[Strengthening Soil Health Systems in West Africa: Development of Appropriate Fertilizer Nutrient Requirements for Specific Crop and Soil Combinations within Prioritized Target Areas]

Report on IPI 1.4

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The authors would like to thank…

About AICCRA Reports

Titles in this series aim to disseminate interim research on the scaling of climate services and climate-smart agriculture in Africa, in order to stimulate feedback from the scientific community.

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Abbreviations

AICCRA	Accelerating Impacts of CGIAR Climate Research in Africa
AU	African Union
AUC	African Union Commission
AUDA	African Union Development Agency
BAU	business as usual
CA	conservation agriculture
CAADP	Comprehensive Africa Agriculture Development Programme
CBA	cost-benefit analysis
CCAFS	Climate Change Agriculture and Food Security
CGIAR	Consultative Group of International Agricultural Research Centres
CIS	climate information services
CSA	climate-smart agriculture
CSAIP	climate-smart agriculture investment plan
CSEP	Climate-Smart Agriculture Education and Policy Project
CSV	climate-smart village
FANRPAN	Food, Agriculture and Natural Resources Policy Analysis Network
FAO	Food and Agriculture Organization of the United Nations
FNS	food and nutrition security
GCCASP	Gender Climate Change and Agriculture Support Programme
ICT	information and communications technology
iNGO	international non-governmental organisation
IRR	internal rate of return
MoAMID	Ministries of Agriculture, Mechanisation and Irrigation Development

MSP	multi-stakeholder platform
NDE	National Designated Entity
NEPAD	New Partnership for Africa's Development
NGO	non-governmental organisation
NPV	net present value
PICZ	Professional Insurance Company of Zambia
REC	Regional Economic Community

SUMMARY

Crop productivity remains perennially lower in West Africa, and this significantly attributed to stale blanket fertilizer recommendations. This is also exacerbated by limited national extension services and widespread soil degradation. In response IITA and other technical partners, with funding from the World Bank are generating validated crop- and soil-specific nutrient combinations in support of the development of locally relevant Integrated Soil fertility Management (ISFM) recommendations through IPI 1.4. This builds on the digital soil mapping information generated through IPI 1.3. Implementation of IPI 1.4 is undertaken in close collaboration with national agricultural research partners. This is being undertaken with focus on Nigeria, Ghana, Togo, Liberia, Sierra Leone, Mali and Senegal in geographies where strategic scaling projects such as FSRP and Soil values are working in. The focus crops were rice, maize and cassava, based on country prioritisation exercises. The machine learning component of the AgWise fertilizer decision support framework was trained using legacy agronomic data from public repositories. The model performance was deemed to be acceptable at R^2 of >0.5 and highly reliable at >0.75. This generated nutrient predictions which have however not undergone field validation (V0). These were validated using crowd sourced peer reviewed literature data. Field data were then used to test against the validated V0 models with a focus on maize Nigeria as these are the only Nutrient Omission Trial (NOT) results available

01. BACKGROUND

The population of West Africa is at least 400 million people with at least 60% of them being youth, with most of the people being in Nigeria, Ghana and Cote d'Ivoire. At least 70% of the population lives with poverty and at less than 1 dollar per day. The economy is predominated by agriculture, fishing and oil. Agriculture is important as it provides food security and other economic benefits to the countries and region (UNECA, 2023). Agricultural productivity is still relatively low relative to the potential (Table 1). Improvement in the agricultural performance provides an opportunity for enhancing livelihood and reduced poverty in West Africa (Hollinger and Staatz, 2015).

Rice, maize and cassava are the key cultivated crops in West Africa. The average rice yields in west Africa are 2 and 4 t/ha for lowland and irrigated respectively, whereas the maximum attainable yields are 6.5 and 8.3 t/ha for lowland and irrigated, with farmers only achieving less than 40% of the target yield. For maize, the current average yields are 2 t/ha compared to attainable yields of 6.5 t/ha, which is achieving less than 40% of the attainable yield. Cassava the mostly widely produced crop yields between 10-15 t/ha in smallholder farming systems against the water limited yield potential of 40t/ha. These vary within countries based on the predominant agro ecologies (Table 1) (MOFA, 2020; Nwokoro et al., 2022).

***Table 1**: Current and potential rice production and the yield gap in West Africa countries.*

Crop	**Actual yield (t ha^{-1})**	**Potential water limited yield (t ha^{-1})**	**% of Potential achieved**
Rice (non-irrigated)	2.5	7.5	33
Rice (Irrigated)	3.5	8.5	41
Maize (non-irrigated)	2.2	6.5	34
Maize (Irrigated)	2.8	7.2	39
Cassava (non-irrigated)	12	34	35
Cassava (Irrigated)	14	38	37

As a result of relatively low crop yields, West Africa imports at least 60% of its staple food, which is rice, as the current regional production only meets 40% of the total demand. Though the yield gap is still high for maize and cassava, the current production meets most of the demand. At least 90% of the maize is locally produced, with the region having a surplus in some seasons. Additionally, at least 98% of the cassava is also produced locally, with little to no imports (OECD/SWAC, 2025).

The low yields are attributed mostly to water, fertilizer and management practices which also include extension and advisory services. With fertilizer and extension/advisory services contributing to at least 50% of the yield gap (Ongoma et al., 2025). The region has very low fertilizer use amounting to an average of less than 20 kg/ha. Specifically, Sierra Leone has about 3 kg/ha of fertilizer use. Ghana and Nigeria have the highest fertilizer in the region at about 25kg/ha, and the rest are less (Vanlauwe et al., 2023). This is also against the recommended of more than 200kg/ha for maize and rice across West Africa. Application of additional of fertilizer to cereal crops particularly maize and rice can potentially increase yields, closing the gap by at least 30% (Srivastava et al., 2023).

The additional yield gap is closed by improved management and extension support. Improvement in Artificial Intelligence (AI) and associated services has increased use and application of digital agriculture extension services, which potentially increases chances of farmers accessing information, thereby further improving their yields (Senthilkumar, 2022).

Digital agro-advisories platforms (DAGP) have reached more than 10 million farmers. Some of the DAGPs such as DG and VIAMO do not produce recommendations, as opposed to AKILIMO which utilises internal engines to generates agronomic recommendations. DG and VIAMO, disseminate, agronomic advisories such as fertilizer recommendations (**https://akilimo.org/**; Digitial green, 2025). The CGIAR has developed the AgWise decision support framework which uses crop and Artificial Intelligence (AI) powered modelling frameworks trained on crop fertilizer response data, to generate site specific fertilizer recommendations (Jizorkuwie et al., 2025). AgWise has been utilised for 5 crops and 8 countries, with at least 40% yield increases in potato and wheat in Ethiopia and Rwanda. AgWise recommendations could potentially be disseminated through established decision support platforms such as AKILIMO, WhatsApp, Interactive Voice responses (IVR) and SMS, so that an access to these platforms is possible even in areas or situation where there is internet limitation. AgWise generates these recommendations using soil and agronomic data and AI modelling frameworks. Specifically, these could be QUEFTS, ML and integrated modelling frameworks (Chernet et al., 2023).

Current blanked based fertilizer recommendations have been in use for more than three decades, with some spanning as far back as 50 years (Maccarthy e al., 2028). On the contrary corresponding variability agro-ecological conditions such as climate, soil and other agro-ecological conditions, have been gradually evolving. As a result, current fertilizer recommendations are now incompatible, leading to inefficient fertilizer use amongst farmers. In addition, there are challenges related to limited extension, attributed to limited knowledge and lack of mobility by farmers. A substantive ecological, climatic, and socio-economic variability exists within the West African landscape. This heterogeneity further underscores the is need for generation of region or site-specific recommendations. Fertilizer companies do not supply and distribute fertilizers to some of the west African countries due to some administrative, financial and technical barriers. The same information can also be utilised to generate fertilizer formulations, which are potentially important for use by fertilizer companies to develop locally specific fertilizer formulations by farmers.

The initiative therefore sought to development site specific nutrient recommendations which are inputs into the generation of fertilizer appropriate formulations to enhance fertilizer use efficiency and soil nutrient balances. The specific objective was to generate fertilizer appropriate formulations for key West African countries.

02. COUNTRY ENGAGEMENT

The Hub operates as a demand-driven mechanism, responding to national and regional needs articulated through ministries, research institutes, and private sector actors. It functions as a technical assistance platform that supports the implementation of countries soil health and fertilizer action plans. In each country, the Hub operates through three coordination mechanisms. A National Focal Point, designated and empowered by the relevant Ministry, serves as the primary point of contact. A National Technical Team, composed of technical experts from relevant organizations and empowered by the Ministry, is responsible for the in-country implementation of the agreed workplans. Another important layer of coordination is the Hub Focal Point, whose role is to ensure continuous liaison between the Regional Hub and the National Technical Teams.

