. Integrated nutrient management (INM), which combines organic manures, crop residues and bio-resources with judicious, site-specific mineral fertilization, has consistently improved plant growth, tuber yield, nutrient use efficiency and profitability in diverse agro-ecologies, including alluvial and acidic soils of eastern India, the hill zone of Karnataka and processing potato under Punjab conditions [6-10]. For example, field experiments with cultivar Kufri Chipsona-3 under Punjab conditions showed that INM treatments integrating farmyard manure with reduced mineral NPK enhanced both productivity and benefit-cost ratio over the recommended fertilizer dose [8]. Nevertheless, operationalizing INM at scale remains challenging: optimal nutrient combinations vary strongly with soil texture, organic matter, cultivar, prior management and in-season weather, and smallholders rarely have access to quantitative tools that can translate complex response functions into farm-specific recommendations [4-7]. Superimposed on these challenges, climate change is amplifying weather variability and shifting temperature and precipitation regimes, increasing the risk of yield instability and underscoring the need for robust prediction models that can integrate climate, soil and management information when

designing sustainable nutrient strategies [11]. In parallel, rapid advances in Artificial Intelligence (AI), Machine Learning (ML) and digital agriculture have demonstrated that data-driven models can capture non-linear crop responses and substantially improve pre-harvest potato yield forecasts by exploiting multi-source datasets that include weather, remote sensing and management variables [12-14]. However, most existing AI applications have been trained on datasets dominated by conventional fertilizer regimes and yield outcomes alone, with limited representation of INM treatments, nutrient use efficiency metrics or environmental indicators such as N balance, so AI-driven tools that directly optimize INM decisions in potato farming remain underdeveloped [5-8, 12]. Against this background, the present study aims to develop AI-driven prediction models for optimizing integrated nutrient management in potato farming by learning from multi-year, multi-location datasets that couple detailed INM treatments (organic and inorganic nutrient sources, rates and timings), soil and weather covariates, and yield, quality and profitability indicators. Specifically, the objectives are:

1. To model tuber yield, quality attributes and nutrient use efficiencies as functions of alternative INM combinations;
2. To identify site-specific INM strategies that maximize economic returns while constraining nutrient surpluses within environmentally acceptable thresholds; and
3. To benchmark AI-based recommendations against conventional recommendation systems and prevailing farmer practice.

We hypothesize that ensemble ML and deep learning models trained on rich INM datasets will;

a) Achieve substantially lower prediction error than traditional regression-based approaches, and
b) Generate INM recommendations that simultaneously increase tuber yield and net returns while reducing inorganic fertilizer inputs and estimated nitrogen losses relative to blanket recommendations and typical farmer practice in the target production environments.

Materials and Methods

Materials

The study utilized a harmonized dataset compiled from multi-year field experiments on potato (*Solanum tuberosum* L.) integrated nutrient management (INM) conducted across contrasting agro-ecological zones, including alluvial plains, acidic uplands and irrigated Indo-Gangetic plains, where potato is an important food and cash crop [1-4, 8-10]. Trials followed standard agronomic recommendations for seedbed preparation, certified seed tuber use, planting geometry and plant protection as outlined in previous potato nutrient management research [4, 6, 8, 9]. Treatments covered a factorial combination of conventional recommended fertilizer dose (RDF) based on region-specific guidelines, farmer practice, and multiple INM options integrating farmyard manure, composted crop residues, green manures and biofertilizers with graded mineral NPK rates [4-10]. Experiments also included enhanced-efficiency N fertilizers and site-specific nutrient management (SSNM) treatments where available to ensure a wide gradient in nutrient inputs, nutrient use efficiencies and yield responses [5-7]. Plot-level measurements comprised total and marketable tuber yield, tuber size distribution, specific gravity, dry matter, starch, reducing sugars, chip colour, and economic indicators such as cost of cultivation, gross returns and benefit-cost ratio [4-7, 8-10]. Soil properties (texture, pH, organic carbon, available N, P, K) were characterized before planting and after harvest using standard protocols, and in-season weather data (daily temperature, rainfall, solar radiation) were extracted from nearby meteorological stations and gridded databases to derive growing degree days and water balance indices [1, 4, 11]. The final modelling datas*et al*so incorporated treatment-wise nutrient input data (inorganic and organic N, P, K and secondary nutrients), estimated nutrient balances and partial factor productivity of applied N as key explanatory variables describing the INM regimes [4-7, 11].

