

# MACHINE LEARNING FOR FERTILIZER RECOMMENDATION IN GHANA



ERIC ASAMOAH

## **Propositions**

1. Machine learning offers a reliable path to site-specific nutrient management.  
(this thesis)
2. Fertilizer recommendations that account for risk and uncertainty are of key importance to smallholder farmers.  
(this thesis)
3. Science communication is most effective when it highlights critique as well as success stories.
4. The illusion of precision in data overrides the absence of meaning.
5. Climate change is marketed more effectively than mitigated.
6. Big data algorithms know you better than your therapist does.

Propositions belonging to the thesis, entitled

Machine learning for fertilizer recommendation in Ghana

Eric Asamoah

Wageningen, 30 January 2026

# Machine learning for fertilizer recommendation in Ghana

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# Machine learning for fertilizer recommendation in Ghana

Eric Asamoah

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# Chapter 1

Introduction

## 1.1 Background

Agriculture remains the backbone of Ghana's economy, employing more than one-third of the labour force and contributing significantly to GDP, food security, and poverty alleviation (Kamassah, 2025; MoFA, 2021). Its importance extends beyond income generation to underpinning rural livelihoods, nutrition, and resilience against socio-economic shocks. For most households, especially in rural areas, agricultural activities are the primary source of sustenance and livelihood security (Dzanku et al., 2015). The sector also contributes to the attainment of multiple Sustainable Development Goals (SDGs), particularly those related to hunger, poverty, and climate action (United Nations, 2022). However, agricultural productivity has not kept pace with population growth in sub-Saharan Africa (SSA), raising concerns about food system sustainability (Jayne and Sanchez, 2021). The COVID-19 pandemic further exposed the vulnerabilities of fragile agricultural systems, disrupting food supply chains and threatening food security (Asare-Nuamah et al., 2023). Strengthening Ghana's agriculture is therefore critical not only for economic growth but also for national development and resilience.

Despite agriculture's importance, crop yields across SSA, including Ghana, remain significantly below their potential. Empirical studies have shown that maize, a major staple, achieves less than 40% of its attainable yield in many smallholder systems (Van Ittersum et al., 2016). This yield gap is largely attributed to poor soil fertility, inadequate use of fertilizer, and limited adoption of improved agronomic practices (Holden, 2018a). Efforts such as the Abuja Declaration of 2006, aimed to increase fertilizer use to 50 kg ha<sup>-1</sup> by 2015 as a means of bridging these gaps, but actual application rates have remained stagnant at 10–20 kg ha<sup>-1</sup> (Macauley and Ramadjita, 2015; Union, 2019). The consequences are profound: food deficits persist, rural poverty remains entrenched, and farmers face difficulty competing in increasingly globalized food markets (Donkor et al., 2019). Renewed policy attention, including the Nairobi Declaration (Lal, 2024; Union, 2024), have emerged, but without addressing the fundamental drivers of fertilizer use and efficiency, yield gaps will remain a pressing concern in SSA and for Ghanaian agriculture.

Fertilizer is widely recognized as central to yield improvement. However, in Ghana, adoption and use is constrained by economic and practical barriers. Smallholders often operate under conditions of financial constraint, making the upfront cost of fertilizer a significant barrier (Adzawla et al., 2024). Moreover, evidence suggests that uniform fertilizer recommendations often fail to deliver sufficient yield responses to justify their cost, thereby reducing incentives for adoption and use (Liverpool-Tasie et al., 2017). Subsidy programs, such as Ghana's Fertilizer Subsidy Program introduced in 2008, have delivered mixed outcomes, often hindered by leakages, delays, and the lack of site-specific targeting (Banful, 2011). Farmers' risk aversion in the face of uncertain climate and volatile market prices further constrains demand for and use of fertilizer inputs (Bold et al., 2017). These realities highlight the urgent need for more efficient, site-specific, and economically viable fertilizer strategies. Thus, while fertilizer

remains central to yield improvement, its adoption and use will continue to be constrained unless profitability and risk-adjusted returns are enhanced in ways that are meaningful to smallholder farmers.

Enhancing nutrient use efficiency defined as the degree to which applied nutrients contribute to yield increases represents a viable strategy for improving both agricultural productivity and economic profitability. Research indicates that the optimization of fertilizer timing, placement, and blending, in conjunction with integrated soil fertility management practices, can considerably enhance efficiency and promote soil health (Vanlauwe et al., 2015). Improving nutrient use efficiency not only benefits farmers through better returns on investment but also reduces environmental externalities such as nutrient leaching and greenhouse gas emission (Zhang et al., 2015). Nevertheless, the attainment of such efficiency is hindered by a significant challenge: the high spatial variability of soils across Ghana's agroecological zones (Simperegui et al., 2025). Blanket fertilizer recommendations which refers to the application of standardized nutrient rates across broad agroecological zones fail to account for spatial and temporal heterogeneity in soil fertility, crop nutrient demand, or management practices, resulting in excessive nutrient application in certain areas while leading to insufficient application in others (Xu et al., 2009). Site-specific nutrient management offers a promising alternative, but its adoption is constrained by the lack of detailed, accessible agronomic spatial datasets in Ghana. This highlights the urgent need for research and innovation to create site-specific fertilizer recommendations that balance productivity gains with environmental and economic sustainability.

Recent advances in data science and machine learning (ML) provide promising avenues to addressing these challenges. ML algorithms can integrate large and diverse datasets including soil properties, weather, crop responses, and socioeconomic data to generate site-specific fertilizer recommendations. Studies in Asia and Latin America demonstrate that ML-based models outperform traditional linear approaches in predicting crop yield responses to fertilizer applications (Khaki et al., 2020; Khaki and Wang, 2019; Srivastava et al., 2022). The potential for integrating data science and ML algorithms in agriculture is increasingly recognized, particularly as agronomic data becomes available. By leveraging ML, Ghana has an opportunity to close persistent yield gaps through the development of more precise and economically viable fertilizer management strategies that meets the local conditions of smallholder farms.

## 1.2 Yield modelling in maize production systems

Yield modelling is essential in agricultural research, providing insights into crop performance under different management and environmental conditions. In maize production, models identify yield-limiting factors and predict responses to inputs such as fertilizer, irrigation, and improved seed varieties. Traditionally, process-based models have been central to yield modelling. Examples include the DSSAT and APSIM models, which simulate crop growth based on physiological, soil, and climate processes

(Holzworth et al., 2014; Hoogenboom et al., 2019). These models represent mechanisms, nutrient cycling, and water balance, making them valuable for diagnostics, scenario analysis, and assessing long-term impacts of climate and management. However, they require extensive calibration, detailed biophysical data, and significant expertise to implement, limiting their use in data-scarce contexts such as SSA, where site-specific measurements are often unavailable (Rötter et al., 2018).

To address these limitations, statistical and more recently ML-based yield models have been developed. These approaches leverage datasets including farm surveys, soil maps, field trials, and satellite observations to generate predictions without needing physiological parameterization (Shahhosseini et al., 2021). By utilizing large and diverse data sources, statistical and ML approaches can complement traditional models, providing scalable alternatives suited for contexts with limited experimental data.

### **1.3 Significance of machine learning data-driven approaches in agriculture**

The integration of ML and other data-driven methods in agriculture has gained increasing attention due to their capacity to manage and analyze large, complex datasets. Traditional approaches often struggle to capture the nonlinear interactions between soil, weather, management practices, and crop growth that drive yield variability (Shahhosseini et al., 2021). ML models, such as random forests, gradient boosting, and neural networks, offer flexible methods for yield prediction and decision-making (Khaki and Wang, 2019). These models can incorporate diverse explanatory variables, ranging from soil characteristics to climatic data, and learn hidden patterns that conventional models overlook. In the context of SSA, where agricultural systems are highly heterogeneous and data availability is improving through remote sensing and field observations, ML approaches present opportunities to enhance productivity. Importantly, ML can enable the generation of site-specific recommendations that can be updated as new data become available, thereby supporting adaptive management strategies.

### **1.4 Variable importance in yield modelling and fertilizer recommendation**

In both classical and modern agronomic modelling, variable importance is crucial for understanding which variables that influence outcomes such as yield. Traditional statistical models assess variable importance through regression coefficients, stepwise regression, and analysis of variance (ANOVA), which quantify the contribution of explanatory variables to model outcomes (Barbur et al., 1994). These methods help identify relevant variables while reducing redundancy, improving model accuracy and interpretability. In data-driven agronomic modelling, particularly ML, variable importance indicates the contribution of each input feature to the predictive accuracy of a model (Kuhn and Johnson, 2013; Molnar et al., 2020). It serves as a diagnostic tool that clarifies the “black box” nature of complex ML algorithms by highlighting which variables the model relies on for predictions. However, not all ML

models provide built-in measures of variables importance. For example, tree-based algorithms such as RF and Gradient boosting offer explicit rankings of variable importance (Breiman, 2001), while models such as SVM, neural networks, among others require additional techniques such as permutation importance to generate importance scores (Lundberg and Lee, 2017). Identifying variables that strongly influence yield is essential for accurate modelling and effective fertilizer recommendations. Variable importance enhances modelling accuracy by guiding feature selection, removing irrelevant or redundant variables reduces noise, prevents overfitting, and improves generalization, especially with limited datasets. Highlighting critical yield drivers also enables the design of efficient, site-specific fertilizer recommendations. Yield in maize production is shaped by interactions among biophysical variables (e.g., soil pH, organic matter, nutrient content), climatic conditions (e.g., rainfall distribution, temperature), and management practices (e.g., planting density, fertilizer application) (Van Ittersum et al., 2016). ML models, particularly random forests, rank variables according to their importance in predicting outcomes, helping identify critical yield drivers. For instance, studies in SSA show that soil organic matter and nitrogen availability are key variables of maize yield (Ndung'u et al., 2021; Zingore et al., 2021). By integrating variable importance analysis into fertilizer recommendation systems, we can shift from generic guidelines to targeted, site-specific advice that improves nutrient use efficiency and farmer profitability.

### **1.5 Uncertainty in maize yield prediction and fertilizer recommendations**

A critical challenge in yield modelling and fertilizer recommendation is accounting for uncertainty (Walker et al., 2003). Model errors and variability in weather, soil conditions and management practices can lead to significant differences between predicted and realized outcomes. For smallholder farmers in Ghana, this uncertainty translates into economic risk, as investments in fertilizer may not always result in profitable yield responses. Traditional fertilizer recommendation systems rarely quantify these uncertainties, which undermines farmer confidence and adoption (Bold et al., 2017). ML models provide an avenue to address this issue by incorporating probabilistic approaches that explicitly quantify uncertainty in predictions. By embedding risk analysis into recommendation strategies, it becomes possible to develop decision-support tools that help farmers and policymakers weigh potential outcomes under different scenarios. This is particularly relevant in Ghana and SSA, where climatic variability and limited access to credit amplify the consequences of prediction errors. Thus, integrating uncertainty analysis into yield modelling and fertilizer recommendations is essential for designing resilient and farmer-friendly solutions.

## 1.6 Problem definition

Summarizing from the above, despite the critical role of maize in Ghana's food security and rural livelihoods, yields remain far below their potential. Fertilizer use is low and often inefficient, largely due to the reliance on generalized recommendations that fail to reflect the spatial heterogeneity of soils and the economic realities of smallholder farmers. This has led to suboptimal input use, poor returns on investment, and persistent yield gaps. While ML offers promising tools for developing more accurate and site-specific yield and fertilizer recommendations, there is limited application of such approaches in Ghana. Furthermore, existing systems do not adequately account for uncertainty, leaving farmers exposed to economic risks. This gap in context-specific, data-driven, and risk-aware recommendation systems constrains the potential of fertilizer to sustainably increase maize productivity. Addressing this problem requires innovative methodologies that integrate ML, variable importance analysis, and uncertainty quantification to produce actionable recommendations tailored to Ghana's diverse production systems.

## 1.7 Objectives and research questions

The overarching objective of this research is to develop and test a novel methodology for yield prediction and fertilizer recommendations for maize production in Ghana using a machine learning-based approach. To achieve this objective, a large data set covering the entire country on many seasons and conditions will be prepared to model the relation between the dependent variables, yield and agronomic efficiency, an index of nutrient use efficiency which measures the yield increase achieved per unit nutrient applied, and identify their main drivers, in order to predict yield and agronomic efficiency in space and time. To achieve the main objective, this thesis has identified four main sub-objectives which are associated with research questions.

1. Development and application of random forest models for predicting maize yield and agronomic efficiency in Ghana.
  - Which explanatory variables should be included in random forest models of yield and agronomic efficiency and what are the associated variable importances?
  - What is the model performance when assessed using test data?
2. Deriving fertilizer recommendations from a calibrated random forest model and their comparison with recommendations from existing fertilizer recommendation approach.
  - How can a random forest model for yield prediction be used to make fertilizer recommendations?
  - How do fertilizer recommendations derived by the random forest model compare with existing recommendations, and QUEFTS, when tested in the field?

3. Development and evaluation of machine learning models other than random forest for predicting maize yields and agronomic efficiency in Ghana.
  - How does model performance vary between machine learning models?
  - How do the explanatory variable importances vary between different machine learning models?
4. Development of a fertilizer recommendation strategy that accounts for uncertainty in model predictions.
  - What methods from statistical risk analysis are suitable for developing fertilizer recommendation strategies under uncertainty?
  - How can uncertainty in the predicted yield be accounted for in optimizing fertilizer application?

### 1.8 Thesis outline

This thesis comprises six chapters, including this introductory chapter. Chapter 2 describes the data collection and preparation process, covering the compilation of a large, multi-season, country-wide dataset for maize production in Ghana. It presents the development and application of the random forest model to predict maize yield and agronomic efficiency. The chapter explores candidate explanatory variables, evaluates their importance, and assesses the predictive performance of the models using test data. In Chapter 3, fertilizer recommendations derived from the random forest model are presented and compared with QUEFTS and fertilizer recommendations derived with conventional approaches. The comparison is based on field data and includes yields and economic outcomes. Chapter 4 investigates alternative machine learning models for yield and agronomic efficiency prediction. The performance of these models is compared with that of the random forest model, and the variability in explanatory variable importance is examined. Chapter 5 develops a fertilizer recommendation strategy that incorporates uncertainty in predicted yields. Methods from statistical risk analysis are applied to assess the impact of uncertainty and risk aversion on fertilizer decision-making. Chapter 6 provides a general discussion that synthesizes findings from all chapters and concludes the thesis with a summary of key contributions and recommendations for future work. Each chapter is based on a published or submitted journal article, resulting in some unavoidable repetition, such as figures of the study area and tables of summary statistics. These redundancies have been retained to keep each chapter self-contained and coherent. I appreciate the reader's understanding.



# Chapter 2

## Random forest machine learning for maize yield and agronomic efficiency prediction in Ghana

This chapter is based on:

Asamoah, E., Heuvelink, G. B. M., Chairi, I., Bindraban, P. S., & Logah, V. (2024). Random forest machine learning for maize yield and agronomic efficiency prediction in Ghana. *Heliyon*, 10(17), e37065.  
<https://doi.org/10.1016/J.HELIYON.2024.E37065>.

## **Abstract**

Maize (*Zea mays*) is an important staple crop for food security in Sub-Saharan Africa. However, there is need to increase production to feed a growing population. In Ghana, this is mainly done by increasing acreage with adverse environmental consequences, rather than yield increment per unit area. Accurate prediction of maize yields and nutrient use efficiency in production is critical to making informed decisions toward economic and ecological sustainability. We trained the random forest machine learning algorithm to predict maize yield and agronomic efficiency in Ghana using soil, climate, environment, and management factors, including fertilizer application. We calibrated and evaluated the performance of the random forest machine learning algorithm using a 5 x 10-fold nested cross-validation approach. Data from 482 maize field trials consisting of 3136 georeferenced treatment plots conducted in Ghana from 1991 to 2020 were used to train the algorithm, identify important predictor variables, and quantify the uncertainties associated with the random forest predictions. The mean error, root mean squared error, model efficiency coefficient and 90% prediction interval coverage probability were calculated. The results obtained on test data demonstrate good prediction performance for yield (MEC = 0.81) and moderate performance for agronomic efficiency (MEC = 0.63, 0.55 and 0.54 for AE-N, AE-P and AE-K, respectively). We found that climatic variables were less important predictors than soil variables for yield prediction, but temperature was of key importance to yield prediction and rainfall to agronomic efficiency. The developed random forest models provided a better understanding of the drivers of maize yield and agronomic efficiency in a tropical climate and an insight towards improving fertilizer recommendations for sustainable maize production and food security in Sub-Saharan Africa.

## 2.1 Introduction

In the era of increasing global population, ensuring food security has become a major challenge for scientists, governments, and non-governmental organizations (Bonilla-Cedrez et al., 2021). It is projected that the world population will reach approximately 8.5 billion by 2030 and 9.7 billion by 2050 (Departamento de Asuntos Económicos y Sociales de las Naciones Unidas, 2019). More than half of this increase will come from Sub-Saharan Africa (SSA), which poses a threat to food security in the region unless critical measures are taken to produce enough food for the growing population (Van Ittersum et al., 2016). The consumption of cereals in SSA is increasing faster than its production, resulting in an over-reliance on imports (Van Ittersum et al., 2016). This situation is exacerbated by the impact of climate change, which poses a significant threat to food security in SSA (Affoh et al., 2022).

Maize is a crucial staple crop grown in all agro-ecological zones of Ghana and is the most consumed crop in the country (Ragasa et al., 2014). Maize makes up over 50% of the country's cereals production, providing an essential feed source for the livestock and poultry industries (Ragasa et al., 2014). It is cultivated on approximately 25% of Ghana's total arable land (MoFA, 2021). The increase in maize production has been primarily driven by land expansion rather than yield improvement, with negative impact on biodiversity and soil organic carbon content (Bashagaluke et al., 2018). Obour et al. (2022) attribute low maize yields in Ghana to factors such as drought, pest and disease infestations, poor soil fertility, inadequate use of fertilizers, and insufficient farmer adoption of good management practices. Understanding the relationships between these factors and yield can significantly inform farmers and other stakeholders on the drivers of maize yields, enhancing relevant decisions to making Ghana self-sufficient in maize production (Danquah et al., 2020; Tetteh et al., 2018).

Agronomic efficiency (AE) is a measure of the yield increase achieved per unit nitrogen (N), phosphorus (P) and potassium (K) applied. Conceptually, crop yield is made up of two elements (Chuan et al., 2019). The first element is the yield produced by the soil's natural supply of nutrients, while the second is the yield increase resulting from fertilizer application. Agronomic efficiencies of N, P and K are affected by climate, soil, and management practices, which can vary among smallholder farms (Kihara et al., 2016; Tittonell et al., 2007). Adequate crop information and understanding the relationships between yield, applied nutrients, soil and climatic conditions, environmental factors, and management practices that influence AE are key for sustainable agriculture (Boullouz et al., 2022). Identifying these drivers can assist decision-makers in determining the ideal nutrient combination and management for maximizing yields and improving AE.

Machine learning-based models have been recognized for their high potential for crop modelling in recent scientific literature. For example, Su et al. (2017) used a support vector machine model to predict rice development stage and yield using meteorological data. Elavarasan et al. (2018) evaluated various machine learning models, including decision trees (DT), random forest (RF), support vector machine

(SVM), Bayesian networks (BN), and artificial neural networks (ANN), to predict crop yields based on climatic and soil data. Everingham et al. (2016) successfully used the RF algorithm to predict seasonal variations in sugarcane yield using simulated biomass from the Agricultural Production Systems sIMulator (APSIM), seasonal climatic indices, and weather data in Northeastern Australia. Pang et al. (2022) evaluated the RF algorithm for predicting wheat yield in southeast Australia using normalized difference vegetation index (NDVI) data derived from high-resolution satellite imagery and weather data. Among the various ML models, RF has proven to perform equally well as other machine learning models in predicting yields of maize, wheat, mango, potato, sugarcane, and rice using environmental and climatic variables (Cao et al., 2021; Coulibali et al., 2020; Fukuda et al., 2013; Guo et al., 2021, 2022, 2023; Kim and Lee, 2016). The RF algorithm is computationally attractive and stands out for its ability to explore non-linear relationships between predictor and response variables using an ensemble approach (Everingham et al., 2016). However, to the best of our knowledge, no study has used the RF algorithm to predict both yield and AE for maize production in SSA.

Uncertainty assessments are crucial in model predictions to inform decision making (Solomatine and Shrestha, 2009), yet previous studies have not thoroughly considered uncertainties in yield predictions. Quantifying prediction uncertainties with the RF algorithm can be achieved with the quantile regression forest (QRF) approach, which estimates the conditional probability distribution of the response variable (Meinshausen, 2006). The QRF provides estimates of prediction intervals which gives a measure of the uncertainty associated with each prediction and also provides insights into how the uncertainty in predictions varies across different regions of the feature space (Wang et al., 2022). Much work has been done on using the RF algorithm for yield prediction (Marques Ramos et al., 2020). However, there is limited information in the literature regarding the AE of N, P, and K predictions, as well as estimating the uncertainties in the models' predictions. In this study, we took advantage of the availability of comprehensive datasets from across the country to develop a predictive model for maize yield and agronomic efficiency for Ghana.

The objectives of this study were to: (i) collect and harmonize data on maize yield, fertilizer application, and environmental variables in Ghana; (ii) calibrate a RF algorithm using hyperparameter optimization and assess the performance of the calibrated RF algorithm for yield and AE prediction through cross-validation; (iii) quantify and evaluate the predictive uncertainty of the RF algorithm for yield and AE prediction using quantile regression forest; and (iv) determine and interpret the relative importance of the RF predictor variables for yield and AE prediction.

## 2.2 Materials and methods

### 2.2.1 Study area

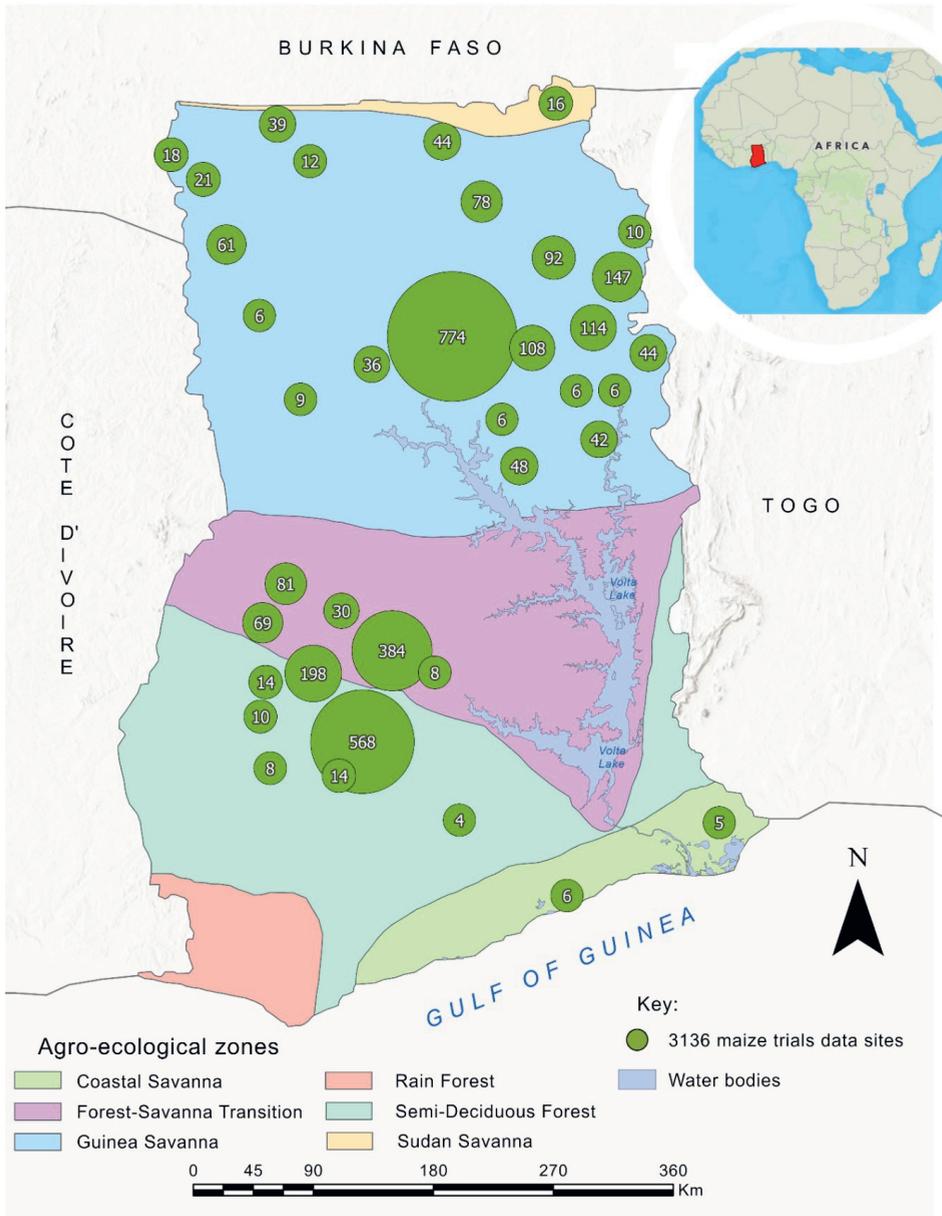
Ghana is located in West Africa between latitude 4° 11' N and 11° 11' N and longitude 3° 11' W and 1° 11' E. It shares borders with Togo in the east, Cote d'Ivoire in the west, and with Burkina Faso in the north. In the south, Ghana is bordered by the Gulf of Guinea. The total land area is 238,533 km<sup>2</sup>, with a population of a little over 30 million, as revealed by the 2021 population census (GSS, 2021). The study area included all agro-ecological zones of Ghana, namely the Guinea Savanna (GS), Sudan Savanna (SS), Forest-Savanna Transition (FST), Semi-Deciduous Forest (SDF) and the Coastal Savanna (CS) zones, except the Rain Forest (RF) (Figure 2.1). The SS and GS have one major annual planting season, starting in May and ending in October. FST, SDF, RF and CS have two planting seasons, a major season from April to July, and a minor season from September to November. Table 2.1 shows general characteristics of each agro-ecological zone.



**Table 2.1:** General characteristics of the agro-ecological zones in Ghana.

Agro-ecological zone	Rainfall range (mm year <sup>-1</sup> )	Mean temperature range (°C year <sup>-1</sup> )	Length of growing season (days)	Major land use systems	Major soil type (WRB Reference Soil Groups)
Sudan Savanna	900 – 1100	26 – 32	MJ: 180 – 200	Annual food crops, cash crops, livestock	Lixisol, Plinthosol, Luvisol
Guinea Savanna	1000 – 1200	26 – 32	MJ: 190 – 230	Annual food crops, cash crops, livestock	Lixisol, Planosol, Plinthosol
Forest-Savanna Transition	1100 – 1400	24 – 28	MJ: 130 – 200 MN: 70	Annual food crops, cash crops	Lixisol, Plinthosol
Semi-Deciduous Forest	1200 – 1500	24 – 28	MJ: 130 – 160 MN: 80	Annual food crops, forest, plantations	Acrisol, Lixisol, Nitisol
Coastal Savanna	800 – 1000	26 – 32	MJ: 100 – 110 MN: 50	Annual food crops	Vertisol, Luvisol, Cambisol
Rain Forest	1700 – 2300	24 – 28	MJ: 90 – 120 MN: 40	Forest, plantations	Ferralsol, Acrisol, Gleysol

MJ: Major season, MN: Minor season. Source: Modified after (MoFA, 2021), WRB – World Reference Base for Soil Resources (WRB, 2022).



**Figure 2.1:** Map showing locations of maize-treatment plots (n = 3136) from 482 fertilizer experimental trials across five agro-ecological zones of Ghana.



## 2.2.2 Datasets and data sources

### 2.2.2.1 Maize trials data and predictor variables

Data used to model and predict maize yield and AE were compiled from three sources: the International Fertilizer Development Center (IFDC) database (Bua et al., 2020), National Research Institutes and Universities (NRI&U) in Ghana, and the IFDC – Fertilizer Research and Responsible Implementation (FERARI) project (<https://ifdc.org/projects/fertilizer-research-and-responsible-implementation-ferari/>). The data from the IFDC database consisted of 263 maize field trials data retrieved from peer-reviewed publications from scientific databases including Google Scholar, Web of Science, Scopus, African Journals Online and the Food and Agriculture Organization of the United Nations. The data from the NRI&U database were derived from 86 field trials retrieved from unpublished Master's and Doctoral theses from three public universities in Ghana, namely Kwame Nkrumah University of Science and Technology, University of Ghana, and University for Development Studies. Finally, the data from the IFDC-FERARI project consisted of 133 maize field trials conducted in 2020. We harmonized the maize field trial datasets from these three data sources into one database. The moisture content at which grain yield was reported ranged from 13 to 15% in the compiled harmonized database. We preprocessed the data to conform to the same standard units for variables and removed redundant information from the combined database. This resulted in 3136 unique georeferenced plot data points from 1991 to 2020 (Table 2.2 and Figure 2.1).

Predictor variables identified to influence yield and AE were climatic variables, soil variables, crop genotype, environmental variables, management practices, and fertilizer application data. Forty predictor variables were prepared for the modelling. A summary of predictor variables is presented in Table 2.3, while Supplementary Information (SI) Tables SI 1-5 provide general research trial information and a detailed description of the predictor variables. Data collection strategies for three of the predictor variable groups are explained in Sections 2.2.2 and 2.2.3.

**Table 2.2:** Sources for fertilizer and maize yield data compilation.

Data source	Number of field trials	Number of treatment plots	Reference
IFDC	263	919	Compiled from published journal articles [32]
NRI&U	86	1017	Compiled from national research institutes (CSIR-SRI, CSIR SARI) and universities (KNUST, UG, UDS)
IFDC – FERARI Project	133	1200	Compiled from FERARI project 2020 field trials
Total	482	3136	

CSIR-SRI: Council for Scientific and Industrial Research – Soil Research Institute, CSIR SARI: Council for Scientific and Industrial Research – Savanna Agriculture Research Institute, KNUST: Kwame Nkrumah University of Science and Technology, UG: University of Ghana, UDS: University for Development Studies.

**Table 2.3:** Predictor variables used in the RF algorithm.

Variable groups (number of predictor variables)	Variables
Climate (6)	Rainfall (annual and total for planting season), temperature at planting season (minimum and maximum), mean relative humidity at planting season, mean evapotranspiration at planting season
Soil (0 – 30 cm) (21)	pH, organic carbon, total nitrogen, cation exchange capacity, available phosphorus, exchangeable bases (calcium, potassium, magnesium and sodium), sand, silt, clay, bulk density, coarse fragment content, electrical conductivity, zinc, iron, total exchangeable bases, base saturation, root zone water holding capacity, soil type
Crop (1)	Genotype
Environmental (3)	Slope, NDVI, Agro-ecological zone
Management practices (3)	Application of any organic amendment (e.g. poultry manure, cattle manure), management type, mode of fertilizer application
*Fertilizer application (6)	Nitrogen, phosphorus, potassium, sulphur, zinc, iron

\*Only considered in predicting yield and not in predicting agronomic efficiencies (see Supplementary Information for a complete list of predictor variables).

## 2.2.2.2 Climatic data

Climatic data (Table 2.4) for each experimental trial were obtained for the planting season of the trial, and values were aggregated over time to correspond to the time period of each trial. Climate station data closest to the experimental trial were obtained from the Ghana Meteorological Service (GMet) for experiments without climate information. Data from 1991 to 2020 were obtained from the GMet archive.

**Table 2.4:** Climatic information for major and minor planting seasons for the agro-ecological zones in Ghana.

Planting Season	Agro-ecological zone	T min (°C)	T max (°C)	RH-mean (%)	Et (mm)	R (mm)
Major	Sudan Savanna	22.9	32.7	70.3	154.7	897.5
	Guinea Savanna	22.6	31.5	76.1	149.9	938.9
	Forest-Savanna Transition	21.8	31.1	74.3	135.5	703.7
	Semi-Deciduous Forest	21.9	30.8	78.8	137.2	809.6
	Coastal Savanna	23.8	30.6	79.0	152.0	572.8
Minor	Forest-Savanna Transition	20.6	30.0	79.5	113.0	430.1
	Semi-Deciduous Forest	21.3	30.1	75.6	124.3	423.4
	Coastal Savanna	22.8	29.8	79.7	147.1	184.9

T min: minimum temperature, T max: maximum temperature, RH-mean: mean relative humidity, Et: mean evapotranspiration, R: rainfall.

## 2.2.2.3 Soil data and other environmental variables

Soil fertility information of the tilled layer (0 – 30 cm) was extracted from the Ghana Soil Information Service (GhaSIS) hosted by CSIR-SRI ([www.csirsoilinfo.org](http://www.csirsoilinfo.org)). The soil type (Reference Soil Group) (WRB, 2022) for each site was identified using the soil map of Ghana (Figure SI 4). Extracted soil fertility information from the existing GhaSIS database was used to fill gaps for sites where such information was missing. Other environmental variables used in the modelling were the slope (Robinson et al., 2014) and the NDVI (Savtchenko et al., 2004).

### 2.2.3 Agronomic efficiency

The nutrient use efficiency indicator modelled in this study was agronomic efficiency (AE). Agronomic efficiency is defined as the unit increase in yield per unit of nutrient applied (Dobermann, 2007) as in Eq. 2.1:

$$AE = \frac{Y_t - Y_c}{F} \quad (2.1)$$

where  $Y_t$  is the grain yield ( $\text{kg ha}^{-1}$ ) from the treatment plot,  $Y_c$  is the grain yield ( $\text{kg ha}^{-1}$ ) from the control plot, and  $F$  refers to the fertilizer input ( $\text{kg ha}^{-1}$ ). We computed the AE of N, P, and K, and thus, yielding three agronomic efficiencies (AE–N, AE–P, and AE–K). The total number of observations used for calculating AE–N, AE–P, and AE–K were 2145, 1897 and 1799, respectively.

### 2.2.4 Random forest modelling

RF is an ensemble-tree technique developed by Breiman (2001). It predicts the dependent variable by averaging decision tree predictions. Each tree is trained using a bootstrap sample from the training set and using a randomly sampled subset of the predictor variables. Each branch node in a tree represents a choice between two alternatives, and each leaf node represents a decision. The RF can identify linear and non-linear relationships between variables for classification and regression purposes. We used RF for regression to predict maize yield and AE from the predictor variables. All predictor variables (Table 2.3) were considered in predicting yield, but for AE, fertilizer application rates were excluded. Fertilizer application was not used as a predictor variable for predicting the agronomic efficiencies as this is used in the definition of the AE (see Eq. 2.1). Predictor variables with zero and near-zero variance were not used for the RF predictions. Figure 2.2 provides an overview of the RF modelling process used in this study.



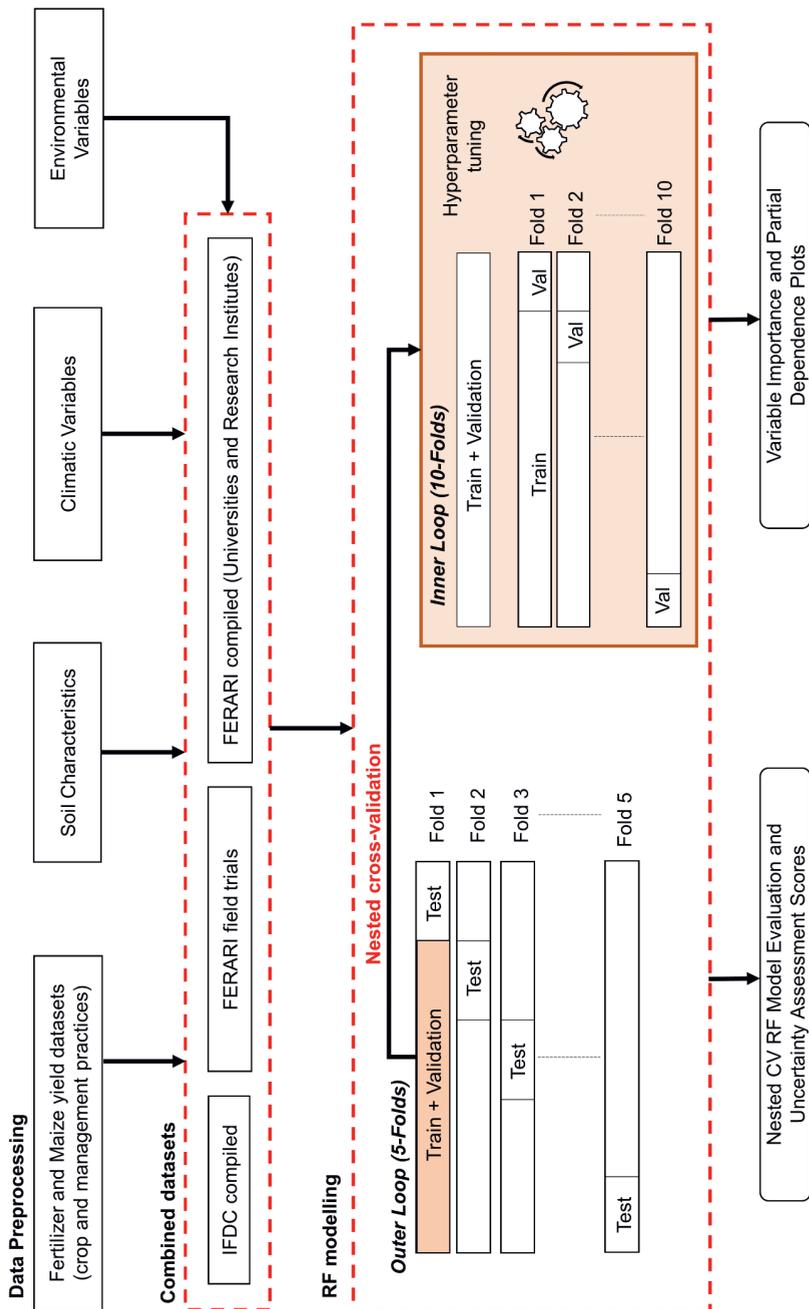


Figure 2.2: Flow diagram for the RF modelling.

#### 2.2.4.1 Hyperparameter tuning and model evaluation

Hyperparameter tuning aims at finding the optimal set of hyperparameter values that maximize the model's predictive performance (Joo et al., 2022). We conducted a full cartesian grid search for the hyperparameters (Table 2.5) using a nested cross-validation (Boehmke and Greenwell, 2019). The number of trees in the forest was not optimized but set to a sufficiently large value (1000 trees) to ensure that it did not decrease the predictive performance (Probst et al., 2018).

The performance of the models was evaluated using a  $5 \times 10$ -fold nested cross-validation approach. Nested cross-validation is a technique for performing hyperparameter tuning and model evaluation on separate datasets. It ensures that the test data are not in any way used in the modelling and hyperparameter estimation. In this way, unbiased estimates of the model performance metrics can be obtained (Pejović et al., 2018). The steps followed for the  $5 \times 10$  nested cross-validation implementation are outlined as follows:

- i. The data were repeatedly split into an outer and inner loop. The outer loop was used for evaluating the model, while the inner loop was used for hyperparameter tuning. In the outer loop, the data were split into 5-folds and each fold was once held out as a test dataset, while the remaining 4-folds were merged.
- ii. Each of the 4 merged outer folds was split into 10 inner folds for training and hyperparameter estimation. We trained the model on a merge of 9 inner folds and evaluated the performance for each hyperparameter combination on the remaining inner fold. The process was repeated 10 times so that each inner fold was used once. In other words, for each combination of hyperparameters, we performed 10-fold cross-validation on the inner folds and recorded the average performance across all 10-folds.
- iii. The hyperparameters of the RF algorithm with the highest frequency based on performance in the 10-fold inner cross-validation were selected.
- iv. The selected hyperparameters were used to calibrate the model on 4 outer folds and tested on the remaining outer fold, and the predictions recorded. This was done 5 times, so that all folds were used for testing once.

**Table 2.5:** Overview of the RF hyperparameters and their values included in optimization.

Hyperparameter	Description	Evaluated values
Mtry	Number of randomly drawn candidate variables in each split for growing a tree	$\sqrt{V}$ , 25 %, 33.3 % and 40 % of V
Node size (minimum.node.size)	Minimum number of observations in a terminal node	1, 3 and 5
Replace	Sampling approach	TRUE (sample with replacement) and FALSE (sample without replacement)
Sample.fraction	Fraction of observations in the calibration dataset to sample in each tree	0.50, 0.63 and 0.80

V: number of predictor variables.

#### 2.2.4.2 Model evaluation

We used the mean error (ME), the root mean square error (RMSE), and model efficiency coefficient (MEC) as evaluation metrics to assess the performance of the RF algorithm for yield and AE prediction based on the test data. The ME measures the systematic difference between the predicted and measured values as shown in Eq. 2.2. The RMSE measures the average magnitude of the errors in the predictions as shown in Eq. 2.3. The MEC measures how well a model predicts the dependent variable compared to just taking the average of the test data, as shown in Eq. 2.4. A MEC of 1 indicates perfect model performance, while a value of 0 indicates that the model has poor performance and does not improve on taking the average. The performance of the models was also visualized using scatter density plots of predicted against measured values.

$$ME = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i) \quad (2.2)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (2.3)$$

$$MEC = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (2.4)$$

where  $n$  is the number of trial plots,  $y_i$  and  $\hat{y}_i$  are the measured and predicted dependent variable at the  $i$ -th trial plot, respectively, and  $\bar{y}$  is the mean of the measurements.

### 2.2.4.3 Uncertainty quantification

To quantify the uncertainty of the RF algorithm predictions for yield and AE, we used QRF (Meinshausen, 2006). QRF generates the quantiles of the conditional probability distribution of the variable of interest. From these quantiles, we computed prediction intervals (PI) to measure the uncertainty of the predictions. The 90% prediction interval (PI90) was computed using the 0.05 and 0.95 quantiles of the conditional distribution. The width of the PI90 was then calculated as shown in Eq. 2.5.

$$PIW = q_{0.95} - q_{0.05} \quad (2.5)$$

The PIW represents the uncertainty associated with each model prediction. To evaluate these uncertainty estimates, PIs were defined for various prediction levels, and the Prediction Interval Coverage Probability (PICP) was calculated for each level. The PICP measures the proportion of true measurements that fall within a PI (Solomatine and Shrestha, 2009) and it assesses whether the PI accurately represents the prediction uncertainty. For instance, approximately 90% of the test data are expected to fall within the PI90, that is the 90% prediction interval, indicating that ideally the PICP of the PI90 should be 0.90. Therefore, a substantially smaller or bigger PICP than the nominal value indicates that the model is not providing reliable uncertainty estimates. Multiple PICPs were calculated for different PI levels to evaluate the reliability of the entire predictive distribution. Accuracy plots were utilized to provide a graphical assessment of the model's performance for all PI levels (Goovaerts, 2001). Ideally, the PICP line shown in an accuracy plot should be close to the 1:1 line (Malone et al., 2017). A PICP line below the 1:1 line indicates an underestimation of prediction uncertainty, a PICP line above the 1:1 line suggests an overestimation of prediction uncertainty (Kasraei et al., 2021).

### 2.2.4.4 Variable importance and partial dependence plots

In addition to making predictions, RF also provides information about variable importance, which is useful for model interpretation. Identifying the most important predictor variables gives insight into the underlying mechanisms, although one must be careful when interpreting these because they do not necessarily reflect causal relationships. We implemented the permutation-based approach to determine the variable importance of each predictor variable (Strobl et al., 2007).

We also used partial dependence plots (PDPs) (Friedman, 2001) to gain insight into the impact of the topmost important variables on yield and AE as determined by the RF algorithm. Partial dependence plots visually depict the functional relationship between a predictor variable of interest and the dependent variable (i.e., yield and AE), while controlling for the effect of other predictor variables (Friedman, 2001). The partial dependence is estimated by marginalizing the predicted targets based on the distribution of the other predictor variables. Therefore, the PDP illustrates how the dependent variable changes with changes in the selected predictor variable.