Though the Regional hub focuses on the entire West Africa and Sahel, the activities of this project commenced with the 5 Wave 1 countries: Nigeria, Ghana, Togo, Liberia, and Sierra Leone. These were the countries with the highest potential of success based on the data availability and country readiness. Within these countries regions were selected based on the presence of scaling programs and other existing CGIAR projects. This enabled achievement of impact relatively faster (Table 2).

***Table 2**: Countries, priority regions, and scaling programs~~.~~*

Country	**Target regions**	**Crops**	**Previous or current scaling initiatives**	**Target area per crop (‘000 ha)**
Togo	Central, Kara, Savane	Maize, Rice	Food system resilience program (FSRP)	891
Liberia	Margibi, Bong, Lofa	Rice	STAR-P, EU-Soils4Liberia project	19.6
Sierra Leone	Bo, Kenema, Moyamba	Maize, Rice	FSRP	28.5
Nigeria	Kaduna, Kano, Bauchi, Jigawa	Maize, Rice	Soil Values project; ACReSAL project	2,600
Ghana	Upper West, Upper East, North-East, Northern, Bono, Ashanti, and Bono East	Maize, Rice	FSRP	2,500
Mali	Moyen Banni, Niger Supérieur, and Haut Banni	Rice	Soil Values project	1,300
Senegal	Thies, Diourbel, Kaolack	Rice	FSRP	454

In Ghana, the project covered the key production regions for maize and rice in the Upper West, Upper East, Northeast, Northern, Bono, Ashanti, and Bono East Regions. The selected sites capture the region’s biophysical diversity, ranging from humid lowlands to sub-humid and dry savannah environments, and were chosen to reflect dominant cropping systems, soil fertility gradients, and climate variability. The annual rainfall in these selected areas ranges from 900 to 1,400 mm in the north to over 1,600 mm in the humid south, with Ferric and Plinthic Acrisols, Lixisols, and Nitisols dominating the soil landscape.

In Nigeria, the analysis focused on major maize- and rice-producing states in the Sudan and Northern Guinea Savannas, specifically the two watersheds (covered by the Soil Values Programme) comprising the states of Jigawa, Bauchi, and Kano. These areas represent high-production zones characterized by mean annual rainfall ranging from 700 – 1,100 mm, sandy to loamy soils with inherently low organic carbon, and a distinct unimodal rainfall pattern supporting one main cropping season (May–October).

In Togo, the focus was on maize- and rice-based systems across the Savanes, Kara, and Centrale Regions, spanning the northern dry savannah to sub-humid transition zones. These areas experience an annual rainfall between 1,000 and 1,200 mm, with sandy-loam soils derived from granite and gneiss parent materials that are typically low in nitrogen and phosphorus.

In Liberia, maize and rice sites were in the Bong, Lofa, and Margibi Counties, representing humid tropical environments with rainfall exceeding 1,800 mm per year. Soils are highly weathered Ferralsols and Acrisols with low base saturation and moderate-to-severe nutrient leaching, necessitating balanced N–P–K management to sustain productivity.

In Sierra Leone, the project districts (Bo, Moyamba, and Kenema Districts) targeted maize and rice production areas, which also typify the country's humid forest and derived savannah agroecological zones. The annual rainfall ranges from 2,000 to 2,500 mm, with deep, weathered soils (mainly Acrisols and Ferralsols) characterized by low inherent fertility and high leaching potential.

In Senegal, activities focus on Thiès, Diourbel, and Kaolack, key agricultural regions in west-central Senegal. Thiès is a coastal peri-urban zone with mixed farming, horticulture, and rainfed cereals, receiving 400–600 mm of irregular rainfall and benefiting from its proximity to Dakar. Diourbel is important for groundnuts, millet, and livestock but faces hot conditions, low rainfall (350–500 mm), frequent dry spells, and declining soil fertility. Kaolack is a major commercial hub for rice, groundnuts, and cereals, with 500–800 mm of rain concentrated in a short season and often experiencing high temperatures and late rains. These regions contain key lowland and upland rice environments where yield gaps persist due to soil degradation, limited nutrient inputs, and climate variability.

In Mali, work builds on the Soil Values project across the Moyen Bani, Niger Supérieur, and Haut Bani watersheds in the Sudano–Sahelian zone. Moyen Bani features floodplains and lowland rice areas with 600–900 mm of seasonal rainfall and periodic flooding. Niger Supérieur experiences high temperatures (often >38°C) and 500–900 mm of rainfall, with irrigated systems buffered from climate shocks compared to vulnerable uplands. Haut Bani receives 600–800 mm of rain with erratic distribution, dry spells, and increasing land degradation. Across these watersheds, short rainy seasons, unpredictable onset of rains, and rising temperatures intensify moisture stress and soil fertility constraints, sustaining large yield gaps and highlighting the need for ISFM and climate-resilient practices.

For IPI 1.4, implementation is currently conducted in collaboration with the Department of Agriculture (DoA) of the Ministry of Food and Agriculture (MoFA) in Ghana; the Institut Togolais de Recherche Agronomique (ITRA) in Togo; the Sierra Leone Agricultural Research Institute (SLARI) in Sierra Leone; the Central Agricultural Research Institute (CARI) in Liberia; and the Center for Dryland Agriculture at Bayero University Kano (CDA-BUK) in Nigeria.

03. METHODOLOGY

3.1. Development of appropriate fertilizer nutrient combinations

Generation of the V0 fertilizer nutrient combinations

Data collation and curation

To develop the V0 nutrient recommendations, this project legacy agronomic data (crop yields, fertilizer rates, including agronomic management, soil properties and weather) were compiled from on-station, on-farm trial and survey data through CAROB (**https://carob-data.org/**) (Table 3). CAROB comprises a large pool of standardised datasets from public repositories from various past agricultural research projects. The data for every specific country-crop combination was therefore retrieved from this pool (Table 3), for the development of recommendation models. This data was further enriched with geospatial layers (soil maps, AEZs, rainfall, temperature) and curated. This ensures that all variables needed for model training (N, P, K, inputs, soil parameters, and climate) are complete. The machine learning models within AgWise were therefore trained on this legacy data.

Exploratory data analysis

Before training the nutrient recommendation models, exploratory data analysis was conducted on the curated data to ensure the quality of data, detect eventual outliers and understand distributions, correlations, and nutrient response patterns. This analysis comprises essentially the generation of visual summaries such as scatterplots, histograms, nutrient response curves among others. It also consisted in identifying the variables having the strongest predictive influence on yield and nutrient demand.

Model training and testing using legacy data

The modelling of the data in this project has been performed using the AgWise Decision Support Tool (DST) framework, specifically the AgWise fertilizer recommendation modules. AgWise is an advanced, data driven agronomic recommendation engine that leverages machine learning, advanced modeling techniques, and field data to provide farmers with tailored insights. It provides site- and crop- specific fertilizer recommendations to optimize nutrient use efficiency and increase productivity. The AgWise Fertilizer Recommendation Module provides several analytical pathways for generating site-specific nutrient recommendations, adaptable to varying data availability, system complexity, and operational objectives. The module offers four distinct data-driven approaches: i) QUEFTS-based approach, ii) Machine Learning-based approach, iii) Integrated QUEFTS & Machine Learning approach, iv) Integrated QUEFTS + Machine Learning + Crop Modeling approach. The choice of approach depends on available data, system complexity, and the specific goal ranging from basic nutrient recommendations to fully integrated, climate-smart advisories. Only the machine learning-based approach has been used for developing the V0 nutrient recommendation models in this project. This approach employs machine learning algorithms to predict yield responses based on nutrient inputs and biophysical variables such as soil data. Before training, the appropriate model was selected. Gradient boosting machine was used in this approach with a grid search for optimising both the number of trees and the maximum depth. The V0 model was then trained using only the curated legacy datasets with the best hyperparameters (number of trees and maximum depth). Afterwards, the model performance was assessed using the coefficient of determination (R^2), a standard metric for assessing goodness of fit in predictive modelling (James et al., 2021). R^2 was computed as:

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

where y_i are the measured yield values, $\hat{y}_i$ are predicted yield values, and $\bar{y}$ denotes the average yield. R^2 represents the proportion of variance in the observed data explained by the model, with higher and positive values indicating stronger explanatory and predictive performance.

This compared measured and predicted yield, after a data set was split into 70:30 for training and testing, respectively. A coefficient value of < and > 0.5 and indicates a weak and moderate relationship between yields of the training and testing data, whereas >0.75 reflects a strong relationship.