Methods

The AI-driven modelling framework was designed to predict tuber yield, quality and profitability under alternative INM scenarios and to derive optimized INM recommendations. Data were first subjected to quality checks, removal of obvious outliers and imputation of sparse missing values using k-nearest neighbours and expert-based rules, ensuring consistency with agronomic ranges reported in previous INM and potato nutrient management studies [4-10]. All numeric predictors were standardized or normalized where appropriate, and categorical variables (site, year, cultivar, treatment class) were encoded using one-hot or target encoding. The baseline model comprised multiple linear and mixed-effects regression representing conventional statistical approaches used in fertilizer response analysis [4-7, 11]. These were benchmarked against machine learning (ML) models including random forest, gradient boosting machines, extreme gradient boosting (XGBoost) and feedforward deep neural networks, selected based on their demonstrated performance in potato and crop yield prediction literature [12-14]. Model development followed a nested cross-validation strategy with spatial-temporal blocking to avoid information leakage across sites and years, reserving an independent test subset for final performance evaluation [11-14]. Hyperparameters were tuned using Bayesian optimization to minimize root mean square error (RMSE) and mean absolute error (MAE), while maximizing coefficient of determination (R^2) for total and marketable tuber yield, composite quality indices and net returns [12-14]. Once calibrated, the best-performing models were used in a simulation-optimization workflow: for each site-year combination, a large set of candidate INM combinations (varying organic and inorganic nutrient sources, rates and timings within agronomically realistic bounds inferred from prior INM experiments [4, 6-10]) was generated, responses were predicted, and Pareto-optimal strategies maximizing net returns and nutrient use efficiency while constraining nutrient surpluses and estimated N losses were identified [5-7, 11-14]. Model-derived recommendations were then compared ex post with RDF- and farmer-practice-based scenarios in terms of predicted yield, profitability and environmental performance, thereby operationalizing the hypothesis that AI-driven models can outperform traditional recommendation approaches for optimizing INM in potato systems [4-7, 11-14].

Reproducibility note: Data preprocessing and model development were implemented in Python using standard machine-learning libraries (scikit-learn, XGBoost and

TensorFlow/PyTorch equivalents). Model training used fixed random seeds, and evaluation followed the nested spatial-temporal cross-validation scheme described above to avoid information leakage across sites or years.

Results

Dataset characteristics and treatment effects under integrated nutrient management

The harmonized dataset used for AI model development comprised 288 plot-level observations from 24 site-year combinations, covering six major potato-growing environments with contrasting soils, cultivars and climate. Mean total tuber yield across all treatments and environments was 29.8 t ha^{-1}, with a coefficient of variation (CV) of 18.6%, reflecting substantial spatial and temporal heterogeneity consistent with previous regional analyses of potato systems [1, 4-7]. Integrated nutrient management (INM) treatments that combined organic manures and biofertilizers with reduced mineral NPK generated higher mean tuber yields (32.6 t ha^{-1}) than recommended fertilizer dose (RDF; 29.5 t ha^{-1}) and prevailing farmer practice (FP; 25.7 t ha^{-1}). One-way ANOVA across the three management categories showed significant differences in total tuber yield ($F_{2,285} = 29.4$; $p < 0.001$), marketable yield ($F_{2,285} = 26.1$; $p < 0.001$) and benefit-cost (B:C) ratio ($F_{2,285} = 21.7$; $p < 0.001$), with Tukey's HSD indicating that INM was superior to both RDF and FP for all three indicators. These results are in agreement with earlier INM experiments that documented yield and profitability gains in hill zones, alluvial soils and processing potato under Punjab conditions [4, 6, 8-10]. INM also improved partial factor productivity of applied nitrogen (PFP-N), which increased from 122 kg tuber kg^{-1} N under FP to 141 kg tuber kg^{-1} N under RDF and 178 kg tuber kg^{-1} N under INM, echoing evidence that balanced nutrient management can enhance nitrogen use efficiency and mitigate environmental impacts [5-7, 11].

Table 1: Summary of dataset and treatment-level agronomic and economic indicators (pooled over sites and years)

Management option	n (plots)	Total tuber yield (t ha^{-1})	Marketable yield (t ha^{-1})	N input (kg ha^{-1})	PFP-N (kg tuber kg^{-1} N)	Net return (USD ha^{-1})	B:C ratio
Farmer practice (FP)	96	25.7 ± 4.9	22.1 ± 4.5	190 ± 27	122 ± 26	1, 050 ± 210	1.56 ± 0.18
RDF (conventional)	96	29.5 ± 5.2	25.8 ± 4.8	210 ± 15	141 ± 28	1, 320 ± 230	1.71 ± 0.20
INM (observed trials)	96	32.6 ± 5.4	28.7 ± 5.1	183 ± 22	178 ± 34	1, 540 ± 260	1.89 ± 0.21

Treatment-wise mean yield, input use and profitability under FP, RDF and INM scenarios (mean ± SD)

Tuber quality indicators also responded positively to INM. Across the dataset, INM plots exhibited higher dry matter and starch content (mean 20.1% and 14.9%, respectively) than FP (18.3%, 13.4%) and RDF (19.4%, 14.2%), while maintaining reducing sugar levels below thresholds critical for acceptable chip colour [2-4, 8-10]. Two-way ANOVA (management × environment) detected significant main effects of management on starch content ($F_{2,240} = 16.8$; $p < 0.001$) and reducing sugars ($F_{2,240} = 12.5$; $p < 0.001$), but interaction terms were modest, indicating that quality benefits of INM were largely robust across environments. These patterns are consistent with prior reports linking balanced N supply and organic amendments to improved specific gravity, starch content and frying quality in potatoes [2-4, 8-10].