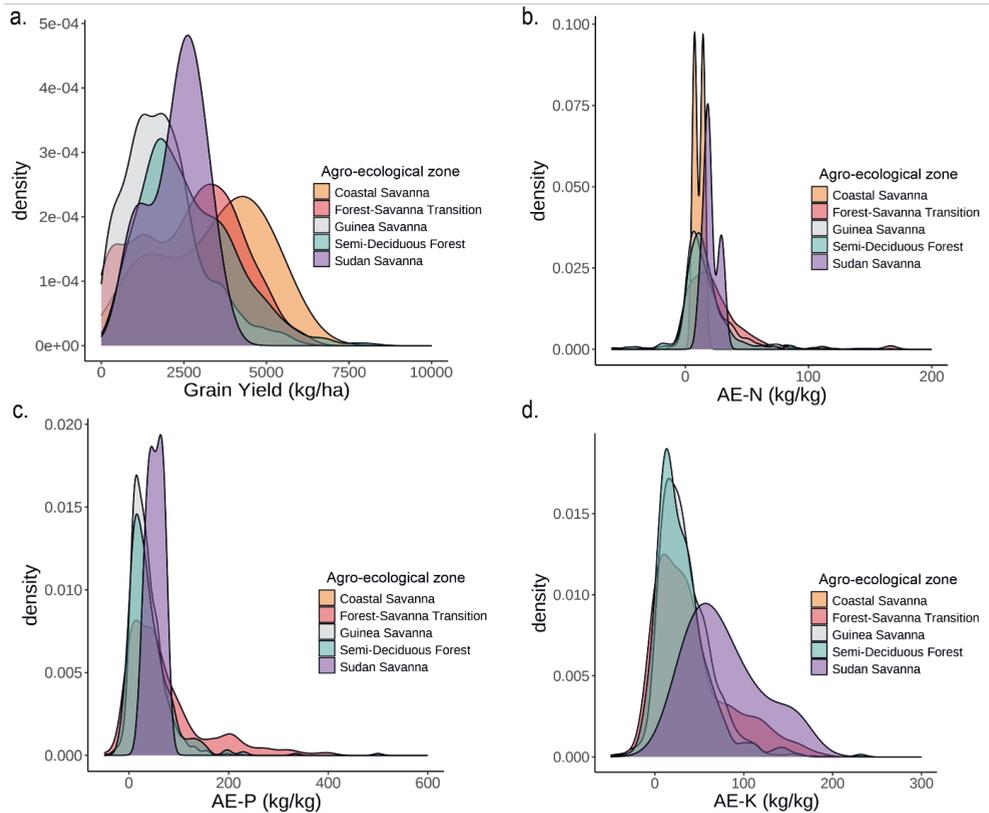
### **2.2.5 Software implementation**

Data preprocessing, exploratory data analysis and modelling were done using the R software for statistical computing (version 4.2.3) (R Core Team, 2024) integrated with RStudio. Data cleaning, handling and structuring were performed using the tidyverse and dplyr packages (Wickham et al., 2019). Data exploration was done using the dlookr package (Rhu, 2022). Handling of spatial and raster datasets was performed using the terra package (Hijmans, 2024). Graphics and visuals were created with the base R package and ggplot2 (Wickham et al., 2019). The caret (Kuhn et al., 2022) and ranger (Wright and Ziegler, 2017) packages were used to build the RF algorithm. We used the ranger package with ‘quantreg’ to apply the quantile regression forest approach to quantify prediction uncertainties. We use the pdp package in R to calculate the PDPs for our analysis.

## **2.3 Results**

### **2.3.1 Descriptive statistics of the datasets: dependent and predictor variables**

The search for data on maize trials conducted across Ghana’s agro-ecological zones yielded data from 3136 plots. As explained in Section 2.2.1, the compiled data from research institutes and universities contained some missing data, mostly for soil properties, which were filled with information from soil property maps for Ghana developed by CSIR-SRI. The gap filling percentages for soil properties, namely phosphorus, exchangeable potassium, calcium, magnesium; pH, soil organic carbon, and total nitrogen, were 25%, 21%, 30%, 31%, 17%, 20%, and 17%, respectively. Table 2.6 shows that the number of measurements for the AE variables were lower than for yield, since these were derived from comparing the yield at a nutrient treatment plot with that of a control plot, as explained in Section 2.3. The median grain yield across all experimental plots was 2000 kg ha<sup>-1</sup> (Table 2.6), with yield ranging from 11 kg ha<sup>-1</sup> to 8230 kg ha<sup>-1</sup> (Table 2.6, Figure 2.3a). Summary statistics and boxplots of the yield and agronomic efficiencies for different values of the predictor variables are presented in Table 2.6 and Tables SI 6–12 and Figures SI 1–3, respectively.



**Figure 2.3:** Density plots of a) maize yield, b) AE-N, c) AE-P, and d) AE-K across the agro-ecological zones of Ghana.

**Table 2.6:** Summary statistics of yield, AE and continuous-numerical predictor variables included in the RF yield and AE modelling.

Class	Variables	Unit	n	Min	Q1	Mean	Median	Q3	Max	SD	IQR	Skewness
Dependent variables	Grain yield	kg ha <sup>-1</sup>	3136	11	1238	2222	2000	3050	8230	1337	1811	0.7
	AE-N	kg kg <sup>-1</sup>	2145	-66.6	6.3	18.8	14.1	25.0	222.2	22.5	18.8	2.8
	AE-P	kg kg <sup>-1</sup>	1897	-57.6	13.5	43.0	31.6	56.3	606.7	50.1	42.8	3.4
	AE-K	kg kg <sup>-1</sup>	1799	-57.6	12.5	34.2	27.9	48.9	335.0	32.4	36.4	1.8
Predictor variables	Climate											
	T min PS	°C	3136	18.0	21.8	22.3	22.3	22.7	31.9	0.9	0.9	1.9
	T max PS	°C	3136	27.0	30.0	30.9	31.0	31.0	40.0	1.3	1.0	0.8
	RH mean	%	3136	61.9	78.8	78.8	78.8	78.8	90.0	3.5	0.0	-0.7
	RA PS	mm	3136	441	593	707	724	825	940	142	232	-0.3
	AR	mm	3136	810	1276	1276	1276	1276	1723	104	0	-0.1
Soil	Av ET	mm	3136	103.9	136.2	136.2	136.2	136.2	156.1	5.1	0.0	-2.7
	pH	-	3136	4.1	5.7	5.9	6.0	6.1	7.3	0.4	0.4	-0.6
	SOC	%	3136	0.16	0.55	0.84	0.68	0.82	4.30	0.63	0.27	3.4
	Total N	%	3136	0.0	0.06	0.07	0.07	0.07	0.30	0.03	0.02	2.2
	CEC	cmol+ kg <sup>-1</sup>	3136	0.08	5.39	7.44	6.29	7.45	82.90	7.79	2.06	8.7
	Av P	mg kg <sup>-1</sup>	3136	0.0	3.7	24.5	18.1	23.9	379.5	57.2	20.2	5.5
	Ex K	cmol+ kg <sup>-1</sup>	3136	0.01	0.12	1.79	0.22	1.79	37.0	5.98	1.67	5.5
	Ex Ca	cmol+ kg <sup>-1</sup>	3136	0.09	0.14	1.51	1.52	1.52	11.71	1.66	1.38	2.2
	Ex Mg	cmol+ kg <sup>-1</sup>	3136	0.02	0.06	0.49	0.49	0.49	3.40	0.52	0.43	1.8
	Sand	%	3136	40.0	58.8	64.8	64.8	70.5	93.0	8.4	11.7	0.0
Clay	%	3136	4.0	16.2	22.5	22.4	29.8	52.0	9.1	13.6	0.2	
Silt	%	3136	2.2	14.1	21.9	23.2	27.1	48.1	8.8	13.0	0.0	

BD	g cm <sup>-3</sup>	3136	1.12	1.21	1.34	1.34	1.47	1.67	0.13	0.26	0.1
TEB	cmol <sub>c</sub> kg <sup>-1</sup>	3136	0.18	0.40	0.41	0.41	0.41	0.81	0.10	0.0	2.1
RZWHC	cm	3136	9.0	10.4	10.4	10.4	10.4	13.0	0.5	0.0	0.4
BS	%	3136	24.1	49.6	49.5	49.6	49.6	82.3	10.5	0.0	0.1
CsFrg	%	3136	13.0	38.2	44.1	45.2	49.9	59.6	9.0	11.6	-0.8
Ex Na	cmol <sub>c</sub> kg <sup>-1</sup>	3136	0.11	0.18	0.26	0.22	0.26	1.47	0.16	0.08	4.5
EC	mS m <sup>-1</sup>	3136	0.05	0.14	1.21	0.17	1.21	34.22	3.36	1.07	6.7
Zn	mg kg <sup>-1</sup>	3136	0.3	1.5	1.8	1.8	1.8	8.5	1.3	0.4	3.3
Fe	mg kg <sup>-1</sup>	3136	1.4	33.7	33.7	33.7	33.7	115.9	14.4	0.0	1.3
Zn	kg ha <sup>-1</sup>	3136	0	0	0	0	0	10	1	0	2.3
S	kg ha <sup>-1</sup>	3136	0	0	2	0	0	15	5	0	2.0
Fe	kg ha <sup>-1</sup>	3136	0	0	0	0	0	5	1	0	3.6
N	kg ha <sup>-1</sup>	3136	0	18	67	60	120	281	51	102	0.2
P <sub>2</sub> O <sub>5</sub>	kg ha <sup>-1</sup>	3136	0	0	24	20	40	120	22	40	0.6
K <sub>2</sub> O	kg ha <sup>-1</sup>	3136	0	0	24	25	40	120	23	40	0.5
Environment Slope	%	3136	0.0	0.6	1.3	0.9	1.7	6.0	1.2	1.1	2.1
NDVI	-	3136	0.2	0.4	0.4	0.4	0.4	0.6	0.1	0.0	-0.8

n: Sample size, Min: minimum, Q1: first quartile, Q3: third quartile, Max: maximum, SD: Standard Deviation, IQR: inter-quartile range, AE-N: Agronomic efficiency of nitrogen, AE-P: Agronomic efficiency of phosphorus, AE-K: Agronomic efficiency of potassium, T min PS: minimum temperature in planting season, T max PS: maximum temperature in planting season, RH mean: mean relative humidity, RA PS: total rainfall amount in planting season, AR: total annual rainfall, Av ET: average evapotranspiration, SOC: soil organic carbon, Total N: soil total nitrogen, CEC: cation exchange capacity, Av P: soil available phosphorus, Ex K: exchangeable potassium, Ex Ca: exchangeable calcium, Ex Mg: exchangeable magnesium, BD: bulk density, TEB: total exchangeable bases, RZWHC: root zone water holding capacity, BS: base saturation, CsFrg: coarse fragment, Ex Na: exchangeable sodium, EC: electrical conductivity, Zn: Zinc, Fe: Iron, S: Sulphur, N: nitrogen, NDVI: normalized difference vegetation index. See Supplementary Information for explanation of the variables.



### 2.3.2 RF modelling

#### 2.3.2.1 Best RF tuning hyperparameters for yield and agronomic efficiency

A 10-fold cross-validation was used to optimize the hyperparameters of the RF algorithm for yield and agronomic efficiency. A full Cartesian grid search was employed to search for the best combination of hyperparameters. The optimized parameters are presented in Table 2.7.

**Table 2.7:** Optimized hyperparameter combination selected by maximum occurrence in the  $5 \times 10$ -fold nested cross-validation for yield and agronomic efficiency RF modelling.

RF Algorithms		Yield	AE-N	AE-P	AE-K
Hyperparameters	mtry	6	5	5	5
	minimum node size	3	5	5	5
	replace	FALSE	FALSE	FALSE	FALSE
	sample.fraction	0.8	0.8	0.8	0.8

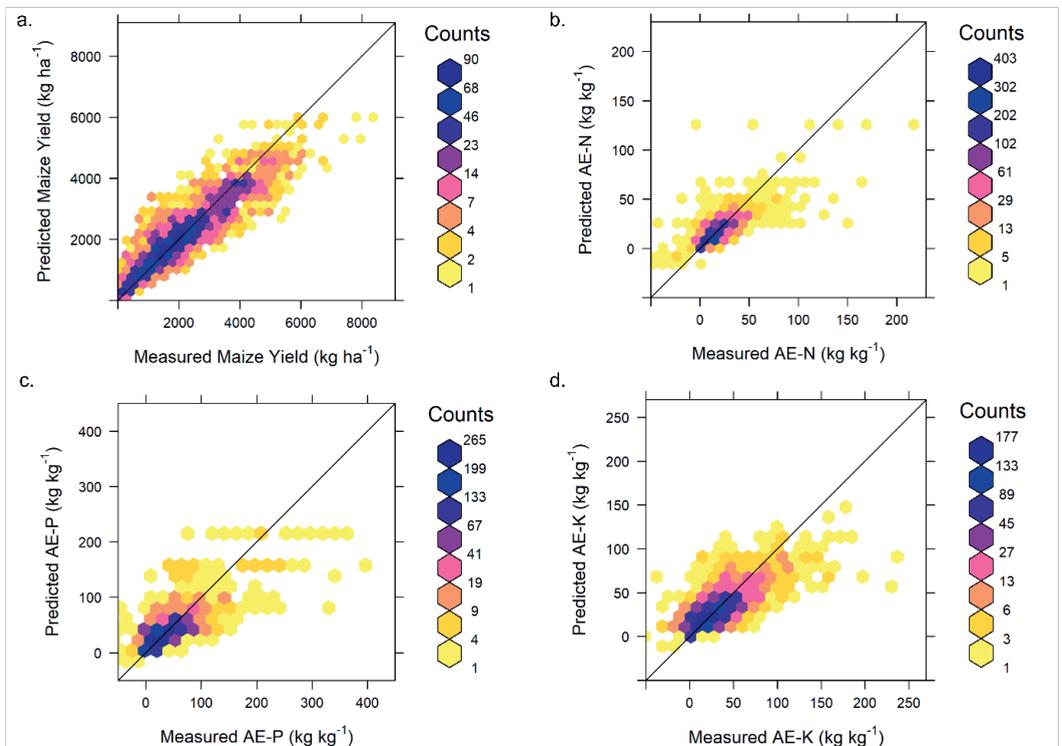
#### 2.3.2.2 Predictive performance

The results of the four RF models (yield, AE-N, AE-P, and AE-K) showed varying performance on the test data (Table 2.8 and Figure 2.4). The yield model showed that systematic errors in the yield predictions were small as the ME was  $0.185 \text{ kg ha}^{-1}$  and negligibly small compared to the RMSE. The mean errors for the agronomic efficiency of N, P and K models were also small (i.e., nearly zero), showing unbiased predictions. The RMSE for the yield model was  $582.2 \text{ kg ha}^{-1}$ , which is substantial but considerably smaller than the yield standard deviation of  $1337 \text{ kg ha}^{-1}$  (Table 2.6). The RMSEs for the agronomic efficiency models ranged from 13.7 to 33.5, with AE-N having the smallest RMSE and AE-P, the largest RMSE. The MECs for all AE models ranged between 0.54 and 0.63, while the yield model had the highest MEC with the model explaining 81% of the variance.

**Table 2.8:** RF algorithm performance for maize yield and agronomic efficiency predictions.

RF Algorithms		Yield	AE-N	AE-P	AE-K
		(kg ha <sup>-1</sup> )	(kg kg <sup>-1</sup> )	(kg kg <sup>-1</sup> )	(kg kg <sup>-1</sup> )
Model performance	ME	0.185	0.001	-0.017	-0.005
metric	RMSE	582.2	13.7	33.5	22.0
	MEC	0.810	0.630	0.554	0.536
Uncertainty	PICP of	89.9	83.3	82.4	82.5
assessment	PI90				

ME: mean error, RMSE: root mean squared error, MEC: model efficiency coefficient, PICP of PI90: 90 % prediction interval coverage probability.

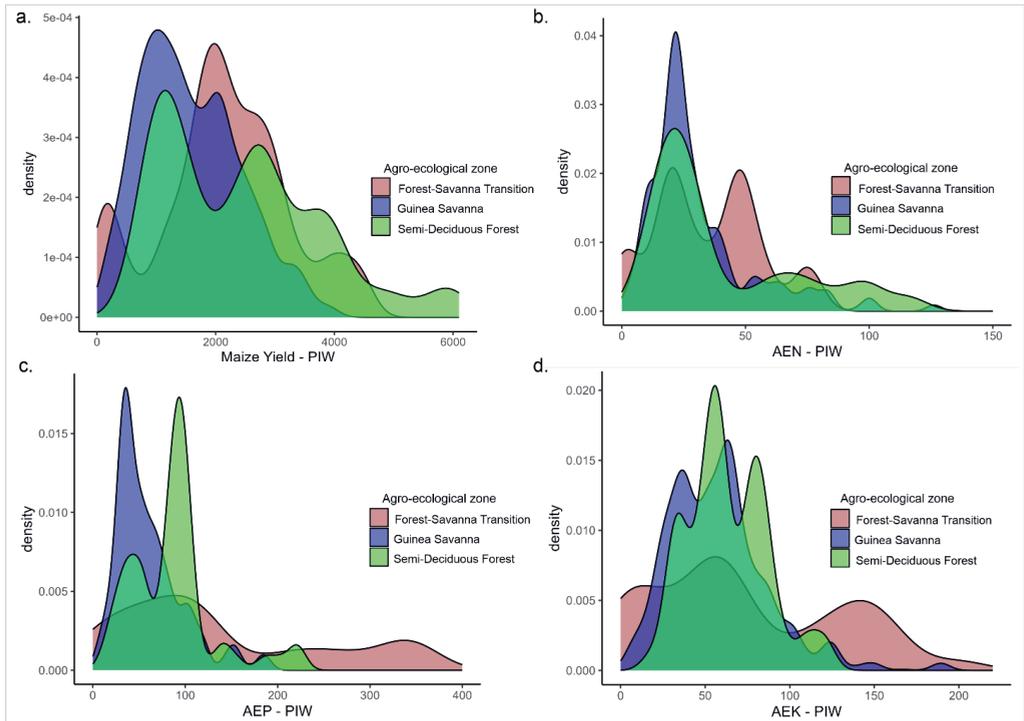


**Figure 2.4:** Scatter density plots (predicted vs measured) of RF algorithm for a) Maize yield, b) AE-N, c) AE-P, d. AE-K.

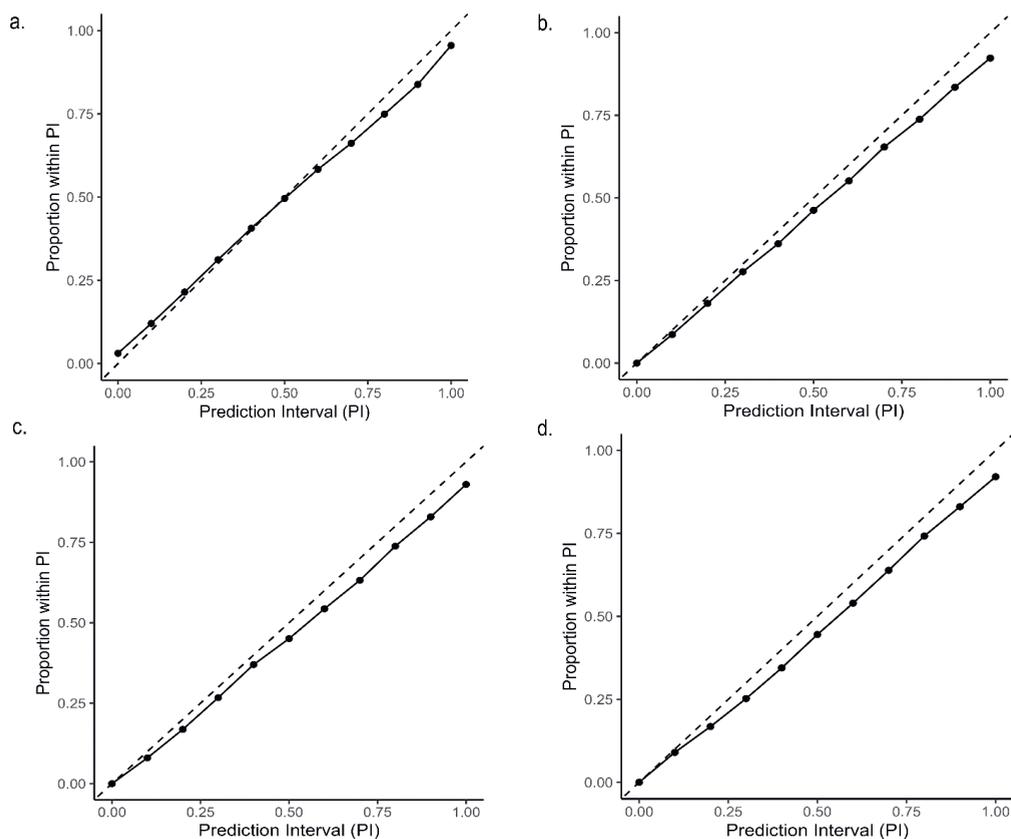
### 2.3.2.3 Uncertainty assessment

Figure 2.5 shows frequency distributions of the PIW for the predicted yield and agronomic efficiency for the three major maize production agro-ecological zones of Ghana. The figure shows that the PIW distribution for yield is fairly symmetrical while those of the agronomic efficiencies are right-skewed. This indicates that for agronomic efficiencies, the prediction intervals are very wide in some cases, particularly for the FST and SDF zones. The PIW distributions of yield are also fairly wide, in particular for the FST and SDF zones (Figure 2.5a), indicating that there are large differences in prediction uncertainty between sites in each zone. The mean and median of the PIW for yield for GS are smaller than those for FST, which implies that for GS the PIW is generally smaller. This indicates that yield predictions in GS tend to be more accurate than for FST (Figure 2.5a). Figures 2.5b, c, and d indicate that the PIW distributions of AE-N, AE-P, and AE-K are widest and right-skewed for the FST zone, indicating that AE predictions in the FST zone are less accurate than in other zones. The distribution of AE-N within the SDF zone shows a larger mass towards zero than for AE-P and AE-K. This indicates that in this zone the AE-N predictions are more accurate than the AE-P and AE-K predictions. Figure 2.5c shows that AE-P predictions have the lowest uncertainty in the GS zone and the highest uncertainty in the FST zone.

The PICP of PI90 measures the proportion of test values that fall within the 90% prediction interval. The PICP of PI90 for the yield model was 89.9%, indicating that the prediction uncertainties were realistically quantified. The PICP of PI90 for the agronomic efficiency of N, P, and K models ranged from 82.4% to 83.3%, indicating that the models somewhat underestimated the uncertainties (Table 2.8). Figure 2.6b – d shows that the prediction uncertainty for AE-N, AE-P, and AE-K was underestimated for all PIs. For yield the PICP values were much closer to the 1:1 line, although PIs lower than 0.30 slightly overestimated the prediction uncertainty and PIs above 0.60 slightly underestimated the prediction uncertainty (Figure 2.6a).



**Figure 2.5:** Frequency distribution of PIW90 for a) maize yield prediction across the three major agro-ecological zones, b) AE-N across the three major agro-ecological zones, c) AE-P prediction across the three major agro-ecological zones, d) AE-K prediction across the three major agro-ecological zones.



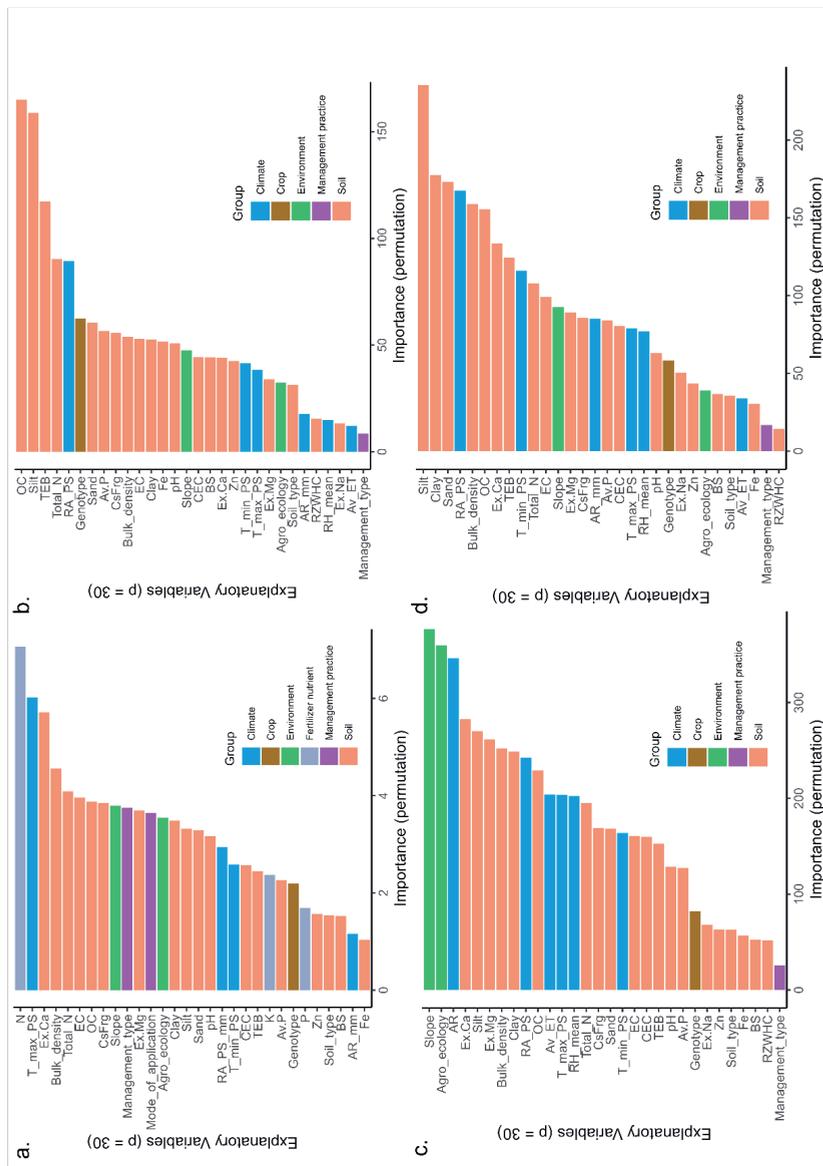
**Figure 2.6:** Accuracy plots for PICP of all measurements for a) maize yield, b) agronomic efficiency of nitrogen, c) agronomic efficiency of phosphorus, and d) agronomic efficiency of potassium.

#### 2.3.2.4 Relative importance of predictor variables for maize yield and agronomic efficiency predictions

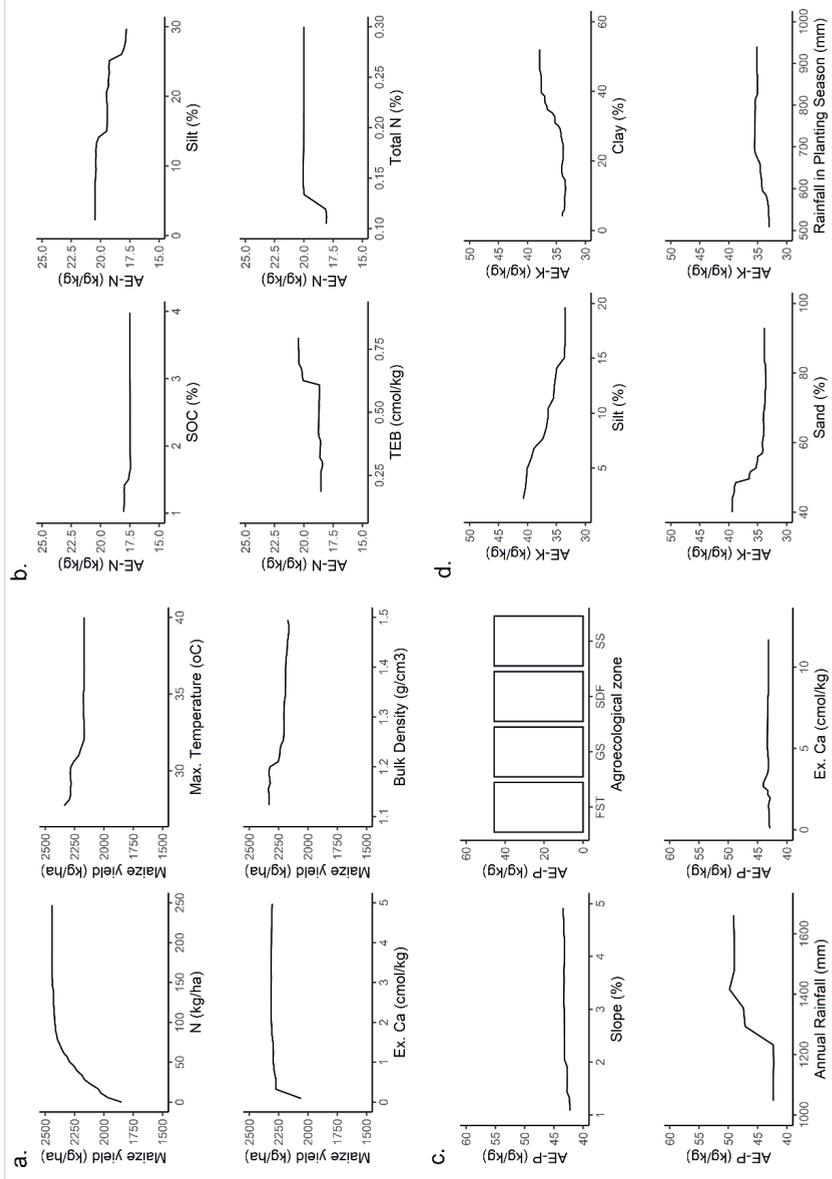
The variable importance plot (Figure 2.7) shows the influence of fertilizer nutrients, soil properties, climatic and environmental variables, crop parameters, and management practices on yield and agronomic efficiency predictions. Figure 2.7a shows that maize yield is primarily influenced by the amount of nitrogen fertilizer applied, maximum temperature during the planting season, and exchangeable calcium content of the soil. Bulk density, total nitrogen content, electrical conductivity, and soil organic carbon content follow in importance, indicating that soil is an important predictor variable with 5 out of 7 most important variables. The slope of the terrain, management type, and mode of fertilizer application are also identified as key variables for predicting maize yield. Figures 2.7b - d reveal that soil organic carbon, soil texture (with silt being the most influential, followed by clay and sand), the amount of rainfall received during the planting season, and bulk density are important

predictor variables for all three agronomic efficiencies. However, there are also notable differences. Slope and agro-ecological conditions are the most important variables for AE-P, while they rank much lower for AE-N and AE-K. A similar observation can be made for total annual rainfall, which is highly important for AE-P but less so for AE-N and AE-K. The variable importance plots show that soil properties contribute the most to yield and agronomic efficiency, followed by climate, crop, and environmental conditions.

The PDPs for yield, AE-N, AE-P, and AE-K are shown in Figures 2.8a, b, c and d, respectively. Not surprisingly, nitrogen fertilizer has a positive relationship with maize yield, which increases from 1800 to 2400 kg ha<sup>-1</sup> as the rate of nitrogen fertilizer increases from 0 to 90 kg ha<sup>-1</sup> across all agro-ecological zones (Figure 2.8a). Increasing the nitrogen application rate even further does not lead to a higher model predicted yield as the PDP curve levels off at nitrogen application rate of 90 kg ha<sup>-1</sup>. An increase in maximum temperature above 30°C leads to a decrease in the yield, as can be seen in the negative relationship between yield and maximum temperature (Figure 2.8a). Figure 2.8a shows that there is no significant relationship between exchangeable calcium and maize yield, except for small values of exchangeable calcium, which leads to lower yields. The relation between bulk density and yield is also negative, which could be due to soils rich in organic matter and nutrients tending to have lower bulk density. Figure 2.8b shows that soil organic content (SOC) above 1.5% has no significant effect on AEN. Silt has a marginal negative effect on AE-N, because AE-N starts to decrease when the silt content of the soil increases from 10 to 30%. The PDPs of the RF algorithms for AE-P and AE-K show a positive relationship between these AEs and rainfall (Figures 2.8c and 2.8d). AE-P is constant across all agro-ecological zones even though it ranked second in variable importance. Calcium has no significant effect on AE-P (Figure 2.8c) whilst increase in silt content leads to decrease in AE-K (Figure 2.8d).



**Figure 2.7:** Variable importance plot from RF algorithm determined by the permutation method for: a) maize yield prediction using 3136 data points, b) AE–N prediction using 2145 data points, c) AE–P prediction using 1897 data points, and d) AE–K prediction using 1799 data points.



**Figure 2.8:** Partial dependence plot of a) maize yield, b) AE-N, c) AE-P, and d) AE-K for the top 4 ranked predictor variables from the variable importance of the RF algorithm. The x-axis plots the range of the predictor variables from the 5 to the 95 percentiles.



## 2.4 Discussion

### 2.4.1 Evaluation of RF algorithm performance and uncertainty assessment for crop production

Nested cross-validation is advantageous in model evaluation as it mitigates the risk of overfitting and provides a more unbiased estimate of model performance (Dinh et al., 2022). By using an outer loop to split the data into training and test sets, and an inner loop for hyperparameter tuning and model selection, it ensures that the test set remains completely independent of the model evaluation process (Dinh et al., 2022). This separation is crucial for obtaining realistic performance metrics, as it simulates the real-world scenario where the model encounters unseen data. The robustness of this method lies in its ability to repeatedly test the model on multiple different splits of the data, thus giving a comprehensive view of how the model is likely to perform in practice. The results from the nested cross-validation of this study provided a robust model evaluation approach and demonstrated that the RF algorithm was effective in predicting yield with a MEC of 0.81 and RMSE of 582 kg ha<sup>-1</sup>, which is akin to other studies that used RF for crop yield prediction. The RF algorithm's effectiveness can be attributed to its ability to handle large datasets with high-dimensional features which makes it particularly suited for agricultural data, which often include a multitude of variables such as soil properties, weather conditions, and management practices (Ramos et al., 2020). For example, Ramos et al. (2020) obtained a MEC of 0.78 and RMSE of 835 kg ha<sup>-1</sup> when modelling maize yield in Brazil, which indicates that our RF model performed slightly better. This could be due to the larger number of predictor variables included in our study. Similarly, Jeong et al. (2016) found that including more predictor variables in RF predictions improved the accuracy of the model. While the yield model developed in this study performed well, prediction performance for agronomic efficiency of N, P, and K prediction was lower, with MECs ranging from 0.54 to 0.63. Apparently, the predictor variables did not explain the spatial variation of agronomic efficiencies well. This may be due to the fact that in many cases, the response of the crop to fertilizer application was not strong. This observation corroborates with that of Zingore et al. (2022), who also observed that in plots where soil fertility was high, applying more fertilizer did not have a significant effect on yield. We accounted for this by including soil nutrient concentrations as predictor variables in the RF model, but it remained challenging to predict AE from the predictor variables. Nonetheless, all AE models explained more than half of the AE variance and are therefore considered useful, despite the significant prediction uncertainty.

We did not include fertilizer application as a predictor variable in modelling AE because it would be awkward to include a predictor variable that is already part of the definition of the AE (Eq. 2.1). For example, if we used N application as a predictor variable, it would make more sense to predict yield gain using a RF model and then divide the result by the known N application to obtain a prediction of AE-N, rather than predicting AE-N directly from a model that includes N application and other predictor variables. This would allow us to better utilize the known N application. While this approach could

potentially improve model performance, it was outside the scope of this research. Including fertilizer application as a predictor variable would likely have a high impact on AE predictions and diminish the effect of other predictor variables, whereas this study focused mainly on the influence of these predictor variables on AE. Therefore, we recommend that future research compare machine learning prediction of AE with and without including fertilizer application as a predictor variable. It is important to note that including fertilizer application as a predictor variable means that AE predictions are dependent on the fertilizer application rate, resulting in AE prediction that are not constant but vary with N, P, and K application rates.

The optimized hyperparameter used to predict yield resulted in an RF algorithm that explained 81% of the variation in the data (Table 2.8). However, despite the optimized hyperparameters being the same for the agronomic efficiencies, the models explained different amounts of variation, ranging from 54 to 63%. A study by Schratz et al. (2019) reported no significant effect of hyperparameter tuning in RF modelling and concluded that the RF algorithm often produces accurate results with default hyperparameter values. We observed that the default hyperparameters for the RF algorithm in our study performed similarly to models with optimized hyperparameters (results not shown). This suggests that, in this study hyperparameter tuning was not a crucial step in RF modelling.

The PIW and PICP results obtained using the RF algorithm for yield prediction showed that the prediction uncertainty was realistically quantified. However, the assessment of uncertainty for agronomic efficiencies showed greater deviations from the ideal value, indicating that the models were less reliable in quantifying uncertainties compared to yield prediction. This could be attributed to the fact that the models for agronomic efficiencies were trained on a skewed dataset that had many extreme values (Table 2.3). Additionally, we observed that the PIW assessment for the agronomic efficiencies in the GS was narrower compared to the FST and SDF zones. This observation may be explained by the model performing more accurately within a zone that had a greater number of trial data, for example, in the case of the GS zone (Figure 2.1; Table SI 12) and a more even distribution within the zone. On the other hand, the FST and SDF agro-ecological zones had fewer field trials data and a less uniform distribution across the zones (Figure 2.1; Table SI 12). These zones also exhibited less local spatial distribution, making accurate predictions more challenging. Our findings support those of Poggio et al. (2021), who reported that uncertainties in the model's predictions were predominantly large in areas with substantial spatial variability and limited data points to capture the spatial variations. Areas with high uncertainty predictions can lead to risk-aversion behaviour among farmers or stakeholders, potentially limiting the adoption of innovative practices. This can result in suboptimal resource allocation leading to lower productivity. For example, if a model predicts crop yield with high uncertainty in a certain zone, farmers may be reluctant to invest in inputs such as fertilizers or high-quality seeds, etc., due to concerns about returns on investment. Farmers can make better informed decisions based on such models' results to avoid incurring significant losses. To improve model

predictions in such zones, the limited data available should be improved with more data for model calibration.

#### **2.4.2 Implications of variable importances for yield and agronomic efficiency for sustainable agriculture**

Figure 2.7 showed the importance of soil exchangeable calcium in driving maize yields and agronomic efficiency of N, P, and K, as this parameter ranked high in determining all four dependent variables, possibly due to the crucial role it plays in stabilizing soil aggregates and in improving soil structure (Edlinger et al., 2023) to enhance nutrient availability for plant uptake. Our findings corroborate a review by Zingore et al. (2022) which identified exchangeable calcium as one of the important determinants of maize yields in SSA. In a study by Mtangadura et al. (2017), the authors identified that a decline in maize yields was linked to the depletion of soil exchangeable Ca, Mg, and K. The deficiency of calcium in the soils of Ghana, as a result of nutrient leaching, leads to decreased pH levels. Agyin-Birikorang et al. (2022) found that applying 2.5 t ha<sup>-1</sup> lime to acidic soils in the GS agro-ecological zone of Ghana improved soil fertility and increased yield coupled with improved efficiency of fertilizer applied. Our study also revealed that rainfall during the planting season plays a significant role in maize yield and agronomic efficiency (Kihara and Njoroge, 2013). Since most cropping systems in SSA are rainfed, the inclusion of supplementary irrigation could be beneficial, especially in the context of climate change (Biazin et al., 2012).

The role of soil texture in influencing maize yields and agronomic efficiencies of N, P, and K was evident in our results, supporting the findings by (Kihara and Njoroge, 2013) who observed increased phosphorus agronomic efficiency as a result of higher soil silt content. Soil texture, due to its impact on the physical and chemical properties of the soil viz. water-holding capacity, aeration, nutrient availability, and root growth, is an important consideration in crop production. The dominant soil types (e.g. Lixisols) in the GS agro-ecological zone (Figure SI 4), generally have sandy to sandy loam textures, which are susceptible to nutrient leaching due to low soil organic carbon content (Osman, 2013). Consequently, our results also clearly indicate the role of soil organic carbon in yield and agronomic efficiency (Zingore et al., 2021). In this study nitrogen fertilizer application emerged as the most important determinant of yield due to its crucial role in plant growth. Our findings corroborate with those of Saito et al. (2021), who identified nitrogen as the most yield-limiting nutrient, and Zingore et al. (2022), who found that nitrogen application accounted for the largest yield response in maize production in SSA. This emphasizes the need for effective nitrogen management in cropping systems in SSA to enhance crop productivity for sustainable agriculture (Bonilla-Cedrez et al., 2021; Davies et al., 2020; Yousaf et al., 2021).

The agronomic efficiency of nitrogen was mainly influenced by soil organic carbon, confirming the findings of Logah et al. (2020) and Owusu et al. (2020), who call for remedial measures of soil organic matter management in cropping systems. Our analysis suggests that adequate increase in soil organic carbon content will improve agronomic efficiencies. As an indicator of soil fertility, organic carbon plays an essential role in nitrogen agronomic efficiency (Bationo et al., 2007). Furthermore, carbon and nitrogen are stoichiometrically linked in the soil matrix. Thus, an increase in soil carbon indicates an increase in nitrogen concentration (Ndung'u et al., 2021).

The RF algorithm identified soil texture as an important variable for the agronomic efficiency of potassium, confirming an earlier study by Rosolem and Steiner (2017) who reported that in tropical soils, soil clay content plays a significant role in the movement of potassium fertilizer within the soil profile. In the context of Ghanaian soils, soil texture can have significant effects on the leaching of fertilizers. Nketia et al. (2018) noted that the GS zone of Ghana predominantly has sandy-textured soil with high permeability and low water-holding capacity, leading to high leaching losses of fertilizers and reduction in the effectiveness of fertilizers. Although soil and climatic variables were both important variables for yield prediction, the soil was identified as most important in this study. This may be due to the high soil variation in the Ghanaian landscape compared to climate (Nketia et al., 2018). Higher variation means a potentially bigger effect on yield because predictor variables that are nearly constant cannot explain spatial variation. Also, most of the maize trials' datasets did not have weather information for the location but relied on the nearest rainfall station, which lead to the climatic datasets for some experiments being the same. In contrast, most of the trials had their soil information from soil samples analyzed from the field and as such the soil variables varied from experiment to experiment, except in limited instances where some missing data were replaced with soil information from maps.

#### **2.4.3 Partial dependence analysis and implications for food security**

The partial dependence analysis was conducted based on the RF algorithm for predicting maize yield and agronomic efficiency with the resulting PDP confirming the importance of nitrogen fertilizer application in maize cultivation. The PDP for yield (Figure 2.8a) showed an increase in maize yield to 2400 kg ha<sup>-1</sup> as nitrogen fertilizer application increased to 90 kg ha<sup>-1</sup>, above which there was no more significant increase in yield. Though other factors may come into play based on local soil conditions, our findings largely confirm earlier results of Tetteh et al. (2018), recommending 90 kg N ha<sup>-1</sup> as the economic application rate for maize production in Ghana. From the PDP, we observed a decline in maize yield as temperatures exceed 30°C, possibly due to induction of physiological stress in the maize plant at high temperatures, leading to reduced growth and development. This stress can result in decreased root growth, impaired nutrient uptake, and increased susceptibility to pests and diseases,

which negatively impact maize yields. Our findings corroborate those of Waqas et al. (2021), who found maize vulnerability to heat stress ( $>30\text{ }^{\circ}\text{C}$ ) and reported a strong reduction in yield above this threshold.

Additionally, we observed that rainfall had a positive relationship with agronomic efficiency, as also reported in Vanlauwe et al. (2015). This can be explained from a direct effect of better moisture conditions on improved rooting density, improved nutrient mobility in the rooting zone, and a higher microbial activity releasing additional nutrients from soil organic matter (Vanlauwe et al., 2015). To maximize the benefits of rainfall for agronomic efficiency, several management practices can be implemented. The application of organic amendments to improve soil structure and nutrient availability, along with mulching and cover cropping to enhance soil moisture retention (Bashagaluke et al., 2019), is essential to optimize fertilizer utilization in maize production (Adzawla et al., 2024).

It is important to note that the findings above need to be interpreted with care. Our study was based on observational data and analyzed with a statistical model, which means that relations found are based on correlations and do not necessarily assess causalities (Kakimoto et al., 2022; Naser, 2021). For instance, found relations might be the result of hidden, confounding variables. To determine causalities, it would be necessary to conduct properly designed field experiments (Kakimoto et al., 2022), which is feasible for control variables such as fertilizer application and management, but much more challenging or practically impossible for other variables, such as soil texture, soil organic carbon, rainfall, temperature and evapotranspiration.