However, the fourth approach (Integrated QUEFTS, ML and Crop modelling) is currently being experimented to further improve nutrient recommendations. This is an advanced approach that integrates QUEFTS, machine learning, and dynamic crop models (e.g., DSSAT) to produce climate-smart, site-specific fertilizer recommendations. It accounts for water-limited yield, seasonal variability, and cultivar effects, offering the most comprehensive and adaptive solution.

This project used the machine learning approach, as it offers key advantages over traditional models like QUEFTS and process-based crop simulations. ML models learn directly from data, capturing complex and nonlinear interactions among soil, weather, crop, and management factors without requiring site-specific calibration. They integrate diverse datasets, including remote sensing and socio-economic variables, enabling flexible, scalable, and highly accurate predictions across regions and crops. ML frameworks are computationally efficient, quickly updated with new data, and support continuous learning, making them ideal for adaptive, real-time agronomic decision support. Overall, ML provides a fast, scalable, and data-driven alternative to conventional modeling approaches.

In all the above approach, soil property data and associated covariates can be derived from the raster database incorporated into the analysis. The soil property rasters, provided at a spatial resolution, represent continuous predictions of key soil attributes across the African continent and were used as spatial predictors in the modelling framework. All raster layers can be reprojected to the WGS 84 coordinate reference system (EPSG:4326).

Model prediction

The trained V0 models were subsequently used to generate nutrient response surfaces and fertilizer requirement estimates based on the highest agronomic efficiency target. These models were also used to produce site-specific fertilizer nutrient combinations (N–P–K), based on soil, climate, and yield targets.

Validation of the model nutrient recommendations

To validate the developed recommendations, fertiliser-response data were collected from open-access peer-reviewed publications from 2000 to 2025. The data were extracted using an automated LLM-driven workflow. This workflow systematically extracts nutrient application rates and their corresponding yield responses from peer-reviewed publications retrieved from multiple scientific databases (Elsevier ScienceDirect, Scopus, OpenAlex, Crossref, Pubmed, Wiley, Semantic Scholar, PubMed, Wiley, arXiv and Springer API). It comprises four main steps: Query generation, Paper retrieval, Data extraction, and Quality control. The first two and final steps were implemented using Python scripts, while data extraction was performed using an open-source large language model (LLM)-based extraction platform.

Query generation: each scientific database uses a distinct Application Programming Interface (API) format. To ensure compatibility and efficiency, a small LLM (GPT-5 Mini) was used to automatically generate appropriate search queries based on user input. Users begin by providing a question in natural language, such as: "What is the fertilizer yield response for maize in Togo?" The model then reformulates the question to match the syntax requirements of each database and expands the search space using synonyms and related terms. For instance, it may replace fertilizer with equivalent expressions such as NPK, urea, or fertiliser. This produces a set of 3-7 alternative queries per database (e.g., [fertiliser OR fertilizer] AND maize AND Togo, [NPK OR urea] AND maize AND Togo). This multi-query approach helps overcome the limitation of most APIs, which rely primarily on exact keyword matches rather than semantic understanding. The generated queries are then passed to the paper retrieval module.

Paper retrieval: the paper retrieval module uses the generated queries to search across the selected databases via their APIs. Typically, 1,000-7,000 papers are initially retrieved per query, many of which may not be relevant. Therefore, several filtering steps are applied to identify studies closely aligned with the user's research question.

Geographic relevance filtering – A semantic model evaluates whether the target location (e.g., "Togo") appears in the paper's abstract or author affiliations. Each paper receives a location likelihood score between 0 and 1.

Semantic similarity scoring – The cosine similarity between the meaning of the user query and the combined title + abstract is calculated (range: 0-1). Higher scores indicate greater relevance.

Relevance classification – Both the query and the paper summary are passed to a smaller LLM to classify the paper as 'Yes', 'No', or 'Maybe' relevant.

Papers with a combined (location + similarity) score below 0.8 and classified as 'No' are excluded. The remaining papers are processed through Unpaywall to retrieve open-access PDF links, which are then downloaded and securely stored in Azure Storage for subsequent data extraction.

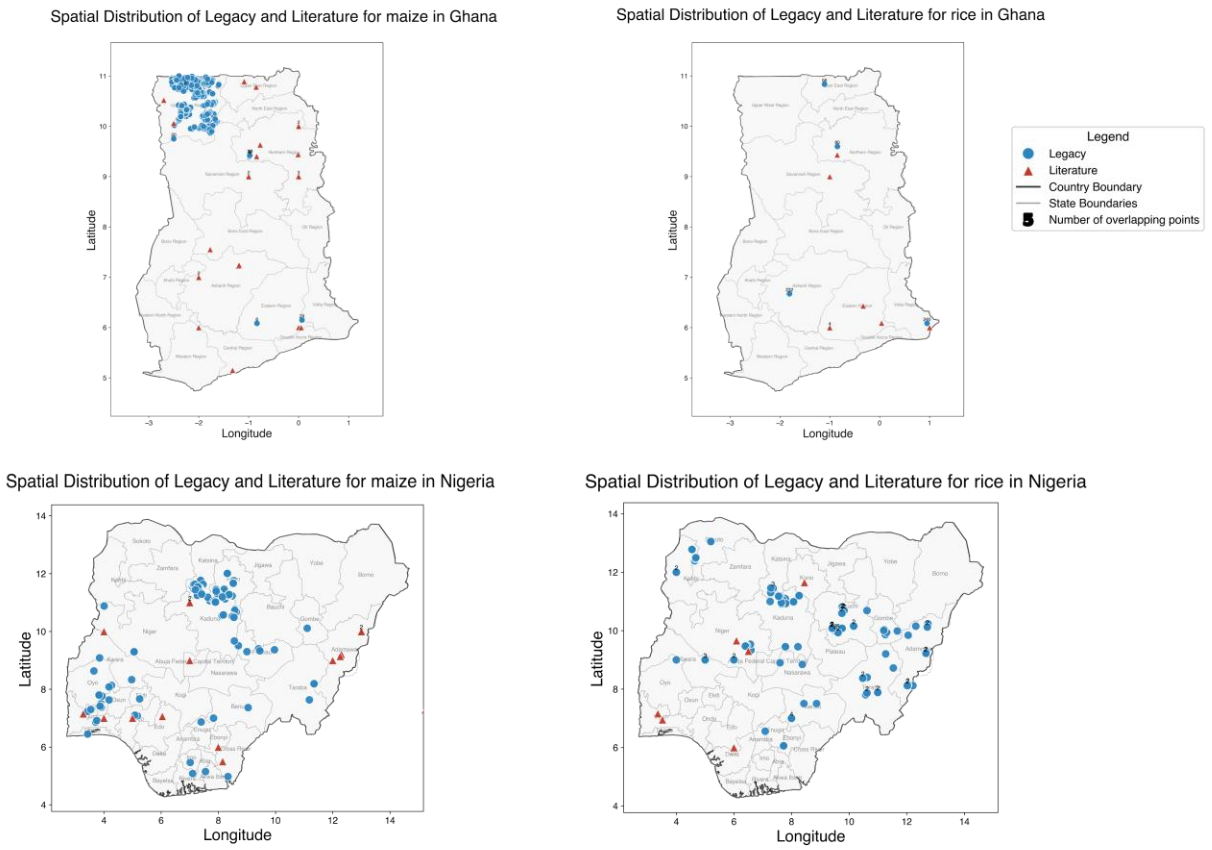
Data extraction: data extraction was performed using the Unstract open-source framework. Within its Prompt Studio environment, prompts were defined targeting macronutrient application rates and their corresponding yield. The extraction used GPT-4.1 as the main LLM and LLM Whisperer tool for converting PDF. This combination enables accurate extraction of both textual and graphical data – including approximate conversion of chart data into tabular form. To validate and improve reliability, Gemini 2.5 Pro served as a challenger model. The extracted outputs from both models were compared, and only data with a ≥95% extraction confidence were retained. The workflow was deployed as pipeline, enabling automated interaction with Azure Storage – fetching papers, extracting data, and saving processed results into designated folders.

Quality control of the extraction: post-extraction data cleaning was conducted to minimise LLM hallucinations and ensure reliability. Each dataset was cross-verified using summaries generated by the GPT-O3 model, which synthesises the figures and tables reported in the paper. Data points with extraction confidence below 95% or inconsistent with the summary were removed. To further assess data quality and consistency, visual analyses were performed using scatterplots and boxplots for various nutrient treatment comparisons. These visual checks provided an additional layer of validation to detect outliers or inconsistencies in the extracted datasets.