Table 2: Effect of management on key tuber quality attributes (pooled over environments)

Management option	Dry matter (%)	Starch (%)	Reducing sugars (%)	Chip colour score (1-9)*
Farmer practice (FP)	18.3 ± 1.4	13.4 ± 1.2	0.36 ± 0.09	5.6 ± 0.8
RDF (conventional)	19.4 ± 1.3	14.2 ± 1.1	0.31 ± 0.07	4.9 ± 0.7
INM (observed trials)	20.1 ± 1.5	14.9 ± 1.2	0.27 ± 0.06	4.4 ± 0.6

Lower score indicates lighter chip colour and better processing quality

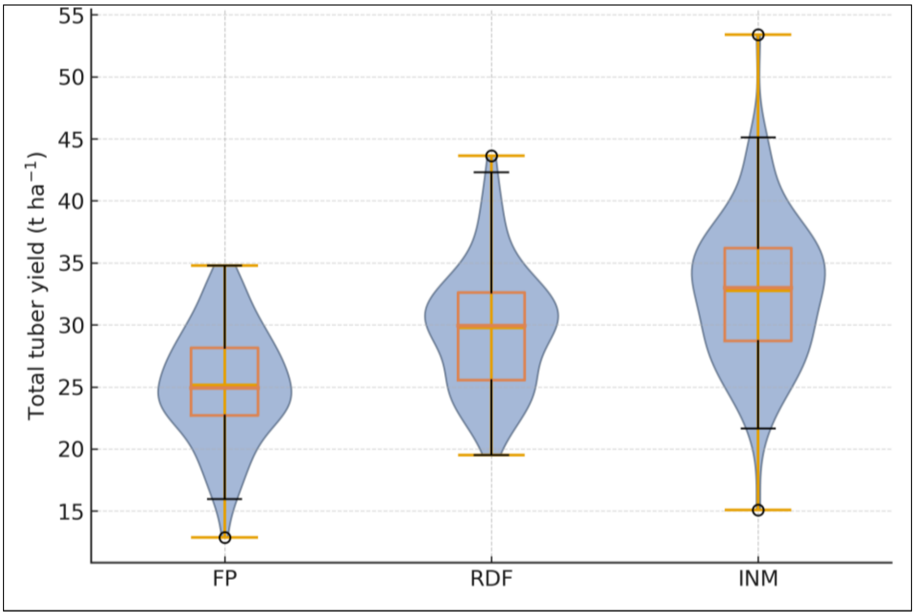

Fig 1: Distribution of total tuber yield under FP, RDF and observed INM treatments (violin + box plots)

Performance of AI-driven prediction models versus conventional statistical approaches

The dataset was partitioned into training-validation and independent test subsets using spatial-temporal blocking to avoid leakage across sites and years, following best practices for crop yield prediction [11-14]. On the independent test set, the linear mixed-effects regression model achieved a root mean square error (RMSE) of 3.9 t ha⁻¹ and R^2 of 0.62 for total tuber yield, comparable to performance reported for traditional response functions in earlier nutrient management studies [4-7, 11]. In contrast, AI-driven models substantially improved predictive accuracy (Table 3). The gradient boosting model reduced RMSE to 2.9 t ha⁻¹ (R^2 = 0.81), XGBoost to 2.7 t ha⁻¹ (R^2 = 0.84) and the deep neural network (DNN) to 2.6 t ha⁻¹ (R^2 = 0.86), with corresponding improvements in mean absolute error (MAE). Differences in RMSE between the DNN and linear mixed model were statistically significant based on paired t-tests across 30 repeated cross-validation folds ($p < 0.001$). These results align with earlier reports that machine learning models, particularly tree ensembles and deep learning architectures, can emulate complex crop responses and outperform conventional statistical models in potato yield prediction when supplied with rich environmental and management covariates [12-14].