#### **2.4.4 Impact of this study**

This study applied a RF machine learning approach to predict maize yield and agronomic efficiency in Ghana and identified the most important predictor variables. Our findings suggest that the model holds significant potential for deriving site-specific fertilizer recommendations, thereby enhancing nutrient use efficiency. The results of the PDP of Figure 2.8a showed an average effect of N application on yield and suggested that, on average, an application rate of  $90\text{ kg N ha}^{-1}$  would be sensible. However, the model allows for deriving this relationship for specific locations with different conditions and values of other predictor variables. This means that for some cases,  $90\text{ kg N ha}^{-1}$  is optimal, but for other cases, this might be another rate, such as  $75\text{ kg N ha}^{-1}$  or  $100\text{ kg N ha}^{-1}$ . Indeed, the model can plot the yield response to fertilizer application for each individual case. Thus, it is a tool that can be used for deriving site-specific fertilizer recommendations. Providing site-specific targeted recommendations, reduces the risk of over-fertilization, thus preventing environmental degradation through nutrient leaching and runoff. Moreover, improved fertilizer use efficiency can translate into economic benefits for farmers by lowering input costs while maintaining or even increasing crop yields. This fosters sustainable agricultural practices by promoting responsible resource utilization and mitigating the negative ecological impacts associated with excessive fertilizer application. Furthermore, it would be very

interesting for future study to put recommendations derived from the machine learning model to the test in field experiments and compare them with existing fertilizer recommendation approaches. Again, by understanding the relationship between maize yield and agronomic efficiency and various predictor variables, this can support farmers and other stakeholders to make informed decisions to maximize yields and implement management practices towards improving agronomic efficiency. Soil variables were observed to have a substantial influence on agronomic efficiency. Hence, management practices such as application of organic amendments to improve soil condition, moisture retention with mulching and cover cropping should be incorporated into farming practices to improve soil condition for maximum efficiency. Overall, the integration of machine learning in agricultural decision-making facilitates precision agriculture approaches, promoting sustainability in modern farming practices.

#### **2.4.5 Limitations of this study**

This study demonstrated that machine learning models can contribute to improving food security in Sub-Saharan Africa by predicting yields and identifying driving factors and agronomic efficiency. This can guide stakeholders in making decisions for sustainable agriculture. However, there are limitations to this study that need to be addressed in future research. For example, the models had limited performance and could not explain all variations in yield and agronomic efficiency. This is likely because the models lacked other important predictor variables, such as agronomic practices, pest and disease infestation, and cropping history information. Unfortunately, these variables were not available in the compiled trial datasets. To address this limitation, research trials managers should report this information, and future research should collect and incorporate these predictor variables to develop more comprehensive and accurate models.

It is important to note that while the Random Forest algorithm has proven to be effective in this study, advanced machine learning models beyond Random Forest could also be applied which may lead to further improvement in prediction. These models including Extreme Gradient Boosting (Chen and Guestrin, 2016), Artificial Neural Networks (Yao, 1999), and Support Vector Machines (Cortes and Vapnik, 1995), may also enhance prediction accuracy.

Although this study was based on a fairly large dataset, a larger training dataset would be ideal. Therefore, continued efforts are needed to collect more data covering different seasons to train these models. Additionally, the quality of training data is crucial. There are significant measurement discrepancies in both the dependent and predictor variables. For example, gap filling was used for some field trial data, which affected the quality of these data. Yield data are also prone to measurement errors due to the lack of standardized protocols.

Another limitation of this study was that data-driven machine learning models cannot easily be extrapolated to situations outside the training data. Therefore, the use of the model is restricted to situations covered by the training data (Meyer and Pebesma, 2021). Applying the model for extrapolation is risky and may lead to lower performance, especially when using the model in other parts of the world or even other parts of West Africa.

## **2.5 Conclusion**

This study assessed the performance of the RF machine learning algorithm for predicting maize yield and agronomic efficiency of nitrogen, phosphorus, and potassium in Ghana and assessed the uncertainties associated with the models' predictions. We conclude that the RF machine learning algorithm can efficiently predict yield and agronomic efficiency of the nutrient using the available predictor variables. Based on the yield prediction model, we showed that nitrogen application beyond 90 kg ha<sup>-1</sup> does not lead to substantial yield increase across all agro-ecological zones of Ghana. Soil variables were important drivers of yield and agronomic efficiency, hence, management practices including application of organic amendments to improve soil condition should be incorporated into farming practices for maximum efficiency. Overall, this research provided much insight into the driving factors for maize yield and agronomic efficiencies in a tropical climate and can guide development of management and fertilizer nutrient recommendations for sustainable maize production in SSA.

## **Supplementary materials**

The supplementary materials can be downloaded from the journal version of this chapter:

Asamoah, E., Heuvelink, G. B. M., Chairi, I., Bindraban, P. S., & Logah, V. (2024). Random forest machine learning for maize yield and agronomic efficiency prediction in Ghana. *Heliyon*, 10(17), e37065. <https://doi.org/10.1016/J.HELIYON.2024.E37065>





# Chapter 3

## Fertilizer recommendations for maize production in Ghana: Comparison of machine learning, semi-mechanistic and conventional approaches

This chapter is based on:

Asamoah, E., Heuvelink, G. B., Logah, V., Leenaars, J. G., & Bindraban, P. S. (2026). Fertilizer recommendations for maize production in Ghana: Comparison of machine learning, semi-mechanistic and conventional approaches. *European Journal of Agronomy*, 174, 127925. <https://doi.org/10.1016/j.eja.2025.127925>

## **Abstract**

Efficient fertilizer application is vital for enhancing maize production and profitability in Sub-Saharan Africa, where soil fertility varies widely across regions. This study aimed to develop a machine learning approach for generating site-specific fertilizer recommendations for maize production in Ghana and to evaluate its performance against conventional and semi-mechanistic approaches. A random forest machine learning model was trained on 482 maize yield experiments, consisting of 3,136 yield observations collected from 1991 to 2020, to predict maize yield response to different fertilizer rates. The model incorporated multiple explanatory variables, including soil properties, climate conditions, and management practices, to generate fertilizer response curves from which fertilizer recommendations were derived for 14 sites across three agro-ecological zones in Ghana. These recommendations were compared with those derived from the Quantitative Evaluation of the Fertility of Tropical Soils (QUEFTS), Conventional Fertilizer Dose Response (CFDR), and Updated Conventional Fertilizer Dose Response (UCFDR) approaches and validated through field experiments. The machine learning approach generally recommended lower rates of phosphorus and potassium than the other approaches, while nitrogen recommendations were comparable. In the Guinea Savannah (GS) zone, the recommendations from the machine learning approach outperformed those from the other approaches, producing higher mean yields for three out of the four sites in the zone. In the Forest-Savanna Transition (FST) zone, the machine learning model recommendations led to higher mean yields at four sites, while the approaches based on QUEFTS and UCFDR performed best at two other sites. In the Semi-deciduous Forest (SDF) zone, the recommendations of the QUEFTS approach resulted in the highest mean yields at three sites, and CFDR at one site. Additionally, the machine learning approach-based recommendations demonstrated higher net profit margins in the GS and FST zones, suggesting cost-effectiveness in these zones. These findings indicate that, site-specific fertilizer recommendations are efficient than blanket recommendations and machine learning approaches offers a promising and innovative approach for generating cost-effective, site-specific fertilizer recommendations compared to the other methods in tropical climates.

### 3.1 Introduction

Maize is the most widely consumed cereal in many Sub-Saharan African (SSA) countries including Ghana, followed by rice and sorghum (Raheem et al., 2021), and plays a significant role in ensuring food security. Additionally, maize serves as animal feed and a primary source of income for most smallholder farmers (Abokyi et al., 2020). However, the maize cropping systems vary across different agro-ecological zones (AEZ) within SSA, with major challenges such as unpredictable rainfall patterns and poor soil fertility (Vanlauwe et al., 2014). The main causes of the low soil fertility in Ghana (T. Jayne et al., 2015) have been attributed to low soil organic matter contents, poor soil fertility management practices and continuous monocropping (Danquah et al., 2020; Essel et al., 2020; Tetteh et al., 2017), resulting in soil nutrient mining, low maize yields and limited profitability. Most yield rates are between 1500 and 2000 kg ha<sup>-1</sup> (Adzawla et al., 2021; Ragasa et al., 2014), which is comparable to that of other African countries but low compared to maize production areas in the United States, Brazil, Argentina, China, and parts of Europe (Faostat, 2022). Although farmers use fertilizers to address the poor soil fertility, the associated high costs and the limited financial resources make farmers only interested in applying fertilizer if proven beneficial and economically viable (Adzawla et al., 2021). It is, therefore, important to optimize fertilizer application to specific soil fertility and other conditions of the farmer's field. Appropriate amounts of nitrogen (N), phosphorus (P) and potassium (K) per unit area are crucial for effectively increasing maize yields, enhancing farmers' income, and mitigating the negative consequences of both excessive and insufficient nutrient applications.

Ghana, like many other SSA countries, has advocated for different strategies and policies to increase the use of inorganic fertilizers to improve crop production (Ichami et al., 2019). Among these strategies and policies is the reintroduction of the government's fertilizer subsidy program since 2008 (Ragasa and Chapoto, 2017), to make balanced inorganic fertilizers accessible to farmers. Recently, Tetteh et al. (2018) also updated the fertilizer recommendation for maize in Ghana using a conventional fertilizer dose-response (CFDR) approach, which involves the use of few experiments which are often not representative of the soil nutrients found in smallholder farms. However, this conventional approach is expensive and time-consuming, taking several months to complete, and sometimes fails due to uncertain climatic conditions (Tanaka et al., 2024). The conducted field experiments also do not comprehensively cover large geographical areas with various soil types, and hence fertilizer recommendations from this approach are often blanket recommendation which are generalized for a large geographic area. Consequently, recommendations derived using the CFDR approach are often not farmer-location specific and do not consider the spatial variabilities that exist within an AEZ. Thus, employing this applications is both economically and environmentally suboptimal, highlighting substantial potential for improvement (Job Kihara et al., 2016).

Mechanistic and semi-mechanistic models are valuable alternative tools to conventional approaches such as the CFDR, for deriving fertilizer recommendations in agricultural systems (Maiti et al., 2006). These models aim to represent the underlying mechanisms and processes of a cropping system through mathematical equations (Craver, 2006). Examples of mechanistic and semi-mechanistic models include the Quantitative Evaluation of the Fertility of Tropical Soils (QUEFTS) (Janssen et al., 1990), Agricultural Production Systems sIMulator (APSIM) (McCown et al., 1996), Decision-Support System for Agro-technology Transfer (DSSAT) (Jones et al., 1998), and Light Interception and Utilization simulator (LINTUL) (Habekotté, 1997) models. These models can predict potential water-limited yield and nutrient-limited yield, but not actual yield if other variables that affect yield are not accounted for (Tanaka et al., 2024). QUEFTS is specifically designed to estimate nutrient requirements for crops in tropical soils based on semi-mechanistic principles of nutrient uptake and internal use efficiencies (Sattari et al., 2014). QUEFTS has been applied in various studies to determine nutrient requirements for crops such as maize, rice, and wheat in SSA, India, China, and the United States (Kang et al., 2020; Kassa et al., 2022; Liu et al., 2006; Tittonell et al., 2008). Although mechanistic and semi-mechanistic models produce site-specific recommendations, they often do so without incorporating the full range of potential factors that might affect the outcome. These models often need data on specific variables for calibration and application, which are often not available (Leroux et al., 2019). In practice, they are often run with proxies or educated guesses of the required input variables, making their recommendations sub-optimal. Therefore, it is helpful to explore other methods that could incorporate a wide range of factors and are not tied to specific and poorly available input variables to derive site-specific fertilizer recommendations.

Machine learning (ML) models can learn from data without the need for explicit programming (Willcock et al., 2018). ML can be used to discover rules and patterns in large datasets and make predictions based on input data. They have been extensively used in crop yield modelling in recent scientific literature (Abbas et al., 2020; Bonilla-Cedrez et al., 2021; Burdett and Wellen, 2022; Tanabe et al., 2023) and are proposed as an alternative for deriving site-specific nutrient recommendations for crops (Bonilla-Cedrez et al., 2021; Zingore et al., 2022). Among ML models, the random forest algorithm has been extensively used in agriculture-related modelling (Halder et al., 2023). This can primarily be attributed to its ability to analyze complex interactions between input features and its reliability in handling outliers (Breiman, 2001). Furthermore, the random forest model is often preferred due to its competitive performance compared to other machine learning models and its ease of use and application (Cutler et al., 2007). It efficiently processes large datasets without being significantly affected by noise or overfitting, as well as its ability to handle both linear and non-linear functions (Fukuda et al., 2013). Meng et al. (2021) used random forest to predict maize yield from 1994 to 2007 in California by incorporating multiple explanatory variables such as climatic, fertilizer, and soil variables. The model explained between 85 - 98% of the yield variance, demonstrating the effectiveness

of the random forest approach for maize yield prediction under different fertilizing systems. In Chapter 2, I applied the random forest model to predict maize yield and agronomic efficiency in Ghana, with the model explaining approximately 80% of the variance in yield and about 50% of the variance in agronomic efficiency. However, despite recent advances in the use of ML models for yield predictions, there is lack of information in the literature regarding its use for fertilizer recommendations and its comparison with recommendations derived using other methods, such as conventional and semi-mechanistic methods.

The aim of this study was to develop and test a machine learning approach to derive fertilizer recommendation for maize cultivation in Ghana and compare it with fertilizer recommendations derived from conventional and semi-mechanistic model approaches. We hypothesize that the ML-based approach can effectively derive fertilizer-yield response curves, enabling the generation of site-specific fertilizer recommendations. These recommendations will be validated against measured yields from field experiments and further assessed through comparison with outputs from conventional and semi-mechanistic modelling approaches. This study had the following objectives: (i) develop a methodology for fertilizer recommendations based on a random forest ML approach that predicts maize yield from fertilizer application and other factors such as soil, crop, weather and other environmental variables; (ii) compare the fertilizer recommendations from the random forest approach with recommendations from conventional and semi-mechanistic approaches; and (iii) evaluate the performance and assess the profitability of the different fertilizer recommendations approaches using field experiments in different agro-ecological zones in Ghana.

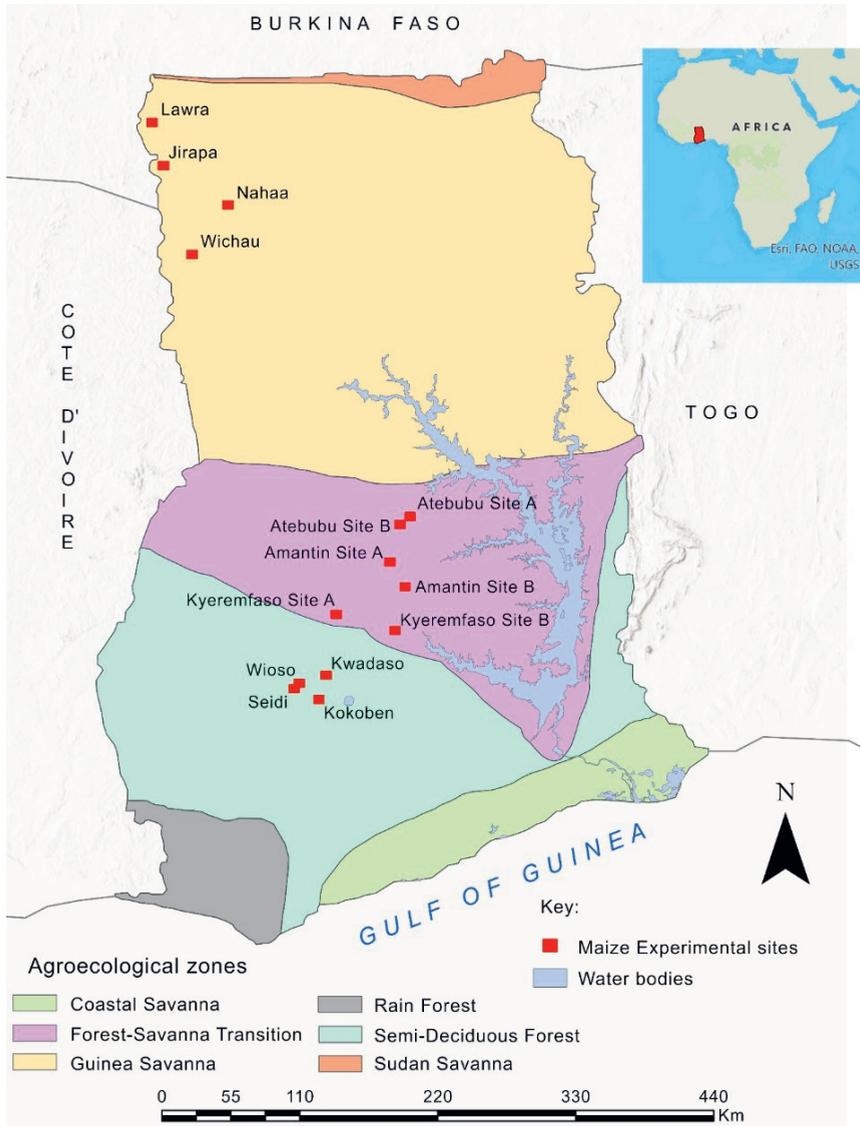
## 3.2 Materials and methods

### 3.2.1 Description of the study area

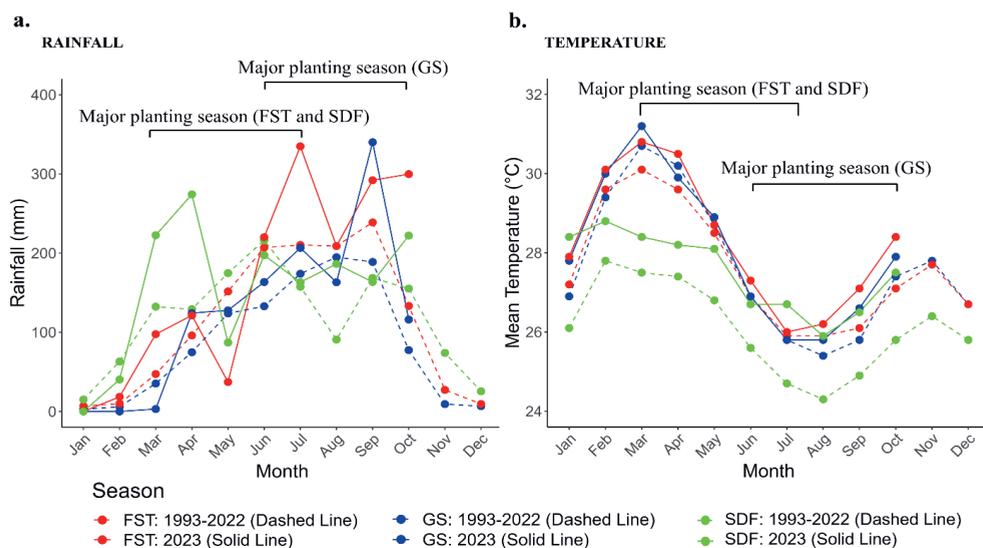
The study area is Ghana, located between latitude 4° 11' N and 11° 11' N and longitude 3° 11' W and 1° 11' E. Ghana shares borders with Togo and Cote d'Ivoire in the east and west respectively, and with Burkina Faso to the north and the Gulf of Guinea in the south (Figure 3.1). The study considers three of six Ghanaian AEZs, namely the Guinea Savanna (GS), Forest-Savanna Transition (FST) and the Semi-deciduous Forest (SDF) zones. These AEZs were selected because they are the major maize growing zones and represent the bread-basket zone in Ghana.

The rainfall pattern in the FST and SDF zones follows a distinct seasonal cycle, with a notable rainy season that lasts from March to July (Figure 3.2). This rainy period typically accounts for more than three-quarters of the total annual rainfall that ranges from 1150 to 1400 mm. In terms of mean monthly temperatures, the FST and SDF zones experience a variation from 24 to 28 °C, with the lowest temperatures recorded in July and August, respectively (Figure 3.2). In contrast, the GS zone displays

a different climate pattern characterized by well-defined wet and dry seasons of approximately equal duration. The total unimodal annual rainfall in this zone ranges between 900 and 1100 mm. Meanwhile, mean monthly temperatures in this zone remain consistently high throughout the year, ranging from 26 °C to 32 °C.



**Figure 3.1:** Map showing AEZs in Ghana with locations of 14 maize experimental sites.



**Figure 3.2:** a) Monthly rainfall distribution, and b) monthly mean temperature distribution, for the year 2023 and a long-term average (1993-2022) for the GS, FST and SDF zones of Ghana (Source: Ghana Meteorological Service, Accra).

### 3.2.2 Soils of the experimental sites

The soils of the experimental sites (Table SI 1) were Petric Plinthosol, Ferric Acrisol, Haplic Luvisol, Gleyic Fluvisol and Ferric Luvisol as described using the World Reference Based for soil resources (WRB, 2022) classification system (Supplementary Information: Tables SI 3 – SI 10). To characterize the soils, soil profile pits were dug at the sites for detailed description. Additionally, composite soil samples were collected from the fields using a "Y" sampling design, ensuring representative sampling for laboratory analysis. The fertility status of the soils at the experimental sites was assessed prior to planting. Standard laboratory procedures were employed to analyze the soil properties (Table SI 2). The soil pH varied significantly, ranging from very strongly acidic at 4.2 to moderately acidic levels up to 5.8. Total nitrogen values ranged between 1.0 and 1.2 g kg<sup>-1</sup> across the sites. Available phosphorus levels also varied across the sites, from a low value of 7.5 mg kg<sup>-1</sup> to a moderate value of 23.4 mg kg<sup>-1</sup>. Exchangeable potassium ranged from 0.11 to 0.41 cmol<sub>c</sub> kg<sup>-1</sup> across the sites whilst soil organic carbon content ranged from 3.8 to 17.5 g kg<sup>-1</sup> (Table SI 2).

### 3.2.3 Fertilizer recommendation approaches

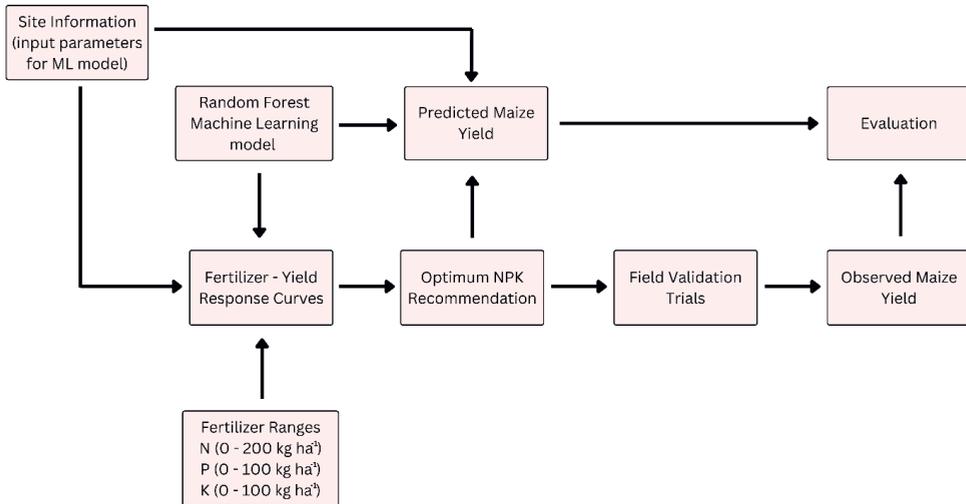
#### 3.2.3.1 Fertilizer recommendation with a random forest model

Random forest is an ensemble-tree technique developed by Breiman (2001). Random forest predicts the dependent variable by averaging the decision tree predictions. Each tree is trained using a bootstrap sample from the training set and using a randomly sampled subset of the predictor variables. Each branch node in a tree represents a choice between two alternatives, and each leaf node represents a decision. The random forest maize yield model developed and described in Chapter 2, was calibrated using data from 482 maize field experiments consisting of 3136 georeferenced treatment plots conducted from 1991 to 2020. This model, represented by the function  $f$  in Eq. 3.1, encompasses a range of 40 predictor variables that predict the output  $Y$  (i.e., yield) from experimental site information described as predictors viz. climate variables ( $C$ ), soil properties ( $S$ ), crop genotype ( $G$ ), other environmental variables ( $E$ ), management type ( $M$ ), and fertilizer nutrients ( $F$ ). I refer to Chapter 2 for a detailed account of the experimental site information and predictors that were compiled for training of the random forest model.

$$Y = f(C, S, G, E, M, F) \quad (3.1)$$

Utilizing the calibrated random forest ML model (Chapter 2), we can predict  $Y$  for any combination of  $F$  ( $N$ ,  $P$  and  $K$ ) and other predictor variables consisting of  $C$ ,  $S$ ,  $G$ ,  $E$  and  $M$  compiled for each experimental site. The predictor variables were collected separately for each site to be used in the model to generate recommendations specific to each site conditions (Table SI 2 – SI 10, Figure 3.2). To compute the optimal economic fertilizer rate of each fertilizer nutrient at a given site, all other predictor variables were held constant whilst keeping two of the  $F$  nutrient rates at their maximum possible rate and varying the third rate from a minimum to a maximum value (Figure 3.3). In this way site-specific fertilizer response curves for each nutrient were derived, by running the model for a range of nutrient application rates between 0 – 200 kg N ha<sup>-1</sup>, 0 – 100 kg P ha<sup>-1</sup>, and 0 – 100 kg K ha<sup>-1</sup>. We anticipated that these fertilizer response curves show increasing values of predicted maize yield with increasing values of  $F$  ( $N$ ,  $P$  and  $K$ ), and that the curve gradually flattens out at higher values of  $F$ , where nutrient supply is no longer limiting. We explored these response curves and utilized expert knowledge (Park et al., 2023; Wieland and Mirschel, 2017) to identify a specific point on the curve (i.e., values for  $N$ ,  $P$  and  $K$ ) where the predicted yield is close enough to the highest efficiency of the nutrient and the slope of the response curve for each nutrient are still steep enough to ensure that the predicted yield increment per unit increase in fertilizer remains economically viable. Note that this procedure was conducted separately for each site due to the dependence of response curves on site-specific predictor variables. We therefore arrive at site-specific fertilizer recommendations for each location. Putting this

recommendation of  $F$  for each site in Eq. 3.1, we computed the predicted yield at the end of the harvest. The modelling process for deriving fertilizer recommendations with the random forest model and field validations is summarized in Figure 3.3.



**Figure 3.3:** Modelling approach for deriving fertilizer recommendations with a calibrated RF model and field validation.

### 3.2.3.2 Fertilizer recommendations by the conventional, updated conventional and the QUEFTS approach

The CFDR approach entails conducting field experiments during the growing season by applying a range of fertilizer doses (Tetteh et al., 2017). Data on crop growth, yield, soil nutrients, and environmental factors collected at the end of the growing season are analyzed to establish relationships between fertilizer rates and yield. This review analysis identifies fertilizer rate that maximizes yield and derives multiple recommendations for validation. Fertilizer response experiments are conducted to test the combinations identified through the review process, and the rate that maximizes yield is identified as the fertilizer recommendation (Tetteh et al., 2017). In the case of Ghana, Tetteh et al., (2017) conducted over 200 field experiments in both on-station and on-farm settings during the 2015 and 2016 seasons to validate fertilizer recommendations derived using this approach for the three AEZs.

In 2020, the CFDR recommendation was updated using additional maize experiment data conducted between 2017 and 2019 (Bua et al., 2020). Fertilizer recommendations were derived using the same approach as for CFDR. About 150 validation experiments were carried out in the AEZs and an updated

fertilizer recommendation based on the outcomes was derived. We refer to the optimal rates of N, P and K derived using the updated datasets and experiments as the “UCFDR” recommendation.

The QUEFTS model (Janssen et al., 1990) was developed to estimate yield responses based on soil nutrients and NPK fertilizers. The QUEFTS model was calibrated following procedures outlined in Jiang et al. (2017) for the study area, using parameters derived from nutrient omission experiment data that were conducted within the AEZs from 1990 to 2020 (see Chapter 2). To refine the calibration, the slopes of the borderlines representing the maximum accumulation and maximum dilution rates of the nutrients, which define the relationship between grain yield and nutrient uptake, were established for each nutrient (Witt et al., 1999). These rates were calculated using the 2.5th and 97.5th percentiles of the internal efficiency of each nutrient. The coefficients for maximum accumulation and dilution rates along with the maximum attainable yield targets (MoFA, 2021) for maize for each zone were determined (Table SI 11). Fertilizer rates of N, P, and K were fixed based on the QUEFTS model by putting the maximum accumulation and dilution values of N, P, and K of the various zones for achieving the target yields for each zone. Observed yields were compared with the target yields and predicted yields (using QUEFTS). The values of N, P, and K were optimised based on the initial site soil fertility of the experimental site (Table SI 2) and the maximum attainable yields for the AEZ's so that the predicted yields were almost the same as the target yields. This process was repeated to determine the fertilizer recommendation for each site.

### **3.2.4 Evaluation of fertilizer recommendation approaches with field experiments**

Field experiments were conducted across three selected agro-ecological zones to evaluate four fertilizer recommendation approaches for maize cultivation. The study was conducted in specific locations known for their extensively cultivated soils within the GS, FST and SDF zones. The choice of sites for these field validation experiments was based on a strategic partnership with local farmers through the Fertilizer Research and Responsible Implementation (FERARI)<sup>1</sup> project. Specifically, the locations were selected in collaboration with farmers who had previously participated in the FERARI project and were willing to allocate their land for the experiments. This approach created a supportive environment for practical agricultural research and strengthened community involvement in scientific activities. The experiments were conducted in 14 sites across diverse areas, each representing the local farming practices and soil types: Wichau, Nahaa, Jirapa, Lawra, Kyeremfaso Sites A and B, Amantin Sites A and B, Atebubu Sites A and B, Wioso, Seidi, Kokoben, and Kwadaso (Figure 3.1). Despite the experiments conducted on farmers' fields, they were researcher managed. The experiments were conducted during the major season of 2023 allowing not only for the testing of different fertilizer

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<sup>1</sup> (<https://ifdc.org/projects/fertilizer-research-and-responsible-implementation-ferari/>)

recommendations but also for an assessment of their adaptability to local conditions. The geographical coordinates of the 14 sites are presented in Table SI 1.

#### 3.2.4.1 Experimental setup

The experiment at each site followed a randomized complete block design with four replicates for each treatment. The maize variety used was Obatanpa, an open-pollinated variety that takes 110 days to mature. The total area for each experiment was 667 m<sup>2</sup> (23 m x 29 m), with each plot measuring 25 m<sup>2</sup> (5 m x 5 m). There were 1 m alleys between adjacent plots. The experimental treatments consisted of fertilizer recommendations derived from four different approaches: (i) CFDR, (ii) UCFDR, (iii) QUEFTS and (iv) ML. Each treatment was replicated four times. The fertilizer types used were a combined NPK fertilizer, Urea, and muriate of potash. Two-thirds of the N fertilizer recommendation for all treatments was applied as a basal, while the remaining one-third was applied as a top-dress, five weeks after planting. Phosphorus and potassium fertilizer recommendations were applied as basal applications for all treatments. All sites also had four replicate control plots, where no fertilizer was applied. All the experiments were researcher-managed, ensuring adherence to good agricultural practices. The layout of the 20 plots within a site are shown in Supplementary Information Figure SI 1.

#### 3.2.4.2 Field validation and models assessment

To assess the performance of the fertilizer recommendation approaches, a comparison between the predicted and observed yield obtained from the field experiments were made. At physiological maturity, grain yield at 13 % moisture content were collected from each plot, within a designated area of 3 x 3 m<sup>2</sup> marked in the middle of each plot. The mean error (ME), root mean square error (RMSE), and the model efficiency coefficient (MEC) were used to evaluate the methods and quantify the deviation between the measured and predicted yields. Here, mean error (ME) represents the average difference between observed and predicted yields, providing insight into potential bias by indicating whether predictions generally overestimates or underestimates the mean actual yields.

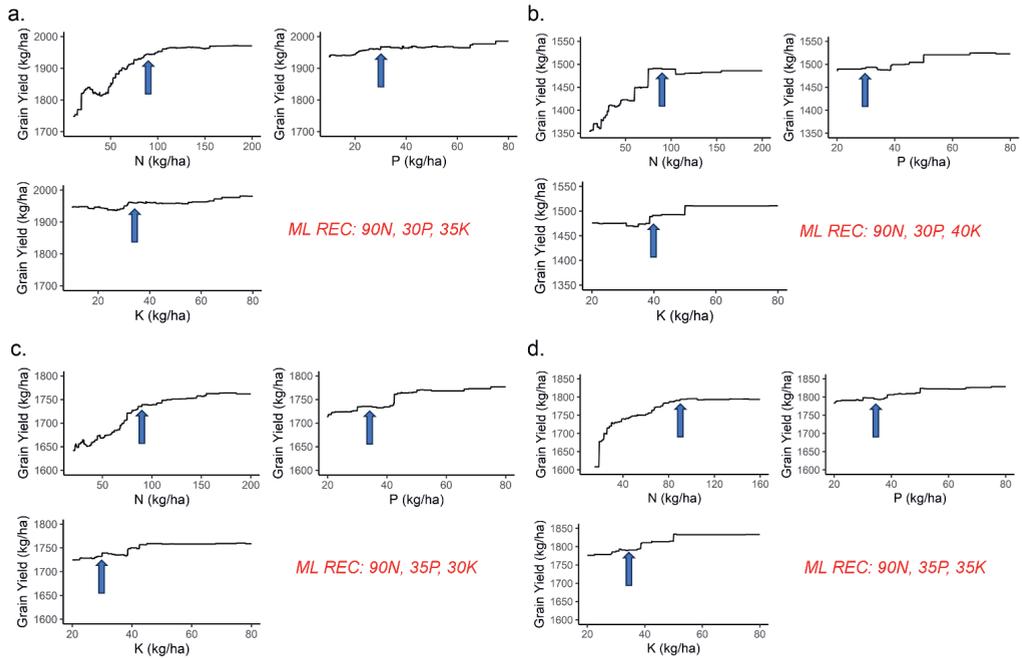
#### 3.2.4.3 Economic assessment

We assessed the profitability of the recommendations using the net profit. The net profit is determined by subtracting the fertilizer cost per hectare from the revenue generated from the sale of maize grain per hectare (Liben et al., 2024). The cost of NPK, Urea and muriate of potash fertilizer for the 2023 planting season was taken as USD 0.65, 0.60, and 0.50 per kg, respectively (VIFAA, 2024). The price of maize per kg for the 2023 season was taken as USD 0.17 (Exchange, 2024).

### 3.3 Results

#### 3.3.1 Fertilizer recommendations derived from the ML approach

Figure 3.4 shows results for ML derived fertilizer recommendations for locations within the GS agro-ecological zone. Results for the FST and SDF zones are presented in Figures SI 2 and SI 3. Figure 3.4a depicts the relationship between NPK application and grain yield at Wichau. Grain yield prediction markedly increased with N application up to about 100 kg ha<sup>-1</sup>, after which the curve plateaued, indicating that additional N will not significantly enhance yield. An expert-based decision was used to select the optimal N application rate from this curve (indicated by the blue arrow in Figure 4a). A similar approach was taken for P and K. However, the response curves for P and K were relatively flat, suggesting that P and K application have a minimal impact on yield in the Wichau experimental site. Also here, expert judgement was used to determine the ML fertilizer recommendation, which for Wichau resulted in 90, 30 and 35 kg ha<sup>-1</sup> for N, P and K, respectively. Expert judgement led to slightly higher P and K levels than suggested by the response curves, as the expert believed that N application alone might be less effective without adequate P and K, thus slightly moderating the ML outcome. Different fertilizer-yield response curves were observed at other experimental sites such as Nahaa, Jirapa, and Lawra (Figures 3.4b, c, and d). Figure 3.4 also shows that inherent site soil fertility, weather variables and other environmental conditions led to differences in the derived fertilizer-yield response curves, even under the same management conditions.



**Figure 3.4:** ML model derived fertilizer-yield response curves for a) Wichau, b) Nahaa, c) Jirapa, and d) Lawra in the GS AEZ. The blue arrow indicates the optimum fertilizer nutrient recommendation rate identified through expert interpretation of the curves.

### 3.3.2 Fertilizer recommendations from the conventional and QUEFTS approach

The CFDR approach recommends high N levels for all sites in the GS zone. Specifically, it recommends NPK of 100:40:40 kg ha<sup>-1</sup> for the GS zone and 90:60:60 kg ha<sup>-1</sup> for both the FST and SDF zones (Table 3.1). The UCFDR approach adjusts the recommendations by reducing N levels in the GS zone and P and K levels in the FST and SDF zones, while slightly increasing P in the GS zone and N in the FST and SDF zones. Across all zones, the UCFDR suggests N at either 73 or 96.5 kg ha<sup>-1</sup>, P at 52.5 kg ha<sup>-1</sup>, and K at 55 kg ha<sup>-1</sup> (Table 3.1). The QUEFTS approach provided more variable NPK rates than the CFDR and UCFDR, adapting its recommendations to specific conditions of each site. However, QUEFTS relied on only the inherent soil fertility of the sites as it assumes soil to be the only factor limiting yield. It recommended the highest N in the FST zone, in contrast to the other approaches, and varied its P and K recommendations depending on the AEZ. Similarly to the QUEFTS approach, the ML approach on average recommended lower P and K application rates than the other methods across all zones. However, N rates recommended by the ML approach were in similar ranges to the other approaches.

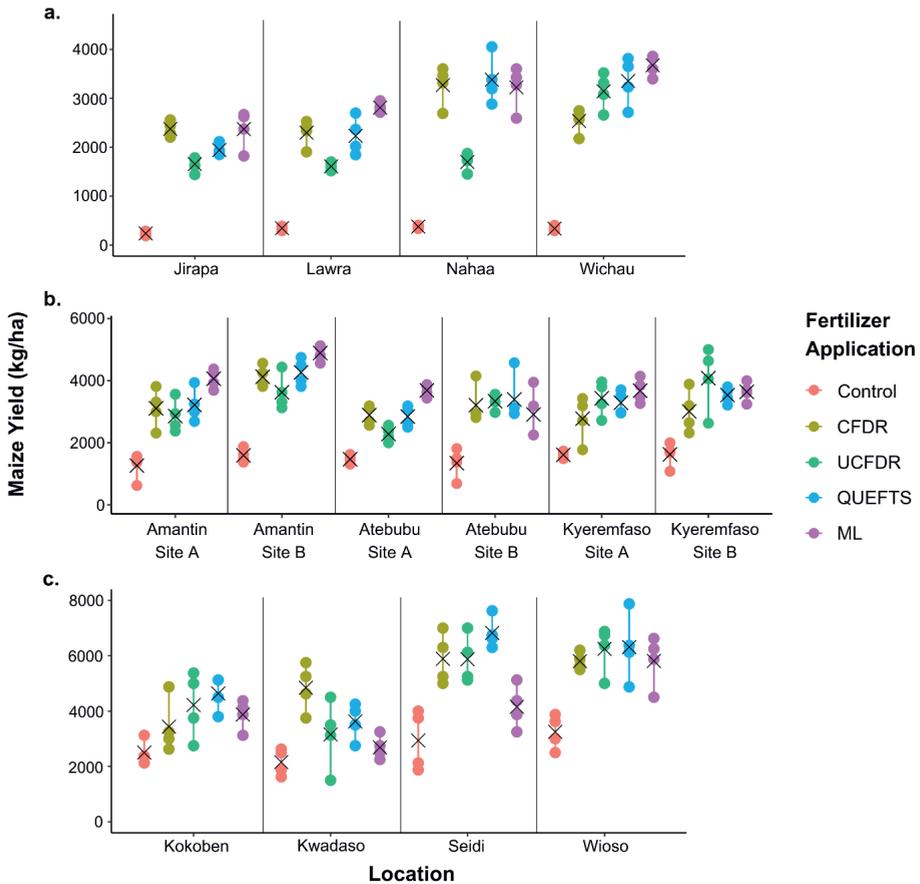
**Table 3.1:** Fertilizer recommendations (N:P:K) of four approaches for the 14 sites.

Experimental sites	AEZ	CFDR (kg ha <sup>-1</sup> )	UCFDR (kg ha <sup>-1</sup> )	QUEFTS (kg ha <sup>-1</sup> )	ML (kg ha <sup>-1</sup> )
Wichau	GS	100:40:40	73:52.5:55	100:40:50	90:30:35
Nahaa		100:40:40	73:52.5:55	90:40:50	90:30:40
Jirapa		100:40:40	73:52.5:55	90:45:55	90:35:30
Lawra		100:40:40	73:52.5:55	100:45:50	90:35:35
Kyeremfaso Site A	FST	90:60:60	96.5:52.5:55	120:60:55	70:30:40
Kyeremfaso Site B		90:60:60	96.5:52.5:55	120:60:55	70:30:40
Atebubu Site A		90:60:60	96.5:52.5:55	120:60:60	100:55:55
Atebubu Sites B		90:60:60	96.5:52.5:55	120:60:60	100:55:55
Amantin Sites A		90:60:60	96.5:52.5:55	110:55:60	90:50:40
Amantin Sites B		90:60:60	96.5:52.5:55	110:55:60	90:50:40
Wioso	SDF	90:60:60	96.5:52.5:55	100:60:60	80:30:30
Seidi		90:60:60	96.5:52.5:55	100:60:60	80:30:30
Kokoben		90:60:60	96.5:52.5:55	110:50:60	100:40:40
Kwadaso		90:60:60	96.5:52.5:55	110:50:60	100:40:40

### 3.3.3 Evaluation of fertilizer recommendation approaches

#### 3.3.3.1 Field validation yield results

The results obtained from the field validation experiments are presented in Figure 3.5, which compares the yield of the four different fertilizer recommendation approaches across multiple experimental sites in the GS, FST and SDF zones. The yield levels in control plots were lowest in the GS zone, intermediate in the FST zone, and highest in the SDF zone. In the GS zone (Figure 3.5a), the ML approach outperformed the other approaches, achieving significantly higher yields across three out of the four sites. In the FST zone, the ML approach recommendations achieved higher yields at Amantin Sites A and B, Atebubu Site A, and Kyeremfaso Site A (4063 kg ha<sup>-1</sup>, 4891 kg ha<sup>-1</sup>, 3680 kg ha<sup>-1</sup>, 3641 kg ha<sup>-1</sup>, respectively), while the QUEFTS and UCFDR approaches produced the highest mean yield at Atebubu Site B (3394 kg ha<sup>-1</sup>) and Kyeremfaso Site B (4081 kg ha<sup>-1</sup>), respectively. Conversely, in the SDF zone, the QUEFTS approach resulted in the highest mean yields at Kokoben (4638 kg ha<sup>-1</sup>), Wioso (6313 kg ha<sup>-1</sup>) and Seidi (6825 kg ha<sup>-1</sup>), followed by the CFDR at Kwadaso (4844 kg ha<sup>-1</sup>).