The maps (Figure 1) show the geographic coverage of both the legacy and the literature (validation) datasets used in this project (Table 3). Administrative boundaries are displayed to highlight regional variation in data availability. In Ghana, maize legacy data are predominantly concentrated in the northern agro-ecological zones, whereas rice trials show a more dispersed pattern, with notable activity in the Volta and Ashanti regions. In Nigeria, maize legacy data are widely distributed across the central and southern states, while rice legacy data extend from the north-central belt to the south-eastern and coastal regions. It also came out from the maps that there are always some validation data points close to the hub of the legacy data in both Nigeria and Ghana for both rice and maize. Together, these maps illustrate the breadth and heterogeneity of spatial coverage across the two countries and across crops, providing a robust basis for the modelling analyses conducted in this project.

Table 3: *Legacy data from CAROB used for training models*

Country	Crop	# used to train model	# used to train model
Nigeria	Maize	11925	5291
	Rice	4671	2320
Ghana	Maize	1446	1174
	Rice	1574	974
Togo	Maize	1341	862
	Rice	890	831



Spatial Distribution of Legacy and Literature for maize in Ghana

Spatial Distribution of Legacy and Literature for rice in Ghana

Spatial Distribution of Legacy and Literature for maize in Nigeria

Spatial Distribution of Legacy and Literature for rice in Nigeria

Figure 1*. Spatial distribution of trial sites and survey locations in Ghana and Nigeria that provided datasets used for model training within the AgWise acquired from for maize and rice.*

Generation of the V1 fertilizer nutrient combinations

Nutrient omission trials (NOTs)

Nutrient omission trials were established to generate agronomic data for: i-assessing current soil nutrient supply, and ii-training models to produce site specific nutrient management recommendations and nutrient formulations. These trials were implemented across five countries and key priority crops: Nigeria (maize, rice), Ghana (maize, rice, cassava), Togo (maize, rice), Sierra Leone (maize, rice) and Liberia (rice). Trial locations were based on the presence of strategic scaling programs, and the crops were based on prioritization by the countries (Table 4). Because soils in Liberia and Sierra Leone are prone to acidity, lime was incorporated into the trial design for these countries (Table 4a). In contrast, in non-acidic countries (Nigeria, Ghana, and Togo), secondary and micronutrients were added (Table 4b). Each of the trials consisted of 7 treatments, including a control and multiple nutrient omission treatments. For each country combination, 50 trials were conducted, with one trial hosted per farmer Across the 10 country–crop combinations, this resulted in a total of 500 nutrient omission trials (Tables 4-7). Due to the differences in the agro-ecological conditions and seasons and crop life cycle. Some of the trials are still maturing or being harvested. Nigeria maize has already been harvested, and their results have been used to validate the current maize fertilizer recommendations for the country.

Table 4a: *Nutrient omission trial (NOT) design treatment structure for rice and maize within the regional hub for fertilizer and soil health for West Africa and the Sahel for countries where soils are (Sierra Leone and Liberia) prone to acidity.*

Plot	Treatment	N*	P*	K*	S*	Mg*	Ca*	Zn*	B*	Lime*
1	Control	0	0	0	0	0	0	0	0	0
2	Control + Lime	0	0	0	0	0	0	0	0	1500
3	NPK + Lime	120	60	60	0	0	0	0	0	1500
4	NP + Lime	120	60	0	0	0	0	0	0	1500
5	PK + Lime	0	60	60	0	0	0	0	0	1500
6	NK + Lime	120	0	60	0	0	0	0	0	1500
7	NPK + SMN +Lime	120	60	60	13.5	10	10	1	0.5	1500

* Unit is kg ha^{-1} ; NB: Control-No fertilizer applied; N-Nitrogen applied; P-Phosphorus applied; K-Applied; SMNs-Secondary and micronutrients

Table 4b: Nutrient omission trial (NOT) design treatment structure for rice, maize and cassava within the regional hub for fertilizer and soil health for West Africa and the Sahel for countries where soils are (Nigeria, Togo and Ghana) not prone to acidity.

Plot	Treatment	N*	P*	K*	S*	Mg*	Zn*	B*
1	Control	0	0	0	0	0	0	0
2	Control+ SMNs	0	0	0	13.5	10	1	0.5
3	NPK + SMNs	120	60	60	13.5	10	1	0.5
4	NP + SMNs	120	60	0	13.5	10	1	0.5
5	PK + SMNs	0	60	60	13.5	10	1	0.5
6	NK + SMNs	120	0	60	13.5	10	1	0.5
7	NPK	120	60	60	0	0	0	0

* Unit is kg ha^{-1} ; NB: Control-No fertilizer applied; N-Nitrogen applied; P-Phosphorus applied; K-Applied; SMNs-Secondary and micronutrients

Data curation and exploratory data analysis

The fresh data from the nutrient omission trials (NOTs) on maize in Nigeria was retrieved from the database. The data was first curated, and exploratory analysis was performed on it as described in the data curation section of V0 model training. This resulted in a clean dataset where anomalies were checked to ensure reliability of nutrient estimates. This data is then compiled on top of all available legacy datasets on maize from Nigeria (same as the one used for the V0 model training) for the training of V1 models.

Model training

The combined legacy + fresh NOT data was used to train the V1 model to capture improved nutrient responses using machine learning following similar approach as per the training of V0 model except the introduction a weight scheme. To emphasise patterns, present in the fresh NOT dataset, a sample weighting scheme (Shyamala & Rajeshwari, 2020) was applied. In this approach recent observations received a weight of 0.6 and legacy observations a weight of 0.4. This approach increases the influence of recent data points during model fitting while preserving the broader variability captured in the historical dataset. In other terms, by weighing the fresh NOT observations more heavily than the legacy data, the model's sensitivity to contemporary patterns is increased to reflect current agronomic conditions while still leveraging the historical dataset to stabilise estimates and capture longer-term variability.

Model evaluation and prediction

The developed V1 model's prediction performance was tested independently using the newly collected NOT data. This was achieved by computing the R2 value and compare it to the legacy data R2 for the V0 model. The final model is then used to produce refined nutrient combinations incorporating NOT-based indigenous nutrient supply estimates. It also helps to generate updated spatial maps of recommended N, P and K, fertilizer rates. Finally, the improvement from V0 to V1 was quantified, based on the computed R2.

3.2. Complementary activity

Engagement of iSDA to deliver site-specific fertilizer recommendations

iSDA (Innovative Solutions for Digital Agronomy) is a non-profit company, hosting the AI-enabled Virtual Agronomist (VA) decision support tool. VA uses information on appropriate fertilizer nutrient combinations to determine site-specific fertilizer recommendations, based on farmer's production objectives and actual soil health and climate conditions for specific crops. The plans are to deliver data-driven fertilizer and soil management recommendations to 70,000 farmers, leveraging AI analytics and national soil databases. This collaboration between the Hub and iSDA represents a scalable, future-ready digital-extension model, reducing dependence on external physical assistance while broadening farmer reach and ensuring continuity beyond project funding.

04. RESULTS

4.1. Quality control

Figure 2 shows scatter plots comparing treatment yields with corresponding control yields for a range of nutrient management practices, including single-nutrient (N, P, K), dual-nutrient (NP, NK, PK), and full macronutrient (NPK) treatments, with or without secondary and micronutrient additions (SMNs) on the literature extracted data. Each point represents an experimental observation, and the 1:1 dashed line provides a reference for assessing the magnitude of treatment effects relative to the control. Across both countries and crops, most observations lie above the 1:1 line, indicating positive fertiliser responses in comparison to untreated controls. Treatments containing N either alone or in combination (e.g., NPK, NP, NK) tended to show the strongest yield improvements, reflecting the strong yield response to nitrogen in both maize and rice systems. P- and K-only treatments displayed more variable or limited responses, consistent with weaker single-nutrient limitations in many sites. The inclusion of secondary and micronutrients (NPK+SMNs or K+SMNs) produced additional yield improvements at some locations, although the magnitude of response varied across environments. The dispersion of points around the reference line reflects substantial environmental and management heterogeneity, suggesting strong site-specific fertiliser effects. Despite this spatial and treatment-specific variability, this dataset is acceptable for validating the V0 fertiliser recommendation models for maize and rice in these countries (Figure 2).