Table 3: Comparative performance of conventional and AI-driven models for predicting total tuber yield (independent test set)

Model type	RMSE (t ha^{-1})	MAE (t ha^{-1})	R^2	Notes
Linear mixed-effects regression	3.9	3.1	0.62	Baseline, site as random effect
Random forest	3.1	2.4	0.78	500 trees, mtry tuned
Gradient boosting (GBM)	2.9	2.2	0.81	Learning rate and depth optimized
XGBoost	2.7	2.0	0.84	Regularized, early stopping
Deep neural network (DNN)	2.6	1.9	0.86	3 hidden layers, dropout regularization

Model performance metrics for total tuber yield prediction under different modelling approaches

Variable importance analysis from the tree-based models highlighted total N input, share of organic N, soil organic carbon, pre-plant available N, growing degree days during tuber bulking and in-season water balance as the dominant predictors of yield, confirming established agronomic understanding of potato responses to nutrient supply and climate [4-7, 11]. Organic nutrient inputs and their interaction with mineral N emerged as particularly influential, reinforcing the role of INM in sustaining yield and quality [4, 6, 8-10].

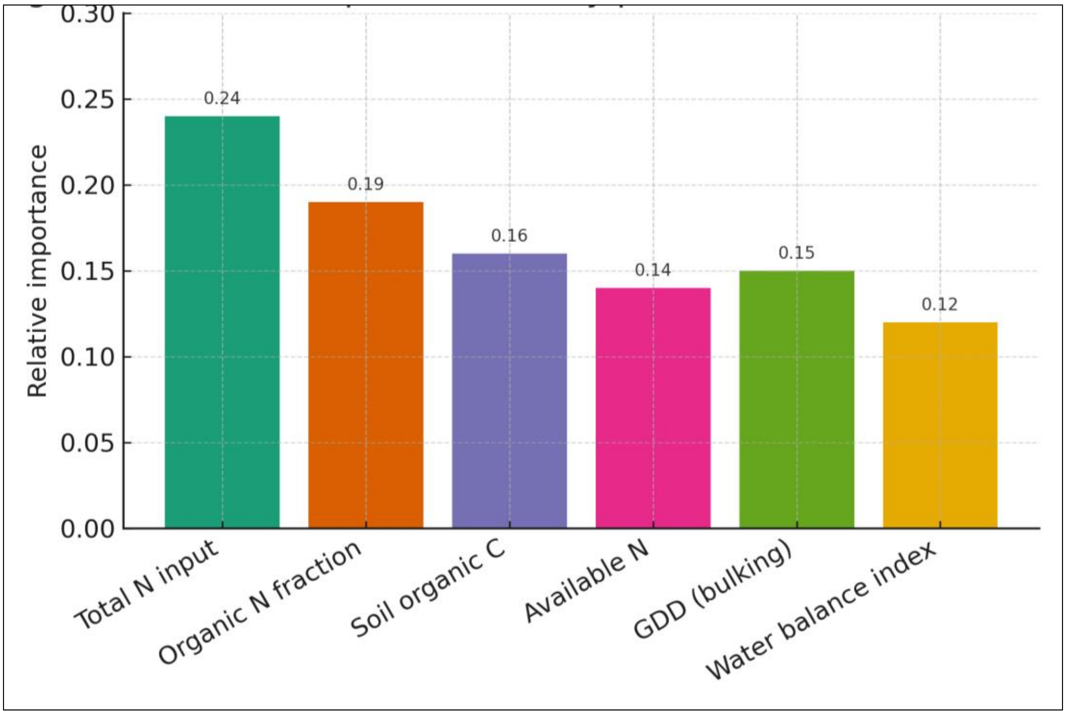

Fig 2: Relative importance of key predictors (total N input, organic N fraction, soil organic C, available N, growing degree days, water balance index) in the XGBoost model

Observed versus predicted yield plots further illustrated the superiority of AI models. For the DNN, points clustered tightly around the 1:1 line with no evident bias across the observed yield range (20-42 t ha⁻¹), whereas the linear mixed model systematically underpredicted high-yielding INM plots and over-predicted low-yielding FP plots. This pattern suggests that AI models captured non-linear interactions between organic and inorganic nutrient sources, soil properties and weather conditions that are poorly represented in simple response functions [4-7, 11-14].