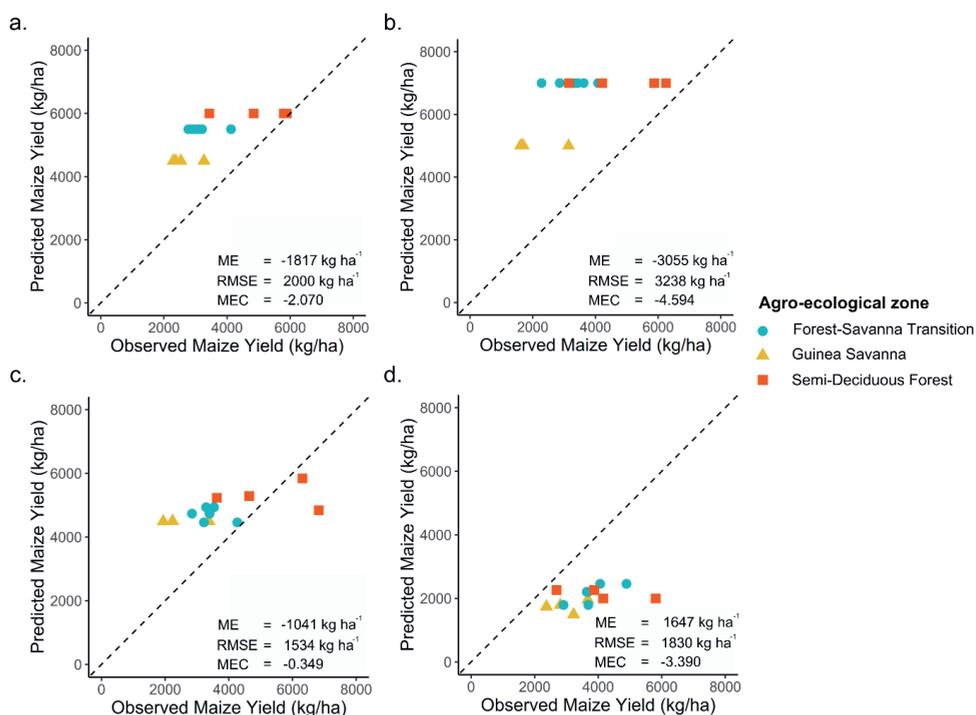


**Figure 3.5:** Distribution of observed maize yields between Control, CFDR, UCFDR, QUEFTS and ML across experimental sites in a) GS, b) FST and c) SDF agroecological zones in Ghana. The black crosses show the mean yield of the four replicates.

### 3.3.3.2 Fertilizer recommendation approaches performances

The scatter plot shown in Figure 3.6a shows that the CFDR and especially UCFDR approaches tended to overestimate maize yields, with a ME of  $-1817$  and  $-3055$  kg ha<sup>-1</sup>, respectively. They also had the highest RMSE's with that of CFDR being slightly better than that of UCFDR at 2000 and 3238 kg ha<sup>-1</sup>, but still indicated a considerable gap between predicted and observed yields. The UCFDR approach displayed a serious overestimate of maize yield with a ME of 3055 kg ha<sup>-1</sup>, which was the highest negative ME among all approaches (Figure 3.6b). The RMSE of UCFDR was also the highest at 3238 kg ha<sup>-1</sup>, indicating that this approach predictions deviated the most from the observed yields. The MEC obtained for the CFDR and the UCFDR were  $-2.070$  and  $-4.594$ , respectively. In contrast, the QUEFTS

approach showed improved performance metrics compared to the other approaches (Figure 3.6c). It recorded a ME of  $-1041 \text{ kg ha}^{-1}$ , showing a tendency to overestimate yields, but to a lesser extent than the other approaches. Its RMSE was the lowest of all 4 approaches at  $1534 \text{ kg ha}^{-1}$ , indicating closer prediction to actual yields compared to the ML approach. But the MEC of  $-0.349$  was higher than that of the ML approach. In contrast, the plot of ML predictions against observations (Figure 3.6d) shows that the ML approach demonstrated poor predictive accuracy, also confirmed by a MEC of  $-3.390$  compared to that of the QUEFTS. The ME was  $1647 \text{ kg ha}^{-1}$ , indicating that the approach underestimated maize yields. The RMSE was  $1830 \text{ kg ha}^{-1}$ , suggesting a considerable deviation between the predicted and observed yields. This was not much bigger than the ME, indicating that systematic prediction errors were large compared to random prediction errors.

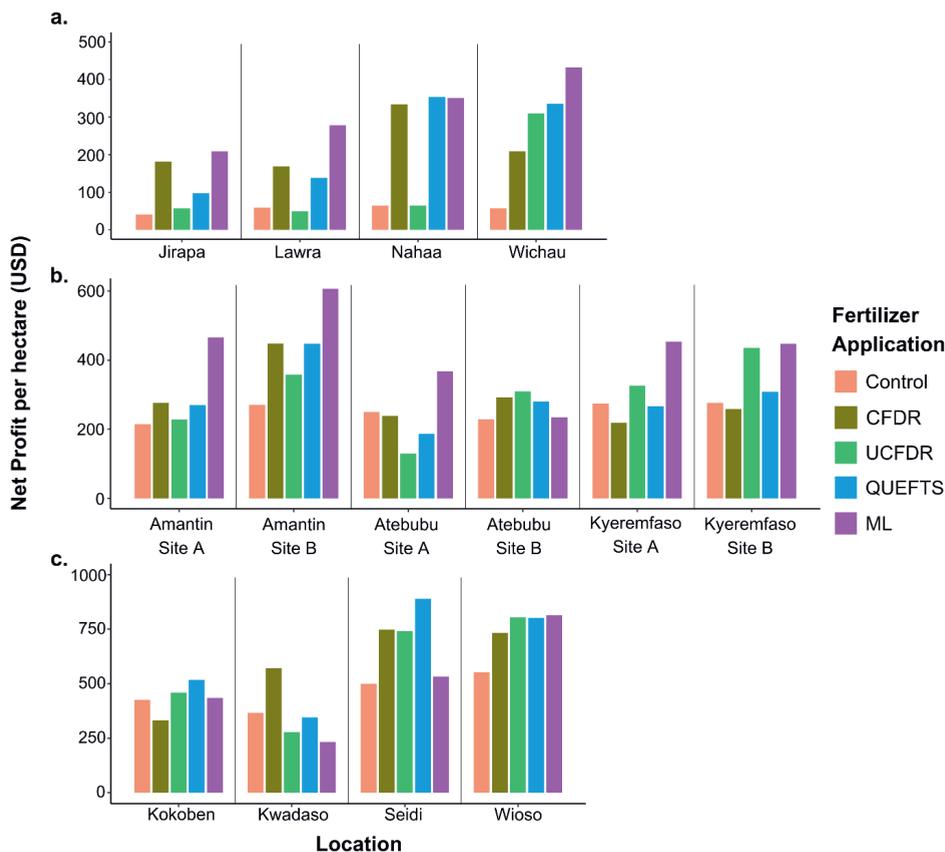


**Figure 3.6:** Scatter plots showing observed maize yields against yields predicted by different approaches: a) CFDR, b) UCFDR, c) QUEFTS, and d) ML.

### 3.3.3.3 Economic assessment

Net profit per hectare for maize cultivation was calculated for each experimental site under different fertilizer recommendation strategies, as shown in Figure 3.7. The figure illustrates the net profit in USD per hectare across various locations for four different fertilizer strategies CFDR, UCFDR, QUEFTS

and ML, compared with a control plot where no fertilizer was applied. Across all locations, the control plot resulted in the lowest net profit per hectare ranging from USD 53 to USD 83 in the GS zone, USD 278 to USD 358 in the FST zone, and USD 474 to USD 715 in the SDF zone. In the GS zone, CFDR and UCFDR generally produced lower profits (ranging from USD 284 to USD 498, and from USD 130 to USD 467, respectively) compared to the ML and QUEFTS approaches (ranging from USD 327 to USD 616, and from USD 194 to USD 522, respectively), except at Wichau, where the net profit of CFDR and UCFDR (USD 337 and USD 467, respectively) was relatively comparable to those of QUEFTS and ML (USD 503 and USD 616, respectively). The ML and QUEFTS approaches yielded the highest profits across most sites, indicating the efficiency of site-specific fertilizer recommendations. For sites in the FST and SDF zones, CFDR and UCFDR showed competitive profits relative to the ML and QUEFTS approaches. However, in the GS zone, the CFDR and UCFDR approaches generally resulted in the lowest profit with the exception of Wichau. The ML approach achieved the highest net profit for most sites in the GS and FST zones, except for Nahaa and Atebubu Site B in the GS and FST zones, respectively. Additionally, sites in the SDF zone exhibited a much higher average net profit compared to those in the other zones. However, in the SDF zone, there was no clear distinction between the performance of different approaches, although QUEFTS generally performed best (Figure 3.7c). Interestingly, in the SDF zone, several sites had net profit values for fertilizer treatments that were lower than those of the control plot, suggesting that in these cases, fertilizer application did result in economic loss instead of gain.



**Figure 3.7:** Net profit of maize yield between Control, CFDR, UCFDR, QUEFTS and ML compared across experimental sites in a) GS, b) FST and c) SDF agroecological zones in Ghana.

### 3.4 Discussion

#### 3.4.1 Deriving fertilizer recommendations using a ML modelling approach

Recent advances in fertilizer recommendation methodologies have over the past decade relied on mechanistic and semi-mechanistic models, which are well-established for their ability to simulate biophysical processes in agriculture relative to traditional approaches (Rurinda et al., 2020; Van Ittersum and Rabbinge, 1997). Despite their ability to make site-specific recommendations, these methods face several challenges, including the need for extensive model calibration with specific target data requirements which are often not available making calibration challenging and affecting the accuracy of the models performance (Jia et al., 2023). As a result, there is growing interest in leveraging

complementary methodologies, such as ML to address these gaps and enhance the efficiency of fertilizer recommendations (Liben et al., 2024).

In this study, we developed a ML model-based fertilizer recommendation approach for deriving site-specific fertilizer recommendations for maize production in Ghana. This was possible due to maize experimental data available and the ease of ML model to learn from the data to derive recommendations. The ML-based modelling approach integrated various inputs, such as soil, climate, environment, management type, fertilizer application rates, and crop variety, to generate fertilizer-yield response curves from which fertilizer recommendations were derived. These fertilizer response curves derived using ML, allows for expert judgement to determine where additional fertilizer application results in negligible yield gains and thus recommend as the fertilizer recommendation for a site. The integration of expert insight ensures that decisions are not solely based on the model's output. For instance, the expert decides that the levels of P and K should not be as low as suggested by the model to ensure adequate interaction with N, which improves nutrient use efficiency (Shi et al., 2021). The expert judgement approach in our ML modelling corroborates with that of Beddows and Leontidis (2024), who incorporated experts' judgement in ML system for strawberry yield forecasting and found that, combining ML with expert-informed forecast outperformed sole forecasts from the ML model. Despite ML models ability to make quite successful predictions, domain experts might have a judgement that might conflict with ML predictions (Park et al., 2023). Park et al. (2023) found that, a possible reason for that is when the ML model is trained on a datasets that are not representative of the outcome it may lead sub-optimal recommendations. Shi et al. (2021) found that balanced amounts of P and K, when combined with N, enhance N uptake and prevent excessive nutrient application and its environmental impacts which agrees with our expert decision to increase the levels of P and K, and not make the recommendation based on only the ML. However, incorporating expert judgement to fine-tune fertilizer recommendations also introduces subjectivity and requires significant effort, as an expert may have to assess each new location individually. Future research efforts should aim to reduce this reliance on expert judgement and improve the training data used for the ML modelling to improve the recommendations based solely from the model. Furthermore, smoothing the response curves so that their slopes could be used to identify when additional fertilizer application offers minimal returns could be a potential solution. It is also worth noting that determining the optimal point in the three-dimensional space of N, P and K is more complex for an expert than for a mathematical algorithm. While exploring the entire NPK range in a mathematical algorithm is feasible, this study simplified the problem by reducing the three-dimensional space to three separate one-dimensional response curves for N, P and K. Future study should explore a mathematical algorithm that considers the three-dimensional N, P, and K combination space to generate more robust recommendations.

Another key factor in the ML approach is the crucial role weather data plays in deriving fertilizer recommendations. Given that recommendations were made before the growing season, we had to

account for the inherent variability and uncertainty of weather conditions. To address this, a 30-year average of climatic data was used as a baseline, providing a stable proxy for typical seasonal patterns while recognizing that actual conditions may diverge significantly, as depicted in Figure 3.2. While the use of long-term weather averages helps to establish a reasonable benchmark, it cannot fully capture the variability of year-to-year weather, and deviations from these averages, such as extreme weather events may contribute to discrepancies between observed and predicted yields, as shown in Figure 3.6. It is recommended that, data on soil water holding capacity (Leenaars et al., 2018) which is a factor buffering the yearly variability of water proves to be highly beneficial. Hochman and Horan (2018) also demonstrated that models incorporating real-time weather forecasts offer improved yield prediction accuracy, particularly under increasingly erratic climate conditions. Future work could focus on updating recommendations by integrating short-term forecasts, thereby accounting for in-season weather shifts and extreme events more effectively.

### **3.4.2 Comparison of yields across different fertilizer recommendation approaches**

We observed that the ML approach tended to underpredict yields across all zones, while CFDR and UCFDR overpredicted them. The QUEFTS approach exhibited lowest prediction errors. However, it slightly underpredicted yield in the SDF zone but overpredicted it in the GS and FST zones (Figure 3.7). One reason for the lower ML predictions could be the nature of the training data used for its calibration. The ML model was trained on actual yield data collected mostly from farmer-managed plots, where agricultural practices and inputs levels are sub-optimal leading to lower yield levels. In contrast, our field experiments were researcher-managed fields, which typically have more controlled conditions compared to farmer-managed fields (Tittonell et al., 2008). This discrepancy in the conditions between the training and validation datasets likely contributed to the ML model's conservative yield estimates. This finding corroborates those of Tittonell and Giller (2013), who observed lower yields from farmer-managed compared to researcher-managed fields. To improve the prediction performance of the ML model, future study could balance the data from both researcher and farmer-managed fields during model training and calibration.

Furthermore, the results of the field experiments showed that the fertilizer recommendations from different approaches produced varying yields (Figure 3.5). The ML approach recommendations resulted in highest mean grain yield responses from two out of four sites in the GS and 4 out of six sites in the FST zone (Figure 3.5). However, in the SDF zone, the QUEFTS produced the highest mean yields in all four sites, outperforming the other approaches. This finding also confirms that site-specific recommendations perform better than blanket recommendations. A possible reason is that site-specific recommendations adapt to local soil, and environmental variability ensuring that fertilizers are applied in the right amounts, at the right time and in the right place. Our findings corroborates with that of

Kumar et al. (2018) who used the QUEFTS model to estimate site-specific NPK requirements for potato yields in India and observed improved yields with the tailored nutrients. Tailoring fertilizer nutrients to specific needs of the soil, enhance nutrient efficiency, maximize yields, and reduce waste, confirming the critical role in sustainable farming (Vanlauwe et al., 2012). We observe that the ML and QUEFTS approach performed fairly similar and hence, developing a combined methodology leveraging ML and mechanistic and semi-mechanistic approaches could lead to a more effective and efficiency fertilizer recommendations. This finding confirms that of Maestrini et al. (2022), who found that, combining the strengths of both ML and mechanistic modelling approaches could lead to improved model outcomes and decision-making. This underscores the need for future studies to combine these fertilizer recommendation approaches to derive recommendations.

### **3.4.3 Assessing variations and profitability in fertilizer recommendations across methods and agro-ecological zones**

This study compares various recommendation approaches, each designed with different optimization goals. The ML and QUEFTS approaches provided site-specific recommendations, while the CFDR and UCFDR approaches provided blanket recommendations across AEZs. The QUEFTS model generated recommendations based only on soil information and attainable yields, while the ML model incorporated a wider range of factors as shown in Chapter 2. The CFDR and UCFDR approaches, due to their generalized nature, ignore within-zone spatial variability, potentially leading to sub-optimal fertilizer application rates, leading to sub-optimal yields (Figure 3.5) (Bationo et al., 2018). This implies that blanket uniform recommendations under- or over-supply nutrients in specific locations, impacting both crop yield and soil health. In contrast, the ML and semi-mechanistic input parameters allow for more tailored fertilizer recommendations within AEZs. A study by Liben et al. (2024) also utilized data-driven ML models to produce site-specific fertilizer recommendations and found that yields were higher, improving farmers profitability.

The UCFDR method suggested lower N but moderate P and K application rates in the GS zone compared to other methods, indicating that P and K are the limiting nutrients in this zone. Meanwhile, the QUEFTS model suggested higher fertilizer rates, particularly for N, across all AEZs. In the FST zone, as shown in Table 3.3, the QUEFTS model recommended higher N rates for Amantin and Kyeremfaso due to their sandy soil texture (Table SI 4a and b), which promotes N leaching and volatilization (Russo et al., 2017). We found that the QUEFTS and CFDR methods recommended on average the highest fertilizer application rates, while the ML and UCFDR methods suggested the lowest rates. The lower rates recommended by the ML model reduce fertilizer costs for farmers, resulting in higher profits even if the yield is slightly lower. This leads to more efficient resource use and better economic outcomes (Figure 3.7).

#### **3.4.4 Implications for maize production**

This study demonstrated that ML-based approaches are promising in deriving fertilizer-yield response curves, which in turn enable the determination of site-specific fertilizer rates to enhance maize yields and increase farmer profitability. Our findings agree with those of Liben et al. (2024) who used ML to derive site-specific fertilizer recommendations for Ethiopia and found that, yields obtained from the recommendations outperformed the recommendations derived from other methods. This advancement is particularly important in SSA, where agriculture is vital to the economic stability and food security (Van Ittersum et al., 2016). Given that maize is a staple crop in Ghana, yield improvements can have substantial positive impacts on farmers' livelihoods and national food security (Kolog et al., 2023). Leveraging on the availability of a vast amount of field experimental data, ML models can be employed to derive meaning solutions to guide decision-making in different agricultural contexts within SSA. Looking forward, combining ML approaches with mechanistic, semi-mechanistic, and traditional models could offer a more robust decision making framework for agriculture.

#### **3.4.5 Limitations and future research**

This study provided valuable insights into optimizing fertilizer recommendations for maize production in Ghana. A key strength is using models to develop fertilizer recommendations and validating by field experiments. However, there are limitations, such as validation of the fertilizer recommendations in one cropping season and only on researcher-managed fields. Future studies should prioritize the validation across multiple cropping seasons and diverse fields conditions and including farmers-managed fields to ensure broader relevance and applicability of the recommendations. Expanding the training dataset and regularly recalibrating ML and semi-mechanistic models as new data becomes available will be key steps in refining the predictive performance. As more data are incorporated, these approaches not only improve in accuracy but also adapt better to varying agricultural contexts, enabling a level of precision that traditional models are less equipped to easily achieve.

Additionally, these model's reliance on soil fertility data poses challenges, as smallholder farmers may be unable to afford soil analysis. However, utilizing mapped soil nutrient data with improved certainty, such as the Ghana Soil Information System ([www.csirsoilinfo.org](http://www.csirsoilinfo.org)), the Africa SoilGrids (Hengl et al., 2017) or SoilGrids (Poggio et al., 2021), could be a potential solution, though this approach has its limitations. However, it is important to acknowledge that mapped data can be limited in resolution and may not fully capture field-specific nutrient variability, which can affect recommendation accuracy. Finally, it is important to note that the current study did not consider the environmental impacts of different fertilizer recommendation methods, such as nutrient losses through leaching, volatilization, and runoff (Vanlauwe et al., 2014). Future research should incorporate assessments of both agronomic

and environmental outcomes to ensure that fertilizer recommendations are not only productive and profitable but also sustainable. This holistic approach would help to balance the goal of improving crop yields with the need to minimize adverse environmental impacts, contributing to more resilient agricultural systems.

### 3.5 Conclusion

This study developed and validated a methodology for generating cost effective and site-specific fertilizer recommendations for maize production in Ghana using a random forest ML model approach, comparing its performance systematically with three other approaches: QUEFTS, CFDR, and UCFDR. The ML model predicted maize yield based on fertilizer application and other key factors, providing a site-specific approach to nutrient management. Our findings show that the ML-based approach recommended lower rates of P and K than the other methods, while N recommendations were comparable across all approaches. The validation process revealed that the recommendations derived from the ML approach produced the highest yields at the greatest number of sites (6 out of 14).

Our findings demonstrate the potential of the ML approach to improve fertilizer recommendations by incorporating site-specific variables and optimizing nutrient management tailored to local conditions. However, the results also underscore the need to enhance the predictive accuracy of the ML model, by expanding its training data, especially in underrepresented agro-ecological zones. Overall, this study suggests that ML-based approaches can serve as an innovative tool for developing cost-effective, data-driven fertilizer recommendations in tropical climates. It has the potential to improve decision-making and achieve higher crop yields, improving farmers profits, ultimately contributing to sustainable agricultural practices and better resource utilization in SSA. Future efforts should focus on expanding training data and integrating socio-economic factors to further enhance the applicability and impact of the ML approach, alongside other approaches, in diverse farming contexts.

### Supplementary materials

The supplementary materials can be downloaded from the journal version of this chapter:

Asamoah, E., Heuvelink, G. B., Logah, V., Leenaars, J. G., & Bindraban, P. S. (2026). Fertilizer recommendations for maize production in Ghana: Comparison of machine learning, semi-mechanistic and conventional approaches. *European Journal of Agronomy*, 174, 127925. <https://doi.org/10.1016/j.eja.2025.127925>



# Chapter 4

## Modelling maize yield and agronomic efficiency using machine learning models: A comparative analysis

This chapter is based on:

Asamoah, E., Heuvelink, G. B., Bindraban, P. S., & Logah, V. (2025). Modeling maize yield and agronomic efficiency using machine learning models: A comparative analysis. *Agronomy Journal*, 117(6), e70206. <https://doi.org/10.1002/agj2.70206>

## Abstract

Machine learning is increasingly being used to enhance yield predictions and optimize agronomic practices in Sub-Saharan Africa. Yet, understanding how these models generalize across heterogeneous ecological context, remains unresolved. This study evaluates in Ghana, the predictive performance of four ML models viz. Random Forest (RF), Support Vector Machine (SVM), K-Nearest Neighbours (KNN), and Extreme Gradient Boosting (XGBoost) for predicting maize yield and agronomic efficiency—defined as the increase in yield per unit of nutrient applied. It also compares variable importances identified by these models and how they influence yield and agronomic efficiency. The analysis used 4,496 georeferenced maize trial datasets from various agroecological zones across Ghana, incorporating 35 variables related to soil properties, climate, topography, crop management, and fertilizer application. Model performance was assessed using three cross-validation techniques: leave-one-out, leave-site-out, and leave-agroecological-zone-out. Accuracy was measured using Mean Error, Root Mean Squared Error, and Model Efficiency Coefficient. When evaluated under leave-one-out cross-validation, XGBoost consistently achieved the highest predictive accuracy with the lowest RMSE for yield ( $639.5 \text{ kg ha}^{-1}$ ) and for agronomic efficiency of nitrogen ( $11.6 \text{ kg kg}^{-1}$ ), which is moderate given the high variability in on-farm nutrient response. RF also performed well, while KNN and SVM showed poor extrapolation under stringent validation. Nitrogen application rate, rainfall, and crop genotype were consistently identified as the most influential explanatory variables across all models, providing insight into key drivers of productivity. These findings demonstrate the power of ML techniques in supporting agricultural planning and improving maize production in Sub-Saharan Africa.

## 4.1 Introduction

Accurate prediction of crop yield and agronomic efficiency (AE) is crucial for optimizing resource use and guiding evidence-based agricultural interventions. The integration of machine learning (ML) into agricultural research and practices has gained significant traction in recent years, driven by its capacity to handle large, complex datasets and generate actionable insights for enhancing productivity and sustainability (Panigrahi et al., 2023). ML algorithms offer powerful tools for real-time analysis of data from sources such as remote sensing, in-field sensors, and historical data records, enabling improved decision-making in crop management, yield prediction, irrigation scheduling and disease detection (Benos et al., 2021; Abioye et al., 2022). These data-driven insights underpin the growing adoption of precision agriculture, which promotes targeted interventions tailored to specific field conditions, resource availability, and climate patterns. Furthermore, ML has the potential to reduce labour costs, automate routine agronomic tasks, and optimize agronomic input use, contributing to more sustainable and climate-resilient agricultural systems (Naveen and Mohan, 2022). Although prior reviews including Liakos et al. (2018), have laid the foundation for understanding the benefits of ML in agriculture, a deeper exploration into its application for smallholder systems in low- and middle-income countries remains limited. In Sub-Saharan Africa (SSA), where smallholder farmers dominate the agricultural landscape, ML offers a transformative opportunity to model yield and AE which is underexplored in current literature.

ML techniques such as the random forest (RF) model has been widely used in crop yield prediction due to its robustness in handling nonlinear relationships and multicollinearity (Breiman, 2001; Rashid et al., 2021). In Ghana, for instance, Chapter 2 applied a RF model to a relatively small dataset for predicting maize yield and AE, reporting promising results. However, their study was limited to a single model and a narrow data scope, which restricts both generalizability and insight into model-specific behaviour. While informative, such studies raise the question of whether similar or better predictive performance can be achieved and generalized when models are trained on larger, more diverse national datasets. In current literature, there remains limited comparative research on how different ML models perform in this context, particularly when trained on real-world agricultural datasets that reflect national variability. ML models, such as support vector machines (SVM), k-nearest neighbours (KNN), and extreme gradient boosting (XGBoost), have also shown promising results in other contexts. Guo et al. (2021) and Shahhosseini et al. (2020) reported the superiority of SVM and XGBoost in predicting rice and maize yields in South China and the United State, respectively, particularly when dealing with complex, high-dimensional datasets. XGBoost, in particular, has gained recognition for its strong predictive power and efficiency in large-scale agricultural datasets due to its gradient boosting framework that iteratively corrects residual errors (Chen and Guestrin, 2016). SVM, on the other hand, excels in classification and regression tasks by identifying optimal separating hyperplanes in feature space (Cortes and Vapnik, 1995), while KNN offers simplicity and ease of interpretation, though it often

struggles with scalability (Mupangwa et al., 2020). This study addresses these gaps by applying and comparing multiple ML models including RF, XGBoost, SVM, and KNN to a large, nationally representative dataset to evaluate whether any model outperforms the RF benchmark established in Chapter 2, and to investigate the generalizability potential and robustness of ML methods when applied to complex, high-variability agronomic data. By so doing, we provide a more comprehensive understanding of the strengths and limitations of ML in maize yield and agronomic efficiency prediction.

Beyond predictive accuracy, an essential yet often underexplored aspect of ML in agriculture is the identification of variable importance, the relative influence of input variables on yield and AE. Understanding which variables most strongly affect yield and AE supports more transparent decision-making and targeted interventions (Guyon and De, 2003; Kuhn and Johnson, 2013). However, comparing the variable importance for yield and AE across different ML models in SSA context remains scarce. Despite the growing body of literature on ML-based yield prediction, there remains a critical gap in evaluating the comparative performance of multiple ML models within diverse agroecological zones of SSA, and in harmonizing variable importance assessments across these models. Most existing studies are concentrated in North America, Europe, or Asia, often relying on homogenous datasets or limited geospatial representation (Pang et al., 2022; Rajakumaran et al., 2024; Tanabe et al., 2023).

This study addresses these gaps by evaluating and comparing the performance of four widely used ML models RF, SVM, KNN, and XGBoost in predicting maize yield and AE across diverse agroecological zones in Ghana. Specifically, it aims to: i) compare and evaluate four ML models for similarity in maize yield and AE predictions; ii) compare and evaluate the prediction performance of the four ML models; iii) compare the variable importances identified by the different ML models; and iv) compare the extrapolatory potential of the different ML models. By leveraging a harmonized dataset of 4,496 maize trials covering 35 agronomic and environmental variables across Ghana's major agroecological zones, this study provides a context-specific analysis of ML model performance in a tropical climatic setting. It evaluates both prediction performance, explanatory power and extrapolation potential, offering insights into which models are best suited not only for predicting outcomes, but also for informing agronomic decisions to improve resource-use efficiency and resilience in smallholder maize production systems across SSA.

## **4.2 Materials and methods**

### **4.2.1 Datasets**

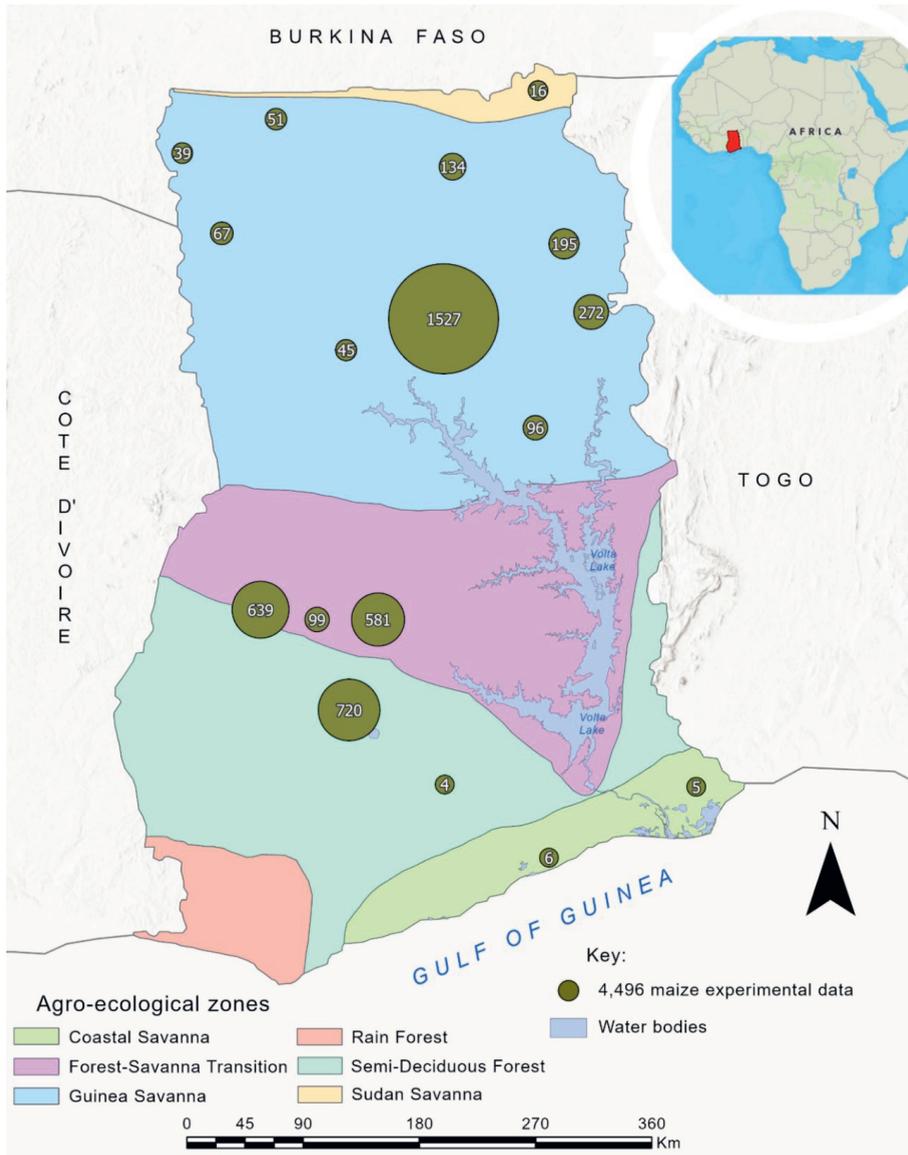
In this study, we updated the maize yield datasets used in Chapter 2 to include an additional 1,360 georeferenced research trials. These trials covered a 25-year period (1996 to 2021) across all

agroecological zones in Ghana, including the Sudan Savanna, Guinea Savanna, Forest-Savanna Transition, Semi-Deciduous Forest, Coastal Savanna, and Rainforest zones (Figure 4.1). The dataset for this study includes a total of 4,496 georeferenced data points related to maize, all of which were utilized for yield modelling. Among these georeferenced data points, subsets of 3106, 2858, and 2760 had both control and treatment plots to support modelling the agronomic efficiencies of nitrogen (N), phosphorus (P), and potassium (K), respectively, following the calculation of AE.

$$AE = \frac{Y_f - Y_c}{F} \quad (4.1)$$

where,  $Y_f$  is the grain yield ( $\text{kg ha}^{-1}$ ) from a fertilized plot (i.e., N, P, or K),  $Y_c$  is the grain yield ( $\text{kg ha}^{-1}$ ) from a control plot, and  $F$  refers to the amount of fertilizer input ( $\text{kg ha}^{-1}$ ).

The datasets spread across the country and include the target variables, maize yield measured in  $\text{kg ha}^{-1}$  and agronomic efficiencies of N, P, and K measured in  $\text{kg kg}^{-1}$ , and 35 explanatory variables described in detailed in Table SI 1, includes 17 soil variables, 6 climate variables, crop genotype, 3 crop management characteristics, 5 other environmental variables and 3 fertilizer nutrient variables, all collected at the experimental plot level. Soil information was obtained from the Soil Research Institute of Ghana's data repository to fill missing soil property records for experiments that did not collect these data. The gap-filling rates for soil properties were as follows: pH (17%), soil organic carbon (20%), total nitrogen (17%), cation exchange capacity (59%), available phosphorus (25%), exchangeable potassium (21%), calcium (30%), magnesium (31%), and 56% for sand, clay and silt, and bulk density at 68%. Daily weather data (1996–2021) were obtained from the Ghana Meteorological Agency (GMet) to fill experimental sites without on-site weather records. Climatic variables (minimum and maximum temperatures, rainfall, average relative humidity, average evapotranspiration, and solar radiation) were missing in 80% of the datasets and were supplemented using GMet records.



**Figure 4.1:** Spatial distribution of maize experimental data across five agroecological zones of Ghana. A 54.0% of the data are from the Guinea Savanna, 29.3% from the Forest-Savanna Transition, 16.1% from the Semi-Deciduous Forest, 0.4% from the Sudan Savanna and 0.2% from the Coastal Savanna zones.

## 4.2.2 Machine learning models

### 4.2.2.1 Random forest

RF is a tree-based learning approach comprising multiple decision trees, each constructed using a distinct subset of the training data and explanatory variables. This approach leverages bootstrap aggregation, where multiple bootstrapped datasets are generated by random sampling with replacement from the original dataset (Breiman, 2001). Each tree is trained on one of these bootstrapped datasets. To enhance diversity among the trees and reduce the risk of overfitting, a random subset of explanatory variables is selected at each tree node for splitting (Hastie et al., 2006). At each node, the algorithm identifies the feature and split point that yield the greatest reduction in the variance of the target variable. The splitting process continues until a predefined stopping criterion is met, such as a minimum number of samples per leaf node (Breiman, 2001). The final prediction is obtained by aggregating the predictions from all trees, typically by taking their average.

### 4.2.2.2 Support vector machine

SVM is a ML model designed to minimize the cost function by maximizing the margin between support vectors, as proposed in Cortes and Vapnik (1995). SVM can be used for both classification and regression tasks. In the context of regression, as in this study, SVM identifies a hyperplane that best approximates the relationship between the input explanatory variables and the target variables while managing the margin of error (Cortes and Vapnik, 1995). To effectively capture nonlinear relationships between the input and target variables, the Gaussian radial basis function kernel was employed as the kernel function.

### 4.2.2.3 K nearest neighbours

The KNN algorithm is a non-parametric ML technique that approximates the relationship between explanatory variables and the target variable by averaging the observations in the same neighbourhood (Zhang, 2016). In regression tasks, the KNN algorithm predicts the output for a given data point by averaging the target variable values of the  $k$  closest points in the training data. This approach ensures that predictions are informed by the most similar observations in the dataset, which is particularly useful when modelling complex, nonlinear relationships. To determine the  $k$  nearest neighbours, the algorithm calculates the Euclidean Distance (ED) between the prediction point and all points in the training set. The ED measures the distance between two points in feature space and is computed using Eq. 4.2.

$$ED[P_1, P_2] = \sqrt{\sum_{i=1}^n (x_i - y_i)^2} \quad (4.2)$$

where  $P_1$  and  $P_2$  are two points in the  $n$ -dimensional feature space that have values  $(x_1, x_2, \dots, x_n)$  and  $(y_1, y_2, \dots, y_n)$ , respectively. Note that it is common to normalize the explanatory variables before ED calculation. Once the  $k$  nearest neighbours are identified, the algorithm calculates the predicted output as the mean of the target variable values of these neighbours.

#### 4.2.2.4 Extreme gradient boosting

XGBoost is a powerful tree-based learning algorithm that constructs a series of decision trees in a sequential manner, with each subsequent tree designed to correct the prediction errors of the previous ones (Chen and Guestrin, 2016). Each decision tree in the ensemble is composed of internal nodes, which split the data based on explanatory variables, and leaf nodes, which store the predicted target values. The algorithm optimizes its performance using a loss function, typically the sum of squared errors in regression tasks, that is the sum of squared differences between the predicted and actual values. This loss function, which is a common feature across many ML algorithms, is crucial for guiding the optimization process to minimize errors and improve prediction accuracy. By iteratively minimizing this loss function, XGBoost improves the accuracy of the model while maintaining computational efficiency (Chen and Guestrin, 2016). Additionally, the algorithm incorporates regularization techniques to prevent overfitting and enhance the model's generalization capabilities. This approach ensures that the final model performance better on unseen data.

### 4.2.3 ML modelling process for yield and AE predictions

#### 4.2.3.1. Data preparation

Data preprocessing was performed to clean and transform the dataset into a format suitable for analysis. This included normalizing the explanatory variables for SVM and KNN, but not for XGBoost and RF. Normalization was done by subtracting the mean and dividing by the standard deviation of each variable, a step that enhances the performance of distance-based algorithms by standardizing scales (Cabello-Solorzano et al., 2023). By reducing the influence of scale differences, normalization allows models such as KNN and SVM to better capture underlying relationships, including non-linear patterns. In addition, exploratory data analysis was carried out to examine the distribution of target variables, detect outliers, and explore relationships among explanatory variables. Histograms and boxplots were used to assess variable distributions, while correlation matrices were employed to evaluate linear

relationships between explanatory variables and target variables (i.e., maize yield and agronomic efficiencies).

#### 4.2.3.2. Hyperparameter optimization of ML models

Hyperparameter tuning was performed for all four ML algorithms to optimize their predictive performance. Each model employs distinct hyperparameters that reflect its unique approach to learning and adapting to the dataset. A systematic evaluation of a range of hyperparameter values (as detailed in Table SI 2) was conducted using a grid search approach combined with ten-fold cross-validation, repeated five times. Grid search systematically explores all possible combinations of specified hyperparameter values, allowing the identification of the most effective configuration for each algorithm. During cross-validation, the dataset was divided into ten-folds, where nine folds were used for training the model and one fold was used as a validation set for hyperparameter estimation. This process was repeated across all folds to ensure that every data point was used for both training and hyperparameter estimation. The Root Mean Squared Error (RMSE) was used as the performance metric to quantify the difference between the predicted and actual values. The optimal hyperparameter combination was identified as the one yielding the lowest average RMSE across the 50 validation folds (10 folds  $\times$  5 repetitions).

#### 4.2.3.3. Models evaluation

Three different cross-validation approaches were employed to evaluate the performance of the ML models for fair comparison. First, a leave-one-out cross-validation (LOOCV) approach was applied. In this approach, the model is trained on all observations except one, and the excluded observation is used for testing (Huang et al., 2024; Takoutsing and Heuvelink, 2022). This process is repeated for each observation, providing a comprehensive assessment of the model's performance. Next, a leave-site-out cross-validation (LSOCV) method was utilized. LSOCV is conceptually similar to K-fold cross-validation, but instead of using individual observations as folds, entire groups of observations belonging to a site were left out (see Tables SI 4, SI 5, SI 6 and SI 7). In this approach, the data for all observations at a specific site were excluded from the training dataset, and the model was trained on the remaining sites. This ensures that the model's performance is tested on unseen sites, providing insights into its ability to generalize across different sites. Finally, a leave-zone-out cross-validation (LZOCV) approach was implemented. In LZOCV, the agro-ecological zones served as the folds. Entire agro-ecological zones were excluded during training, ensuring that the model was tested on spatially distinct agro-ecological zone. This method evaluates the model's ability to extrapolate to other agro-ecological zones to reflect its performance in real-world scenarios, where predictions are made for agro-ecological zones

with varying conditions. Metrics such as the Mean Error (ME), RMSE, and Model Efficiency Coefficient (MEC) were employed for comprehensive performance assessment. MEC is mathematically equivalent to the coefficient of determination ( $R^2$ ) (Nash and Sutcliffe, 1970).

$$ME = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i) \quad (4.3)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (4.4)$$

$$MEC = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (4.5)$$

where  $n$  is the number of trial plots,  $y_i$  and  $\hat{y}_i$  are the  $i^{\text{th}}$  measured and predicted target variable, respectively, at a certain trial plot, and  $\bar{y}$  is the mean of the measurements.

Scatter density plots compared predicted versus observed values, as well as predicted versus predicted values across models, for correlation assessment and model comparison.

#### 4.2.3.4 Variable importance

Identifying variable importance is a critical step in ML, as it highlights the explanatory variables that have the greatest influence on model performance, offering deeper insights into their roles in prediction. In this study, variable importance was evaluated separately for each model using the permutation method applied to the full dataset (Chen and Guestrin, 2016; Wright and Ziegler, 2015). The permutation approach involves shuffling (or permuting) the values of each explanatory variable one at a time while keeping the rest of the dataset unchanged. The model then predicts the outcomes using this permuted data, without refitting the model. The importance of a variable is quantified by the increase in mean squared error, calculated as the difference between the mean squared error obtained with the permuted data and the baseline mean squared error (i.e., the mean squared error using the original data). A larger increase in mean squared error indicates that the variable plays a more significant role in the model's predictions, as its permuted values disrupt the model's accuracy to a greater extent (Louppe, 2014). This method provides an intuitive and model-agnostic way to evaluate the relative importance of input explanatory variables, helping to identify key variables that contribute most to predictive performance.

#### 4.2.3.6. Workflow

The RF model was implemented using the ranger package (Wright and Ziegler, 2017). XGBoost was implemented using the xgboost package (Chen and Guestrin, 2016). SVM with a radial kernel was implemented via the svmRadial method in the caret package (Kuhn et al., 2020). KNN was implemented using the caret package (Max Kuhn et al., 2020). The modelling procedures were conducted using the R statistical software version 4.4.1 (R Core Team, 2024), employing a structured framework illustrated in Figure 4.2.

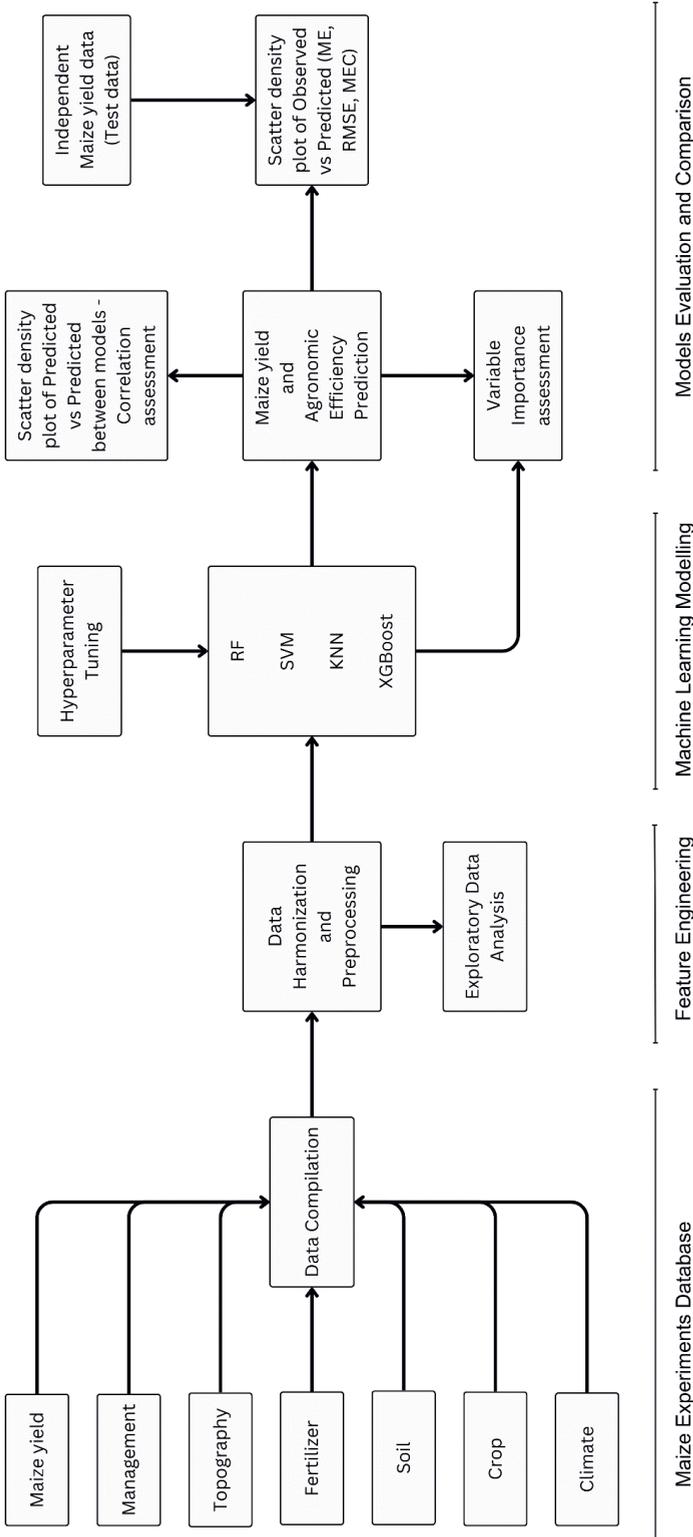


Figure 4.2: Framework of the modelling process.