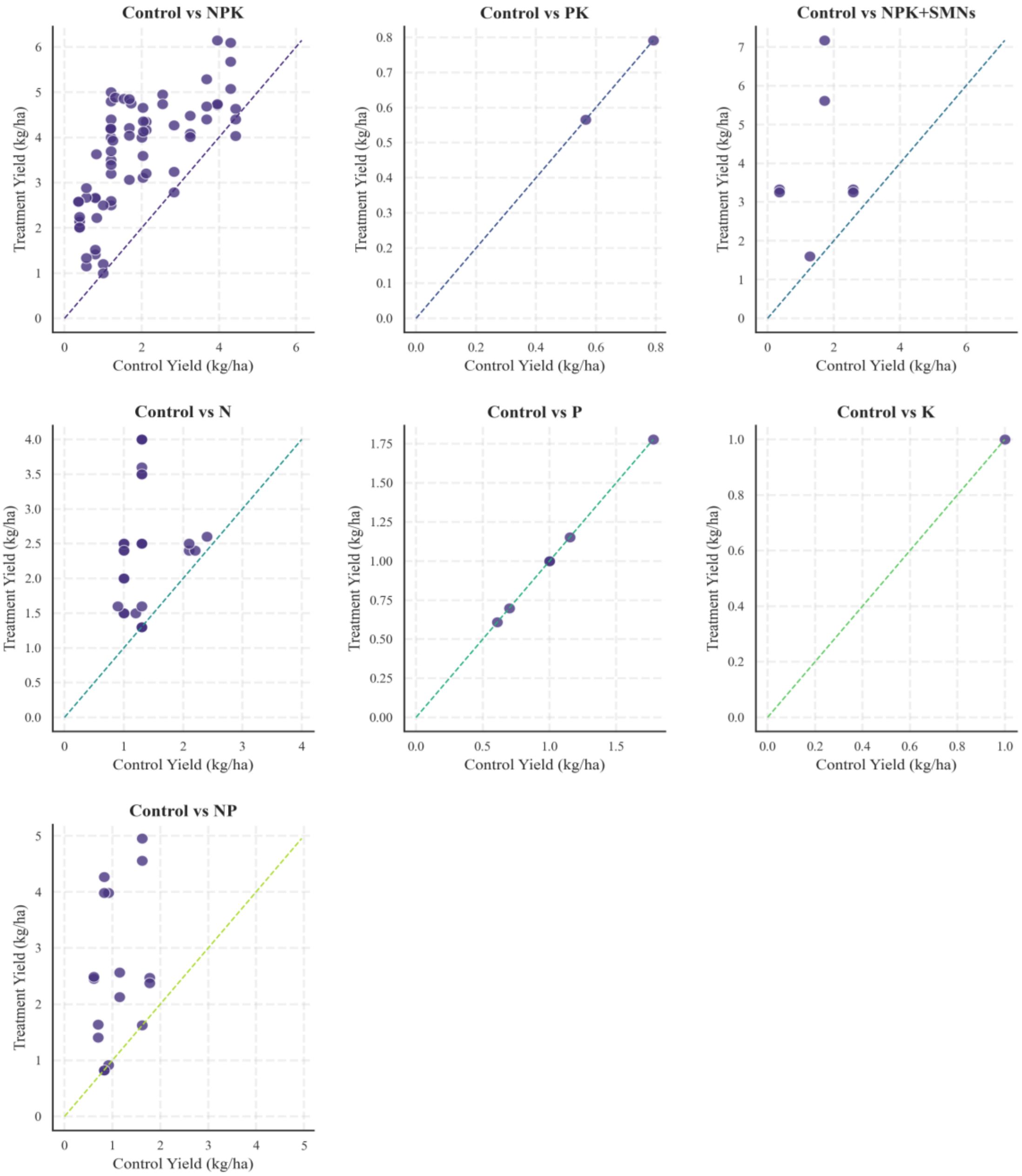


***Figure 2a**. Relationship between treatment yield and control yield across fertilizer treatments for maize in Ghana.*

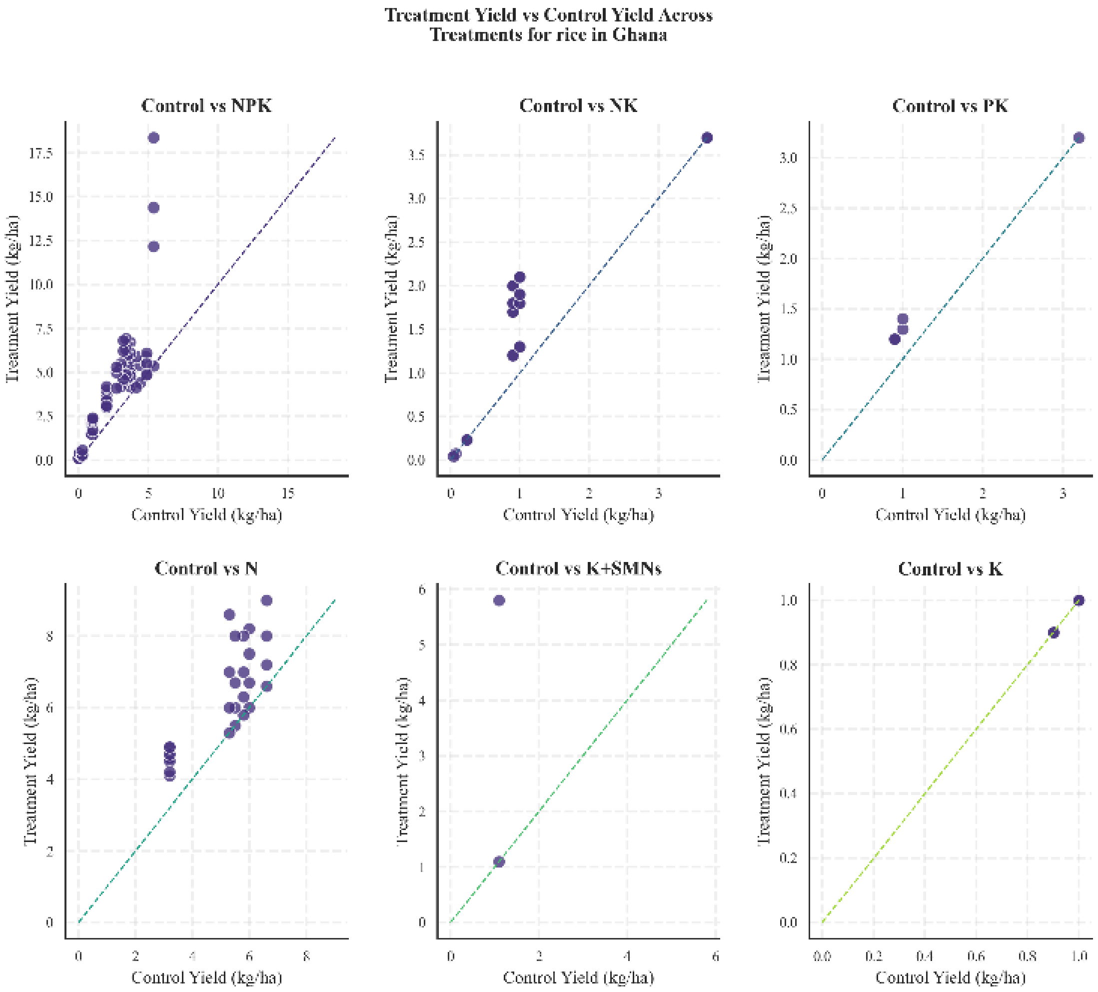


Figure 2b. *Relationship between treatment yield and control yield across fertilizer treatments for rice in Ghana.*

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Figure 2c. *Relationship between treatment yield and control yield across fertilizer treatments for maize in Nigeria.*