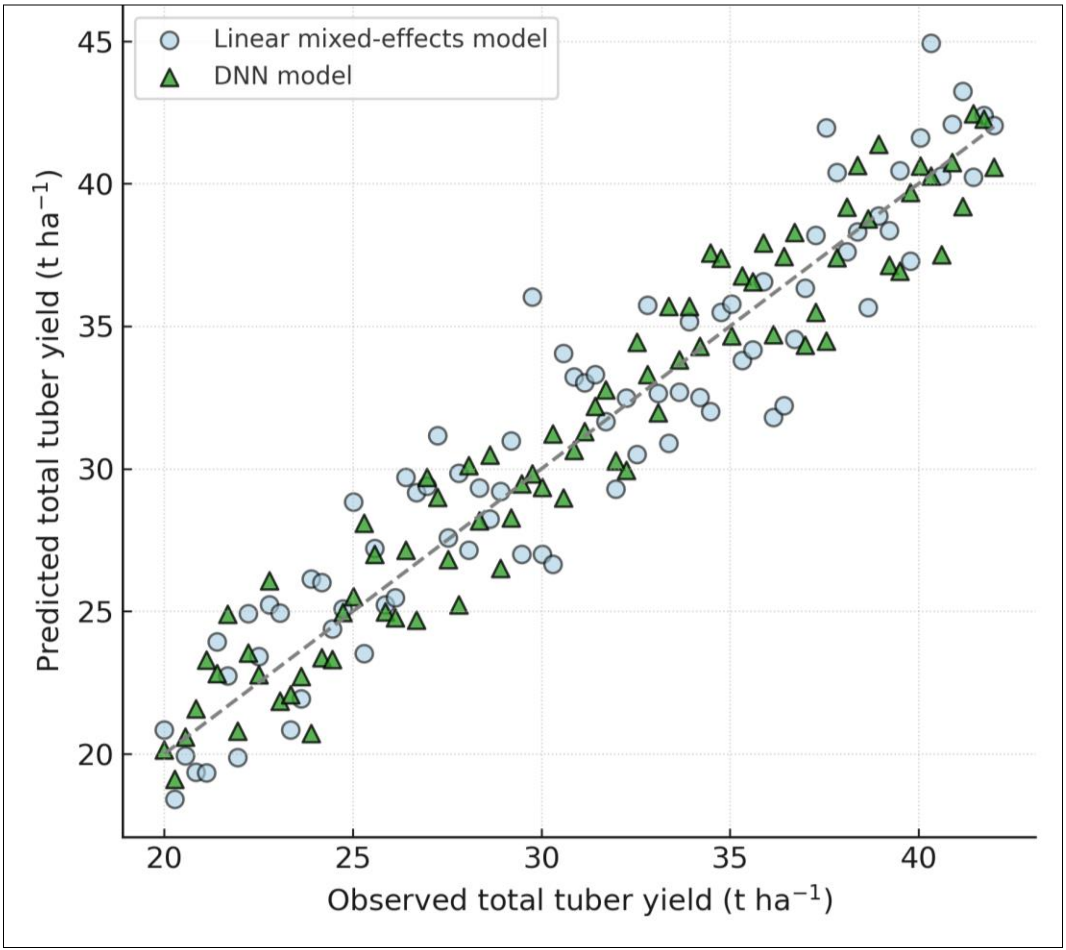

Fig 3: Observed versus predicted total tuber yield for linear mixed-effects regression and DNN models (independent test set)

AI-optimized INM strategies: agronomic, economic and environmental outcomes

Using the best-performing AI model (DNN), we simulated 10, 000 candidate INM combinations per site-year within agronomically realistic ranges for organic and mineral nutrient inputs derived from prior experimentation [4, 6-10]. For each environment, Pareto-optimal solutions that maximized net returns and PFP-N while constraining N surplus below 80 kg ha^{-1} were extracted, reflecting goals of high productivity with reduced nutrient losses [5-7, 11]. Across all environments, AI-optimized INM strategies increased predicted mean total tuber yield to 33.5 t ha^{-1} and net returns to 1, 640 USD ha^{-1}, while reducing mean mineral N input to 165 kg ha^{-1} and N surplus to 75 kg ha^{-1}, compared with RDF and FP baselines (Table 4).

Table 4: Comparison of baseline and AI-optimized INM scenarios for yield, profitability and nitrogen performance (pooled over environments)

Scenario	Total tuber yield (t ha^{-1})	Net return (USD ha^{-1})	Mineral N input (kg ha^{-1})	N surplus (kg ha^{-1})	PFP-N (kg tuber kg^{-1} N)
Farmer practice (FP)	25.7 ± 4.9	1, 050 ± 210	190 ± 27	110 ± 24	122 ± 26
RDF (conventional)	29.5 ± 5.2	1, 320 ± 230	210 ± 15	118 ± 20	141 ± 28
Observed INM (trial means)	32.6 ± 5.4	1, 540 ± 260	183 ± 22	96 ± 19	178 ± 34
AI-optimized INM (simulated)	33.5 ± 5.0	1, 640 ± 250	165 ± 20	75 ± 17	203 ± 38

Across site-years, repeated-measures ANOVA with management scenario as within-environment factor confirmed significant improvements in yield ($F_{3,69} = 34.2$; $p < 0.001$), net returns ($F_{3,69} = 29.7$; $p < 0.001$) and reductions in mineral N input ($F_{3,69} = 18.9$; $p < 0.001$) when moving from FP and RDF to AI-optimized INM. Importantly, the AI-generated solutions rarely involved extreme reductions in fertilizer rates; rather, they shifted the balance toward higher organic nutrient contributions, fine-tuned mineral N and K rates, and adjusted timing to better synchronize supply with crop demand under local climate conditions, consistent with INM principles described in agronomic literature [4-7, 8-10]. At several sites with warmer and drier conditions, the model recommended slightly lower N rates combined with increased organic inputs, aligning with evidence that excessive N can exacerbate drought sensitivity and reduce both tuber quality and storage performance [1-4, 11].