## 4.3 Results

### 4.3.1 Descriptive statistics

Descriptive statistics of selected variables are presented in Supplementary Information (SI) (Table SI 3). The maize yield varied from 11 to 8815 kg ha<sup>-1</sup> across the agro-ecological zones of the country (Figures SI 1a and 2a). The mean agronomic efficiencies of N, P, and K across the study area were 16.9, 41.1, and 35.4 kg kg<sup>-1</sup>, with standard deviations of 19.8, 45.1, and 32.5 kg kg<sup>-1</sup>, respectively. Minimum and maximum temperatures ranged from 18.0 to 31.9 °C and 27.0 to 40.0 °C, respectively. Total rainfall recorded during the planting season ranged from 344 to 1049 mm. Soil pH, organic carbon and bulk density ranged from 4.1 to 7.3, 0.02 to 0.43 g kg<sup>-1</sup> and 1.1 to 1.7 g cm<sup>-3</sup>, respectively.

### 4.3.2 Optimized hyperparameters

The number of trees in the RF model was optimized at 1000 for stable prediction. The number of variables sampled at each split, controlled by *mtry*, varied by target variable: 15 for yield, and 14, 6, and 14 for AE-N, AE-P, and AE-K, respectively (Table 4.1). The minimum node size was optimized at 3 and 5 for yield and AE-N, respectively, while it was 1 for AE-P and AE-K. The sample fraction for training individual trees was optimized at 0.80 for all target variables except AE-P, which had an optimized value of 0.63 for increased sampling diversity (Table 4.1). The SVM model used two hyperparameters, Cost and Epsilon, balancing model complexity and error tolerance. Cost was optimized at 0.9 for yield, AE-N and AE-K, whereas for AE-P, it was 0.7. Epsilon varied across target variables, with optimized values between 0.1 and 0.9 for yield, AE-N, and AE-P, while AE-K had a stricter value of 0.5 (Table 4.1). The KNN model relies on a single hyperparameter, *k*, optimized at 2 for all target variables, emphasizing proximity-based learning. This simplicity contrasts with the more complex parameterization of XGBoost and RF, reflecting KNN's focus on feature similarity. For XGBoost, the number of boosting rounds or *nrounds* was optimized at 300 across all target variables. The learning rate-*eta*, was set at 0.3 to balance step size and prevent overfitting. Gamma, which controls the minimum loss reduction for a split, was optimized at 0 for yield and AE-N and at 0.1 for AE-P and AE-K. *Subsample* and *colsample\_by\_tree* were both optimized at 1, ensuring the model utilizes the entire dataset and all variables. Maximum tree depth varied between 6 and 10, with AE-K requiring deeper trees to capture specific patterns.

**Table 4.1:** Optimized parameters of the ML models.

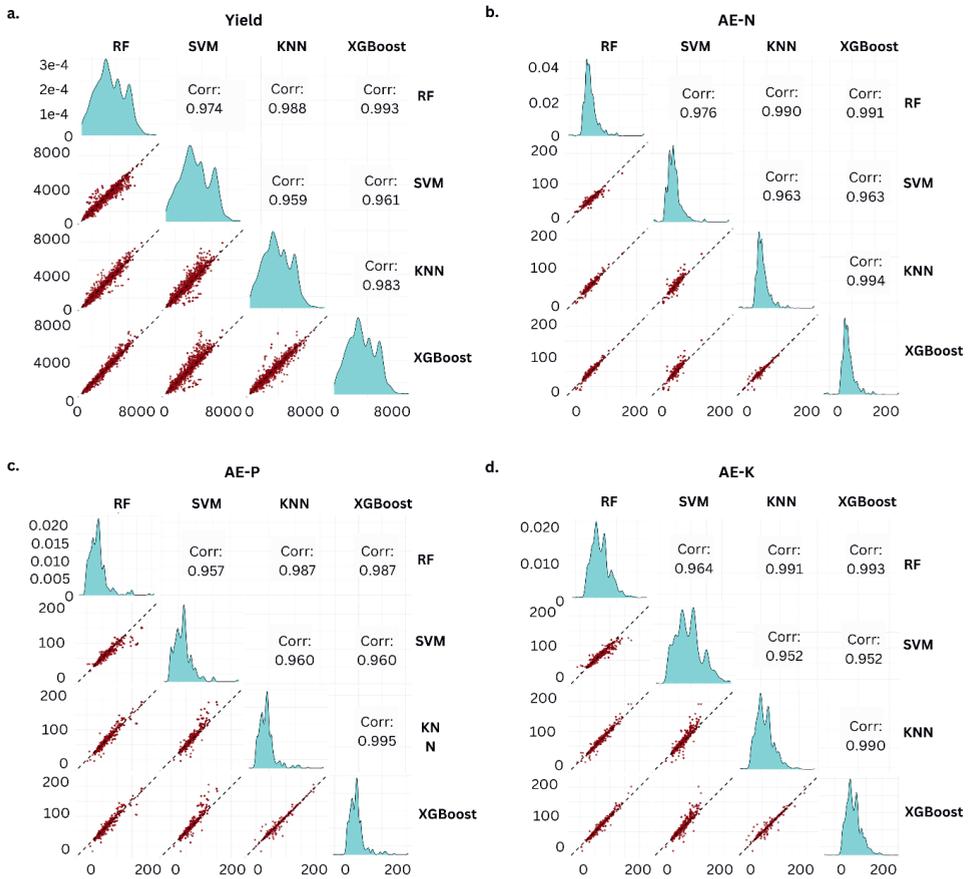
ML model	Hyperparameter	Yield	AE-N	AE-P	AE-K
RF	num.trees	1000	1000	1000	1000
	Mtry	15	14	6	14
	min.node.size	3	5	1	1
	sample.fraction	0.8	0.8	0.63	0.8
SVM	Cost, C,	0.9	0.9	0.7	0.9
	Epsilon	0.1	0.9	0.9	0.5
KNN	k	2	2	2	2
XGBoost	Nrounds	300	300	300	300
	Eta	0.3	0.3	0.3	0.3
	Gamma	0.1	0.1	0.1	0.1
	Subsample	1	1	1	1
	min_child_weight	1	1	1	1
	colsample_bytree	1	1	1	1
	max_depth	6	6	6	10

### 4.3.3 Comparison and evaluation of ML models

#### 4.3.3.1 Comparison of maize yield and AE predictions across ML models

For crop yield prediction, the results demonstrated strong agreement among models (Figure 4.3a). Histograms along the diagonal revealed similar distributions of predicted yield values across the four algorithms. Pairwise scatter plots highlighted strong linear relationships between predictions, supported by high Pearson correlation coefficients (0.959 to 0.993). The highest correlation was observed between RF and XGBoost, indicating alignment in their predictions. The consistency in predictions extended to AE-N (Figure 4.3b). Histograms for AE-N predictions showed similar distributions, and scatter plots indicated strong linear relationships. The Pearson correlation coefficients ranged from 0.963 (SVM vs. XGBoost) to 0.994 (KNN vs. XGBoost), signifying strong agreement (Figure SI 4). The high correlations suggest that these models capture similar patterns in AE-N, with XGBoost and KNN showing the highest agreement. Predictions for AE-P showed comparable consistency across models (Figure 4.3c). The histograms were nearly identical in shape, indicating highly aligned distributions of predicted values. Scatter plots reinforced this finding, showing tight clusters around the diagonal lines of perfect agreement. The Pearson correlation coefficients ranged from 0.957 (RF vs. SVM) to 0.995 (KNN vs. XGBoost) (Figure SI 5). AE-K predictions also exhibited high concordance across models (Figure 4.3d). The histograms confirmed similar distributions, while scatter plots demonstrated strong

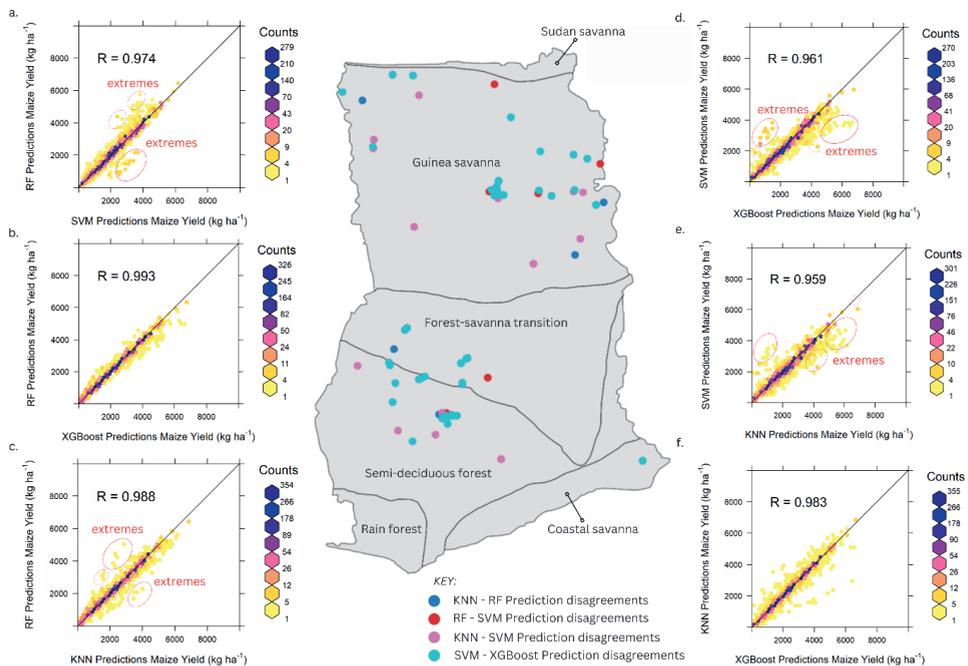
linear relationships. The Pearson correlation coefficients ranged from 0.952 (SVM vs. KNN) to 0.993 (RF vs. XGBoost) (Figure SI 6). These results underscore the similarities of the models for predicting AE-K, with RF and XGBoost displaying the highest pairwise similarity.



**Figure 4.3:** Correlation matrix plots between the predictions generated by the four different ML models (RF, SVM, KNN, and XGBoost) for a) yield, b) AE-N, c) AE-P, and d) AE-K.

Figure 4.4 combines scatter density plots and a map to highlight cases of strong disagreement in predictions between models across different agroecological zones of Ghana. The predictions of RF and SVM show that while most points cluster tightly around the diagonal, a few disagreements are evident, highlighted by red ellipses (Figure 4.4a). These disagreements indicate locations where SVM underestimates yields compared to RF. RF and KNN predictions also show that most points align closely with the diagonal, though some locations exhibit disagreements. SVM and XGBoost predictions

show more disagreements compared to RF-XGBoost, particularly at lower yield ranges (Figure 4.4d). The comparison between SVM and KNN reveals a greater spread of disagreements and systematic deviations in yield predictions for specific agroecological zones. Predictions from KNN and XGBoost show few extremes, indicating that these models tend to smooth yield predictions (Figure 4.4f). The agroecological zone map of Ghana in Figure 4.4 visualizes the geographic distribution of locations categorized by the pair of models in disagreement. The spatial pattern of prediction disagreements varies by agroecological zone. Large disagreements between models were relatively sparse in the Guinea Savanna zone, indicating minor discrepancies. In contrast, the Forest-Savanna Transition and Semi-Deciduous Forest zones showed increased disagreement, suggesting less consistent predictions in areas with varied environmental gradients.

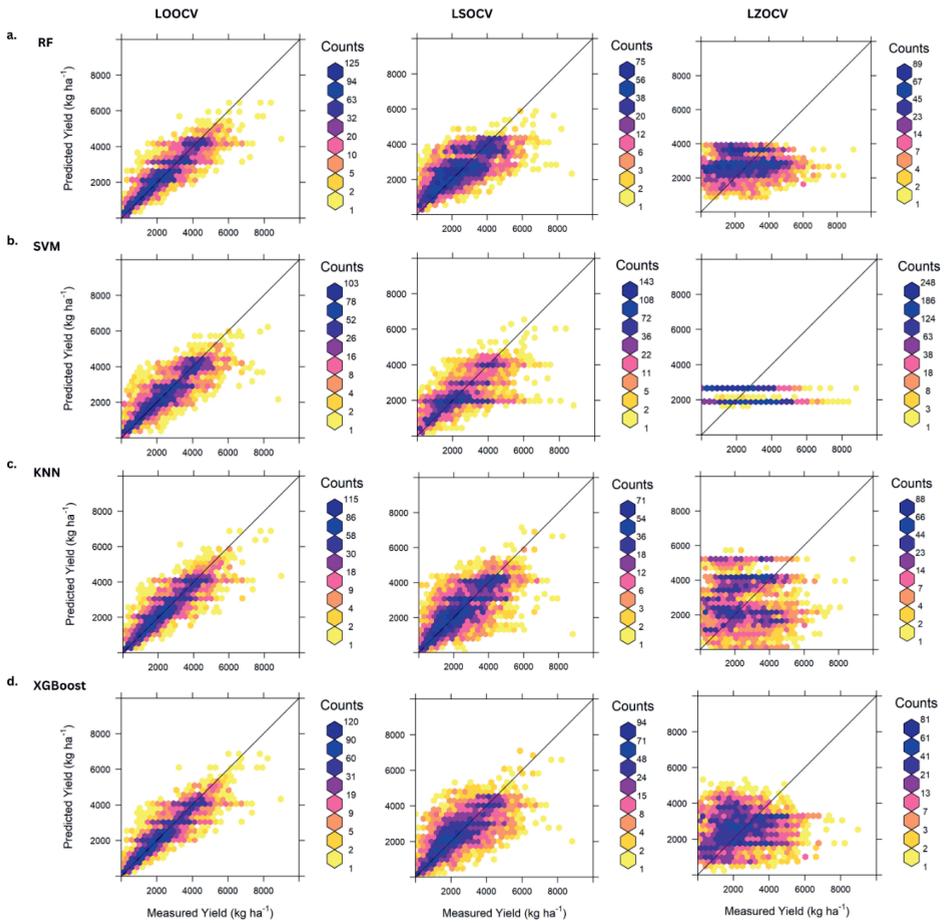


**Figure 4.4:** Scatter density plots comparing maize yield predictions across different ML models showing disagreements in model predictions presented on Agroecological zones of Ghana.

### 4.3.4 Evaluation of ML models

#### 4.3.4.1 Yield prediction

For maize yield prediction, XGBoost demonstrated the lowest RMSE (639.5 kg ha<sup>-1</sup>) and the highest MEC (0.795) under LOOCV, indicating its superior predictive accuracy and efficiency compared to the other models (Table 4.2). SVM had the highest RMSE of 740.4 kg ha<sup>-1</sup> and a slightly lower MEC of 0.725, reflecting a modestly inferior performance compared to the other models. Under LSOCV, all models demonstrated increased RMSE values when compared with LOOCV, indicating reduced accuracy when predicting yields for sites excluded from the training dataset. This decline underscores the challenge of generalizing to new locations not represented during training. The LZOCV approach revealed a substantial deterioration in model performance across all models. Although XGBoost still maintained the lowest RMSE (1580.6 kg ha<sup>-1</sup>) (Table 4.2) (Figure 4.5), its MEC dropped to -0.154, indicating very poor predictive efficiency. A negative MEC indicates that predictions are worse than taking the average of the observations as a prediction. RF and SVM showed similar patterns, with slightly worse RMSE and MEC values. KNN records the highest RMSE (1935.3 kg ha<sup>-1</sup>) and the most negative MEC (-0.880), indicating that the model is not good for extrapolation.

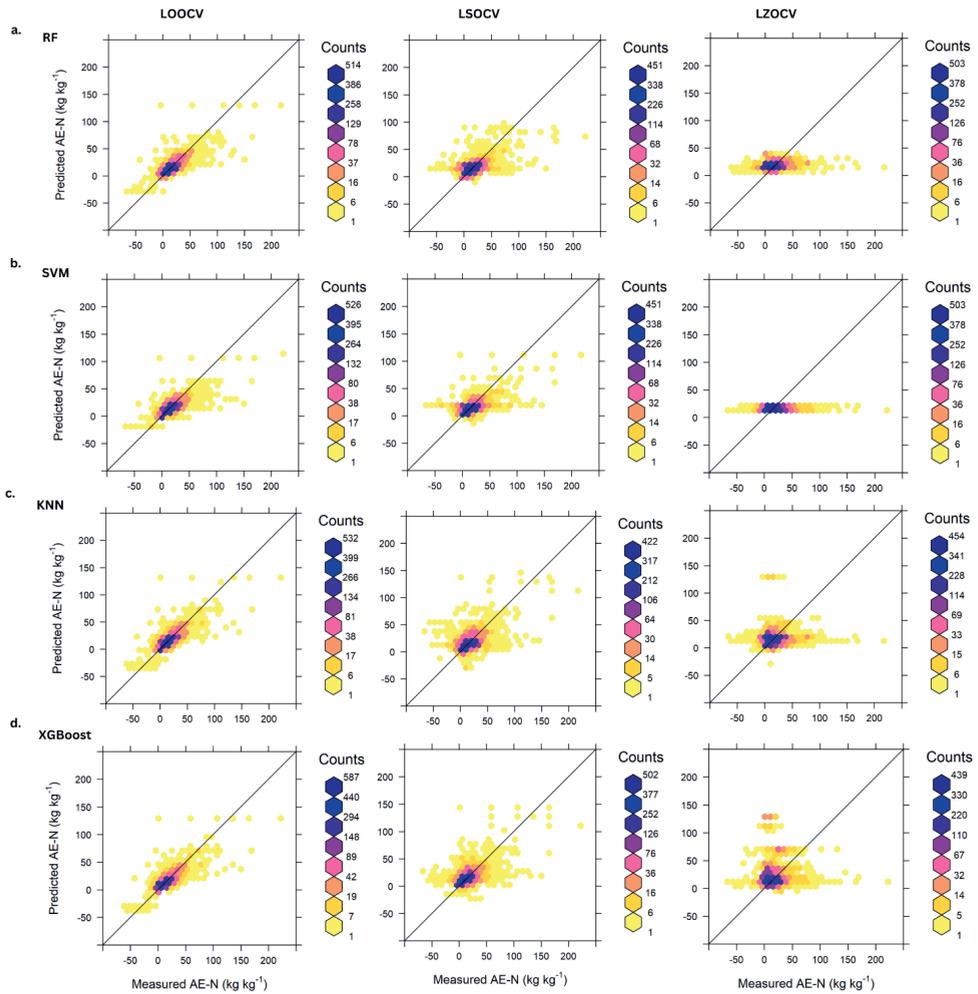


**Figure 4.5:** Scatter density plot of predicted against actual yields with a. RF, b. SVM, c. KNN, d. XGBoost with LOOCV, LSOCV and LZOCV.

#### 4.3.4.2 AE predictions

XGBoost achieved the lowest RMSE (11.6 kg kg<sup>-1</sup>) and the highest MEC (0.657) under LOOCV for AE-N predictions, indicating strong predictive performance (Table 4.2). SVM had the highest RMSE (12.7 kg kg<sup>-1</sup>) and the lowest MEC (0.592), suggesting limited accuracy. Under LSOCV, model performances declined. LZOCV results showed a significant drop in performance compared to LOOCV and LSOCV, with negative MEC values for all models. SVM and RF had the highest accuracy despite the decline, while KNN and XGBoost performed worse. XGBoost showed the best performance under LOOCV for AE-P, followed by RF, KNN, and SVM (Table 2 and Figure SI 7). Under LSOCV, RF slightly outperformed XGBoost, while SVM and KNN had similar performance, but all models had MEC values close to zero, indicating poor prediction performance. LZOCV exacerbated performance differences, with XGBoost maintaining the best relative performance despite declines, while SVM and KNN performed poorly. For AE-K predictions, XGBoost achieved the lowest RMSE and the highest MEC under LOOCV, followed by RF and KNN; SVM performed slightly worse across all metrics (Table 2 and Figure SI 8). Under LSOCV, notable performance declines occurred, with XGBoost and RF maintaining similar RMSE values but reduced MECs. LZOCV results revealed consistent performance degradation.

XGBoost consistently exhibited the best performance across most validation methods and metrics, particularly for maize yield and AE-N. However, its performance declined significantly under LZOCV, reflecting challenges in handling geographically excluded zones. The models showed reduced accuracy and efficiency as the validation method becomes more stringent, with LZOCV revealing significant weaknesses, as all models had negative MEC values for AE-N and AE-P, indicating difficulty generalizing across agro-ecological zones. RF and KNN performed comparably to XGBoost in many scenarios, with slightly higher RMSEs but competitive MEC values. KNN showed high accuracy in LOOCV and LSOCV scenarios. However, SVM consistently lagged behind other models in MEC and RMSE, particularly for maize yield and AE-P, suggesting its less suitability for this study.



**Figure 4.6:** Scatter density plot of predicted against actual AE-N with a. RF, b. SVM, c. KNN, d. XGBoost, ML models with LOOCV, LSOCV and LZOCV.

**Table 4.2:** Validation metrics of different ML models in predicting yield and AE of N, P, and K.

Target variable	CV method	XGBoost			SVM			RF			KNN			
		RMSE	ME	MEC	RMSE	MEC	ME	MEC	RMSE	MEC	ME	MEC	RMSE	MEC
Yield (kg ha-1)	LOOCV	639.5	0.1	0.795	740.4	31.9	0.725	655.6	675.5	-0.4	0.784	675.5	-1.2	0.771
	LSOCV	970.1	11.2	0.528	1026.4	159.0	0.471	977.4	975.8	-45.6	0.520	975.8	7.1	0.522
	LZOCV	1580.6	-12.7	-0.154	1574.8	231.8	-0.245	1515.0	1935.3	-262.8	-0.152	1935.3	-278.7	-0.880
AE-N (kg kg-1)	LOOCV	11.6	0.0	0.657	12.7	1.0	0.592	11.9	11.7	0.0	0.642	11.7	0.0	0.649
	LSOCV	16.5	-0.1	0.311	15.5	1.3	0.391	16.2	17.0	-1.0	0.330	17.0	-0.1	0.263
	LZOCV	28.3	-5.2	-1.039	19.9	-0.2	-0.003	20.1	23.6	-1.7	-0.022	23.6	-1.2	-0.419
AE-P (kg kg-1)	LOOCV	30.5	0.0	0.543	32.4	2.5	0.485	31.0	30.7	-0.1	0.527	30.7	-0.1	0.538
	LSOCV	44.3	1.1	0.034	41.8	5.6	0.140	41.4	45.2	-2.2	0.158	45.2	1.4	-0.006
	LZOCV	87.4	-41.5	-2.755	46.0	-1.4	-0.042	48.8	58.2	-9.2	-0.173	58.2	-6.0	-0.667
AE-K (kg kg-1)	LOOCV	22.8	0.0	0.509	24.0	1.2	0.455	23.0	23.0	0.0	0.499	23.0	-0.1	0.498
	LSOCV	30.2	1.4	0.136	29.0	2.6	0.206	30.4	31.2	-3.7	0.128	31.2	0.9	0.079
	LZOCV	42.0	-13.3	-0.670	32.5	-1.4	0.000	36.2	39.3	-11.0	-0.237	39.3	3.5	-0.459

SVM = Support vector machines, XGBoost = Extreme gradient boosting, RF = Random Forest, KNN = K nearest neighbour, LOOCV = Leave-one-out cross-validation, LSOCV = Leave-site-out cross-validation, LZOCV = Leave-zone-out cross-validation, RMSE = Root mean square error, ME = Mean error, MEC = Model efficiency coefficient. Note: MEC is mathematically equivalent to  $R^2$  computed against the 1:1 line.<sup>2</sup>

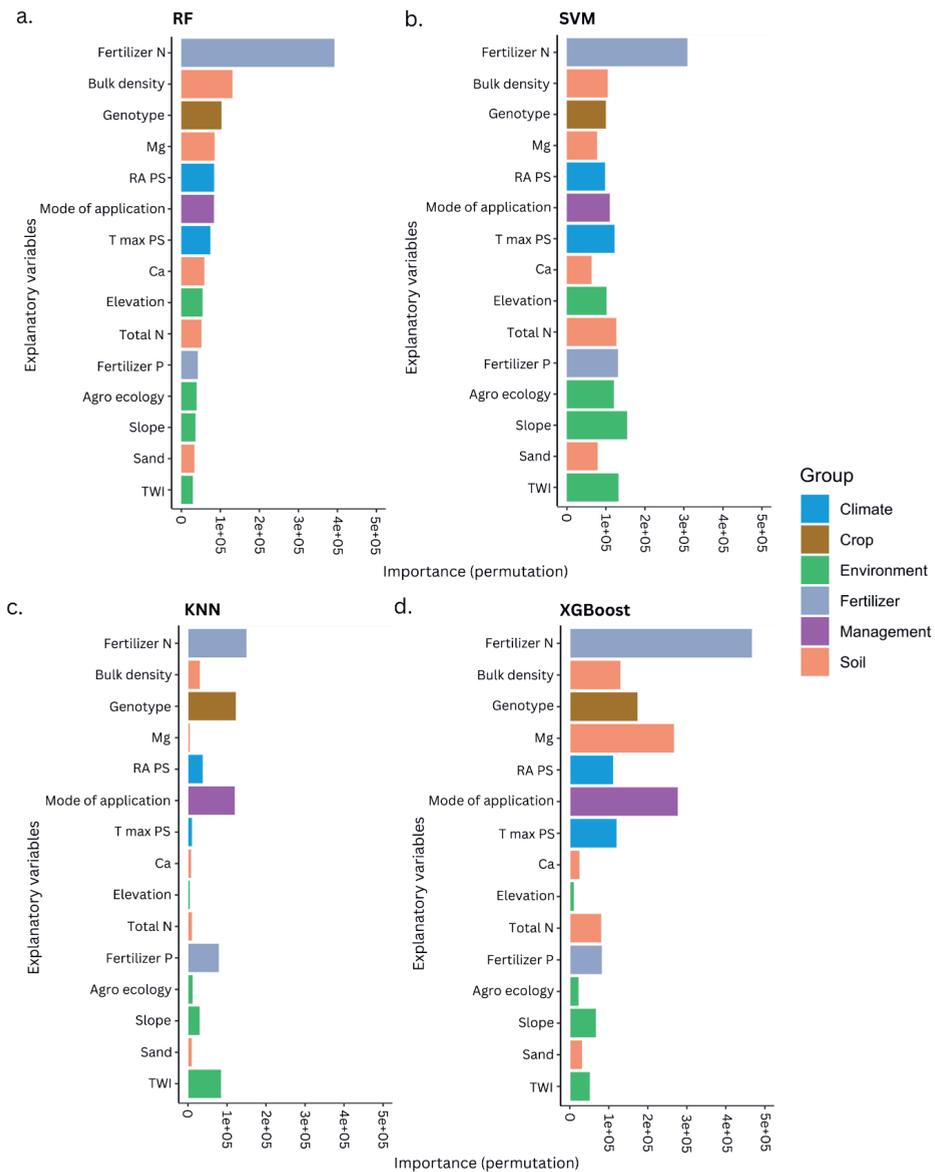
### 4.3.5 Variable importance for yield and AE from different models

Figure 4.7 shows variable importance plots generated using four different ML models for predicting yield based on the first 15 explanatory variables identified by the RF model, categorized into five groups: climate, crop, environment, fertilizer, and soil. The plots follow the same order of explanatory variables as the RF model, which serves as a reference and displays variable importances in decreasing order. The RF model highlights fertilizer nitrogen as the most influential variable by a significant margin (Figure 4.7a). Other important variables include soil bulk density and crop genotype. Variables such as exchangeable magnesium, rainfall during the planting season, and mode of fertilizer application exhibit moderate importance. Maximum temperature during the planting season and elevation receive relatively moderate weights, while sand, slope, and topographic wetness index are assigned low importance (Figure 4.7a). The RF model reflects a balanced weighting across variable groups but emphasizes fertilizer and crop-related variables, consistent with their direct impact on yield.

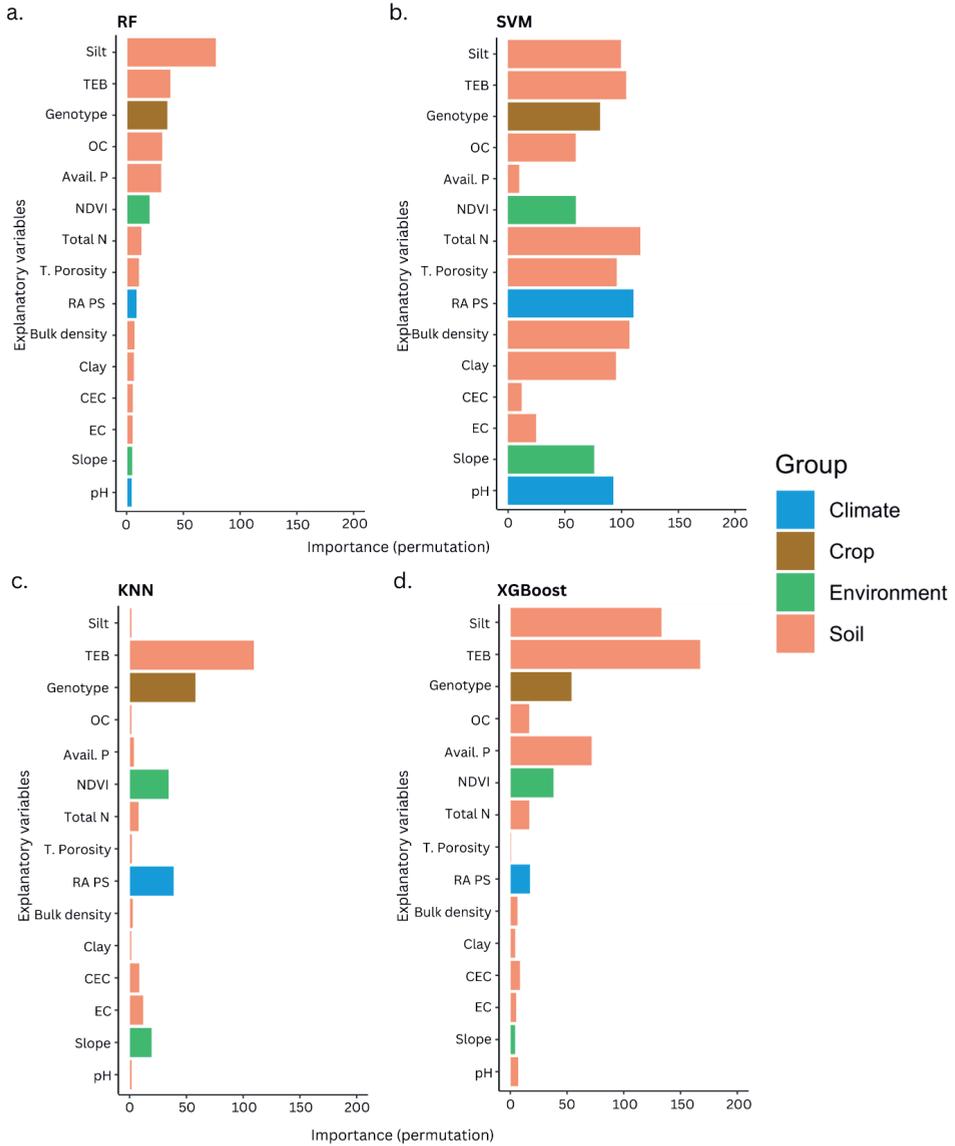
The SVM model also ranks fertilizer nitrogen as the most important explanatory variable, indicating agreement with RF regarding the role of nitrogen fertilizer application (Figure 4.7b). However, bulk density and crop genotype are assigned greater importance than in RF, suggesting SVM places a stronger emphasis on soil structure and crop genetics. Mode of fertilizer application and rainfall during the planting season remain moderately important, similar to RF. Maximum temperature, elevation, total nitrogen, agroecology, slope, and topographic wetness index receive slightly higher importance in SVM compared to RF, while exchangeable magnesium, calcium, and sand retain low importance rankings (Figure 4.7b). This suggests that SVM captures certain variables differently, reflecting its kernel-based approach to modelling data.

The KNN model displays a different distribution of variable importance compared to RF and SVM. While nitrogen fertilizer is still the most important variable, its dominance is less pronounced (Figure 4.7c). Instead, crop genotype rises to near-equal importance, highlighting the role of crop-specific traits when modelled using a distance-based approach such as KNN. Variables such as bulk density, rainfall during the planting season, and slope exhibit moderate importance. However, mode of fertilizer application, fertilizer phosphate, and topographic wetness index hold the highest importance relative to the RF model (Figure 4.7c). Exchangeable magnesium, maximum temperature during the planting season, exchangeable calcium, elevation, total nitrogen, and sand exhibit the lowest importance relative to RF and SVM models. XGBoost showed notable differences from the RF model in variable importance (Figure 4.7d). Similar to RF, fertilizer nitrogen is the most important variable, followed by mode of fertilizer application and exchangeable magnesium. However, XGBoost assigned moderate importance to crop genotype, bulk density, rainfall during the planting season, and maximum temperature during the planting season.

The analysis of variable importance depicted in Figure 4.8 provides insights into how different ML models prioritize explanatory variables in predicting AE-N. Across all models, soil variables emerge as the most critical contributors to AE-N prediction, with silt consistently ranking as the most important variable. This indicates the foundational role of soil texture in influencing AE-N. Total exchangeable base (TEB), another soil property, is highlighted as a significant variable across models, reinforcing the significance of soil fertility and nutrient exchange in determining AE-N. In RF, the importance of soil variables is pronounced, with silt and TEB overshadowing all other variables. This model places less emphasis on variables from other groups, such as environment and climate, suggesting that RF's prediction of AE-N relies heavily on soil-related explanatory variables. Similarly, XGBoost follows a comparable pattern, with silt and TEB dominating its predictions. Both models exhibit a narrow focus on a few key variables, downplaying the importance of others. In contrast, SVM adopts a more balanced approach, distributing importance across a wider range of variables. While silt remains a top contributor, SVM assigns significant importance to variables from other categories, such as crop genotype, rainfall, bulk density, NDVI, clay, pH, and total nitrogen. This diversity suggests that SVM captures a broader spectrum of factors influencing AE-N, including soil properties, crop characteristics, and environmental conditions. KNN emphasized very few variables, notably TEB, crop genotype, NDVI, and rainfall, while downplaying the importance of others. The variable importance identified by the models for AE-N was similar to those for AE-P (Figure SI 9) and AE-K (Figure SI 10).



**Figure 4.7:** Variable importance rankings for different machine learning models used to predict maize yield. The models include (a) RF, (b) SVM, (c) KNN, and (d) XGBoost. The variable importances are arranged in the order of the RF model ranking.



**Figure 4.8:** Variable importance rankings for different machine learning models used to predict AE-N. The models include (a) RF, (b) SVM, (c) KNN, and (d) XGBoost. The variable importances are arranged in the order of the RF model.



## 4.4 Discussion

### 4.4.1 Comparison of predictions across models

Figure 4.3 shows a strong agreement among different ML models for maize yield and AE prediction. The high pairwise correlation coefficients ( $>0.95$ ) indicate consistency in predictive outcomes. This suggests that the specific choice of ML algorithm may be less critical, as various models produce similar predictions, simplifying model selection for practitioners. This aligns with findings in the literature. For instance, Meroni et al. (2021) demonstrated that while ML methods improved crop yield forecasting, differences in predictions among models were not always practically significant. Similarly, Srivastava et al. (2022) found that nonlinear models such as convolutional neural networks, deep neural networks, and XGBoost were more effective in understanding crop yield relationships compared to linear models. These studies indicate that while ML methods enhance predictive performance, the choice among different approaches may not lead to significant differences in yield prediction accuracy.

The SVM model exhibited lower correlation values compared to KNN, RF, and XGBoost, indicating distinct predictive differences, particularly in handling outliers and complex data structures. These differences may stem from inherent algorithmic mechanisms. RF and XGBoost, as tree-based algorithms, effectively manage larger, heterogeneous datasets through adaptive partitioning of the feature space. In contrast, SVM defines optimal hyperplanes in transformed feature spaces, which becomes challenging in poorly separable data, especially with high dimensionality and complexity. The many explanatory variables in this study exacerbate SVM's sensitivity to noise. Consequently, kernel-based approaches such as SVM often show reduced predictive accuracy with heterogeneous datasets. These findings align with previous research, highlighting that SVM's dependence on clearly defined boundaries makes it less effective with numerous explanatory variables compared to tree-based approaches (Abbas et al., 2020; Mountrakis et al., 2011).

### 4.4.2 Comparison of prediction performance across models

Among the evaluated ML models, XGBoost consistently outperformed RF, SVM, and KNN in predicting yields and AE for N, P, and K, as demonstrated by its high MEC values across all cross-validation (CV) methods (Table 4.2). This finding aligns with previous research by Huber et al. (2022), who also reported XGBoost's effectiveness in managing complex explanatory variables for yield predictions. XGBoost's advantage stems from its additive boosting strategy, which corrects prediction errors by capturing intricate non-linear relationships between agronomic variables and crop performance. This capability explains its superior performance across varied validation scenarios (LOOCV, LSOCV, LZOCV). RF also demonstrated substantial predictive strength, particularly in yield predictions under LOOCV (MEC = 0.784), benefiting from its tree-based learning framework that

aggregates predictions across multiple decision trees. This approach effectively mitigates overfitting and improves model generalization, particularly important in agricultural settings as confirmed in Cutler et al. (2007). In comparison to SVM, RF and XGBoost, KNN exhibited relatively less stable performance, especially under rigorous validation conditions such as LZOCV, indicated by substantially lower or negative MEC values. For instance, KNN performed poorly in yield prediction using LZOCV (MEC = -0.880), likely due to its sensitivity to data heterogeneity, which is consistent with the conclusions of Zhang (2016) and with  $k = 2$  probably not a good hyperparameter for LZOCV. Similarly, SVM's effectiveness diminished under heterogeneous datasets, reflecting its dependency on precise kernel functions and hyperplane optimization, making it particularly vulnerable to heterogeneous datasets (Ben-Hur and Weston, 2010; Cortes and Vapnik, 1995).

The usefulness of ML models in agronomic predictions varies depending on data availability and environmental similarity between training and target sites. The LOOCV results indicate strong predictive capability (e.g., MEC = 0.795 for yield prediction with XGBoost) when training data from the same site and season are available. However, predictive accuracy diminishes when training data from the exact location are unavailable, as seen with LSOCV, where MEC for XGBoost yield predictions decreases to 0.528. The performance deteriorates further under conditions lacking environmental similarity (LZOCV), with negative MEC values across all models, suggesting predictions become worse than using an average, rendering the ML models less effective in such scenarios. Agronomic decision-making often aligns closely with the LSOCV scenario, wherein training data from similar sites or conditions are accessible. Therefore, while predictions in this context remain useful (e.g., MEC = 0.528 for XGBoost), these results underscore the importance of having sufficient data from comparable environmental and climatic contexts to maintain reliable predictions.

#### 4.4.3 Comparison of model performance across validation schemes

The performance of all models declined under LSOCV and LZOCV when compared with LOOCV. This issue is well-documented in agricultural ML research, with Bonilla-Cedrez et al. (2021) reporting similar declines in spatial generalization when models were trained without data from specific geographic zones. The observed degradation in predictive accuracy under LSOCV and LZOCV underscores the inherent difficulty of capturing heterogeneity when training data lack adequate representation of diverse environmental conditions (Meyer et al., 2018). Notably, Figure 4.5 reveals that the predictions of some models, particularly SVM, tend to be identical for many locations under LZOCV, as shown by the horizontal patterns. The reason for this behavior lies in the way SVM constructs decision boundaries in high-dimensional feature spaces. Unlike tree-based models, which adaptively partition feature space based on data distributions, SVM relies on a fixed kernel function to map input variables into a higher-dimensional space before defining an optimal hyperplane for classification or regression (Cortes and

Vapnik, 1995). When faced with completely unseen zones, the absence of representative training samples in that region forces SVM to rely excessively on its learned hyperplane, leading to overly generalized predictions with limited variability (Smola and Schölkopf, 2004). This issue is further exacerbated by SVM's sensitivity to feature scaling and kernel selection, particularly in agronomic datasets characterized by complex interactions. Previous studies, such as Abbas et al. (2020) and Mountrakis et al. (2011), have shown that SVM struggles when applied to heterogeneous data, as it assumes a uniform distribution of feature spaces that may not hold true across different environmental zones. In contrast, tree-based ensemble methods such as RF and XGBoost demonstrate superior adaptability in LZOCV settings due to their ability to capture nonlinear feature interactions and minimize bias through recursive partitioning (Breiman, 2001; T. Chen and Guestrin, 2016).

While KNN performed competitively in LOOCV, its accuracy deteriorated markedly under LSOCV and LZOCV for AE predictions. This pattern reinforces concerns about KNN's sensitivity to localized patterns and its heavy reliance on distance-based metrics. Prior studies, such as Fu et al. (2019), have shown that KNN's performance is highly dependent on the distribution of training samples, making it less effective in extrapolating to heterogeneous datasets.

#### **4.4.4 Interpreting predictive performance across models**

Across all ML models evaluated in this study, predictive performance was generally modest to poor, particularly for AE across all cross-validation strategies of LOOCV, LSOCV, and LZOCV, and for yield under the LZOCV approach. This trend persisted even when separate models were trained per agroecological zone (results not shown), suggesting that poor model performance cannot be attributed solely to systematic differences between these zones. Rather, these results highlight broader limitations in modelling agronomic outcomes given the constraints of available data. Our findings align with previous studies in agronomic ML that report challenges in achieving high predictive accuracy when target variables are influenced by complex, site-specific interactions and unobserved contextual factors. For instance, Khaki and Wang (2019) show that high-dimensional agronomic models often struggle with generalizability when key drivers are missing or inconsistently measured. Antle et al. (2017) argue that predictive accuracy in complex agricultural systems is limited by insufficient data on management and environmental variability.

Several factors likely contributed to the limited model performance in our study. First, AE exhibits high intrinsic variability and is influenced by nonlinear interactions among fertilizer rates, soil properties, genotype-by-environment dynamics, and variable management practices, many of which are difficult to measure or encode systematically (Cassman et al., 2003). Second, measurement noise and missing contextual data, such as cropping history, pest and disease incidence, or labour availability, were not available in our dataset but are known to significantly impact yield and input-use efficiency (Lobell,

2013). Third, management practices were often represented categorically or at coarse resolution, missing important temporal aspects such as fertilizer timing or irrigation scheduling. Prior studies (van Klompenburg et al., 2020) have shown that including fine-grained management data can enhance model accuracy.

The decline in model performance under the most stringent validation approach (i.e., LZOCV) underscores the challenge of extrapolating predictions across agroecological boundaries. When entire zones are excluded from training, the model must make predictions in entirely new environments, often with limited transferable patterns. This generalization gap reflects the limitations of pure data-driven approaches when faced with heterogeneous biophysical systems. Importantly, these limitations should not be viewed as a failure of ML algorithms, but rather as a reflection of the inherent complexity and data constraints associated with modelling yield and efficiency at national scales. Future efforts may benefit from integrating high-resolution environmental and temporal datasets, including variables such as in-season weather, pest dynamics, or crop phenology. Hybrid modelling approaches that combine ML with process-based crop models or expert agronomic rules may also provide more accurate predictive frameworks (Antle et al., 2017; Hochman et al., 2017). Ultimately, the consistent patterns observed across models, validation strategies, and zones highlight the need for cautious interpretation of ML performance in agronomic contexts. While ML can offer useful insights, especially in data-rich environments, its application in diverse smallholder systems must contend with fundamental data and system complexity limitations.