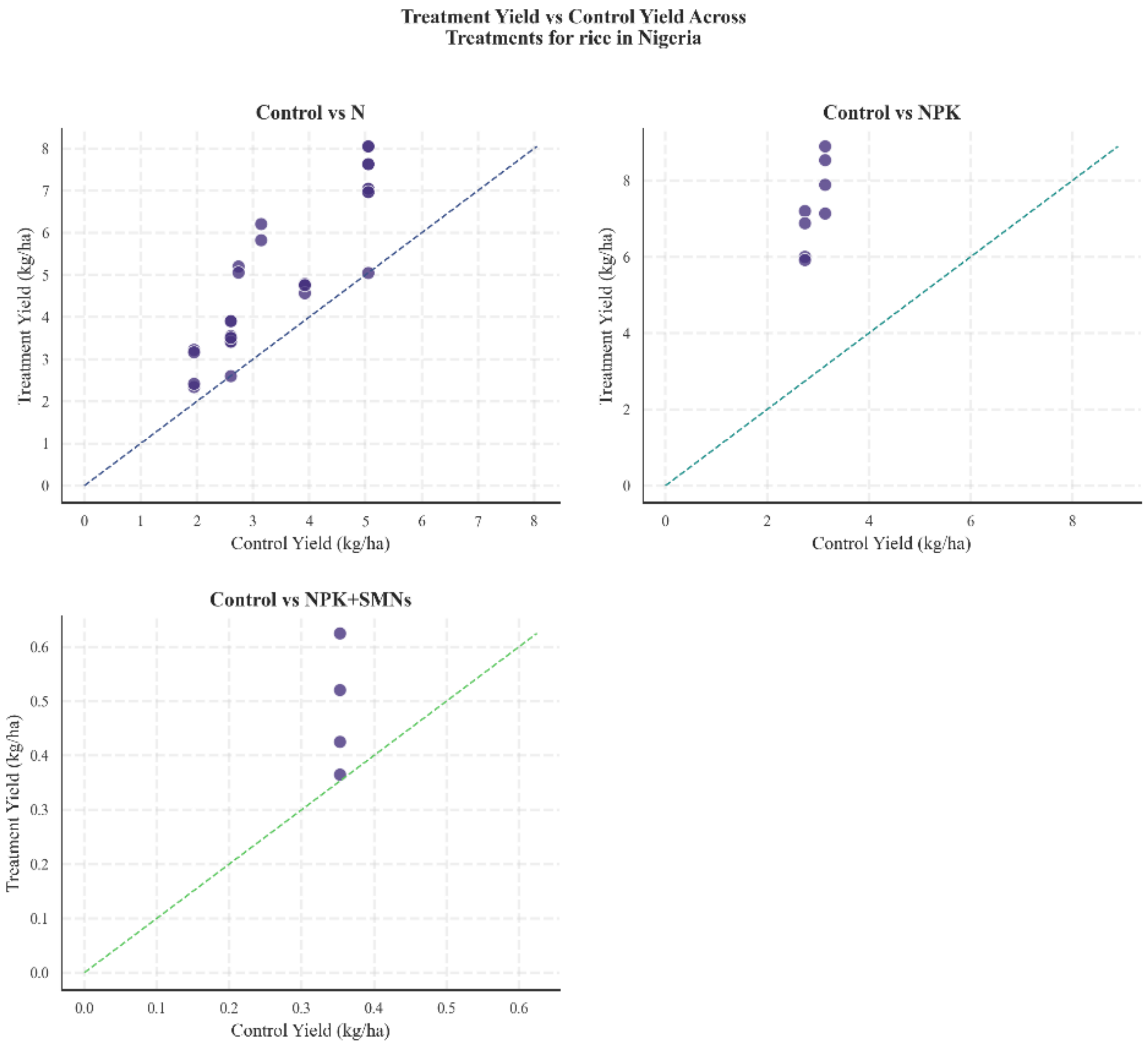

***Figure 2d**. Relationship between treatment yield and control yield across fertilizer treatments for rice in Nigeria.*

4.2. Partial dependency plots

From the analysis of crop fertilizer response yield data, the partial dependence analysis revealed distinct yield responses to individual fertilizer nutrients. Maize yield increased sharply with nitrogen application up to approximately 60 kg N ha⁻¹, after which it plateaued, indicating diminishing marginal returns beyond the optimum range. Phosphorus exhibited a strong positive yield response at lower rates, with yield stabilizing around 20 kg P ha⁻¹, suggesting that additional P inputs above this level provide minimal benefit once soil P sufficiency is reached. In contrast, potassium showed a declining yield trend beyond 40 kg K ha⁻¹, implying potential nutrient imbalance or antagonistic effects under excessive K supply. Additionally, this informs of Nigerian soils having high inherent soil K, hence in most cases there is limited need to apply K fertilizers. Overall, the response curves highlight nitrogen as the most yield-limiting nutrient, while phosphorus and potassium exhibit threshold effects typical of nutrient-sufficient systems (Figure 3a-c).

4.3. Feature selection

The gradient boosting machine (GBM) model provided valuable insights into the relative influence of biophysical and management variables on maize yield in Nigeria. The variable importance plot highlights nitrogen fertilizer (N_fertiliz) as by far the most dominant predictor, underscoring the critical role of nitrogen availability in driving maize productivity across Nigerian agroecological zones. This strong influence reflects the generally nitrogen-deficient soils characteristic of many maize-growing areas, where yield responses to applied N are typically steep. Following nitrogen, key predictors included soil total carbon (isda_c.tot), soil iron (isda_fe), incoming solar radiation (srad_g_len_4), and phosphorus fertilizer rate (P_fertiliz). These variables represent important aspects of soil fertility and energy input to crop growth. Moderate contributions were observed from soil potassium (isda_k), calcium (isda_ca), and cation exchange capacity (cec), indicating that overall soil nutrient balance and cation availability also influence yield formation. In contrast, terrain and texture-related attributes such as topographic position index (TPI), clay content (isda_clay.tot.psa), aspect, and bulk density (isda_db.od) showed relatively low importance, implying that topographic and structural soil properties exert only marginal effects within the modelled yield domain. (Figure 4a)

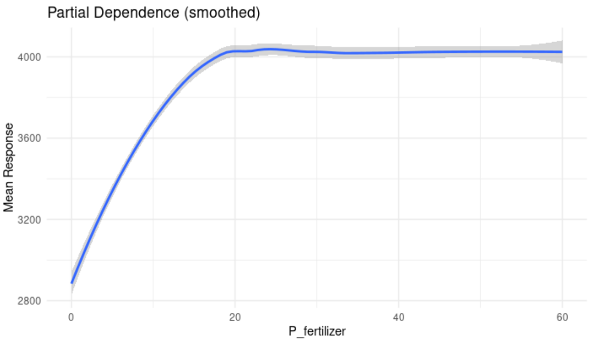

Figure 3: *Partial dependence plots illustrating the response of maize yield to (a) nitrogen (N), (b) phosphorus (P), and (c) potassium (K) fertilizer rates in Nigeria.*

The SHAP summary plot provides deeper interpretability by showing both the magnitude and direction of feature effects on model predictions. Higher nitrogen fertilizer rates (depicted by red to pink points with positive SHAP contributions) were consistently associated with higher predicted yields, while low rates (blue points toward negative SHAP values) led to yield declines, confirming the pronounced responsiveness of maize to nitrogen application. A similar but less pronounced positive pattern was evident for phosphorus fertilizer, reflecting its supplementary role in supporting N uptake and root development. Soil total carbon exhibited a generally positive influence, suggesting that fields with higher organic matter content tend to achieve better nutrient retention and improved yield potential. Soil iron and calcium also showed positive SHAP contributions, emphasizing the broader role of micronutrient sufficiency and soil chemical fertility in sustaining maize productivity. Conversely, higher bulk density and steeper terrain positions contributed negatively, consistent with potential limitations in root penetration, aeration, and water infiltration (Figure 4b).

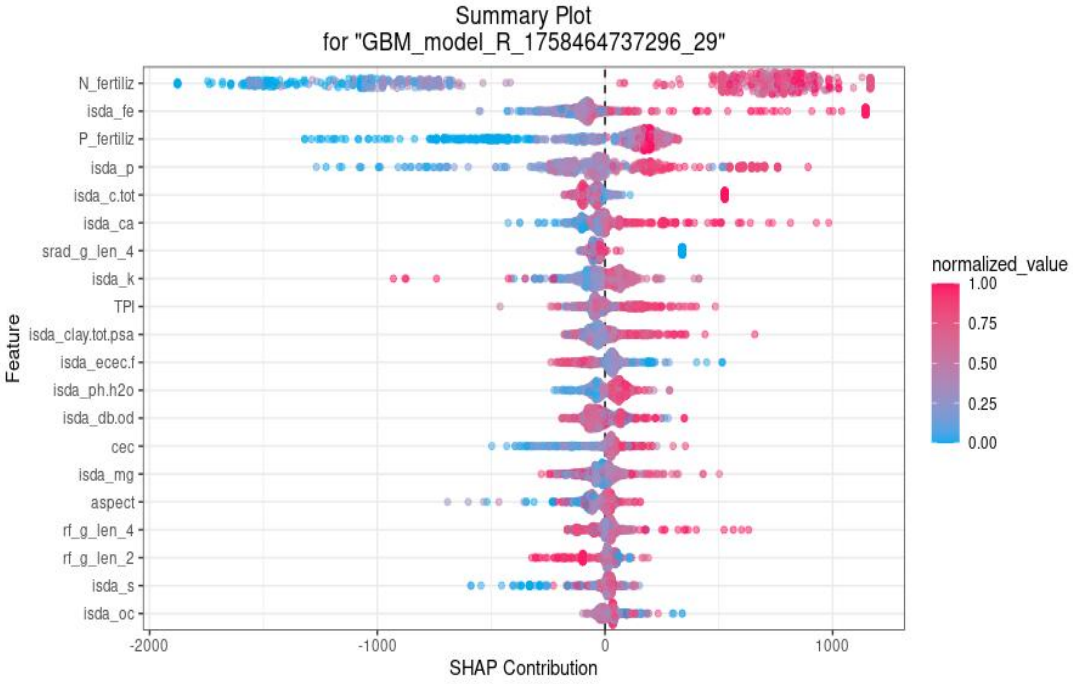

Figure 4: Visualisation of (a) Variable importance and (b) SHAP summary plots showing feature importance and direction of effect in the GBM model predicting maize yield in Nigeria.