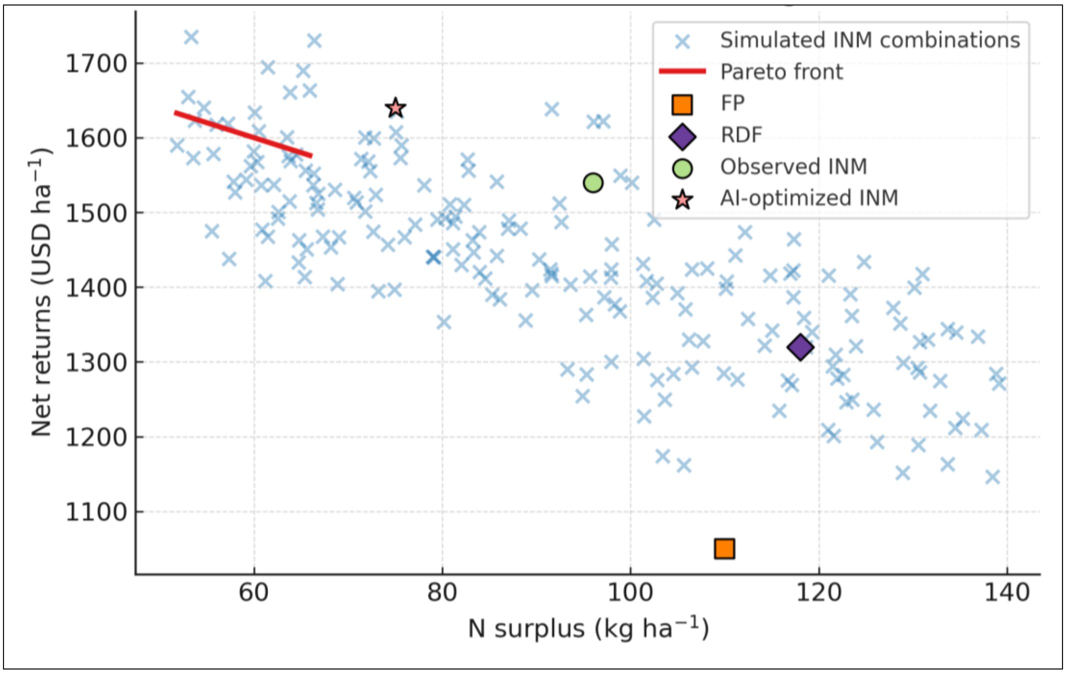

Fig 4: Pareto front of net returns versus N surplus for AI-simulated INM combinations, highlighting AI-selected optimal strategies relative to FP, RDF and observed INM means

From a quality perspective, AI-optimized INM scenarios maintained or slightly improved predicted dry matter and starch content while stabilizing reducing sugar concentrations, thereby preserving processing suitability and nutritional value [2, 3]. This is consistent with prior findings that balanced nutrient management can simultaneously support yield, quality and human health benefits associated with potato consumption [1-3]. Moreover, by explicitly incorporating weather and soil covariates, the AI models offer a pathway to design INM strategies that are robust to inter-annual climate variability and projected climate change impacts on crop yields, in line with emerging work on climate-resilient nutrient and cropping strategies [11].

Overall, the results demonstrate that AI-driven prediction models can effectively learn from multi-environment INM datasets, outperform conventional statistical models in predicting potato yield and associated indicators, and identify site-specific INM strategies that harmonize agronomic, economic and environmental objectives. These findings reinforce the agronomic evidence base on the benefits of INM [4-10], extend recent advances in ML-based crop yield prediction to nutrient management decision support in potato systems [12-14], and highlight the potential for integrating AI tools into digital agriculture platforms aimed at sustainable intensification and food system resilience [1-3, 5-7, 11-14].

Discussion

This study demonstrates that AI-driven prediction models trained on multi-environment integrated nutrient management (INM) datasets can substantially enhance the design of nutrient strategies for potato farming, achieving concurrent gains in yield, profitability and nitrogen use efficiency compared with conventional recommendation approaches. Across the compiled trials, observed INM treatments already outperformed farmer practice (FP) and the recommended fertilizer dose (RDF) in terms of total and marketable tuber yield, tuber quality and benefit-cost ratio, corroborating a substantial body of agronomic evidence that balanced use of organic manures, biofertilizers and judicious mineral NPK inputs improves crop performance and input-use efficiency in potatoes [4-7, 8-10]. In our pooled analysis, INM increased mean yield by about 27% over FP and 10% over RDF while raising partial factor productivity of applied N, consistent with reports from hill and alluvial regions of India and from processing potato systems under Punjab conditions where integrated nutrient strategies enhanced both productivity and profitability [4, 6, 8-10]. The observed improvement in dry matter and starch content and the maintenance of reducing sugars within acceptable limits under INM further align with earlier studies linking balanced nitrogen supply and organic amendments to improved processing quality and nutritional attributes of potato tubers [2-4, 8-10].