#### 4.4.5 Key variables for yield and AE prediction

Across all models, nitrogen fertilizer emerged as the most influential variable for maize yield, aligning with the findings of Mueller et al. (2012), who identified nitrogen as a primary driver of yield variability. Soil properties such as bulk density and pH, were identified as critical factors, reinforcing existing agronomic research on the role of soil factors in crop productivity (Oldfield et al., 2019). While bulk density emerged as a significant predictor for maize yield and AE, this reflects a statistical association rather than a tested causal relationship. Establishing causality would require experimental or mechanistic modelling approaches, which were beyond the scope of this study. However, agronomic literature supports the causal influence of bulk density on crop performance, as high bulk density is linked to increased soil compaction, restricting root penetration, reducing water infiltration, and limiting nutrient uptake, ultimately impairing plant growth and yield potential (Hamza and Anderson, 2005; Lipiec et al., 2003; Ocloo et al., 2014). Identification of bulk density as a key predictive variable suggests that improving soil physical condition could enhance nutrient use efficiency and yield outcomes. The consistent importance of bulk density across models underscores the need to consider soil physical constraints in integrated nutrient and crop management strategies.

Despite shared key variables, the importance assigned to explanatory variables varied across models. Notably, SVM and KNN emphasized crop genotype and environmental factors more than tree-based methods such as RF and XGBoost. This divergence in rankings can be attributed to differences in how these models process input data. Tree-based models prioritize variables that yield the greatest reduction in impurity (Breiman, 2001; Chen and Guestrin, 2016), while distance-based methods such as KNN and margin-based classifiers such as SVM are sensitive to data distribution and local patterns (Hastie et al., 2006). Previous applications of ML in yield prediction (Jeong et al., 2016; Khaki and Wang, 2019) highlight that while different ML models may achieve comparable predictive accuracy, they often diverge in identifying the underlying drivers of predictions. Relying on a single model for interpretation can lead to biased conclusions. Recent studies advocate for interpretation techniques such as SHAP (SHapley Additive exPlanations) values to provide a more reliable understanding of variable influence across models (Lundberg and Lee, 2017; Shrikumar et al., 2017; Kouame et al., 2023).

While variable importance analysis helps identify patterns, this study did not aim to establish causal relationships between input variables and outcomes. Variable importance indices reflect associative strength and are influenced by model architecture, input distributions, confounding variables, and variable interactions. Establishing cause-and-effect relationships would require different methodological approaches (Kouame et al., 2025), which were outside this study's scope. Nevertheless, our findings provide a valuable starting point for identifying candidate variables for further investigation, experimental testing, or inclusion in integrated decision-support systems. Future work should explore hybrid approaches that combine ML prediction with agronomic expertise and causal modelling to derive actionable insights. Ensemble-based interpretation strategies that integrate results across multiple ML models can offer a more accurate and comprehensive understanding of key agronomic drivers, improving transparency and decision-making while guiding future interventions for nutrient-use efficiency, genotype selection, and context-specific input optimization (Meyer et al., 2018).

While identifying key variables such as nitrogen fertilizer application rate, rainfall, and genotype is valuable, this study's findings do not translate directly into specific field-level recommendations, such as how much fertilizer to apply or which maize genotype to plant. For ML predictions to inform management decisions, future tools would need to incorporate economic thresholds and optimization frameworks to deliver actionable recommendations. Nonetheless, identifying cross-model important variables lays the groundwork for such tools and supports broader efforts in site-specific data-informed agricultural decision-making under variable field conditions.

#### **4.4.6 Implications of the findings**

The observed performance trends have significant implications for yield and AE modelling and decision-making. The enhanced accuracy of tree-based methods, particularly RF and XGBoost,

demonstrates their suitability for yield and AE prediction tasks, especially in agroecological zones with considerable variability. These algorithms effectively model complex, nonlinear interactions among soil properties, climatic conditions, and management practices, which single-model approaches often lack. However, this effectiveness depends on having training data that closely resembles the target prediction areas. The decline in predictive performance under LZOCV highlights a significant limitation of current ML approaches in agronomy, their inadequacy in extrapolating to areas without similar feature representations. This challenge aligns with Bonilla-Cedrez et al. (2021) who noted that ML models often underperform when applied to geographically distinct or unseen areas due to environmental heterogeneity. A key implication is the need to avoid feature extrapolation, which can be addressed by assessing similarity indices, as suggested by Meyer et al. (2018) to ensure predictions remain within the training data's feature space. Data collection strategies should aim to fill gaps in the feature space, enhancing the model's applicability across diverse conditions. Wadoux et al. (2019) explored optimal sampling designs for mapping with RF in digital soil mapping, highlighting the importance of strategic sampling to improve model performance. As datasets expand and more data are shared publicly, the potential for building accurate models with reduced extrapolation issues increases, promising enhanced predictive capabilities and more reliable agronomic decision-making over time.

#### 4.4.7 Limitations of this study

While ML offers powerful tools for predictive modelling in agriculture, it presents important limitations, particularly for management decisions in complex, smallholder farming systems. One key limitation observed in this study was the relatively low predictive accuracy for AE, especially under rigorous cross-validation schemes such as LZOCV. This indicates limited generalizability across diverse agroecological zones, a critical barrier for using ML to support wide-scale, site-specific recommendations.

Additionally, the models were trained on observational data that lacked key agronomic details, such as fertilizer timing, application method, pest and disease incidence, and prior land use history, all known to influence yield and nutrient use efficiency (Tittonell and Giller, 2013). The absence of such variables contributed to prediction uncertainty and limited the models' performance. Moreover, the use of non-causal, black-box ML algorithms restricts causal interpretability and may lead to misleading inferences if model outputs are used without agronomic validation (Antle et al., 2017).

While individual ML models were extensively compared, this study did not explore ensemble stacking methods, which have shown potential in improving predictive stability and accuracy (Zhou, 2012). Future research should investigate these ensemble approaches, particularly in the context of evaluation methods such as LZOCV, to further enhance model performance and generalization.

## 4.5 Conclusion

This study highlighted the growing impact of ML in agricultural yield predictions, particularly for staple crops like maize in Ghana. Our analysis of four ML models, XGBoost, RF, SVM, and KNN revealed three key findings. First, in terms of prediction accuracy, the models performed comparably, with SVM showing slightly weaker results and XGBoost the best. Second, model prediction performance remained relatively similar across cross-validation methods, although performance dropped significantly under extrapolation, highlighting the challenges of applying these models beyond their training data. XGBoost and RF exhibited better extrapolation capabilities than KNN and SVM. Third, while the models generally agreed on key explanatory variables, notable differences in variable importance rankings suggest that relying on a single model may provide an incomplete picture. From these findings, we conclude that while the choice of ML model is not critical for yield and AE prediction, it plays an important role in extrapolation and variable importance analysis. Therefore, we recommend using multiple models to derive more reliable insights into key factors influencing maize productivity. Additionally, yield prediction proved more straightforward than AE prediction, indicating that further refinement of input variables or modelling techniques is needed for improved efficiency estimates. Given the significant drop in performance under extrapolation scenarios, future research should focus on improving model generalizability across diverse agroecological zones by collecting data in the entire feature space. By leveraging multiple models and refining extrapolation strategies, ML can serve as a powerful tool for data-driven agricultural planning, ultimately contributing to sustainable crop production in sub-Saharan Africa.

### Supplementary materials

The supplementary materials can be downloaded from the journal version of this chapter:

Asamoah, E., Heuvelink, G. B., Bindraban, P. S., & Logah, V. (2025). Modeling maize yield and agronomic efficiency using machine learning models: A comparative analysis. *Agronomy Journal*, 117(6), e70206. <https://doi.org/10.1002/agj2.70206>





# Chapter 5

Accounting for uncertainty in fertilizer recommendation strategies: Example of smallholder maize production in Ghana

This chapter is based on:

Asamoah, E., Heuvelink, G. B. M., & Logah, V. (2026). Accounting for Uncertainty in Fertilizer Recommendation Strategies: Example of Smallholder Maize Production in Ghana.

Accepted, with revision, Field Crops Research

## **Abstract**

### Context

Fertilizer management in smallholder maize production systems in sub-Saharan Africa faces major challenges due to high environmental variability, uncertain input-output prices, and diverse farmer risk preferences. Conventional fertilizer recommendations often fail to account for these factors, resulting in poor adoption rates and inefficient fertilizer use.

### Objective

This study aimed to develop a fertilizer recommendation framework that integrates yield uncertainty and farmer risk profiles to improve fertilizer application decision-making. Specifically, it examined how uncertainty and farmer risk preferences affect optimal nutrient application rates.

### Methods

Using 4,496 maize field experimental observations, a Quantile Regression Forest model was trained to predict maize yield responses to nitrogen, phosphorus, and potassium and assessed their profitability in 14 representative sites across three agro-ecological zones in Ghana. A utility-based economic model was then applied to simulate farmer decisions under varying levels of risk aversion.

### Results

Nitrogen emerged as the key yield-limiting nutrient, with yield responses increasing steeply up to approximately 90 kg N ha<sup>-1</sup>. Phosphorus and potassium showed minimal agronomic and economic benefits under prevailing farmer conditions. Profit-maximizing nitrogen rates generally ranged from 60–90 kg ha<sup>-1</sup> but declined to 10–80 kg N ha<sup>-1</sup> under risk-sensitive scenarios, particularly for strongly risk-averse farmers. Importantly, our approach revealed site-level heterogeneity in optimal strategies, even within the same agroecological zone.

### Conclusions

Incorporating uncertainty and farmer behaviour into fertilizer decision-making produces more realistic and relevant nutrient recommendations.

### Implications

By accounting for uncertainty and farmer behaviour, this study offers a framework to improve the relevance and efficiency of fertilizer recommendations. The findings provide new insights into adaptive agronomy within the context of sustainable intensification and support a shift toward yield-enhanced, site-specific, and risk-informed nutrient management strategies that better reflect the realities of smallholder decision-making under increasingly uncertain conditions.

## 5.1 Introduction

Small-scale maize farming remains a cornerstone of food security in Ghana and much of sub-Saharan Africa. Yet, its productivity is increasingly undermined by persistent challenges such as declining soil fertility, climate variability, and limited access to quality agricultural inputs (Droppelmann et al., 2017). Fertilizers are critical for restoring soil nutrients and enhancing yields, and over recent decades, their use has underpinned major gains in global food production (Penuelas et al., 2023). However, their misuse whether through over-application or underutilization can lead to serious environmental degradation, economic inefficiencies, and diminished long-term soil health (Bisht and Chauhan, 2020).

In Ghana's smallholder farming systems, fertilizer use is often inconsistent with agronomic recommendations. While under-application in staple crop systems contributes to nutrient mining and declining productivity, over-application in high-value or subsidized crop systems has resulted in nutrient runoff, soil degradation, and economic waste. For example, fertilizer use among tomato and onion growers in the Upper East Region has exceeded recommended rates by up to 50%, driven by misconceptions about yield response and the availability of subsidized inputs (Akolgo et al., 2025). Similarly, excessive fertilizer application in maize fields in southern Ghana has contributed to nutrient leaching and algal blooms in coastal ecosystems (Davies-Vollum et al., 2024). These trends underscore the urgent need for more context-sensitive, efficient, and sustainable nutrient management strategies.

While the agronomic benefits of fertilizer are well-established, a central challenge remains: the variability of agronomic efficiency, defined as the yield gain per unit of nutrient applied, is high and difficult to predict under the diverse and dynamic conditions faced by smallholder farmers (see Chapter 2). Environmental heterogeneity, including variable soil types and unpredictable weather patterns, complicates the ability to prescribe optimal fertilizer rates. These uncertainties are exacerbated by climate change, which disrupts historical weather norms and alters nutrient cycling (Thorburn et al., 2024), and by volatile fertilizer prices and global supply chain disruptions, which increase financial risk for smallholders (Rosenzweig et al., 2014). In this context, fertilizer decision-making must not only optimize yields but also manage uncertainty and risk, particularly for resource-constrained farmers for whom input failure carries substantial economic consequences.

Recent advances in data science and precision agriculture offer promising avenues to address these challenges. Machine learning (ML) models, especially those trained on localized and heterogeneous datasets, can capture complex, nonlinear interactions between soil characteristics, weather conditions, and crop response (Abera et al., 2022; Liben et al., 2024; Zingore et al., 2022). Among these, Quantile Regression Forest (QRF) offers a notable advantage by providing both point predictions and associated prediction uncertainty essential for informed, risk-sensitive decision-making in highly variable smallholder contexts. QRF models enable farmers and advisors not only to predict expected yields but also to understand the range of possible outcomes under different fertilizer regimes. Despite their

potential, machine learning models are not without limitations. They often function as "black boxes," lacking transparency and interpretability. However, recent advances in explainable AI (XAI), such as SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations), have begun to address these limitations, enhancing model transparency and farmer trust (Molnar et al., 2020). Importantly, the predictive power of ML models hinges on access to high-quality, representative data, yet such data are often scarce or fragmented in smallholder systems.

Beyond technical agronomic considerations, farmer decision-making is deeply influenced by risk preferences. Many smallholders are risk-averse, preferring predictable, stable outcomes to strategies that promise higher returns but come with greater uncertainty (Dadzie et al., 2022). Traditional fertilizer recommendations often neglect this behavioral dimension, failing to align with the economic realities and psychological risk tolerances of farmers. High fertilizer application may maximize yield potential but simultaneously expose farmers to financial loss if expected outcomes are not realized. Conversely, overly cautious fertilizer use may protect resources but limit productivity. Optimizing fertilizer strategies thus requires an integrated framework that accounts for both yield uncertainty and farmer-specific risk attitudes. This study addresses a critical gap at the intersection of agronomy, data science, and behavioral economics by proposing an integrated fertilizer recommendation framework that explicitly incorporates both yield uncertainty and farmer risk profiles. While prior research has applied ML to predict crop yields in agriculture, to the best of our knowledge, no studies have combined quantile-based yield prediction and farmer-centric risk modelling into a unified decision-making tool tailored to smallholder maize production systems.

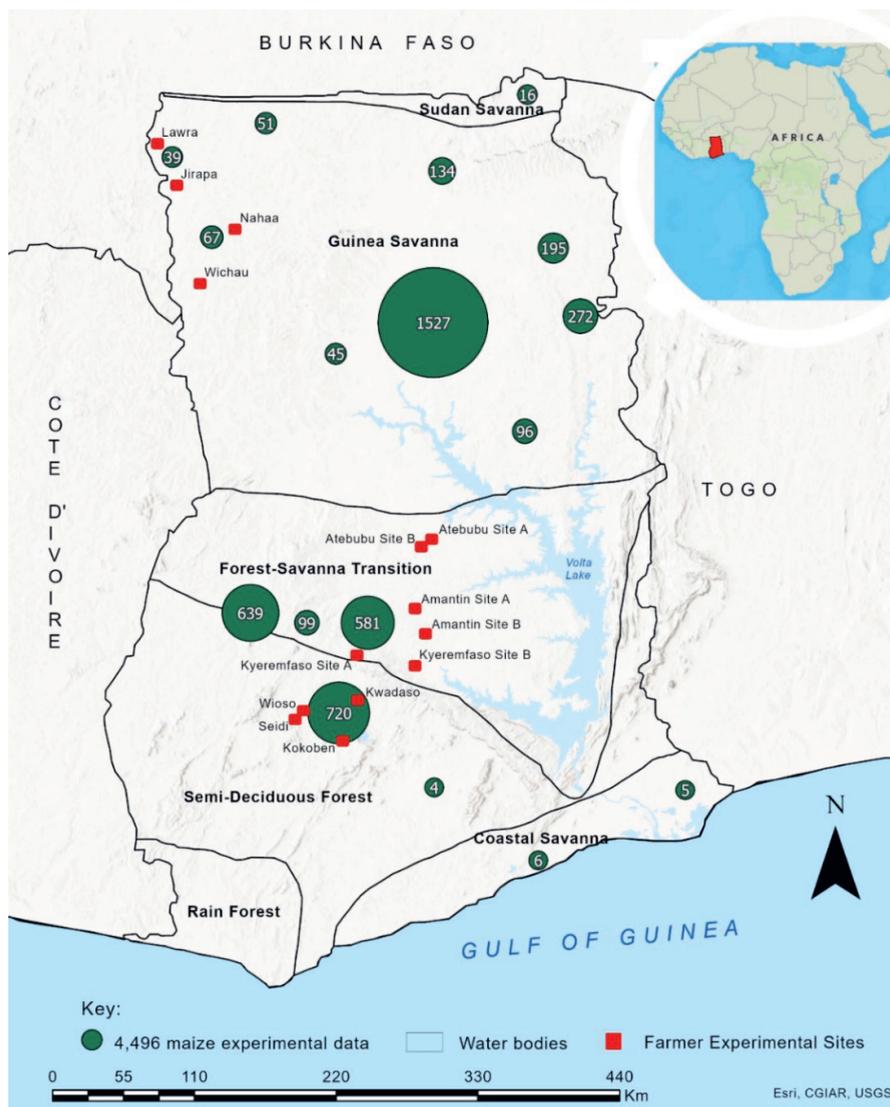
The main objective of this study is to develop a fertilizer recommendation framework that integrates yield uncertainty and farmer risk profiles to improve fertilizer application decision-making. Specifically, the study aims to: i) quantify uncertainty in yield prediction using QRF; ii) quantify how farmers perceive risks through developing risk profiles; iii) develop a methodology that optimizes fertilizer recommendation while accounting for yield uncertainty and farmer's risk profiles; and iv) apply the developed methodology to optimize fertilizer recommendations specifically for smallholder farm maize production in Ghana.

## **5.2 Materials and methods**

### **5.2.1 Study area, experimental datasets and explanatory variables**

This study was conducted in Ghana, a West African country bordered by Togo to the east, Côte d'Ivoire to the west, and Burkina Faso to the north. To the south, Ghana meets the Gulf of Guinea (Figure 5.1). Covering a total land area of 238,533 km<sup>2</sup>, Ghana has a population of just over 30 million, according to the 2021 population census (GSS, 2021). The study encompasses all agroecological zones in Ghana,

including the Guinea Savanna (GS), Sudan Savanna (SS), Forest-Savanna Transition (FST), Semi-Deciduous Forest (SDF), and Coastal Savanna (CS) zones, while excluding the Rain Forest (RF) (Figure 1). The data used in this study comprise 4,496 maize experimental yield data used in Chapter 2 and data from 14 experimental sites representing local farming conditions: Wichau, Nahaa, Jirapa, Lawra, Kyeremfaso Sites A and B, Amantin Sites A and B, Atebubu Sites A and B, Wioso, Seidi, Kokoben, and Kwadaso (Figure 5.1). The maize yield data have a minimum of 11 kg ha<sup>-1</sup>, a maximum of 8,815 kg ha<sup>-1</sup>, and a mean of 2,524 kg ha<sup>-1</sup>. Explanatory variables identified to influence yield were climatic variables, soil variables, crop genotype, other environmental variables, management practices, and fertilizer application data. A summary of the 40 explanatory variables prepared for the modelling is presented in Table SI 1. Detailed descriptions of the study area and the experimental datasets are provided in Chapter 2.

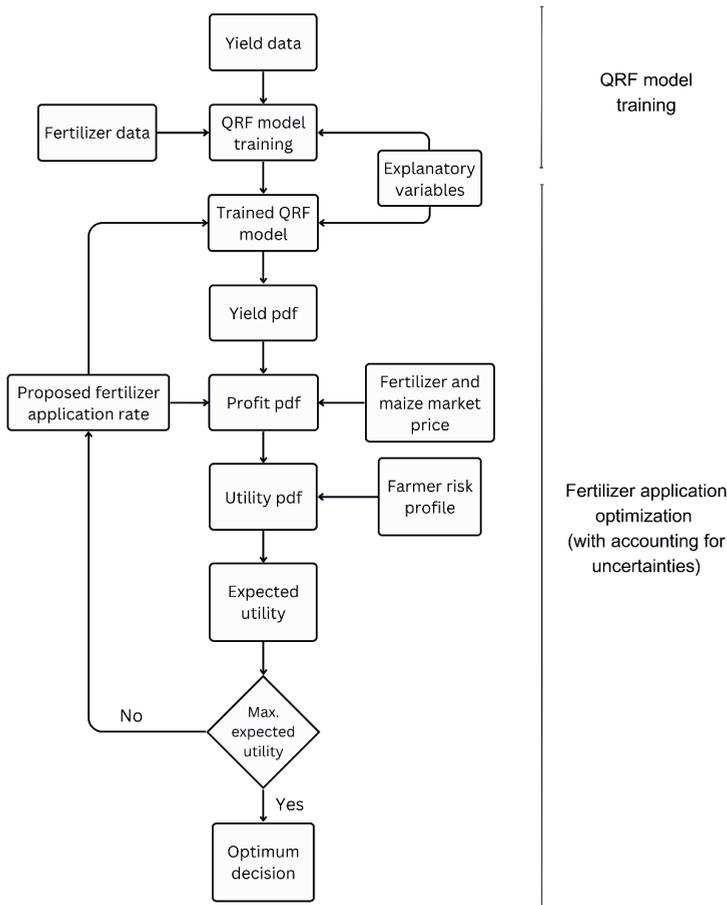


**Figure 5.1:** Map showing distribution of the maize experimental data across the agroecological zones of Ghana for modelling and locations of farmer experimental sites for deriving fertilizer recommendations.

### 5.2.2 Incorporation of farmer risk profiles in fertilizer application optimization

Fertilizer application optimization is central to this study, addressing yield prediction uncertainty and farmers' risk perceptions. The approach integrates data-driven decision-making, predictive modelling, and economic evaluation to provide effective and viable recommendations for smallholder farmers. A

QRF model predicts maize yield distributions under varying fertilizer rates and environmental conditions, which are analyzed to derive optimal strategies. The optimization process includes defining farmer risk profiles through utility functions, conducting economic evaluations of net returns, and applying optimization algorithms to identify fertilizer application strategies that align with individual risk preferences. The goal is to maximize expected utility while ensuring practical, risk-aware recommendations. Figure 5.2 illustrates the optimization framework, with its main components explained in subsequent sub-sections.



**Figure 5.2:** Framework for optimizing fertilizer application for maize production with accounting for uncertainties and farmer’s risk profiles (pdf = probability distribution function).

### 5.2.3 Machine learning yield prediction model: Quantile regression forests

In our yield prediction framework, we implemented a Quantile Regression Forest (QRF) model following the approach described in Chapter 2, which builds on the conventional Random Forest (RF)

algorithm. Like RF, the QRF model constructs an ensemble of decision trees trained on bootstrapped samples of the data and subsets of explanatory variables (Breiman, 2001). However, QRF distinguishes itself by offering a probabilistic output estimating the full conditional distribution of the target variable (in this case, maize yield) rather than providing a single-point prediction (Meinshausen, 2006).

In a standard RF model, the prediction for a new input point  $x$  is the average of the observations in the terminal nodes of the individual decision trees where  $x$  falls. Mathematically, this is expressed as a weighted average over the  $n$  observations in the training dataset:

$$\hat{y}(x) = \sum_{i=1}^n w_i(x) \cdot y_i \quad (5.1)$$

Here,  $w_i(x)$  represents the weight of observation  $y_i$  for the input  $x$ , based on its frequency across the terminal nodes reached by  $x$  in the forest. QRF extends this by estimating the entire conditional cumulative distribution function  $F_{Y|X}(y) = P(Y \leq y | X = x)$ . The estimated conditional distribution is given by:

$$\hat{F}(y|X = x) = \sum_{i=1}^n w_i(x) \cdot \mathbf{1}_{\{y_i \leq y\}} \quad (5.2)$$

where  $\mathbf{1}_{\{y_i \leq y\}}$  is an indicator function that equals 1 when  $y_i \leq y$ , and 0 otherwise. This formulation allows QRF to approximate the full distribution of yield outcomes at each prediction point.

By solving for  $y$  such that:

$$\hat{F}(y|X = x) = q \quad (5.3)$$

we can obtain the conditional quantile  $q$ , which corresponds to a probability level of the predicted outcome. For example, the 0.05 and 0.95 quantiles are typically used to construct a 90% prediction interval, providing a range within which the yield is expected to fall with 90% probability.

The ability to extract conditional quantiles makes QRF particularly well-suited for uncertainty quantification. In this study, we approximated the full conditional yield distribution for each fertilizer rate by drawing repeated samples from the QRF model. Each sample was generated by randomly selecting a tree from the forest and then randomly selecting a training observation from the terminal node corresponding to the input  $x$ , with observations in smaller terminal nodes being sampled more frequently due to their higher relative weight in the QRF formulation. This probabilistic output allowed us to propagate uncertainty into downstream economic analyses, such as profit prediction and utility-based decision-making.

### 5.2.4 Evaluation of QRF model

The QRF model was evaluated using a nested  $10 \times 5$ -fold cross-validation as in Chapter 2 to assess predictive performance of the model. We used standard accuracy metrics including mean error (ME), root mean squared error (RMSE), and the model efficiency coefficient (MEC). For uncertainty evaluation, we employed the Prediction Interval Coverage Probability (PICP), which quantifies how well the predicted intervals cover the actual observed values. The PICP is computed as shown in Eq. 5.7, where  $\hat{y}_i^L$  and  $\hat{y}_i^U$  are the lower and upper bounds of the prediction interval for observation  $i$ , respectively, and  $I(\cdot)$  is the indicator function, which equals 1 if the observed value  $y_i$  falls within the interval and 0 otherwise. Additionally, reliability plots were used to visually inspect the alignment between predicted intervals and observed frequencies (Schmidinger and Heuvelink, 2023).

$$ME = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i) \quad (5.4)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (5.5)$$

$$MEC = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (5.6)$$

$$PICP = \frac{1}{n} \sum_{i=1}^n I(y_i \in [\hat{y}_i^L, \hat{y}_i^U]) \quad (5.7)$$

### 5.2.5 Profit computation and utility-based decision making in fertilizer application rate

The cost of NPK, Urea and muriate of potash fertilizers for the 2023 planting season were USD 0.65, 0.60, and 0.50 per kg, respectively (VIFAA, 2024). The price of maize per kg for the 2023 season was USD 0.17 (Exchange, 2024). Profit from maize production is calculated using Eq. 5.8, which expresses profit as the difference between total revenue and total cost. Revenue is derived from the product of maize yield and market price, while cost is determined by the amount of fertilizer (N, P, and K) applied and its unit cost.

$$P = M. Yield \times MMP - \sum_{i=1}^3 F. rate_i \times F. cost_i \quad (5.8)$$

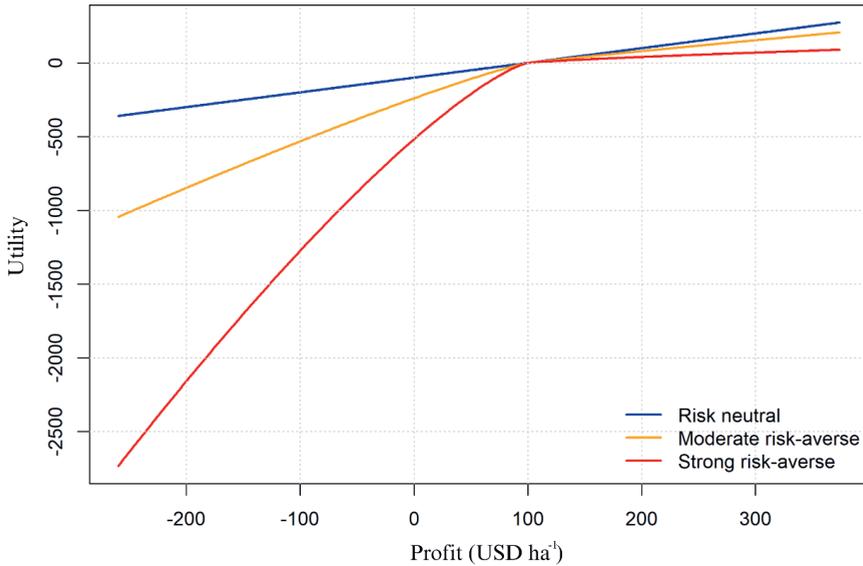
where,  $P$  is the profit in USD  $ha^{-1}$ ,  $M. Yield$  represents maize yield measured in  $kg ha^{-1}$ ,  $MMP$  represents maize market price in USD  $kg^{-1}$ ,  $F. rate_i$  represents the fertilizer application rate measured in  $kg ha^{-1}$ , and  $F. cost_i$  is the fertilizer cost in USD  $kg^{-1}$ . Index  $i$  runs from 1 to 3 and refers to N, P, and K. Equation 5.8 provides a straightforward method for estimating economic returns under specific input conditions. However, maize yield itself is subject to considerable uncertainty as quantified by the QRF conditional

distribution. Propagating this yield uncertainty through Eq. 5.8 leads to uncertain profit values. In other words, for a given fertilizer rate, the profit is no longer a fixed number, but it becomes a probability distribution (profit pdf), as derived from the yield distribution produced by the trained QRF model.

Farmers do not base their decisions solely on expected profit. Their choices are strongly influenced by risk preferences, which shape how they evaluate different fertilizer strategies under uncertainty (Tevenart and Brunette, 2021). To reflect these preferences, we used utility functions that formally represent how farmers trade off risk and reward. Specifically, we applied expected utility theory to convert predicted net return distributions into utility values (Schmeidler and Wakker, 1990). This allowed us to derive fertilizer recommendations based on farmer-specific risk attitudes. Farmers were classified into three main profiles based on their risk behavior: risk-neutral, moderate risk-averse and strong risk-averse. Risk-neutral farmers focus solely on maximizing expected net returns. Their utility functions are linear, implying that uncertainty in profit does not affect their decision-making. However, risk-averse farmers exhibit a greater sensitivity to losses than to equivalent gains, leading to asymmetric concave utility functions. Their decisions prioritize minimizing potential losses over maximizing gains. The power utility function shown in Eq. 5.9 was used to derive farmers' risk tolerances.

$$U(P) = \begin{cases} P^{1-\gamma}, & P \geq 100 \\ -\lambda(-P)^{1-\gamma}, & P < 100 \end{cases} \quad (5.9)$$

$U(P)$  is the utility associated with profit  $P$ ,  $\gamma$  is the risk aversion coefficient, which measures individual farmers attitude towards risk,  $\gamma = 0$  represents risk-neutral, while  $\gamma > 0$  represents risk-averse (with higher  $\gamma$  indicating stronger aversion to risk). Parameter  $\lambda$  is the loss aversion coefficient, which accounts for the farmers' sensitivity toward loss. A loss aversion coefficient greater than 1 indicates a greater sensitivity towards loss, whereas  $\lambda = 1$  indicates an indifference between losses and gains. The threshold value  $P = 100$  USD ha<sup>-1</sup> in the utility function serves as a benchmark profit level, distinguishing gains from losses. Profits equal to or above 100 are treated as gains and follow the standard power utility formulation, while profits below 100 are treated as losses and are subject to a loss-adjusted utility that includes the loss aversion factor  $\lambda$ . This benchmark reflects the implicit costs farmers face, such as labor and equipment use, and thus even zero profit is perceived as a loss. It is important to note that the chosen utility parameters ( $\gamma$  and  $\lambda$ ) were selected for illustrative purposes and not based on empirical estimates. They are intended to demonstrate the qualitative effects of varying risk preferences. Figure 5.3 illustrates the power utility functions with the parameter values selected for the three farmer profiles considered in this study: a risk-neutral farmer, a moderately risk-averse farmer, and a strongly risk-averse farmer.



**Figure 5.3:** Power utility function for a risk-neutral farmer ( $\gamma = 1$ ,  $\lambda = 1$ ), moderate risk-averse farmer ( $\gamma = 0.95$ ,  $\lambda = 1.2$ ) and strong risk-averse farmer ( $\gamma = 0.8$ ,  $\lambda = 1.3$ ).

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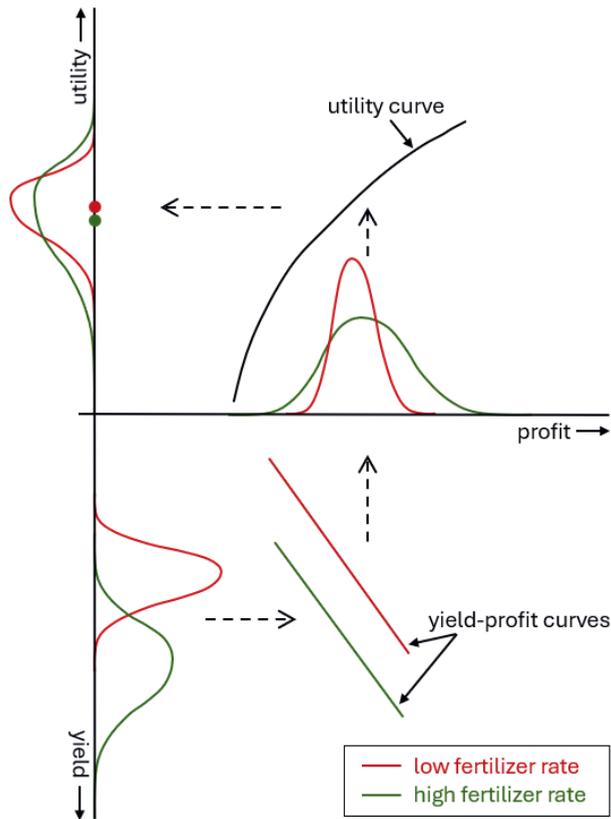
### 5.2.6 Optimization strategy

The optimization strategy utilizes a grid search approach, chosen for its effectiveness in systematically exploring complex decision spaces. Specifically, it aims to identify the combination of N, P, and K fertilizer application rates that maximize the expected utility for each farmer type. To implement this, we constructed a predefined three-dimensional grid of possible fertilizer rates: 61 discrete values for N, and 31 values each for P and K (Table 5.1). This results in a total of  $61 \times 31 \times 31 = 58,621$  unique fertilizer rate combinations. The grid search evaluates each combination by computing the expected utility, ultimately selecting the one that yields the highest value.

**Table 5.1:** Fertilizer application rates for optimization (61 values for N, 31 for both P and K).

Fertilizer	Application rates
N	0 – 300, increment by 5
P	0 – 150, increment by 5
K	0 – 150, increment by 5

For each combination, we used the trained QRF model to simulate the probability distribution of crop yield outcomes associated with these fertilizer application rates. To approximate this distribution and propagate uncertainty through to the outcome, we employed a Monte Carlo simulation approach. Specifically, for each combination of fertilizer application rates, we performed 5000 Monte Carlo runs. In each run, we sampled a possible yield value from the predicted pdf of the yield produced by the QRF. This resulted in a set of 5000 simulated yield outcomes whose variability represent the uncertainty inherent in the prediction. Next, for each of these 5000 simulated yields, we computed the corresponding profit with Eq. 5.8. This step effectively transforms the pdf of yield into a pdf of profit. We then applied the power utility function to each of these profit values, reflecting the farmer’s risk preferences. This returns 5000 utility values, forming an empirical probability distribution of the utility. Finally, we computed the expected utility by averaging the 5000 utility values obtained from the Monte Carlo runs. This expected utility served as our decision criterion, choosing that fertilizer application rate combination that maximized the expected utility. Figure 5.4 shows a graphical summary of the derivation of the expected utility from the yield pdf for a risk-averse farmer.



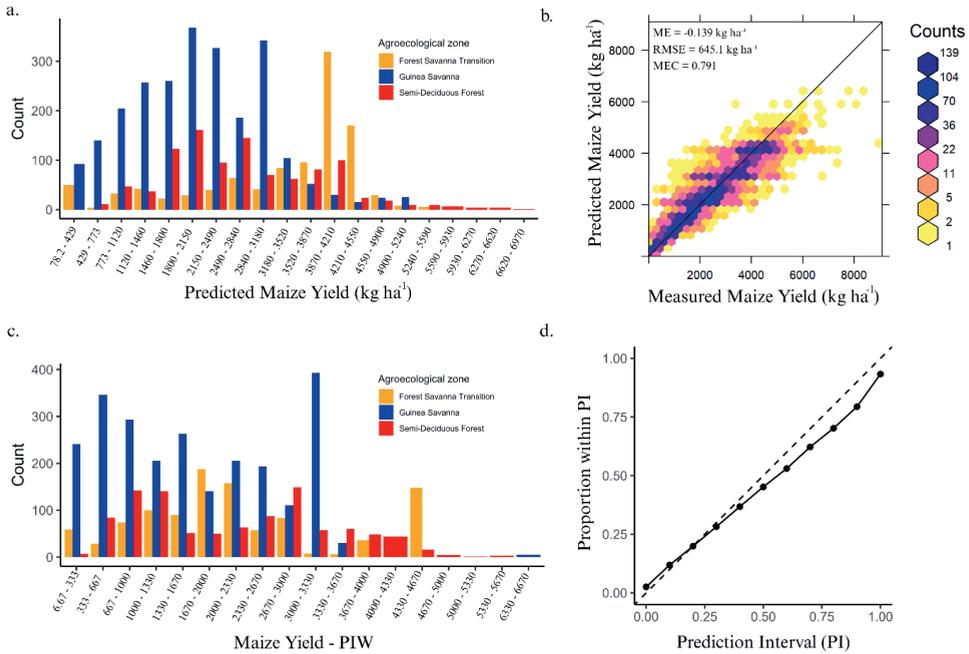
**Figure 5.4:** Graphical illustration of deriving the expected utility (solid discs) from the yield probability distribution and yield-profit and utility curves for a risk-averse farmer. Note that the large left tail of the utility probability distribution for the high-fertilizer case causes its expected utility to be smaller than that of the low-fertility case.

## 5.3 Results

### 5.3.1 Random forest yield modelling and uncertainty quantification

The performance of the maize yield prediction model was evaluated across agroecological zones in Ghana (Figure 5.1), using a suite of diagnostic plots and statistical metrics (Figure 5.5). Figure 5.5a shows the distribution of predicted maize yields stratified by agroecological zone. The majority of predicted yields ranged from 400 to 3600 kg ha<sup>-1</sup>, with the GS zone accounting for the highest number of observations. The GS zone shows a relatively normal distribution centered around 1800-2400 kg ha<sup>-1</sup>. In contrast, the FST zone exhibited a more dispersed distribution, including a higher number of observations with yields exceeding 3600 kg ha<sup>-1</sup>, while the SDF zone generally showed lower and more

variable predicted yields. Model accuracy and agreement were assessed in Figure 5.5b using a hexbin density plot comparing predicted and measured maize yields. The majority of predictions clustered around the 1:1 line, indicating a good agreement. The model had a ME of  $-0.14 \text{ kg ha}^{-1}$ , suggesting minimal bias with a RMSE of  $645.1 \text{ kg ha}^{-1}$ , indicating a moderate level of prediction error, and a MEC of 0.791, demonstrating strong predictive performance. Figure 5.5c shows the distribution of 90% prediction interval width (PIW) for yield predictions across agroecological zones, providing insight into model uncertainty. The GS zone consistently showed narrower PIWs, reflecting higher confidence in yield predictions. Conversely, the FST and SDF zones exhibited wider distributions of PIWs, indicating greater uncertainty in these zones. Figure 5.5d evaluates the model's predictive uncertainty using a reliability diagram. The plot compares the nominal prediction interval (PI) with the actual proportion of test observations falling within those intervals. The reliability curve closely follows the 1:1 line at PIs lower than 0.40, suggesting that the model provides reliable quantification of uncertainty, a critical feature for decision-making in agricultural planning and risk assessment. However, PIs above 0.40 slightly underestimated the prediction uncertainty.



**Figure 5.5:** Evaluation of maize yield prediction QRF model performance across agroecological zones.

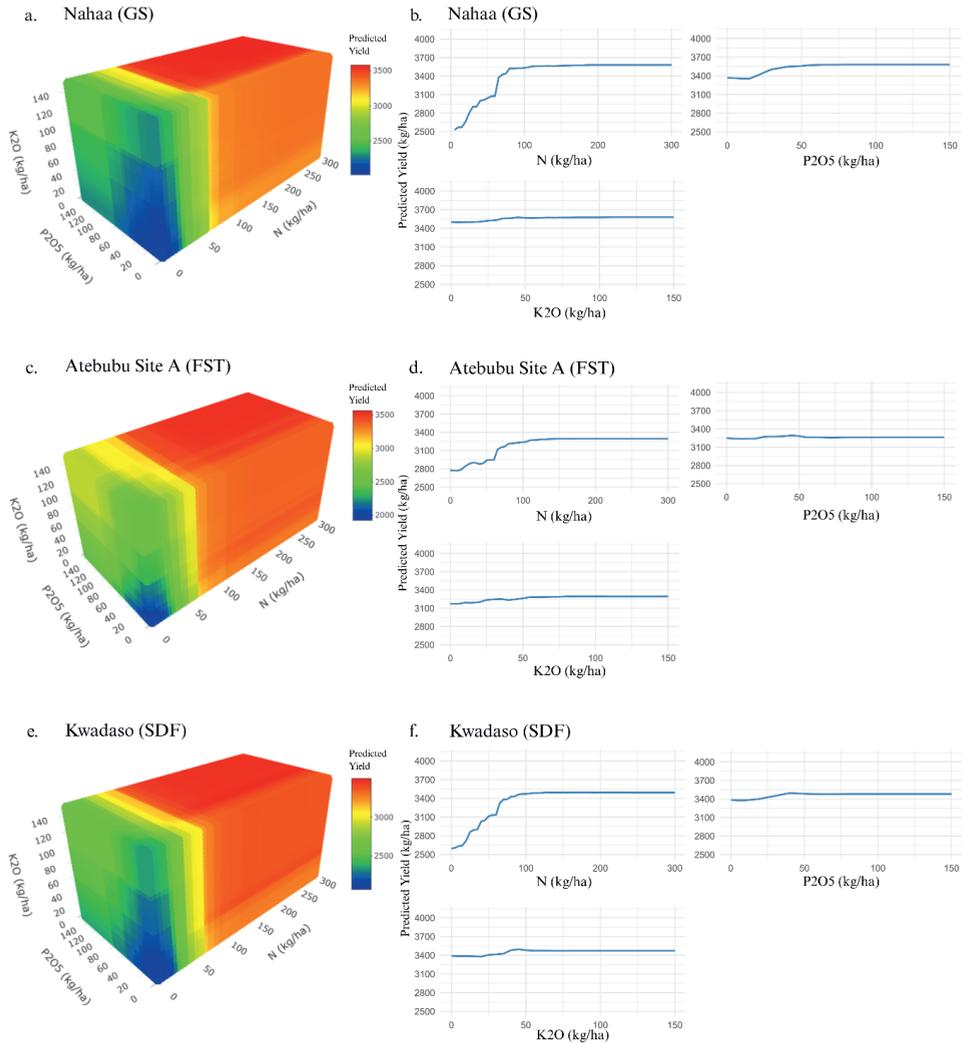
a) Histogram showing the distribution of predicted maize yields (kg ha<sup>-1</sup>) categorized by agroecological zones: FST (orange), GS (blue), and SDF zone (red); b) Hexbin plot comparing predicted versus measured maize yields (kg ha<sup>-1</sup>). Hexagons are color-coded by observation count (legend at right). The solid black 1:1 line indicates perfect prediction agreement; (c) Histogram of 90% PIW for maize yields across agroecological zones, reflecting the uncertainty in yield predictions; (d) Reliability plot assessing the validity of prediction intervals. The y-axis shows the proportion of test observations falling within the prediction interval (PI), and the x-axis represents the nominal PI levels. The solid line shows the actual model result while the dashed line represents the ideal case (1:1 line).

### 5.3.2 Effect of NPK on maize yield

Across all sites and agroecological zones, N emerged as the dominant nutrient influencing maize yield, with yield showing the most pronounced response to increasing N rates (Figure 5.6 and Figures SI 1 to SI 6). The response curves typically rose steeply at low N rates and plateaued slightly beyond 100-350 kg N ha<sup>-1</sup>. In contrast, responses to P and K were generally flatter, with marginal increases in yield observed at low to moderate application levels, and minimal additional gain beyond ~30 kg ha<sup>-1</sup> for either nutrient. In Nahaa in the GS zone, N response was initially steep, with predicted yields increasing from ~2,600 kg ha<sup>-1</sup> at 0 N to ~3,400-3,600 kg ha<sup>-1</sup> at 90 kg N ha<sup>-1</sup> (Figure 5.6a and b). Beyond this

threshold, yield responses plateaued, indicating diminishing returns. Phosphorus and K showed much flatter curves, with small yield gains observed up to 30-40 kg ha<sup>-1</sup>. Notably, Jirapa exhibited the lowest absolute yield response across the zone, while Lawra, Wichau and Nahaa showed the highest (Figures SI 5 and SI 6).