4.4. Site specific nutrient recommendations and formulations

Version Zero (V0) Nutrient recommendation models

Maize-Nigeria

The recommendations for maize in Nigeria are detailed in Figures 5 and 6 covering Nitrogen (N) and Phosphorus (P) recommendations. Nitrogen (N): The V0 Nitrogen recommendation map for maize (Figure 5) indicates a required application range of 22 to 130 kg/ha. The spatial distribution of these recommendations is concentrated in the north-central part of Nigeria. The highest application rates, between 108 and 130 kg/ha, are recommended for the northeastern portion of this target area. Surrounding this high-need zone, a band of medium application rates (65-87 kg/ha) is observed, which then transitions to lower rates of 22-44 kg/ha in the peripheral areas.

Phosphorus (P): The V0 Phosphorus recommendation map for maize (Figure 6) shows a recommended application range of 0 to 40 kg/ha. The geographic distribution of these recommendation mirrors that of Nitrogen. The highest phosphorus needs, from 32 to 40 kg/ha, are also found in the northeastern part of the target area. This is followed by a zone of medium recommendations (16-24 kg/ha) and lower recommendations (0-8 kg/ha) in the surrounding regions.

These patterns highlight the need for spatially differentiated fertilizer management rather than blanket national recommendations. The model's predictions suggest that nitrogen remains the primary limiting nutrient for maize across most production areas, while phosphorus supplementation is essential for sustaining optimal nutrient uptake and yield potential in low-P soils. Integrating these spatially optimized N and P recommendations into extension systems can improve resource-use efficiency, reduce fertilizer wastage, and enhance profitability for smallholder farmers.

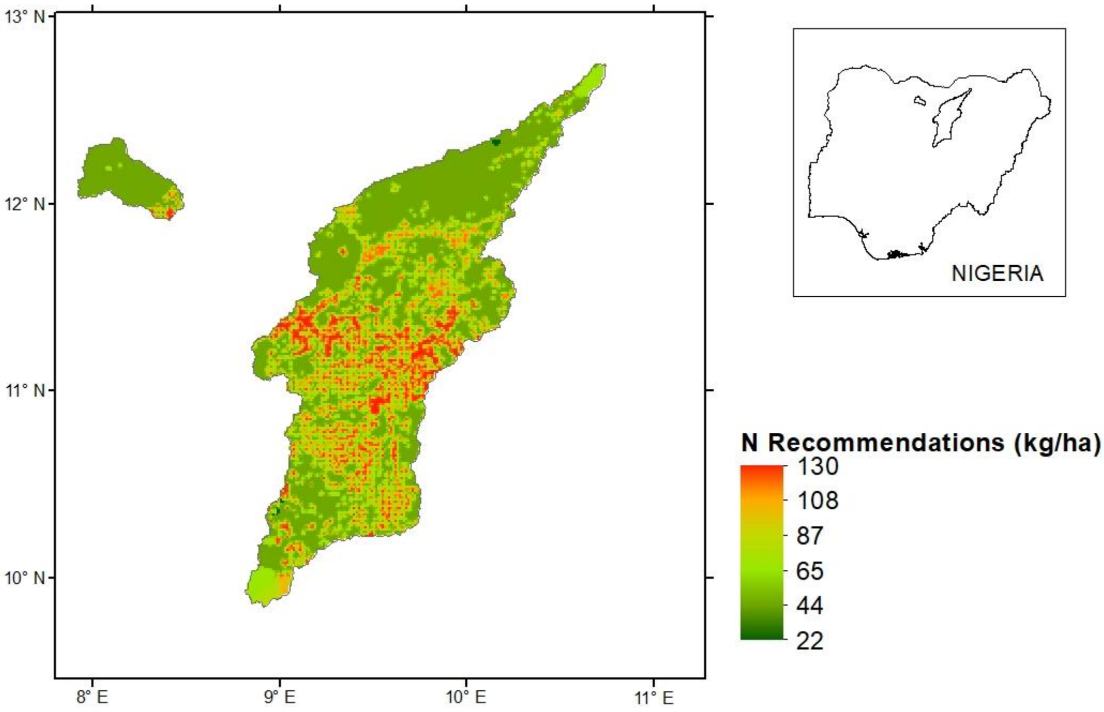

Figure 5: *V0 Nitrogen Recommendation Map for Maize of the Target Area, Nigeria.*

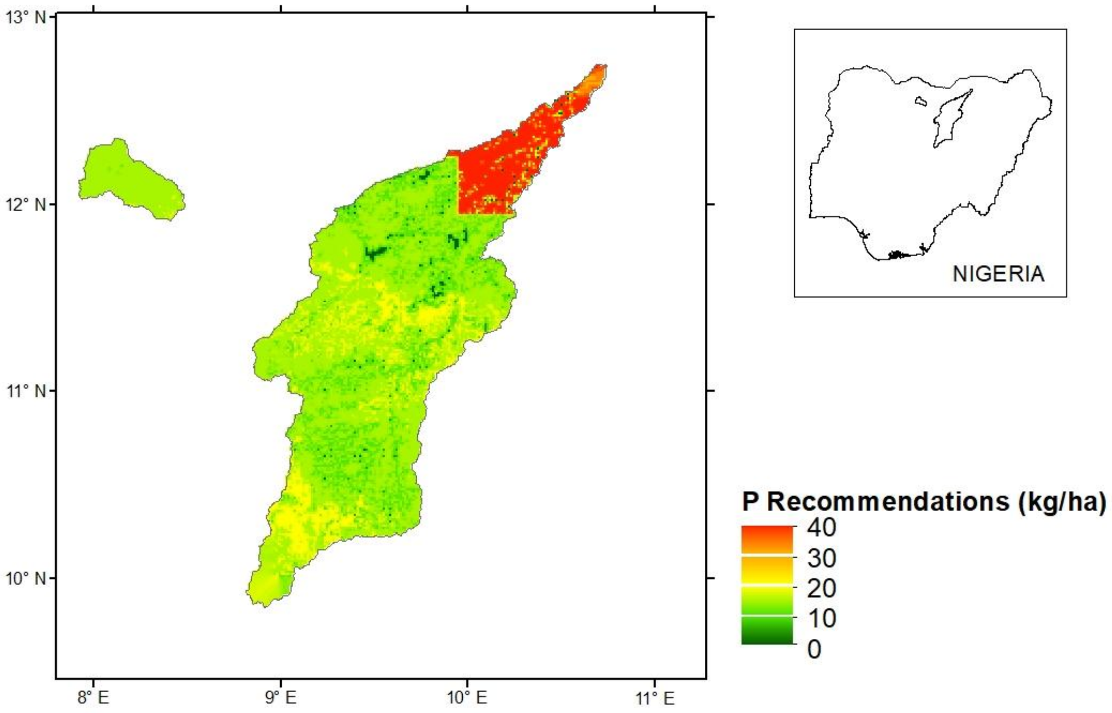

***Figure 6**: V0 Phosphorus Recommendation Map for Maize of the Target Area, Nigeria.*

Rice-Nigeria

The nutrient recommendations for rice in Nigeria are presented in Figures 7 and 8, covering Nitrogen (N) and Phosphorus (P).

Nitrogen (N): The V0 Nitrogen recommendation map for rice (Figure 7) suggests an application range of 3 to 80 kg/ha. The target area is similar to that for maize, located in the north-central region. The highest nitrogen recommendations, from 64 to 80 kg/ha, are for the northern parts of this area. This is followed by recommendations of 49-64 kg/ha and 34-49 kg/ha in the central and transitional zones, with the lowest application rates (3-18 kg/ha) in the peripheral areas.

Phosphorus (P): The V0 Phosphorus recommendation map for rice (Figure 8) indicates a much lower application range of 0 to 15 kg/ha. The highest recommendations, from 12 to 15 kg/ha, are for the northeastern part of the target area. The central parts of the area have medium recommendations of 6-9 kg/ha, while the surrounding regions have low recommendations of 0-3 kg/ha.

Figure 7*: V0 Nitrogen Recommendation Map for Rice of the Target Area, Nigeria.*

Figure 8: *V0 Phosphorus Recommendation Map for Rice of the Target Area, Nigeria.*

Maize –Ghana

The recommendations for maize in Ghana are provided in Figures 9, 10, and 11, detailing the requirements for Nitrogen (N), Phosphorus (P), and Potassium (K).