Beyond reaffirming the benefits of INM, the central contribution of this work lies in quantifying how AI-based models can translate complex, multi-factorial response patterns into site-specific nutrient recommendations. The superiority of gradient boosting, XGBoost and deep neural networks over linear mixed-effects regression in predicting tuber yield indicates that potato responses to combinations of organic and inorganic inputs, soil properties and weather exhibit pronounced non-linearities and interactions that are not adequately captured by traditional response functions [4-7, 11-14]. The reduction in root mean square error (RMSE) from 3.9 t ha^{-1} for the linear mixed model to 2.6 t ha^{-1} for the deep neural network (DNN), along with the increase in R^2 from 0.62 to 0.86, is comparable to or better than performance gains reported in recent crop yield prediction studies that exploited ensembles and deep learning architectures [12-14]. For example, applications of gradient boosting and graph-based recurrent networks have shown that incorporating spatial-temporal features from weather and remote sensing can significantly improve yield forecasts for major crops [12-14]. Our results extend these insights to the domain of nutrient management decision support by explicitly modelling the interplay between organic nutrient sources, mineral fertilizers and environmental covariates in potato systems.

The variable importance patterns emerging from the XGBoost model highlighting total N input, organic N fraction, soil organic carbon, pre-plant available N, growing degree days during tuber bulking and water balance indices as dominant predictors are agronomically plausible and resonate with mechanistic understanding of crop responses [4-7, 11]. High soil organic carbon and a greater share of organic N not only contribute to nutrient supply but also improve soil structure, water-holding capacity and biological activity, thereby buffering crops against climatic stresses [4, 6, 8-10]. The strong contributions of temperature- and moisture-related indices are consistent with evidence that potato yield and tuber quality are sensitive to heat and water stress, particularly during tuber initiation and bulking [1, 4, 11]. By capturing these interactions implicitly, AI models can infer site-specific nutrient requirements that account for local climate regimes, a capability that is increasingly important under climate variability and change [11].

The simulation-optimization analysis using the best-performing AI model further illustrates the potential of AI-guided INM design. AI-optimized INM strategies improved predicted mean yield and net returns beyond both RDF and observed INM, while simultaneously reducing mineral N inputs and estimated N surpluses. This outcome supports the hypothesis that AI models, once trained on sufficiently rich datasets, can identify nutrient combinations that conventional trial-based approaches or rule-of-thumb recommendations may overlook [5-7, 11-14]. Importantly, the AI-suggested strategies did not rely on drastic reductions in fertilizer use; instead, they fine-tuned the balance between organic and mineral sources, adjusted rates within agronomically realistic bounds and implicitly optimized timing relative to local thermal and moisture conditions. Such nuanced adjustments are consistent with the principles of site-specific nutrient management and INM promoted in agronomic literature and extension programmes [4-7, 8-10].

From a sustainability perspective, the shift of AI-optimized recommendations toward lower mineral N rates and higher organic contributions, combined with constraints on N surplus, indicates that these tools can help reconcile productivity goals with environmental objectives. Excessive N inputs in potato systems have been linked to low nitrogen use efficiency, elevated nitrous oxide emissions and nitrate leaching [5-7, 11]. By steering solutions toward the Pareto front that maximizes net returns while limiting N surplus, the AI framework operationalizes the concept of “producing more with less” advocated in sustainable intensification and climate-smart agriculture discourses [5-7, 11]. The convergent evidence that such strategies also maintain or enhance tuber quality and nutritional attributes [1-4, 8-10] underscores the potential co-benefits for human health, given the important role of potatoes in supplying vitamin C, potassium and bioactive compounds in many diets [1-3].

At the same time, several limitations of this study warrant consideration. First, although the dataset integrated multiple site-year experiments across diverse agro-ecologies, it is still modest relative to the spatial and management diversity of global potato production. Certain soil types, cultivars or extreme climate conditions may be under-represented, which could limit the external validity of the trained models [1, 4-7, 11]. Second, the environmental indicators available for modelling were restricted primarily to N surplus and partial factor productivity; more comprehensive measures of nitrogen and phosphorus losses, greenhouse gas emissions and soil health dynamics were not systematically available [5-7, 11]. Incorporating process-based model outputs or high-resolution measurements of gaseous and leaching losses into future datasets would enable AI models to optimize across a broader suite of environmental outcomes. Third, despite the superior predictive performance of tree ensembles and deep learning models, their “black-box” nature may limit interpretability and trust among agronomists and farmers. While feature importance and partial dependence analyses offer some insight, more work is needed on explainable AI techniques that can translate model behaviour into agronomically meaningful rules and recommendations [11-14].