In the FST zone (Amantin Site A and B, Atebubu Site A and B, Kyeremfaso Site A and B), yield increases were again dominated by N application (Figure 5.6c and d, Figures SI 1 and 2). Kyeremfaso Site A and Kyeremfaso Site B had steeper N response curves, showing yields increasing from ~2,600 kg ha<sup>-1</sup> at baseline to ~3,400-3,500 kg ha<sup>-1</sup> at ~80 kg N ha<sup>-1</sup> (Figure SI 2). Sites such as Amantin Sites A and B and Atebubu Sites A and B showed more linear N responses with less curvature, indicating low returns to N application (Figure 5.6c and d). Phosphorus and K effects remained limited but slightly more pronounced than in the Guinea Savanna, particularly in Atebubu sites. The SDF zone sites (Kokoben, Kwadaso, Seidi, Wioso) displayed the highest yield potentials, with predicted yields reaching ~3,800 kg ha<sup>-1</sup> at optimal N levels (~60-80 kg N ha<sup>-1</sup>) (Figure 5.6e and f, Figures SI 3 and 4). These sites also exhibited a slightly less visible response to P and K applications, suggesting that these nutrients may not be limiting in these environments. Nevertheless, N remained the key driver of yield increases, with a steeper and more sustained positive slope compared to other zones.

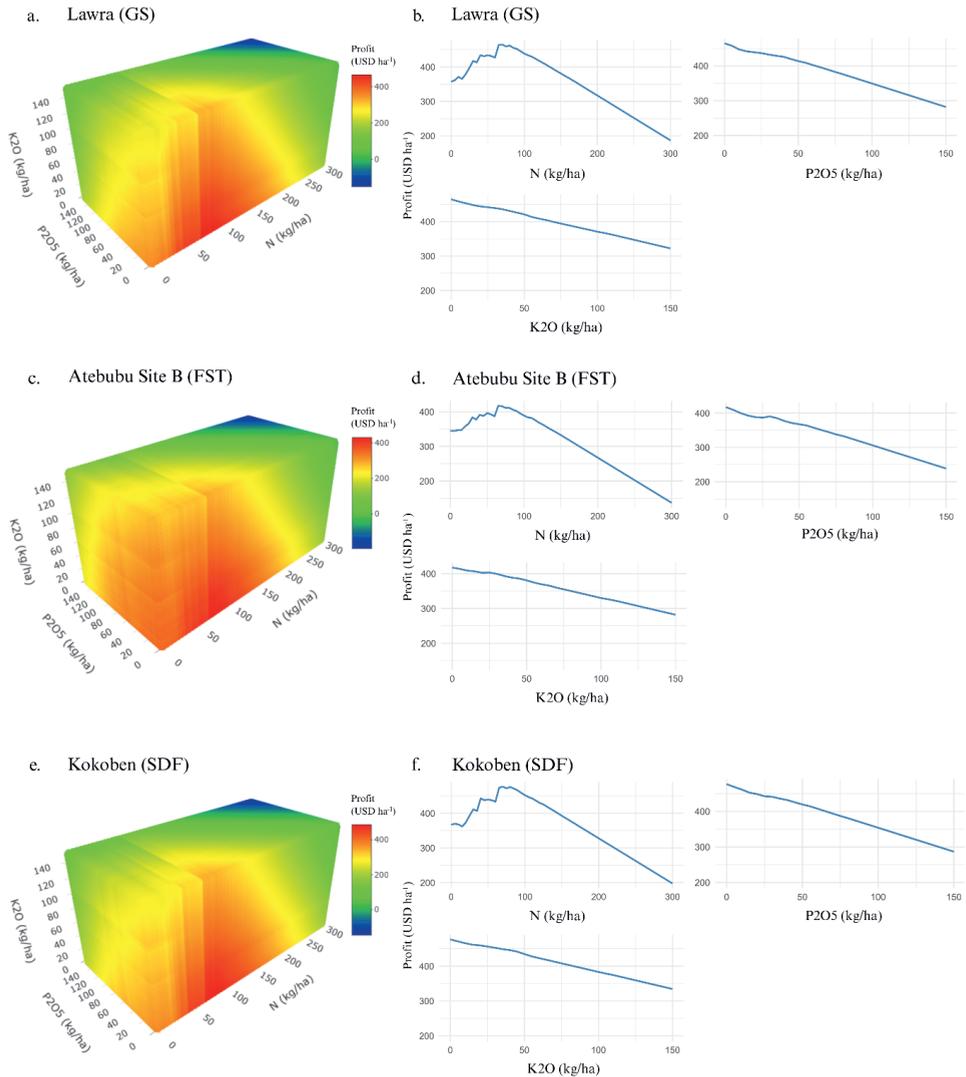


**Figure 5.6:** Predicted maize yield response to N, P, and K fertilizer application across three agroecological zones in Ghana. Panels a, c, e: Three-dimensional response surfaces showing predicted maize yield ( $\text{kg ha}^{-1}$ ) as a function of N, P, and K fertilizer application rates at three representative sites: (a) Nahaa (GS), (c) Atebubu Site A (FST), (e) Kwadaso (SDF). Panels b, d, f: One-dimensional response profile curves for each nutrient, depicting predicted yield as a function of individual nutrient application while holding the others on the value that produces the highest yield. (b) Nahaa (GS), (d) Atebubu Site A (FST), (f) Kwadaso (SDF).

### 5.3.3 Effect of NPK on profit

Nitrogen application generated the most substantial and consistent economic response across all sites. As shown in the 3D response surfaces (Figure 5.7, Figures SI 7, SI 9 and SI 11), profit increased sharply with N application up to a certain point ( $\sim 80 \text{ kg ha}^{-1}$ ), beyond which additional N reduced profitability due to diminishing yield returns and rising input costs. The profit curves (Figure 5.7, Figures SI 8, SI 10 and SI 12) clearly show a peak in profit followed by a decline. At sites in the SDF zone (Kokoben, Seidi, Kwadaso, and Wioso), maximum profit was achieved with N applications around  $60\text{-}80 \text{ kg ha}^{-1}$ , with values exceeding USD  $450 \text{ ha}^{-1}$ . Lawra, Naha, and Kyeremfaso Site B also showed strong profit responses to moderate N rates, though profit declined noticeably beyond  $80\text{-}90 \text{ kg ha}^{-1}$ . In lower-yielding areas like Jirapa and Amantin Site A, peak profits were lower, and the economic optimum N rate occurred at lower rates. Phosphorus application generally resulted in declining profit curves across all sites. The 3D plots exhibited negative gradients along the P axis, and the 2D profiles (Figure 5.7 and Figures SI 7 to SI 12) show that increasing P rates reduced profit in all locations. Atebubu Sites A and B, Wichau, Kokoben, and Lawra showed steady declines in profit as P increased, indicating that P application did not provide an economic return. Potassium, like P, showed minimal to negative economic impact. Across all sites, the 3D surfaces and marginal K profiles (Figure 5.7 and Figures SI 7 to SI 12) revealed declining profit curves as K rates increased. Seidi, Kwadaso, and Kyeremfaso Site A displayed moderate declines in profit with increasing K, reinforcing that excessive K application is unlikely to be economically beneficial. Some sites (e.g., Wioso and Lawra) showed minor fluctuations, but these were not large enough to warrant consistent investment in K.

While N consistently contributed to profit increases up to an optimum threshold, the most profitable rates varied by site. High-profit sites like Seidi, Kokoben, and Wioso reached peak profits above USD  $450 \text{ ha}^{-1}$  at moderate N levels ( $60\text{-}80 \text{ kg ha}^{-1}$ ). Intermediate-profit sites such as Lawra, Nahaa, and Kyeremfaso Site B peaked between USD  $350\text{-}400 \text{ ha}^{-1}$ . Lower-profit locations like Jirapa and Amantin Site A peaked earlier with more modest profits ( $\sim \text{USD } 300\text{-}360 \text{ ha}^{-1}$ ), suggesting limited potential for high input use. Importantly, in nearly all cases, P and K inputs reduced profitability unless not applied at all.

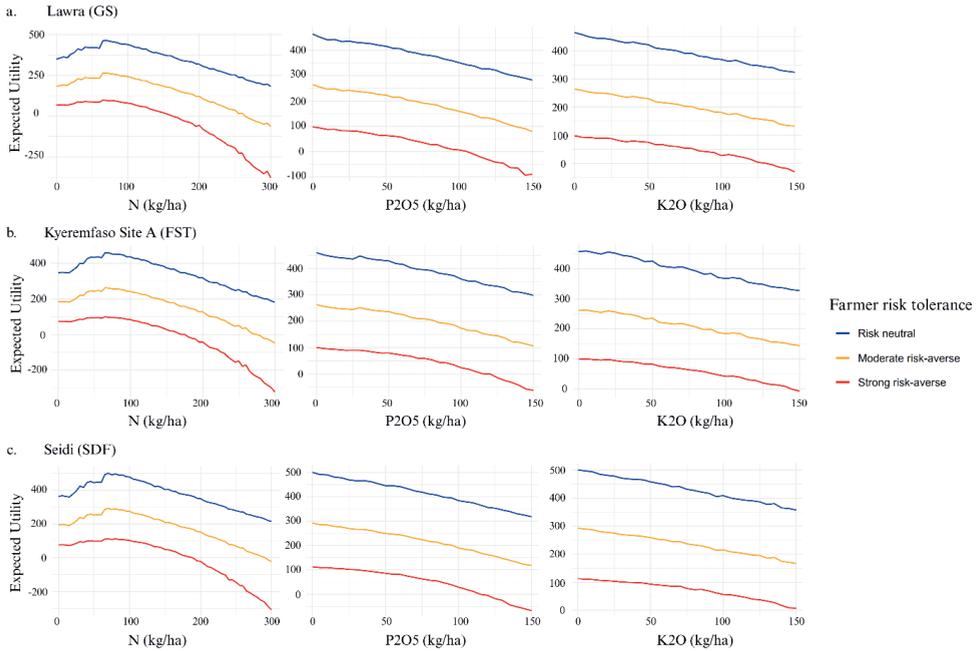


**Figure 5.7:** Predicted profit response to N, P, and K fertilizer application across three agroecological zones in Ghana. Panels a, c, e: Three-dimensional response surfaces showing predicted profit (USD ha<sup>-1</sup>) as a function of N, P, and K application rates for three representative sites: (a) Lawra (GS), (c) Atebubu Site B (FST), (e) Kokoben (SDF). Colour gradients represent profit magnitude, with red indicating lower profits and green indicating higher profits. The shapes of the surfaces reveal site-specific interactions between nutrient inputs and profitability. Panels b, d, f: One-dimensional response profile curves for each nutrient, depicting predicted profit as a function of individual nutrient application while holding the others on the value that produces the highest profit. (b) Lawra (GS), (d) Atebubu Site B (FST), (f) Kokoben (SDF).

### 5.3.4 Effect of NPK on expected utility

The utility-based optimization results revealed systematic variation in fertilizer application strategies depending on farmer risk preferences, with N consistently dominating utility outcomes across all farmer utility profiles and sites. As shown in Figure 5.8 and Figures SI 13 to SI 26, expected utility increased sharply with N application for risk-neutral farmers (blue line), peaking around 60-90 kg N ha<sup>-1</sup>, after which it declined due to diminishing marginal yield gains and increasing costs. For moderately risk-averse farmers (orange line), the optimal N rates were lower typically 50-70 kg N ha<sup>-1</sup> and for strongly risk-averse farmers (red line), the utility peaks occurred earlier, often between 30-60 kg N ha<sup>-1</sup>, or in some cases not at all. This pattern highlights how rising risk aversion shifts utility-maximizing decisions toward more conservative input levels. The vertical positioning of the utility curves in Figure 5.8 reflects the utility function's sensitivity to both profit magnitude and risk (Figure 5.3). The blue curve lies above the others because risk-neutral farmers value profit linearly, whereas risk-averse farmers perceive negative profit more strongly than positive profit of equal magnitude. Thus, while the absolute values of utility differ due to scaling in the power utility function, the more meaningful insight lies in the horizontal distance between the curves how the optimal N rate shifts as risk aversion increases and how steeply utility declines beyond that peak. For instance, in Seidi and Lawra, utility dropped sharply at high N rates under strong risk aversion, underscoring the potential downside risk of over-application under volatile conditions.

Phosphorus and K showed minimal contributions to utility across all farmer risk profiles and sites. Both 2D and 3D utility surfaces (Figure 5.8 and Figures SI 13 to SI 26) revealed consistently declining gradients with increasing P and K rates. This suggests that the perceived benefits of P and K are negligible under current soil and market conditions and are further diminished by risk aversion. Particularly under strong risk aversion, utility curves for P and K declined almost linearly, indicating that their cost outweighs any potential yield or profit gains under these conditions. At the site level, some variation was observed. High-performing sites such as Kokoben, Kwadaso, and Kyeremfaso Site B exhibited the highest expected utility under risk-neutral and moderately risk-averse conditions, consistent with their greater N responsiveness and stable profitability. Conversely, sites such as Amantin Site A and Jirapa displayed flatter utility curves, with lower peaks and rapid declines, reflecting limited yield potential and greater exposure to downside risk. In such contexts, even modest N applications often failed to deliver utility gains under risk-averse profiles.



**Figure 5.8:** Expected utility response to fertilizer application under varying farmer risk preferences across agroecological zones in Ghana. Each panel shows the marginal effects of N, P, and K application rates on expected utility for three representative sites: (a) Lawra (GS), (b) Kyeremfaso Site A (FST), (c) Seidi (SDF), depicting expected utility as a function of individual nutrient application while holding the others on the value that produces the highest expected utility.

### 5.3.5 Optimization under uncertainty

Table 5.2 presents the optimal N, P, and K fertilizer application rates ( $\text{kg ha}^{-1}$ ) for maximizing expected utility across different farmer risk tolerances within three agroecological zones in Ghana. Note that these are the fertilizer application rates where the profile expected utility curves shown in Figure 5.8 and Figures SI 13 – SI 23 reach their maximum. Across all sites, the optimization consistently resulted in a positive N application rate, while optimal values for P and K were often zero. This pattern reinforces the yield-response analysis in Figure 5.6, where N application most reliably led to yield gains, whereas responses to P and K were typically weak or absent.

Considering differences among farmer profiles, risk-neutral and moderately risk-averse farmers showed highly similar recommendations. For most locations, both profiles recommended moderate to high N rates ( $30\text{--}80 \text{ kg ha}^{-1}$ ), with site-level differences dominating over risk-level effects. However, strong risk-averse farmers deviated substantially from the other two profiles at certain sites. Most notably, they

applied significantly lower N in Jirapa and across all sites in the GS zone, dropping to as low as 5-10 kg ha<sup>-1</sup>. This reflects a stronger aversion to uncertain returns at sites with low yield response to N application.

Phosphorus was not recommended at any site, regardless of the farmer's risk profile. K was only recommended at a few locations and at low rates (5-10 kg ha<sup>-1</sup>), almost exclusively under risk-neutral or moderate risk-averse farmers. Wioso and Kyeremfaso were exceptions where a low K rate (5 kg ha<sup>-1</sup>) persisted across all farmer types, likely due to consistent marginal benefit from K at those sites.

Site-specific patterns also emerged. Jirapa was the most conservative, receiving low N rates under all farmer profiles. In contrast, Amantin Site B in the FST and Seidi in the SDF zones received the highest N rate (80 kg ha<sup>-1</sup>) under risk neutrality, while Amantin Site A had the lowest (30 kg ha<sup>-1</sup>). Kyeremfaso, Kokoben and Kwadaso sites maintained relatively high and stable N recommendations (65-70 kg ha<sup>-1</sup>) across all risk profiles, indicating that agronomic conditions at these locations offset the effect of risk aversion. In the SDF zone, Wioso also received relatively high N recommendations (up to 70 kg ha<sup>-1</sup>), along with no P and lower K, suggesting favourable yield potential and lower P and K nutrient investment risks.

**Table 5.2:** Optimal fertilizer recommendations ( $\text{kg ha}^{-1}$ ) for maximizing expected utility across different farmer risk tolerances and agroecological zones in Ghana.

Agroecological zone	Location	Risk neutral farmer				Moderate risk-averse farmer				Strong risk-averse farmer			
		N ( $\text{kg ha}^{-1}$ )	P ( $\text{kg ha}^{-1}$ )	K ( $\text{kg ha}^{-1}$ )	( $\text{kg ha}^{-1}$ )	N ( $\text{kg ha}^{-1}$ )	P ( $\text{kg ha}^{-1}$ )	K ( $\text{kg ha}^{-1}$ )	( $\text{kg ha}^{-1}$ )	N ( $\text{kg ha}^{-1}$ )	P ( $\text{kg ha}^{-1}$ )	K ( $\text{kg ha}^{-1}$ )	( $\text{kg ha}^{-1}$ )
GS	Lawra	70	0	0	0	70	0	0	0	65	0	0	0
	Nahaa	70	0	0	0	70	0	0	0	70	0	0	0
	Jirapa	30	0	10	10	30	0	5	5	10	0	0	0
	Wichau	70	0	0	0	70	0	0	0	65	0	0	0
FST	Atebubu Site A	70	0	0	0	70	0	0	0	30	0	0	0
	Atebubu Site B	70	0	0	0	70	0	0	0	30	0	0	0
	Amantin Site A	30	0	0	0	30	0	0	0	10	0	0	0
	Amantin Site B	80	0	0	0	70	0	0	0	10	0	0	0
	Kyeremfaso Site A	65	0	5	5	65	0	5	5	65	0	5	5
	Kyeremfaso Site B	65	0	5	5	65	0	5	5	65	0	5	5
SDF	Kokoben	65	0	0	0	65	0	0	0	65	0	0	0
	Kwadaso	70	0	0	0	70	0	0	0	70	0	0	0
	Seidi	80	0	0	0	80	0	0	0	80	0	0	0
	Wioso	70	0	5	5	70	0	5	5	70	0	5	5

## 5.4 Discussion

### 5.4.1 Effect of NPK on predicted yield

Nitrogen consistently emerged as the most influential nutrient affecting maize yields across agroecological zones in Ghana. Numerous studies have confirmed nitrogen's role as the most limiting nutrient in low-input, rainfed systems typical of sub-Saharan Africa (Kihara et al., 2016; Vanlauwe et al., 2011). Yield responses in our study were steepest within the 0-90 kg N ha<sup>-1</sup> range and tended to plateau around 90-300 kg N ha<sup>-1</sup>, a trend that aligns with agronomic theory on diminishing returns (Cassman and Dobermann, 2022). Seidi and Kokoben sites exhibited higher yield potentials with N application exceeding 3,800 kg ha<sup>-1</sup> at rates of 60-90 kg N ha<sup>-1</sup>. In contrast, sites such as Jirapa or Amantin Site A had yield ceiling at much lower rates of N, with optima between 60-80 kg N ha<sup>-1</sup>. Interestingly, similar patterns were observed in MacCarthy et al. (2025) in semi-arid northern Ghana, where 90 kg N ha<sup>-1</sup> was identified as the economic optimum for maize production. Their work emphasizes that while higher N rates may continue to increase yield slightly upward, it is economically not cost effective with possible environmental consequences.

Phosphorus and K on the other hand, demonstrated no responses in most locations. This may be due to the acidic nature of soils within the study area (Table SI 2). Acidic conditions are known to restrict the availability of most nutrients by promoting fixation especially of P and limiting root growth, particularly in early growth stages (Regasa et al., 2025). Unless addressed through liming, even well-timed P applications may not translate into improved plant uptake (Regasa et al., 2025). In the FST zone, Kyeremfaso Site B outperformed Amantin Site A by a significant margin. The former approached 3,900 kg ha<sup>-1</sup> at optimal N levels, while the latter stalled closer to 3,200 kg ha<sup>-1</sup>. This could be driven by the variable soil conditions of these locations. Kihara et al. (2016) and Rurinda et al. (2020) emphasize that soil organic carbon, pH, and texture are often the key determinants of crop response to fertilizer inputs in maximizing attainable yield. In this study, Kyeremfaso's superior performance reflects a more favourable mix of these soil characteristics (Table SI 2), which may improve fertilizer use efficiency.

### 5.4.2 Effect of NPK on profitability

Maximum profits were generally achieved at moderate N application rates ranging between 60–90 kg N ha<sup>-1</sup>, beyond this range, profitability began to decline, even though yield continued to plateau. This divergence between yield and profit reflects the interaction between biological yield responses and economic thresholds, whereby the additional revenue generated by incremental yield gains fails to compensate for the rising cost of fertilizer inputs (Vanlauwe et al., 2023). The peak in profitability at lower N rates compared to yield-maximizing rates is consistent with evidence from smallholder maize systems in southern Africa, where similar patterns of reduced profitability at higher N rates have been

reported (Kamanga et al., 2010). This discrepancy highlights a critical risk in fertilizer advisory services that recommendations targeting maximum yield without regard for economic efficiency can inadvertently promote over-application of N, increasing production costs without proportionate income gains. Furthermore, this practice may exacerbate financial risk, particularly under volatile market conditions, and contribute to negative environmental externalities such as N runoff and greenhouse gas emissions (Chen et al., 2011; Zhang et al., 2015).

In contrast, P and K did not lead to an increase in yield and profit across the study locations. Profit response curves for P and K show a decline with increasing application rates, indicating negative economic returns. These findings align with previous research in West Africa, which similarly reported poor economic returns from P and K applications (Liverpool-Tasie et al., 2017; Sheahan et al., 2013). From a practical perspective, these findings suggest that N should remain the priority nutrient in maize fertilizer management, with P and K applied selectively based on site-specific diagnostic information such as soil tests or field response trials. This supports broader recommendations in the literature to shift to policies towards more tailored, site-specific approaches that account for profitability and resource use efficiency (Holden, 2018; Steward et al., 2018) in addition to local adaptations including liming of acid soils. Optimizing N application while minimizing expenditure on P and K in acidic soils unless liming is applied not only enhances farmer profitability but also reduces the risks of input wastage and environmental degradation, contributing to more sustainable and climate-smart maize production systems (Kihara et al., 2020; Vanlauwe et al., 2015).

#### 5.4.3 Effect of NPK on farmer utility under risk

Incorporating farmer risk preferences into fertilizer recommendations revealed important shifts in optimal nutrient strategies for some sites that have both practical and policy relevance. Notably, N remained the only nutrient consistently contributing to positive expected utility outcomes across all risk profiles. However, the intensity of N use varied markedly depending on farmers' risk attitudes. Risk-neutral farmers tended to favour higher N application rates (30-80 kg ha<sup>-1</sup>), largely mirroring profit-maximizing thresholds. This is expected, since without aversion to downside variability, they can justify fertilizer investment purely on average or expected return. In contrast, strongly risk-averse farmers opted for slightly lower N rates, often in the range of 10-80 kg ha<sup>-1</sup> and in some marginal environments even less. This downward adjustment in optimal N input is in line with classical expected utility theory (Hardaker et al., 2004), which predicts that individuals with greater loss aversion will prefer strategies that reduce exposure to bad outcomes, even if average returns are sacrificed. From a behavioral economics standpoint, the more conservative N choices by risk-averse farmers reflect a rational response to the real and perceived risks posed by unpredictable input/output prices and other uncertain situations, and limited safety nets. Similar behaviour has been documented in other sub-Saharan African

contexts. Wossen et al. (2017) in Ethiopia and Holden and Lunduka (2012) in Malawi reported significantly lower fertilizer use among risk-averse farmers, even when agronomic potential was high.

These findings are important in two respects. First, they highlight the mismatch that often exists between technically “optimal” recommendations and those that farmers are willing or able to adopt in practice. If risk is ignored in extension advice, recommendations may appear profitable on paper but still be rejected in the field as reported by Marenya and Barrett (2009) as the “adoption paradox.” Second, they raise the question of how best to balance agronomic efficiency with behavioural realism. Utility-based optimization, as implemented in this study, provides a promising route forward by embedding farmer preferences directly into decision frameworks. That said, one important caveat to our approach must be acknowledged, the risk aversion ( $\gamma$ ) and loss aversion ( $\lambda$ ) coefficients in the utility function were selected by choosing reasonable parameter values, for illustrative purposes. While they do allow us to demonstrate the directional influence of risk attitudes on fertilizer decisions, the lack of empirical calibration limits the precision of the utility estimates obtained in this study. In reality, risk preferences are heterogeneous and context-specific, varying not only across individuals but also over time and between decisions (Tevenart and Brunette, 2021). Our choice of parameter values  $\gamma = 0.80$  for strong risk aversion,  $\gamma = 0.95$  for moderate was informed by behavioral literature but not derived from direct elicitation. As such, the exact thresholds should be interpreted cautiously. To move beyond this limitation, future research should explore ways to empirically estimate risk parameters using participatory methods, field experiments, or econometric modelling (Adzawla et al., 2021).

Additionally, hybrid models that combine utility-based reasoning with machine learning based prediction could potentially enhance both the behavioral realism and predictive power of fertilizer advisory systems. It is worth underscoring the negligible and often negative utility impact of P and K across all sites and risk profiles. Even in risk-neutral farmer situations, marginal utility from P and K tended to decline due to their weak yield responsiveness (as shown in earlier sections) coupled with high upfront costs. Under risk-averse scenarios, the downside financial risk of these inputs especially in the absence of strong yield signals led to even sharper declines in utility. These findings align with those of Kihara et al. (2016) and Sheahan et al. (2013), who report that poorly targeted P and K investments may amplify rather than mitigate risk in low-input systems. Taken together, these results suggest that a risk-informed advisory system should prioritize N management while recommending the exact P and K rates required only when site-specific diagnostics or strong local evidence justify such rates.

#### **5.4.4 Site-specific fertilizer optimization under uncertainty**

Our analysis demonstrated pronounced site-specific variability in optimal N application rates, even though N was consistently identified as the primary yield-limiting nutrient across all sites. High-

productivity sites such as Seidi, Kokoben, Nahaa and Lawra exhibited yield and profitability responses at N application rates of 60-90 kg N ha<sup>-1</sup>. In contrast, sites with lower productivity potential, including Jirapa and Amantin Site A, showed optimal economic returns at considerably lower N rates, ranging from 30-70 kg N ha<sup>-1</sup>. This heterogeneity reflects the combined influence of agroecological conditions particularly baseline soil fertility, rainfall distribution, and farmer management capacity which jointly determine crop nutrient responses in smallholder production systems (Kihara et al., 2016; Vanlauwe et al., 2015). These patterns are consistent with previous research showing that underlying soil characteristics, such as nutrient reserves, soil texture, and water-holding capacity, significantly modulate fertilizer efficiency and crop productivity (Hagglade et al., 2011; Tittonell and Giller, 2013). Well-endowed sites with deeper soils and more reliable rainfall tend to achieve higher agronomic returns from N investment, while nutrient responses rapidly diminish in degraded soils with lower input intensities more appropriate (Balemi et al., 2019).

This site-specific differentiation has important implications for fertilizer recommendations and extension strategies. The widespread use of blanket fertilizer recommendations, common in most national agricultural programs across sub-Saharan Africa, disregard local production realities and may inadvertently encourage inefficient fertilizer use. Multiple studies have highlighted the limitations of blanket fertilizer recommendations, noting their contribution to poor adoption rates and limited productivity gains (Liverpool-Tasie et al., 2017; Sheahan et al., 2013). Our findings provide empirical evidence supporting the shift toward localized, responsive nutrient management that accounts for spatial differences in biophysical conditions and economic returns. Crucially, incorporating risk-adjusted utility metrics into fertilizer optimization further reinforces the need for context-specific fertilizer recommendations. Farmers operating in more vulnerable environments where climatic risks and liquidity constraints are more pronounced achieved higher expected utility at lower N rates, reflecting their aversion to financial risk and fertilizer input-related losses. This result aligns with recent work showing that site-specific recommendation domains not only enhance agronomic efficiency but also reduce farmer exposure to economic risks, thereby improving input adoption and sustainability (Kihara et al., 2020; Steward et al., 2018).

Our findings echo the growing body of evidence supporting the use of site-specific fertilizer advice, often facilitated by diagnostic tools such as soil testing and yield response functions. Such approaches have shown promise in increasing nutrient use efficiency, improving profitability, and minimizing environmental trade-offs in diverse farming systems (Rurinda et al., 2020b). Embedding these strategies within adaptive, risk-aware frameworks represents a critical step towards making agronomic intensification both profitable and sustainable for smallholder farmers. Our results strengthen the case for differentiated fertilizer recommendations, calibrated not only to agroecological potential but also to farmer risk preferences and livelihood conditions. Such tailored approaches are fundamental to closing

yield gaps, improving profitability, and enhancing the resilience of maize production systems in Ghana and comparable rainfed environments across sub-Saharan Africa.

### 5.4.5 General discussion

#### 5.4.5.1 Implications of the findings

The results of this study provide critical insights into the optimization of fertilizer use within smallholder maize production systems, with direct implications for agronomic policy, advisory services, and farmer decision-making. Foremost, the consistent dominance of N in driving maize yield and profitability across all agroecological zones underscores the necessity of placing N at the center of any input intensification strategy. This finding aligns with extensive agronomic literature which identifies nitrogen as the most limiting nutrient in sub-Saharan African cropping systems, where continuous nutrient mining and low external inputs have depleted soil N reserves (Kihara et al., 2016; Kouame et al., 2025). Our results not only reaffirm N as the principal yield-limiting and profit-driving nutrient across agroecological zones in Ghana but also show how its optimal rate is heavily influenced by farmers' willingness to accept risk.

Secondly, incorporating farmer risk preferences into fertilizer recommendations emerges as a critical step towards bridging the gap between profitability and real-world adoption. Interestingly, however, one of the key contributions of this study lies not in showing large differences in optimal rates across farmer risk profiles as expected. While expected utility optimization did lead to somewhat lower fertilizer recommendations for more risk-averse farmers, the overall magnitude of change was often modest. Profit-maximizing N rates generally ranged from 60-90 kg N ha<sup>-1</sup>, with risk-averse optima typically 10-30 kg ha<sup>-1</sup> lower. In practical terms, this suggests that yield and profit considerations alone can serve as a reasonable starting point for recommendations, but that incorporating risk can fine-tune those recommendations to better match farmer preferences and reduce downside risk. Our approach aligns with behavioral economic studies showing that input underuse often stems less from lack of knowledge and more from aversion to financial loss under uncertainty (Marenya and Barrett, 2009; Wossen et al., 2017). Tailoring fertilizer strategies to reflect not only biophysical response but also risk tolerance can therefore enhance input adoption, stabilize incomes, and improve food security outcomes.

Thirdly, the negligible yield and profitability responses to P and K, particularly under risk-averse scenarios, suggest substantial opportunities for cost savings. Routine applications of P and K common in many public fertilizer programs may lead to unnecessary expenditures without corresponding agronomic returns, especially in fields with low soil acidity unless liming is incorporated to improve the soil pH to equally improve responses to P and K. This supports previous findings indicating that blanket NPK recommendations often fail to deliver economic efficiency, especially where soil

heterogeneity is high (Balemi et al., 2019; Sheahan et al., 2013). A more targeted approach, where P and K are applied only in response to diagnosed deficiencies, has been shown to improve both profitability and nutrient use efficiency (Kihara et al., 2020; Steward et al., 2018).

These findings also contribute to a growing literature on adaptive, demand-responsive fertilizer policies. There is increasing recognition that subsidy programs should focus on efficiency and equity, encouraging fertilizer use where it is most needed and most likely to pay off (Jayne et al., 2018; Liverpool-Tasie et al., 2017). Our results provide quantitative support for targeted subsidies that incentivize efficient N use while discouraging over-application of P and K where unwarranted.

#### 5.4.5.2 Strengths and limitations of this study

A major strength of this study lies in its integrative, multi-criteria approach, which evaluates yield, profitability, and farmer utility across multiple agroecological zones. This comprehensive framework moves beyond conventional agronomic assessments by incorporating behavioral dimensions specifically, risk preferences into fertilizer decision-making. In doing so, it brings the model closer to the realities that smallholder farmers face, where decisions are not made in a vacuum of averages, but under uncertainty, trade-offs, and financial constraints (Hardaker et al., 2015; Koundouri et al., 2009).

Nonetheless, the analysis is not without limitations. First, the optimization framework assumes static input and output prices. In reality, both fertilizer and maize prices fluctuate widely and unpredictably. Fertilizer prices, in particular, have become increasingly volatile in recent years due to global supply shocks, energy markets, and policy shifts. This volatility could substantially affect both profit and utility-maximizing fertilizer rates. Future modelling efforts should incorporate stochastic or dynamic price scenarios to better reflect market uncertainty and inform more resilient recommendations. Secondly, another limitation relates to the scope and assumptions of the utility model itself. While the study introduces farmer utility as a decision criterion, the risk and loss aversion parameters were chosen rather than empirically estimated. Future work should explore empirical elicitation of risk attitudes, either through field-based experiments, surveys, or revealed preference approaches.

Lastly, While P and K showed limited yield and economic returns in this study, their long-term omission could deplete soil reserves, leading to imbalances or gradual productivity declines (Vanlauwe et al., 2015). Although soils with low pH may limit short-term P uptake, liming could mitigate these constraints and enhance P responsiveness. This underscores the need for multi-season trials that monitor both nutrient stocks and yield trends, especially where soil acidity is a known barrier to nutrient availability. Taken together, while this study offers strong evidence in support of N-centered, site-specific, and risk-adjusted fertilizer strategies, future research must go further. By incorporating market dynamics, climate variability, long-term soil fertility, and context-specific risk profiling, future models

can provide more actionable and adaptive recommendations. These refinements will be critical for designing fertilizer recommendations that are not only agronomically sound, but also economically viable and resilient in the face of uncertainty.

## **5.5 Conclusion**

This study offered a novel, integrated approach to fertilizer decision-making for smallholder maize systems in Ghana by explicitly accounting for both agronomic uncertainty and farmer risk preferences. Across diverse agroecological zones, N emerged as the most influential driver of maize yield, profitability, and utility, whereas P and K provided little benefit under most existing farmer and soil conditions. The observed yield and profit plateau at moderate N rates reinforcing economic theory around diminishing returns and highlights the importance of optimizing but not maximizing input use.

Importantly, when farmer risk aversion was incorporated, optimal N rates declined, particularly in less productive environments. This underscores the reality that smallholders operate under significant uncertainty, and that fertilizer recommendations must consider not only biological response in terms of yield but also behavioral and financial contexts. The consistent lack of response to P and K across sites suggests that blanket NPK strategies remain potentially suboptimal and economically not viable. Instead, data-driven, site-specific approaches supported by soil diagnostics hold promise for improving crop yield and fertilizer efficiency.

By incorporating agronomy, machine learning, and behavioral economics, this study contributed to the growing evidence base for adaptive, farmer-centric nutrient management in the era of sustainable intensification. Future research should build on this work by incorporating dynamic price scenarios, multi-season variability, and long-term soil health outcomes. For policymakers and practitioners, these findings argue for a shift toward demand-driven fertilizer schemes that reflect both the spatial diversity of farming environments and the economic realities of the farmers they serve.

## **Supplementary materials**

The supplementary materials can be downloaded from the following link:

<https://github.com/AsamoahEric/MUAC5/blob/main/Supplementary%20Information.docx>





# Chapter 6

Synthesis

## **6.1 Introduction**

The aim of this thesis was to explore how ML methods can enhance agronomic decision-making in Ghana's maize-based smallholder systems. Specifically, the research addressed four challenges: improving the accuracy of yield and AE prediction; generating site-specific fertilizer recommendations; quantifying prediction uncertainty; and accounting for farmer risk preferences in decision support. These challenges reflect broader constraints in African agriculture, where blanket fertilizer recommendations, limited site-specific data, and the risk-averse behavior of smallholders often hinder effective agronomic advice and technology adoption (Kihara et al., 2016; Marenya and Barrett, 2009; Vanlauwe et al., 2012).

In this synthesis chapter, I reflect on the extent to which the thesis objectives (Section 1.7) were achieved, identify cross-cutting lessons particularly the importance of data quality, the complementary roles of ML and mechanistic models, and the value of expert- and behaviorally guided ML and outline implications for research, policy, and practice. In this chapter, I highlight the scientific and practical contributions of this work and positions it within an evolving paradigm where ML is viewed not as a replacement for conventional approaches, but as a complementary tool for building farmer-centered, data-driven, and risk-aware agronomic decision-support systems.

## **6.2 Overview and implications of findings**

The goal of this thesis was to develop and test a novel methodology for generating site-specific fertilizer recommendations for maize production in Ghana using machine learning. Utilizing a large database of agronomic maize trials across various agroecological zones, this thesis aimed to demonstrate the potential of machine learning models to predict maize yield and AE and to translate these predictions into practical, site-specific fertilizer recommendations.

### **6.2.1 Assessing the effectiveness of machine learning model in predicting yield, agronomic efficiency, uncertainty in model predictions and identifying important variables**

Random Forest was selected as the modelling approach in Chapter 2 because it is a well-established and widely applied ML algorithm in agronomic research. RF can capture nonlinear relationships and complex interactions between variables without requiring strong parametric assumptions, is robust to noisy and heterogeneous field data, and provides tools for model validation and variable importance assessment (Breiman, 2001). These features make RF suitable for datasets that integrate diverse soil, climate, and environmental data, as is often the case in agricultural field trials. RF is one of the most widely used baseline models in crop yield prediction and agronomic studies, consistently demonstrating strong performance across different crops, environments, and scales (Everingham et al., 2016; Jeong et

al., 2016; Pang et al., 2022; Silva et al., 2023). Its ability to rank explanatory variables importance supports agronomic interpretation, enabling researchers and policymakers to identify key drivers of productivity.

The findings in Chapter 2 demonstrate that the development and application of RF models for yield prediction in Ghanaian maize systems were successful. Using a large, multi-season, and multi-location dataset from extensive maize field trials, the RF model was trained and validated through a nested cross-validation framework to prevent information leakage and ensure evaluation reliability. This methodological rigor resulted in a model explaining 81% of the variation in maize yield and showed good generalization across unseen datasets. These results validate the feasibility of applying machine learning in smallholder-dominated production systems and establish a benchmark for model performance in contexts where data are often scarce and fragmented. The outcome reinforces the consensus that RF models are well suited for agricultural prediction tasks, where complex nonlinearities and multiple interacting variables exist.

Central to this success was the availability of the extensive maize field trials datasets that were collected for modelling. Machine learning models depend on data quality, quantity, and representativeness, which are critical for model accuracy and interpretability. The multi-year, multi-location dataset captured diverse agronomic, soil, and climatic conditions across Ghana, allowing the RF algorithm to learn from a large and variable geographical space. This diversity enabled the model to account for variability within and across agroecological zones and enhanced its ability to generalize to new data. The maize field trial database established the foundation for the modelling effort, offering both breadth to capture variability and depth to train a robust predictive model.

While yield prediction achieved high accuracy, modelling AE was more challenging, as reflected in the lower variance explained (54–63%). These results are significant because AE is inherently more complex to model than yield. Agronomic efficiency is influenced by various biophysical and management factors, including soil fertility, rainfall variability, farmer practices, timing of operations, and nutrient interactions, many of which are difficult to measure or were not systematically captured. The decision to exclude fertilizer application rates as an explanatory variable in the AE model was methodologically justified to avoid circular reasoning but constrained the model's ability to account for the dominant driver of nutrient efficiency. This methodological compromise illustrates both the strengths and limits of using observational datasets in modelling efficiency metrics and highlights the need for more integrated datasets that include biophysical variables, detailed farmer management data, pest and disease incidence, and input-output relationships.

A major contribution of the RF modelling exercise is its ability to identify influential explanatory variables and quantify their importance in shaping yield and AE outcomes. Key predictors included nitrogen fertilizer application, soil exchangeable calcium, organic carbon, rainfall, pH, and soil texture.



The prominence of soil organic carbon and exchangeable calcium emphasizes soil health as a foundational factor in crop productivity, echoing findings by Zingore et al. (2021, 2022), who noted that soil degradation hinders improved nutrient use efficiency in Sub-Saharan Africa. The significance of rainfall and temperature variables reflects maize production's vulnerability to climatic variability, reinforcing earlier work by Schlenker and Lobell (2010) on climate sensitivity in African agriculture. These results demonstrate that the RF model is not only predictive but also informative, revealing underlying system dynamics consistent with established agronomic knowledge. The model bridges predictive analytics with interpretative insights, offering dual scientific value.

Despite these strengths, the results reveal important limitations and vulnerabilities linked to data availability and quality. Prediction uncertainty was greatest in zones with sparse trial coverage or underrepresented agroecological conditions. This spatial unevenness in model confidence reflects a broader issue in applying machine learning to smallholder systems: where data are scarce or unevenly distributed, predictions become less reliable and potentially misleading. This aligns with warnings by Lobell et al. (2009) and Hardaker et al. (2015), who noted that statistical and machine learning models are sensitive to data distribution and may underperform when extrapolated beyond well-sampled conditions. Uncertainty was particularly high for AE, partly due to the exclusion of key explanatory variables such as pest and disease incidence and localized micro-climatic effects. These unobserved variables likely account for part of the unexplained variance, underscoring the need for more comprehensive and integrated datasets. Expanding data collection to include management-level variables and increasing trial spatial density will be essential for improving future models. This requires coordinated efforts in experimental design, standardized data collection protocols, and establishing open-access agricultural trial databases across SSA.

From a scientific standpoint, these findings support the utility of RF and similar machine learning models in agronomic research and decision support. The results show that RF can handle the nonlinearities, noise, and data heterogeneity characteristic of smallholder farming systems. Beyond predictive accuracy, the RF model's ability to rank variable importance provides insights into the underlying drivers of yield and efficiency, enabling researchers and policymakers to identify intervention leverage points. This dual functionality prediction and interpretation add considerable value, supporting both empirical analysis and knowledge generation. Importantly, including uncertainty estimates in yield and AE predictions enhances the realism of agronomic recommendations. Rather than deterministic prescriptions, the modelling framework acknowledges inherent variability and risks, aligning more closely with smallholders' realities, who must adapt to uncertain environments.

The practical implications of this work are significant. The RF model could serve as the backbone of digital agronomy platforms designed to deliver site-specific fertilizer and management advice. Such platforms can promote sustainable intensification by improving nutrient use efficiency, enhancing farmer profitability, and reducing environmental risks. Insights into variable importance can guide

policymakers in prioritizing investments, such as emphasizing soil fertility management or supporting climate-smart agricultural interventions in regions where rainfall variability is a key yield constraint. Integrating ML-based insights into national fertilizer subsidy programs, extension services, and climate adaptation strategies could improve the targeting and effectiveness of these initiatives. In this sense, the modelling framework developed here shows a direct pathway from scientific research to tangible development impact, providing new knowledge and actionable tools for addressing food security challenges in Ghana and beyond.

### **6.2.2 Assessing effectiveness of machine learning derived recommendations against conventional recommendation approaches**

The analysis in Chapter 3 evaluated the performance of ML-derived fertilizer recommendations compared to conventional approaches, including the Conventional Fertilizer Dose Response (CFDR), the Updated Conventional Fertilizer Dose Response (UCFDR), and the QUEFTS semi-mechanistic model. The objective was to determine whether ML approaches, utilizing large and diverse datasets, could improve existing recommendation frameworks in Ghanaian maize production systems. Unlike conventional methods that apply blanket fertilizer rates across broad agroecological zones, ML-derived recommendations were site-specific, reflecting localized soil constraints, climatic variability, and management practices. This differentiation is critical because blanket approaches often fail to capture the fine-scale heterogeneity typical of smallholder systems in SSA. Validation trials indicated that ML-based recommendations led to significant yield gains and profitability improvements across most experimental sites, particularly where localized soil and weather conditions make uniform recommendations inefficient.

Field validation provided strong evidence of ML's advantages. Across six trial sites in the Forest and Guinea Savanna zones, ML-derived recommendations produced higher maize yields in four sites, outperforming both CFDR and UCFDR approaches. However, performance varied by zone: in the Semi-Deciduous Forest, the QUEFTS model outperformed ML, producing the highest mean yields in all four sites. This mixed performance pattern emphasizes that while ML excels in many contexts, no single approach universally dominates across all agroecological zones. Importantly, the superiority of site-specific over blanket recommendations supports earlier findings by Vanlauwe et al. (2012) and Kumar et al. (2018), reinforcing the need for adaptive, context-sensitive models for sustainable intensification.

A notable innovation in the ML framework was the integration of expert agronomic judgment into the recommendation process. While the model identified nitrogen as the primary yield-limiting nutrient, it sometimes suggested low or no P and K applications in certain zones. Expert knowledge indicated that moderate applications of these nutrients would enhance nitrogen use efficiency, particularly in soils

with known P and K deficiencies. Adjusting recommendations through this human-in-the-loop process improved agronomic soundness and yield reliability. This integration of model outputs with domain expertise aligns with observations by Park et al. (2023) and Beddows and Leontidis (2024), highlighting that hybrid systems combining data-driven predictions with expert oversight outperform purely algorithmic approaches. Therefore, the findings contribute to a broader methodological conversation: while ML offers powerful pattern recognition capabilities, its greatest potential lies in complementing, not replacing, agronomic expertise.

Another strength of the ML-based recommendations was their ability to incorporate a broader range of explanatory variables compared to mechanistic approaches like QUEFTS. Whereas QUEFTS relies primarily on soil nutrient supply and assumes linear relationships between nutrient input and yield response, the ML model integrated climatic variables (e.g., rainfall and temperature), soil properties (e.g., exchangeable calcium, organic carbon, texture), and other environmental variables. This multidimensional scope allowed the ML approach to account for complex interactions that influence yield outcomes, providing a more holistic representation of field conditions. However, this advantage also introduced trade-offs: reliance on historical climate data, such as 30-year rainfall averages, limited the model's ability to reflect year-to-year weather variability. As noted by Hochman and Horan (2018), integrating near real-time weather forecasts into recommendation frameworks could substantially improve adaptability and predictive accuracy. These findings highlight a methodological challenge: while ML models can capture complexity, they remain constrained by the timeliness and resolution of available data.

The economic dimension of the analysis supports ML-derived recommendations. In many zones, particularly the Forest and Semi-Deciduous Forest, conventional methods recommended high nitrogen application rates that were not always justified by crop response. In contrast, the ML model proposed more moderate fertilizer rates, resulting in lower input costs without compromising yield outcomes. This efficiency translated into higher profitability and greater resource-use efficiency, critical for resource-constrained smallholder farmers. The ability of ML to optimize input use while maintaining productivity also has environmental benefits, reducing risks of nutrient leaching, eutrophication, and greenhouse gas emissions associated with excessive fertilizer use. These findings align with Liben et al. (2024), who reported that ML-based fertilizer recommendations improved both yield prediction accuracy and farm profitability, reinforcing ML's potential to support more economically and environmentally sustainable nutrient management strategies.

However, the results also reveal limitations of the ML approach. Model performance was sensitive to the composition and quality of the training dataset. Much of the training data typically showed higher variability and lower yields from the maize trials data. This bias may have affected the generalizability of model outputs, particularly under controlled conditions where management intensity differs. Moreover, several critical agronomic variables such as pest and disease incidence, crop rotation history,

irrigation practices, and farmer decision-making processes were not systematically captured in the dataset. Their exclusion likely constrained the explanatory power of the model and limited its ability to capture unexpected yield outcomes. Similar challenges have been highlighted by Cravero et al. (2022), emphasizing that missing variables often represent the greatest bottleneck in developing robust ML applications in yield prediction. Addressing these data gaps through more comprehensive and standardized data collection protocols remains a priority for future research in ML prediction models.

In Chapter 3, I demonstrated that ML-derived fertilizer recommendations represent a significant advancement in adaptive nutrient management. While not universally superior to mechanistic models like QUEFTS, their capacity to generate site-specific recommendations, integrate multiple explanatory variables, and improve both profitability and environmental sustainability positions ML as a promising tool for smallholder agriculture in SSA. Importantly, the combination of ML insights with expert agronomic judgment points toward the most effective pathway forward: hybrid systems that leverage the strengths of both data-driven models and human expertise. Future research should focus on integrating ML with mechanistic models, incorporating real-time weather and management data, and developing interactive digital platforms that make these recommendations accessible and usable by farmers and extension agents. By advancing in these directions, ML-based systems can contribute to more resilient, scalable, and sustainable agronomic advisory services, aligning scientific innovation with the practical needs of African farmers.

### **6.2.3 Significance of machine learning models in agronomic decision making**

Chapter 4 evaluated the role of ML models in predicting maize yield and AE in Ghana's smallholder maize farming systems, focusing on the comparative performance of four widely used ML algorithms: RF, XGBoost, SVM, and KNN. Two core research questions were addressed in chapter 4: how do these algorithms differ in predictive performance, and which explanatory variables are most important across models? These questions, built on earlier findings from Chapters 2 and 3, where RF models were effective in yield prediction and generating site-specific fertilizer recommendations. Chapter 4 positioned the broader family of ML algorithms within the agronomic decision-making context, allowing for a synthesis of their comparative strengths and limitations.

The results confirm that all four ML models demonstrated strong predictive ability for maize yield and AE, though with differences in accuracy and robustness. Tree-based models (RF and XGBoost) consistently outperformed kernel-based (SVM) and instance-based (KNN) methods, particularly under stringent cross-validation conditions like leave-zone-out cross-validation (LZOCV). These findings show that while ML models can achieve high predictive accuracy, their performance diverges under conditions of spatial heterogeneity and limited representativeness, challenges inherent in smallholder agricultural systems. The superior performance of RF and XGBoost highlights their capacity to handle

nonlinearity and high-dimensional interactions between soil, climate, and management factors, supporting earlier conclusions in Chapter 2 about RF's value in diverse agroecological contexts. This aligns with findings in Huber et al. (2022) and Srivastava et al. (2022), which reported that tree-based methods outperform alternatives in agricultural prediction tasks because they accommodate data irregularities without extensive calibration.

Variable importance analysis provided further insights into the significance of ML for agronomic decision-making. Across models, there was both convergence and divergence in how explanatory variables were prioritized. Nitrogen fertilizer rate, rainfall, soil organic carbon, and bulk density consistently emerged as influential, particularly in RF and XGBoost, while SVM and KNN highlighted genotype and environmental factors. This consensus on the critical role of nitrogen, rainfall, and soil organic matter echoes findings from Chapters 2 and 3, where N was identified as the dominant yield driver and organic carbon was crucial for nutrient use efficiency. At the same time, divergences across models illustrate that variable importance is shaped by algorithmic architecture and data structure. Khaki and Wang (2019) and Jeong et al. (2016) noted that ML algorithms vary in how they weight explanatory variables, impacting result interpretation in agronomic applications. Thus, variable importance should be viewed as model- and context-dependent, relevant for researchers and policymakers prioritizing agronomic interventions.

The implications of these results are significant. The identification of soil bulk density and organic carbon as key predictors of AE underscores underutilized levers for improving nutrient use efficiency in smallholder systems. Such insights could support more holistic interventions, such as organic matter management, residue retention, and conservation agriculture practices that improve soil structure and fertility. These findings build on evidence from Chapter 3, where ML-based fertilizer recommendations highlighted the limits of focusing narrowly on nitrogen inputs, pointing to broader soil health factors as constraints to productivity. By integrating these insights into agronomic decision-making, ML models can guide not only nutrient management but also complementary practices that enhance long-term system resilience.

At the same time, the results underscore important limitations. The performance decline of all models under LZOCV highlights the sensitivity of ML algorithms to data representativeness, reflecting challenges in extrapolating predictions across agroecological zones. This observation aligns with Bonilla-Cedrez et al. (2021), which showed that ML models trained in one zone often struggle when applied to unseen regions due to soil and climate heterogeneity. For agronomic decision-making, this means that while ML can be a powerful tool for site-specific recommendations, its reliability diminishes in data-scarce regions. This finding complements conclusions from Chapter 2, where prediction uncertainty was greatest in under-sampled zones, emphasizing that the utility of ML is ultimately bounded by the quality of available datasets. Addressing these data gaps is essential for ML to reach its full potential in agricultural advisory systems.

The comparative evaluation of ML algorithms in Chapter 4 reinforces earlier findings by showing that ML has substantial significance for agronomic decision-making but that algorithm choice, data quality, and contextual factors shape its utility. RF and XGBoost emerged as the most reliable models, offering both predictive accuracy and interpretative value, while variable importance analyses provided nuanced insights into the drivers of yield and AE. The convergence across models on the role of soil organic matter, bulk density, and rainfall demonstrates consistency across multiple modelling frameworks. These findings position ML as a valuable tool for agronomic decision-making that integrates soil health, climate resilience, and nutrient management. Thus, ML's significance lies in its predictive capacity and its ability to provide actionable insights for sustainable intensification and resilience in SSA farming systems.

#### 6.2.4 Uncertainty and risk affect decision making in fertilizer decision making

Chapter 5 advanced the development of fertilizer recommendation strategies by incorporating predictive uncertainty and farmer risk preferences, two dimensions often absent in conventional agronomic advisory approaches. The chapter addressed research questions concerning the role of risk-based frameworks, the impact of predictive uncertainty on fertilizer optimization, and how different risk profiles shape fertilizer use among smallholder maize farmers. The study employed a combination of quantile regression forests, expected utility theory, and multi-scenario optimization under uncertainty, developing a methodology that integrates statistical uncertainty with behavioral economics. This framework extended findings from Chapters 2 and 3, where ML models generated accurate yield predictions and fertilizer recommendations, by adding critical dimensions of risk and uncertainty that influence farmer adoption. It contributed to the broader thesis objective of exploring how ML can support adaptive, realistic, and farmer-centered agronomic decision-making.

Results across agroecological zones confirmed that nitrogen remains the dominant nutrient influencing maize yield, profitability, and expected utility, consistent with prior evidence from SSA (Kihara et al. 2016; Vanlauwe et al. 2011). However, the novel contribution of this chapter lies in demonstrating how the optimal rate of N fertilizer shifts with farmer risk preferences. While yield- and profit-maximizing recommendations generally ranged from 60–90 kg N ha<sup>-1</sup>, risk-averse farmers preferred much lower rates (10–80 kg N ha<sup>-1</sup>). This finding addressed the research question on the behaviour of risk-averse users: they reduced fertilizer use, sacrificing some profit potential to mitigate downside risk. These results align with expected utility theory (Hardaker et al., 2015) and resonate with empirical studies from Ethiopia and Malawi (Holden and Lunduka, 2012; Wossen et al., 2017), where risk-averse smallholders adopt lower-input strategies under uncertainty. The study demonstrated that fertilizer optimization cannot be understood solely in terms of agronomic or economic returns; it must also reflect the behavioral realities of smallholders facing high levels of production and financial risk.



A particularly important insight concerns the disconnect between technically optimal recommendations and behaviorally acceptable ones, often described as the “adoption paradox” (Marenya and Barrett, 2009). Agronomic trials and models often assume risk-neutral behaviour, prescribing input rates that maximize yield or profit under average conditions. Yet, smallholder farmers, particularly in Ghana’s risk-prone production zones, often reject these prescriptions because they cannot absorb financial shocks from poor harvests. Chapter 5 showed that by modelling behavioral responses through expected utility functions, it is possible to generate fertilizer recommendations that are both agronomically sound and behaviorally aligned. This builds on evidence from Chapter 3, where ML-generated fertilizer recommendations proved effective but required expert judgment adjustments for greater acceptability. Together, these chapters suggest that recommendations must be both technically and behaviorally viable for wide adoption, underscoring the need for agronomic advisory systems to integrate behavioral economics alongside biophysical science.

The chapter also addressed how uncertainty quantification can be incorporated into fertilizer optimization. Rather than relying on point estimates from predictive models, the study employed statistical tools such as predictive intervals and quantile-based methods to characterize uncertainty in yield response. These measures were combined with expected utility reasoning to generate risk-sensitive recommendations. This approach marks a methodological advance, operationalizing concepts of probabilistic reasoning in a domain traditionally dominated by deterministic prescriptions. Similar calls for uncertainty-aware agronomic modelling have been made in the literature (Antle et al., 2017; Jones et al., 2017), but few studies have demonstrated their feasibility at scale in smallholder African systems. This thesis not only filled a methodological gap but also linked back to insights from Chapter 2, which highlighted that prediction accuracy and uncertainty varied across zones depending on data availability. Together, these results underscore the importance of explicitly integrating predictive uncertainty into decision-making frameworks for smallholder agriculture.

Another valuable contribution of Chapter 5 lies in its nuanced treatment of P and K fertilizers. The analysis revealed negligible agronomic or economic benefits from P and K application unless site-specific deficiencies were present. Even risk-neutral farmers had little justification for applying these nutrients under prevailing conditions. This result mirrors findings from West Africa (Liverpool-Tasie et al., 2017; Sheahan et al., 2013) and validates the need for soil diagnostics before recommending P and K inputs. It builds on findings in Chapter 3, where ML-derived fertilizer recommendations sometimes proposed low or no P and K application, and expert judgment suggested modest adjustments to ensure balanced nutrient use. By incorporating uncertainty-aware and risk-adjusted reasoning, the current approach offers a stronger justification for discouraging unnecessary expenditures on P and K, promoting nutrient-use efficiency, and reducing environmental externalities such as nutrient runoff and soil degradation.

The broader significance of Chapter 5 is that it confirmed farmers operate under complex trade-offs: between maximizing yields and ensuring household food security, between investing in inputs and preserving resilience in lean years, and between expected returns and potential losses. By explicitly modelling these trade-offs, this thesis demonstrated that fertilizer optimization is not a one-size-fits-all exercise but a dynamic balancing act shaped by biophysical, economic, and behavioral constraints. This insight complements earlier chapters, where ML models predicted yields and guided fertilizer recommendations but did not fully capture adoption barriers. Chapter 5 provided the missing behavioral lens, showing that the effectiveness of agronomic models depends as much on their alignment with farmer realities as on their predictive power.

Integrating uncertainty and risk preferences into fertilizer decision-making provides a stepping stone toward multi-objective, integrated decision-support systems. As climate volatility intensifies and market conditions remain unpredictable, incorporating probabilistic reasoning and farmer heterogeneity into agronomic advisory services becomes increasingly essential. This finding aligns with the synthesis of Chapters 2 through 4, which demonstrated the predictive power of ML and its value in identifying key drivers of yield and efficiency. By adding uncertainty quantification and risk-sensitive optimization, Chapter 5 expanded this foundation into a more comprehensive, farmer-aligned framework for decision-making. Policymakers, extension agents, and researchers must recognize that uncertainty and behavioral responses are not peripheral issues but central determinants of whether new technologies and recommendations are adopted.

### **6.3 Reflection**

This thesis explored how ML methods can enhance agronomic decision-making in Ghana's maize-based smallholder systems by addressing four interrelated challenges: yield and efficiency prediction, fertilizer recommendation, uncertainty, and farmer risk behaviour. Reflecting across the four chapters, it is evident that the work has achieved important advances in the methodological and applied domains of digital agriculture, while also opening new lines of inquiry. Taken together, the findings demonstrate that ML is not merely a technical innovation but a decision-support framework whose value depends on the integration of accurate data, expert agronomic knowledge, and an understanding of farmer behaviour.

#### **6.3.1 Data quality for machine learning modelling**

A key lesson from this research is that the effectiveness of ML in agronomy depends fundamentally on the quality, representativeness, and coverage of data. In Chapter 2, the RF model explained substantial maize yield variation when applied to a large, multi-season, multi-location dataset. This result demonstrates ML's potential to capture complex, nonlinear interactions in crop systems and affirms that

data quality is essential in modelling (Cravero et al., 2022). However, the outcomes also underscore key limitations, particularly regarding the generalizability of models across diverse agroecological contexts.

One significant challenge is the distributional dependency of ML models. Models trained on data from specific environments typically produce reliable predictions only within similar distributions, while predictive accuracy declines in regions with distinct climatic, soil, or environmental conditions. This limitation was evident in our study, where prediction uncertainty was highest in under-sampled regions and model performance dropped substantially under leave-zone-out cross-validation. Meyer and Pebesma (2021) cautioned against extrapolating predictions beyond the “area of applicability” defined by the training data. Similarly, Takoutsing and Heuvelink (2022) and de Bruin et al. (2022) showed that clustered or spatially structured validation schemes reveal lower and more realistic performance estimates in poorly sampled zones. These results highlight the fragility of extrapolating across agroecological zones with sparse training data. Additionally, the absence of critical explanatory variables including pest incidence, disease pressure, farmer management practices, and other socio-economic factors further constrains model performance in low-data environments.

Addressing these constraints requires systematic investments in regionally dense and representative datasets. In SSA, where agricultural systems are highly heterogeneous, the availability of robust and context-specific datasets is essential for reliable agronomic modelling. Several initiatives are attempting to close this gap. For example, the recently developed Africa-wide agricultural production database provides spatially explicit datasets to support yield modelling and regional policy design (Geyman et al., 2025). Complementary approaches such as the Synthetic Agricultural Data Generation and Augmentation (SAGDA) toolkit offer opportunities to mitigate data scarcity by simulating plausible agricultural data for underrepresented zones (Belgaid and Ennaji, 2025). At the institutional level, collaborative platforms are critical. The Global Open Data for Agriculture and Nutrition (GODAN) promotes transparency and accessibility of agricultural data across jurisdictions (Musker and Schaap, 2018), while the Alliance for a Green Revolution in Africa (AGRA) is spearheading programs that integrate digital advisory services, farmer surveys, and remote sensing technologies to strengthen data infrastructures across multiple African countries (von Braun et al., 2023).

Advancing ML in SSA cannot be reduced to algorithmic innovation alone. The success of predictive agronomy will depend on building robust data ecosystems, principled generalization strategies, and regional collaboration frameworks. Such investments are essential for ensuring that ML-driven recommendations are reliable and scalable across the diversity of African farming systems.

### 6.3.2 The shifting paradigm: will machine learning replace mechanistic models in agronomy?

Chapters 3 and 4 offered a reflective contrast between ML and established semi-mechanistic frameworks (e.g., QUEFTS). The empirical evidence largely supports the view that ML-based fertilizer recommendation systems can outperform conventional approaches by adapting to local variability and tailoring recommendations to site-specific conditions (Kumar et al., 2018; Bernard Vanlauwe et al., 2012). In practice, these data-driven systems often capture finer variation than static, rigid mechanistic formulations. Our results show that in the Semi-Deciduous Forest zone, QUEFTS delivered higher mean yields than ML, indicating that semi-mechanistic models remain valuable. However, these findings are based on a single season and a small number of sites, so it is too early to draw firm conclusions. More research is needed, with broader and longer-term comparisons, to determine whether ML outperforms mechanistic approaches or if hybrid approaches may provide the best solution. Similarly, while tree-based ML models (RF, XGBoost) dominated in capturing nonlinearity relative to kernel or instance methods, they remain prone to overfitting in low-data regimes (Bonilla-Cedrez et al., 2021).

Semi-mechanistic models offer interpretability, theoretical consistency, and portability, making them a strong basis for hypothesis testing and extrapolation. However, their capacity to accommodate complex interactions is limited; calibration burdens are high, and they fail with noisy, heterogeneous data characteristic of smallholder systems (Jones et al., 2017). In contrast, ML models are flexible, data adaptive, and excel at uncovering nonlinear dependencies in large datasets (Huber et al., 2022; Srivastava et al., 2022), but they tend to be black boxes, struggle to generalize beyond training data, and depend heavily on representative data coverage. Rather than posing a binary substitution, the evidence increasingly supports convergence between ML and mechanistic modelling. Hybrid or physics-informed ML frameworks combine the strengths of both paradigms, using physical constraints to regularize ML models or embedding learned corrections within process models (Shi et al., 2025). For example, recent research demonstrated that hybrid models outperform pure mechanistic or deep learning approaches in biomass prediction while maintaining interpretability (Shi et al., 2025). Similarly, Kenny et al. (2024) showed that coupling grass-growth mechanistic models with ML residual corrections improved predictive capacity and robustness.

In the broader agronomic modelling and digital agriculture landscape, current initiatives mirror this hybrid vision. The CGIAR Platform for Big Data in Agriculture promotes open data, interoperable standards, and cross-scale analytics to enable data-driven agronomy across diverse environments (Basel et al., 2023). Its “Data-Driven Agronomy” community emphasizes fusion of modelling and ML to generate actionable insights (Arnaud et al., 2020). Meanwhile, Cock et al. (2023) highlight how operations research and ML can be integrated to optimize crop management using farmer-provided data streams. Synthetic data tools such as SAGDA are also emerging to mitigate data scarcity in African

contexts, enabling improved ML training and hybrid modelling experiments (Belgaid and Ennaji, 2025). Additionally, across policy and infrastructure domains, recent reviews stress the need to build digital capacity, data governance, and inclusive ecosystems for hybrid modelling to scale (Finger, 2023). The European Union's SmartAgriHubs and AgData/AKIS programs now actively promote precision agriculture and digital extension methods that integrate sensor networks, ML, and simulation models (Ronzhin et al., 2025).

The path forward is not replacement but integration. The next generation of agronomic decision support systems will likely rest on hybrid frameworks that anchor mechanistic rigor within data-driven adaptability. These tools, underpinned by open data platforms and institutional ecosystems, offer the promise of scalable, interpretable, and resilient agronomic models fit for a changing world.

### **6.3.3 Expert knowledge-guided machine learning for agronomic decision-making**

In Chapter 3, I found that ML alone may be insufficient for producing agronomically applicable recommendations. For example, the ML model suggested minimal or no P and K application in some zones, despite deficiencies in the soils. Expert agronomic judgment was essential to refine the nutrient recommendations, highlighting the role of human-in-the-loop systems. This finding aligns with literature emphasizing that domain knowledge increases the robustness and legitimacy of ML outputs (Beddows and Leontidis, 2024; Park et al., 2023).

The same principle can be extended through physics-informed ML (PIML) (Karniadakis et al., 2021) and knowledge-guided ML (KGML). Physics-informed ML integrates biophysical process knowledge such as crop growth dynamics, nutrient balances, and water–soil interactions into ML algorithms, constraining models to respect known scientific laws while allowing flexibility to capture data-driven patterns. In agronomy, this could mean embedding QUEFTS-like nutrient response functions or crop growth models into ML training to prevent implausible recommendations (e.g., negative responses to nitrogen). Similarly, knowledge-guided ML formalizes the role of expert agronomists in model development by encoding rules, heuristics, or domain priors into ML structures (Beddows and Leontidis, 2024; Park et al., 2023). Together, these approaches offer a middle ground: ML systems that retain predictive flexibility but are grounded in biophysical realism and expert judgment.

The importance of such hybrid approaches is increasingly recognized in global initiatives. For example, the FAO's Hand-in-Hand Initiative integrates advanced geospatial analytics and expert knowledge to guide agricultural investments for food security (Canton, 2021). The CIMMYT-led Excellence in Agronomy (EiA) Platform emphasizes site-specific agronomic recommendations through digital tools co-designed with farmers and experts (Govaerts et al., 2021). Similarly, the CGIAR Digital Innovation Initiative advances “responsible AI” approaches for agriculture that blend expert knowledge with data-

driven insights (Dara et al., 2022). In parallel, OpenTEAM (Open Technology Ecosystem for Agricultural Management) is pioneering open-source, expert-informed decision support systems to enhance soil health and climate resilience (Everett et al., 2023). These initiatives illustrate a shift from “pure prediction” to “guided decision support,” where domain expertise anchors ML systems in practical agronomic realities.

This study findings point in this direction. Chapter 3 showed how expert judgment corrected ML’s underestimation of nutrient needs, while Chapter 5 highlighted how behavioral knowledge improved fertilizer recommendations. Embedding such “layers of guidance” points towards the future of agronomic decision support: models that are both data-driven and scientifically grounded, balancing predictive flexibility with agronomic realism. Ultimately, advancing hybrid ML approaches has the potential to strengthen the accuracy of fertilizer recommendations, and long-term sustainability of digital agronomy innovations.

### 6.3.4 Future research

Reflecting on Chapters 2–5, the thesis highlights several critical next steps. First, expanding and standardizing field trial datasets is an urgent priority. Data gaps and uneven spatial coverage were recurring limitations, and establishing open-access, harmonized trial databases would ensure that ML models are trained on representative samples (Cravero et al., 2022). Second, the integration of new explanatory variables including pest and disease incidence, crop rotation, irrigation, and real-time weather data would enhance model accuracy and interpretability. Third, there is a need to further develop hybrid modelling approaches that merge the explanatory structure of mechanistic models with the adaptability of ML, leveraging the strengths of both (Kenny et al., 2024). Fourth, designing platforms that operationalize uncertainty-aware and behaviorally aligned recommendations could be a practical frontier. Building on the methods demonstrated in Chapter 5, such platforms could deliver site-specific, farmer-centered advisory services that balance yield, profit, risk, and sustainability. By pursuing these directions, future research can extend the foundation laid in this thesis toward agronomic decision-support systems that are accurate, adaptive, and aligned with the realities of smallholder farming in Sub-Saharan Africa.

### 6.4 Conclusion

Across all chapters, this thesis demonstrated that ML, particularly tree-based algorithms such as RF and XGBoost, can be used for predicting maize yield and AE, deriving site-specific fertilizer recommendations, and incorporating uncertainty and farmer risk preferences into advisory tools. The results clearly show that ML on its own, even without mechanistic modelling or human expertise, can

already provide valuable insights and decision-support for agronomic systems. This underscores the importance and potential of ML in agronomy and crop science, especially in contexts such as SSA where such applications have been limited to date.

However, the findings also highlight that ML does not and should not replace mechanistic models or agronomic expertise. Instead, the future of agronomic innovation lies in collaborative approaches where ML complements rather than substitutes domain knowledge, causal reasoning, and contextual awareness offered by human experts and process-based models. These two techniques have as yet rarely been used together in agronomy or crop science, and almost certainly not in SSA, making their integration a promising focal point for future research.

In conclusion, I have the strong conviction that the future of agronomic decision-making in smallholder systems does not rest on choosing between ML and mechanistic modelling, or between ML and human expertise, but on strategically combining their strengths. By doing so, it becomes possible to deliver agronomic recommendations that are not only scientifically sound and economically viable, but also socially acceptable, environmentally responsible, and tailored to the lived realities of African farmers.



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## Summary

Maize is a staple food for millions of households in Ghana and across Sub-Saharan Africa (SSA), yet yields remain far below their potential. Persistent soil fertility challenges, inefficient fertilizer use, and reliance on blanket fertilizer recommendations that overlook site-specific variability are major constraints. These inefficiencies undermine both productivity and profitability, limiting the ability of smallholder farmers to achieve sustainable livelihoods. Mechanistic models such as QUEFTS have deepened our understanding of nutrient dynamics and crop responses, but their effectiveness is constrained by the need for extensive calibration data. In many SSA contexts including Ghana such detailed datasets are scarce, leading to recommendations that fail to capture the heterogeneity of smallholder farming systems. Consequently, nutrient management advice often remains generalized, providing little guidance for farmers facing diverse soils, climates, and management practices. Compounding this challenge, smallholder farmers typically operate with limited resources in highly uncertain environments. Erratic rainfall, degraded soils, fluctuating input prices, and volatile markets force them to adopt risk-averse strategies. Conventional fertilizer recommendation systems, however, largely overlook these socioeconomic and behavioral realities, assuming farmers can and will implement technically optimal but often costly and risky strategies.

Recent advances in machine learning (ML) offer a promising pathway to address these gaps. By leveraging large, diverse datasets, ML can capture nonlinear interactions among soil, climate, and management factors to generate site-specific, data-driven predictions. Yet, important questions remain unanswered. Can ML models reliably predict yield and fertilizer responses under the diverse and data-scarce conditions of SSA? How can issues of data quality, representativeness, and variable selection be addressed to ensure credible outputs? And critically, how can predictive uncertainty and farmer risk preferences be integrated into ML-based decision-support systems so that recommendations are not only technically sound but also practical and adoptable? This thesis responds to these challenges by evaluating the potential of ML for maize production systems in Ghana. Specifically, it explores ML's capacity for yield prediction, fertilizer recommendation, uncertainty quantification, and risk-aware decision-making. By addressing these gaps, the study aimed to lay the groundwork for farmer-centered, data-driven agronomic decision-support systems that complement mechanistic models and better reflect the realities of smallholder farming in SSA. This thesis focuses on four prospects to explore how ML can derive site-specific fertilizer recommendations for maize production: modelling yield and agronomic efficiency using random forest ML (Chapter 2), deriving fertilizer recommendations from calibrated random forest models and comparing them with recommendations from conventional approaches through field experiments (Chapter 3), modelling yield and agronomic efficiency with other ML models and comparing their performance (Chapter 4), and developing a fertilizer recommendation strategy that accounts for uncertainties in models predictions (Chapter 5). Each chapter aimed to tackle

challenges related to data quality, model performance, variable importance, and optimal fertilizer recommendations.

In Chapter 2, I assessed the effectiveness of ML for predicting maize yield and agronomic efficiency in Ghana's smallholder systems was examined. Using a large, multi-season, multi-location maize field trials made up of 3136 georeferenced treatment plots observation data from 482 maize trials from 1991 to 2020, I trained a Random Forest (RF) ML model and evaluated it's performance using a nested cross-validation approach. The RF model explained 81% of yield variation and moderately predicted agronomic efficiency (54–63%). I further assessed the uncertainties of the RF models predictions for yield and agronomic efficiency by computing the prediction interval coverage probability (PICP). I observed that prediction uncertainties were adequate quantified for yield than for yield. However, predictions uncertainties for yield and agronomic efficiency were more accurate in the Guinea Savanna zone than for the Forest-Savanna Transition. To understand which explanatory variables were driving maize yield and agronomic efficiency, I performed a variable importance assessment of the explanatory variables. I observed that key important variables included nitrogen fertilizer application, temperature, rainfall, soil organic carbon, and bulk density, which climate variables being more profound in the variable importance assessment. These findings highlighted that data quality and representativeness was critical for reliable ML outputs, confirming that ML can provide powerful tools for yield prediction and variable prioritization in heterogeneous systems, but systematic data expansion and integration of management practices data are necessary to improve the models predictions, setting the foundation for using ML in site-specific fertilizer recommendations which I explored in Chapter 3.

In Chapter 3, I derived fertilizer recommendations from the calibrated RF model and compared them with recommendations from conventional methods such Conventional Fertilizer Dose Response (CFDR), Updated CFDR (UCFDR), and QUEFTS through field experiments. The field validations experiments were conducted across three main maizes growing agroecological zones in Ghana, namely, the Semi-Deciduous Forest (SDF), Forest-Savanna Transition (FST) and the Guinea Savanna (GS) zones. I observed that the machine learning approach generally recommended lower rates of phosphorus and potassium than the other approaches, while nitrogen recommendations were comparable. In the GS zone, the recommendations from the machine learning approach outperformed those from the other approaches, producing higher mean yields for three out of the four sites in the zone. In the FST zone, the machine learning model recommendations led to higher mean yields at four sites, while the approaches based on QUEFTS and UCFDR performed best at two other sites. In the SDF zone, the recommendations of the QUEFTS approach resulted in the highest mean yields at three sites, and CFDR at one site. Additionally, I observed that the machine learning approach-based recommendations demonstrated higher net profit margins in the GS and FST zones, suggesting cost-effectiveness in these zones. These findings indicated that site-specific fertilizer recommendations are efficient to blanket recommendations and machine learning approaches offers a promising and innovative approach for

generating cost-effective, site-specific fertilizer recommendations compared to the other methods in tropical climates. In this chapter, I emphasized the potential of ML for adaptive and resource-efficient fertilizer advice while highlighting the need to combine data-driven approaches with agronomic expertise in informing site-specific decision making, positioning ML as a complement to mechanistic models.

In Chapter 4, I assessed the performance of four ML algorithms RF, XGBoost, SVM, and KNN using a larger, more diverse maize trial dataset of 4496 georeferenced observations. The goal was to assess whether alternative algorithms could outperform RF model developed and used in Chapter 1 and to identify consistency in explanatory variable importance from different models. I assessed model performance using three cross-validation techniques: leave-one-out, leave-site-out, and leave-agroecological-zone-out and measured their accuracy using mean error, root mean squared error, and model efficiency coefficient. I found that tree-based models (RF and XGBoost) consistently outperformed SVM and KNN, particularly under heterogeneous and data-scarce agroecological zones. However, I observed that XGBoost slightly outperformed RF, but both models effectively captured nonlinear relationships. Analyzing variables from the different models revealed convergence across models: nitrogen fertilizer application, rainfall, soil organic carbon, and genotype emerged as key explanatory variables of maize yield and agronomic efficiency. However, the differences across variables importance from different models indicated that variable importance is model-dependent, influenced by algorithm structure and data distribution. This chapter reinforced earlier conclusions that ML is valuable for both prediction and explanation but underscored the importance of algorithm choice.

In Chapter 5, I introduced a novel approach by integrating predictive uncertainty and farmer risk preferences into fertilizer recommendations, addressing smallholder decision-making realities. Specifically, I examined how uncertainty and farmer risk preferences affect optimal nutrient application rates. Using the 4,496 maize field experimental observations, I trained a Quantile Regression Forest model to predict maize yield responses to nitrogen, phosphorus, and potassium and assessed their profitability in 14 representative sites across three agro-ecological zones (Chapter 3) in Ghana. I implemented a utility-based economic model to simulate farmer decisions under varying levels of risk aversion. Results indicated nitrogen as the dominant driver of yield, profitability, and expected utility. Yield- and profit-maximizing nitrogen rates ranged from 60–90 kg N ha<sup>-1</sup>, but risk-averse farmers, particularly in marginal environments, preferred lower rates (10–80 kg N ha<sup>-1</sup>). This demonstrated that while technical optima maximize returns, behavioral optima reduce exposure to loss. Phosphorus and potassium rarely showed strong returns, suggesting the value of soil diagnostics to inform fertilizer recommendations. I found that ignoring uncertainty and farmer risk preferences leads to recommendations unlikely to be adopted. By explicitly modelling these dynamics in this chapter, I was able to bridge the gap between agronomic potential and farmer realities, offering a framework for risk-aware agronomic decision-making.

Chapter 6 reflected on the implications for data-driven agronomy, the relationship between ML and mechanistic models, and future research directions. A central lesson was that ML's power lies in handling complex, nonlinear datasets, but its effectiveness is constrained by data quality, representativeness, and the exclusion of key variables. Across chapters, nitrogen consistently emerged as the dominant yield driver, with soil organic carbon, bulk density, and rainfall also playing crucial roles. The thesis demonstrated that ML complements rather than replaces mechanistic models: mechanistic approaches provide interpretability and biophysical grounding, while ML offers flexibility and predictive strength. Hybrid approaches, such as physics-informed and knowledge-guided ML, were identified as the next frontier, integrating domain knowledge with data-driven adaptability. The chapter emphasized the importance of expert-in-the-loop systems and risk-sensitive modelling to enhance credibility and adoption. Future research priorities include expanding harmonized datasets, integrating new explanatory variables, advancing hybrid modelling frameworks, and developing interactive, risk-aware digital platforms. Overall, the thesis established a foundation for farmer-centered, data-driven agronomic decision-support systems capable of supporting sustainable intensification and resilience in smallholder maize systems in Sub-Saharan Africa.

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## About the author



Eric Asamoah was born on 31 May 1988 in Asotwe, near Kumasi in the Ashanti Region of Ghana. His early curiosity for numbers and the natural world nurtured a passion for science, and modelling. This interest guided his academic journey, leading him to pursue science in secondary school in 2003, laying a foundation for his future in engineering and research. In 2007, he enrolled at the Kwame Nkrumah University of Science and Technology (KNUST) to study Geomatic Engineering. There, he developed a keen interest in Geographic Information Systems and Remote Sensing,

particularly in agricultural research. After graduating in 2011, Eric joined the Council for Scientific and Industrial Research – Soil Research Institute (CSIR-SRI), where he worked on the transition from analogue to digital soil mapping and was part of the team that developed the Institute’s first soil geodatabase. His work modernized soil data management systems and laid the groundwork for digital soil mapping in Ghana. In 2016, Eric pursued a MPhil in Soil Health and Environmental Resource Management, deepening his understanding of soil science and its role in sustainable agriculture. His commitment to bridging science and practice inspired him to explore advanced computational tools for agricultural challenges. In 2021, Eric began a PhD focused on machine learning for fertilizer recommendation in Ghana, aiming to provide data-driven solutions to optimize fertilizer use, enhance crop yields, and support sustainable farming practices. His work blends his interests in science, modelling, and practical application to improve lives and livelihoods. Beyond his PhD, Eric continues to explore innovative applications of machine learning in agriculture, striving to create tools that empower farmers and advance food security in Ghana and beyond.

## Peer-reviewed journal publications

**Asamoah, E.,** Heuvelink, G. B., Logah, V., Leenaars, J. G., & Bindraban, P. S. (2026). Fertilizer recommendations for maize production in Ghana: Comparison of machine learning, semi-mechanistic and conventional approaches. *European Journal of Agronomy*, 174, 127925. <https://doi.org/10.1016/j.eja.2025.127925>

**Asamoah, E.,** Heuvelink, G. B., Bindraban, P. S., & Logah, V. (2025). Modeling maize yield and agronomic efficiency using machine learning models: A comparative analysis. *Agronomy Journal*, 117(6), e70206. <https://doi.org/10.1002/agj2.70206>

Simperegui, K. B., Kouame, A. K., Kwesie, B., Bindraban, P. S., Adzawla, W., **Asamoah, E.**, & El Gharous, M. (2025). Digital mapping of Ghana's soil properties and nutrients: performance of spline and weighted average approaches. *Geoderma*, 459, 117365.

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Kome, G. K., Kundu, C. A., Okon, M. A., Enang, R. K., Mesele, S. A., Opio, J., **Asamoah, E.**, & Khurshid, C. (2025). Soil Pollution Mapping Across Africa: Potential Tool for Soil Health Monitoring. *Pollutants*, 5(4), 38. <https://doi.org/10.3390/pollutants5040038>

Mesele, S. A., Mechri, M., Okon, M. A., Isimikalu, T. O., Wassif, O. M., **Asamoah, E.**, Ahmed, H. A., Moepi, P. I., Gabasawa, A. I., Bello, S. K., Ayamba, A. E., Owonubi, A., Olayiwola, V. A., Soremi, P. A. S., & Khurshid, C. (2025). Current problems leading to soil degradation in africa: Raising awareness and finding potential solutions. *European Journal of Soil Science*, 76(1), e70069. <https://doi.org/10.1111/ejss.70069>

**Asamoah, E.**, Heuvelink, G. B., Chairi, I., Bindraban, P. S., & Logah, V. (2024). Random forest machine learning for maize yield and agronomic efficiency prediction in Ghana. *Heliyon*, 10(17). <https://doi.org/10.1016/j.heliyon.2024.e37065>

Amissah, E., Adjei-Gyapong, T., Antwi-Agyei, P., **Asamoah, E.**, Abaidoo, R. C., Jeppesen, E., Andersen, M. N., & Baidoo, E. (2023). Implications of changes in land use on soil and biomass carbon sequestration: a case study from the Owabi reservoir catchment in Ghana. *Carbon Management*, 14(1), 1-10. <https://doi.org/10.1080/17583004.2023.2166871>

### Conference contributions

**Asamoah, E.**, Heuvelink, G., Chairi, I., Bindraban, P., and Logah, V.: Modelling Maize Yield and Agronomic Efficiency Using Machine Learning Models: A Comparative Analysis, EGU General Assembly 2025, Vienna, Austria, 27 Apr–2 May 2025, EGU25-9987, <https://doi.org/10.5194/egusphere-egu25-9987>, 2025.

### Other contributions

CABI, ISRIC World Soil Information and **Asamoah E.** A Roadmap towards a sustainable Soil Information System in Ghana [version 1; not peer reviewed]. *Gates Open Res* 2024, 8:142 (document) (<https://doi.org/10.21955/gatesopenres.1117178.1>)

## PE&RC Training and Education Statement

With the training and education activities listed below the PhD candidate has complied with the requirements set by the Graduate School for Production Ecology and Resource Conservation (PE&RC) which comprises of a minimum total of 30 ECTS (= 22 weeks of activities)



### Review/project proposal

- Machine learning for fertilizer recommendation in Ghana (6 ECTS)

### In-depth / Topical / On-site Postgraduate Courses

- Hands-on Digital Soil Mapping    ISRIC – World Soil Information, 2021 (1.1 ECTS)
- Geostatistics, PE&RC, 2021 (1.5 ECTS)
- Companion Modelling, PE&RC, 2024 (1.5 ECTS)

### Methodological / Statistical Postgraduate Courses

- Structural Equation Modelling, PE&RC, 2020 (1.5 ECTS)
- Statistical Uncertainty Analysis of Dynamic models, PE&RC, 2022 (1.5 ECTS)

### Deficiency, refresh, brush-up courses

- Systems Analysis and Modelling, WUR, 2021 (6 ECTS)
- Inventory Techniques for Geoscience, WUR, 2021 (6 ECTS)
- Machine Learning, WUR, 2022 (6 ECTS)

### Laboratory training and working visits

- Deriving soil property maps as covariates for fertilizer recommendation modelling, ISRIC, 2021/2022 (3 ECTS)
- Deriving fertilizer recommendation with machine learning    Mohammed VI Polytechnic University, 2022 (6 ECTS)

### Invited review of journal manuscripts

- Bragantia, SOYBEAN CULTIVATION IN PLINTHOSOLS: yield, climate and economic interactions, 2025 (1 ECTS)

**Competence, skills and career-oriented activities**

- Competence assessment, WUR, 2021 (0.3 ECTS)
- Project and time management, WUR, 2021 (1.5 ECTS)
- The essentials of scientific writing and presenting, WUR, 2021 (1.2 ECTS)

**Scientific Integrity/Ethics in science activities**

- Scientific Integrity, WGS, 2021 (0.6 ECTS)

**PE&RC Retreat, PE&RC Day, and other PE&RC events**

- PE&RC Day, 2021 (0.3 ECTS)
- PE&RC Weekend, 2021 (0.9 ECTS)
- PE&RC Last Years Weekend, 2024 (0.6 ECTS)

**National/local scientific meetings, seminars, and discussion groups**

- 1st African Conference on Precision Agriculture, 2020 (0.3 ECTS)
- GRS time series and sentinel group, 2021 (0.3 ECTS)
- Modelling and Simulation discussion group, 2021 – 2025 (3 ECTS)
- American Society of Agronomy: Sustainable Agronomy Conference – Utilizing Artificial Intelligence and Unmanned Aerial Vehicles for Sustainable Crop Management, 2023 (0.3 ECTS)
- American Society of Agronomy: 2023 Sustainable Agronomy Conference – Preserving Pest Management Options through Integrated Pest Management, 2023 (0.3 ECTS)
- American Society of Agronomy: Sustainable Agronomy Conference – Building Sustainable Management Systems through the 4R Principle, 2023 (0.3 ECTS)
- American Society of Agronomy: Sustainable Agronomy Conference – Decoding the Basics of Carbon and Ecosystems Services Markets for Short and Long term Success, 2023 (0.3 ECTS)
- Ghana Soil Information System Roadmap Development Workshop, 2024 (0.6 ECTS)
- "Future Proofing: Unified Action for Soil Health and Food Security" IFDC symposium, 2024 (0.3 ECTS)
- 'Soil fertility management through a transdisciplinary lens' discussion group, 2024-2025 (3 ECTS)

- Strengthening collaboration on Soil Carbon: Roles and opportunities for the African Chapter of the International Research Consortium, 2025 (0.3 ECTS)

**International symposia, workshops and conferences**

- Fertilizer Research and Responsible Implementation Project Coordination Conference  
Tamale, Ghana, 2022 (1.6 ECTS)
- Fertilizer Research and Responsible Implementation Project PhD Symposium, Wageningen,  
Netherlands, 2024 (1.3 ECTS)
- European Geosciences Union General Assembly, Vienna, Austria, 2025 (2.5 ECTS)

**Committee work**

- ISRIC – World Soil Information: Soil Information Community of Practice Ambassador, 2024 (1 ECTS)

**BSc/MSc thesis supervision**

- Research topic 1: Mapping root zone plant-available water holding capacity in soils of Ghana (3 ECTS)

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