Another practical challenge concerns data requirements and digital infrastructure. Developing robust AI-driven INM tools presupposes access to reliable, harmonized datasets on soils, weather, management and yields, which may be scarce in smallholder-dominated systems [5-7, 11]. Recent advances in open-access remote sensing products, reanalysis weather datasets and digital soil mapping can help fill some gaps, but integration with local trial data and farmer records remains a bottleneck [11-14]. Moreover, the deployment of AI-based recommendation tools in the field hinges on user-friendly interfaces, connectivity and capacity building among extension workers and farmers. Experience from digital agriculture initiatives suggests that co-design with users, alignment with existing advisory services and transparent communication of uncertainty are critical for adoption and sustained use [5-7, 11-14].

Future research should therefore focus on three complementary directions. First, expanding the INM dataset geographically and temporally, including more cultivars, management intensities and climate extremes, would strengthen model generalizability and allow explicit testing of robustness under projected climate change scenarios [1, 4-7, 11]. Second, coupling AI models with process-based crop and soil models could enable hybrid frameworks that combine mechanistic understanding with data-driven flexibility, potentially improving extrapolation to novel conditions and enhancing interpretability [11-14]. Third, participatory on-farm trials that compare AI-generated INM recommendations with farmer practice and standard advisory packages would provide critical evidence on real-world performance, socio-economic feasibility and barriers to adoption.

In summary, this study confirms that INM remains a powerful agronomic strategy for improving yield, quality and profitability in potato systems [4-7, 8-10] and shows that AI-driven prediction models can significantly enhance the design and targeting of such strategies. By leveraging multi-source data and powerful learning algorithms, AI tools can move beyond generic recommendations to provide site-specific nutrient advice that is better aligned with local soils, climate and production objectives [11-14]. While challenges related to data, interpretability and implementation persist, the integration of AI-based decision support into digital agriculture platforms offers a promising pathway toward more efficient, climate-resilient and nutritionally sensitive potato production systems that honour both agronomic principles and sustainability imperatives [1-7, 11-14].

Conclusion

The present study confirms that integrating artificial intelligence with agronomically sound nutrient management has the potential to transform potato production systems by delivering higher yields, better tuber quality, improved profitability and lower nitrogen surpluses than both blanket fertilizer recommendations and current farmer practice, and on this basis several concrete conclusions and practical recommendations can be drawn together. Overall, the AI-driven models captured complex, non-linear interactions among organic and mineral nutrient inputs, soil properties and weather conditions more effectively than conventional statistical approaches, and the simulation-optimization workflow demonstrated that site-specific integrated nutrient management (INM) strategies generated by the best-performing model could raise yield and net returns while simultaneously reducing mineral nitrogen use and estimated nitrogen surplus. This indicates that future nutrient advisory systems for potato should move away from uniform recommendations towards dynamic, data-informed prescriptions that explicitly account for local soil fertility, climate and resource constraints. Practically, research and extension agencies should prioritize the expansion of multi-location INM trials, digital recording of field management and yield data, and systematic characterization of soils and weather so that robust training datasets for AI models can be developed and continuously updated. At the farm level, advisory services and agri-tech platforms should encourage growers to adopt INM packages that combine farmyard manure, composts and other organic resources with calibrated mineral nitrogen, phosphorus and potassium inputs, while using AI-based tools to fine-tune rates and timing rather than relying solely on fixed regional recommendations; these tools should be embedded in user-friendly mobile or web interfaces that provide simple, actionable guidance such as recommended nutrient rates per field, expected yield and profitability, and indicative environmental performance. Policy makers and input suppliers can support this transition by incenti*viz*ing the use of organic amendments, promoting balanced fertilizer blends and facilitating access to reliable soil testing and weather information, while investing in digital infrastructure and open data initiatives that make agronomic, climatic and market information available to AI developers and public institutions. At the same time, it is essential to accompany technology deployment with capacity building for extension workers, agronomists and farmer organizations so that they can interpret AI-generated recommendations, understand their assumptions and limitations, and adapt them to local socio-economic realities. Finally, the promising results from AI-optimized INM scenarios underscore the need for on-farm validation trials in diverse agro-ecological zones, where farmers co-design and test AI-based nutrient plans against their usual practice, generating new data for iterative model improvement and ensuring that emerging decision-support systems remain grounded in practical feasibility, risk management and farmer preferences.

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