Nitrogen (N): The V0 Nitrogen recommendation map for maize (Figure 9) indicates a wide application range of 0 to 120 kg/ha. The recommendations are distributed across multiple regions. The northern regions (10-11°N) generally show lower nitrogen needs (0-24 kg/ha), while the central regions (7-8°N) have the highest requirements, ranging from 72 to 120 kg/ha. There are also mixed zones with medium application rates of 48-72 kg/ha.

Phosphorus (P): The V0 Phosphorus recommendation map for maize (Figure 10) shows a recommended application range of 0 to 50 kg/ha. The highest phosphorus needs are concentrated in the central regions (7-8°N), with recommendations of 40-50 kg/ha. The northern regions, in contrast, have much lower phosphorus requirements, ranging from 0 to 20 kg/ha. This indicates a clear spatial differentiation in phosphorus needs for maize in Ghana.

Potassium (K): The V0 Potassium recommendation map for maize (Figure 11) is also provided, with a recommended application range of 0 to 50 kg/ha. The recommendations are primarily for the central regions (7-8°N). The majority of this area shows low potassium requirements (0-10 kg/ha), with only small pockets of medium (20-30 kg/ha) and high (40-50 kg/ha) recommendations.

Figure 9*: V0 Nitrogen Recommendation Map for Maize of the Target Area, Ghana.*

Figure 10*: V0 Phosphorus Recommendation Map for Maize of the Target Area, Ghana.*

Figure 11*: V0 Potassium Recommendation Map for Maize of the Target Area, Ghana.*

Rice-Ghana

The nutrient recommendations for rice in Ghana are presented in Figures 12 and 13, covering Nitrogen (N) and Phosphorus (P).

Nitrogen (N): The V0 Nitrogen recommendation map for rice (Figure 12) suggests an application range of 0 to 80 kg/ha. The recommendations are for multiple scattered regions across the country. The highest nitrogen needs (64-80 kg/ha) are in the southern-central regions (7-8°N). The central zones have medium-high recommendations of 48-64 kg/ha, while the northern regions have medium recommendations of 32-48 kg/ha. There are also scattered areas with lower requirements of 0-16 kg/ha, indicating a more heterogeneous distribution compared to maize.

Phosphorus (P): The V0 Phosphorus recommendation map for rice (Figure 13) shows a recommended application range of 0 to 15 kg/ha. The distribution is as scattered as that for nitrogen. The highest phosphorus needs (12-15 kg/ha) are in the northern regions (10-11°N). The central-northern zones (9-10°N) have medium-high recommendations of 9-12 kg/ha, while the central regions (7-8°N) show high variability. The southern regions have the lowest phosphorus requirements, from 0 to 6 kg/ha.

Figure 12: *V0 Nitrogen Recommendation Map for Rice of the Target Area, Ghana.*

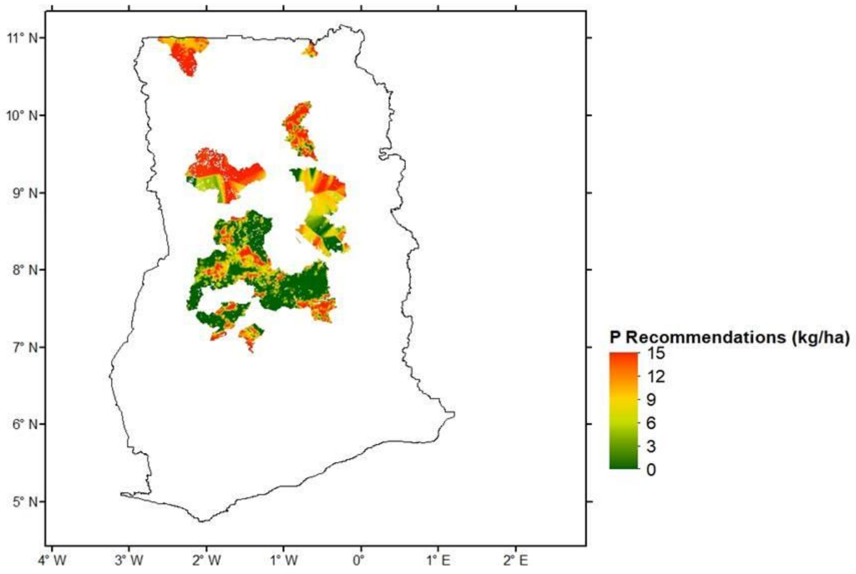

***Figure 13**: V0 Phosphorus Recommendation Map for Rice of the Target Area, Ghana.*

Maize-Togo

For maize cultivation, the nutrient recommendations span a wide range, indicating diverse soil conditions across Togo (Figure 14, 15 and 16).

Nitrogen (N): Recommendations for Nitrogen are substantial, ranging from 0 to 110 kg/ha (Figure 14). The northern and central regions of Togo exhibit the highest demand for N, with large areas requiring 66 to 110 kg/ha. The southern areas, in contrast, show lower requirements. Phosphorus (P) and Potassium (K): The needs for Phosphorus (Figure 15) and Potassium (Figure 16) in maize cultivation are also high, with recommendations for both nutrients ranging from 0 to 50 kg/ha. Similar to Nitrogen, the northern and central regions show the highest requirements, while the southwestern Togo has lower needs.

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Figure 14: *V0 Nitrogen Recommendation Map for Maize of the Target Area, Togo.*

Figure 15*: V0 Phosphorus Recommendation Map for Maize of the Target Area, Togo.*

***Figure 16**: V0 Potassium Recommendation Map for Maize of the Target Area, Togo.*

Rice-Togo

Nitrogen (N): The recommended Nitrogen application for rice ranges from 1 to 80 kg/ha (Figure 17). The northern and central regions again show the highest demand, with requirements between 64 and 80 kg/ha.

Phosphorus (P): Phosphorus recommendations for rice are between 0 and 15 kg/ha and are concentrated in the northern half of the country (from approximately 8°N to 11°N latitude) (Figure 18). The distribution is mixed, indicating moderate to high requirements in these specific areas.

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***Figure 17**: V0 Nitrogen Recommendation Map for Rice of the Target Area, Togo.*

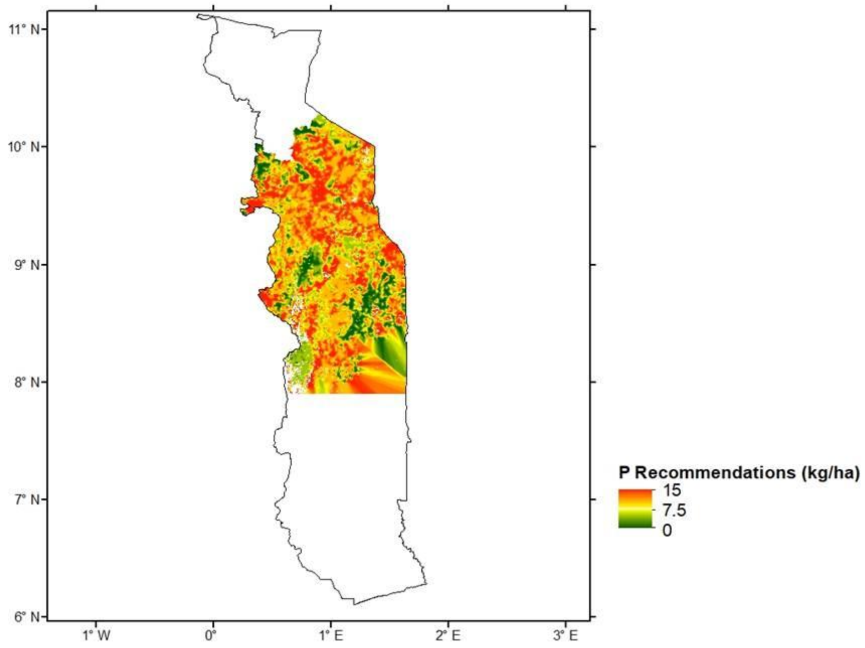

***Figure 18:** V0 Phosphorus Recommendation Map for Rice of the Target Area, Togo.*

Rice-Mali

The recommended application rates for Nitrogen in the targeted rice-growing areas of Mali range from 10 to 60 kilograms per hectare (kg/ha) (Figure 19). The maps show small, clustered zones with moderate to high N requirements, indicating that while the need for nitrogen is not widespread across the entire country, it is a significant input for optimal yields in the designated cultivation areas.

The requirements for Phosphorus (Figure 20) and Potassium (Figure 21) are comparatively lower than for Nitrogen. Phosphorus recommendations range from 0 to 10 kg/ha, suggesting low to moderate needs. Similarly, Potassium recommendations fall between 0 and 30 kg/ha, with the maps predominantly showing lower-end requirements. This indicates that while P and K are necessary, the soil in the target region may already possess a baseline level of these nutrients.

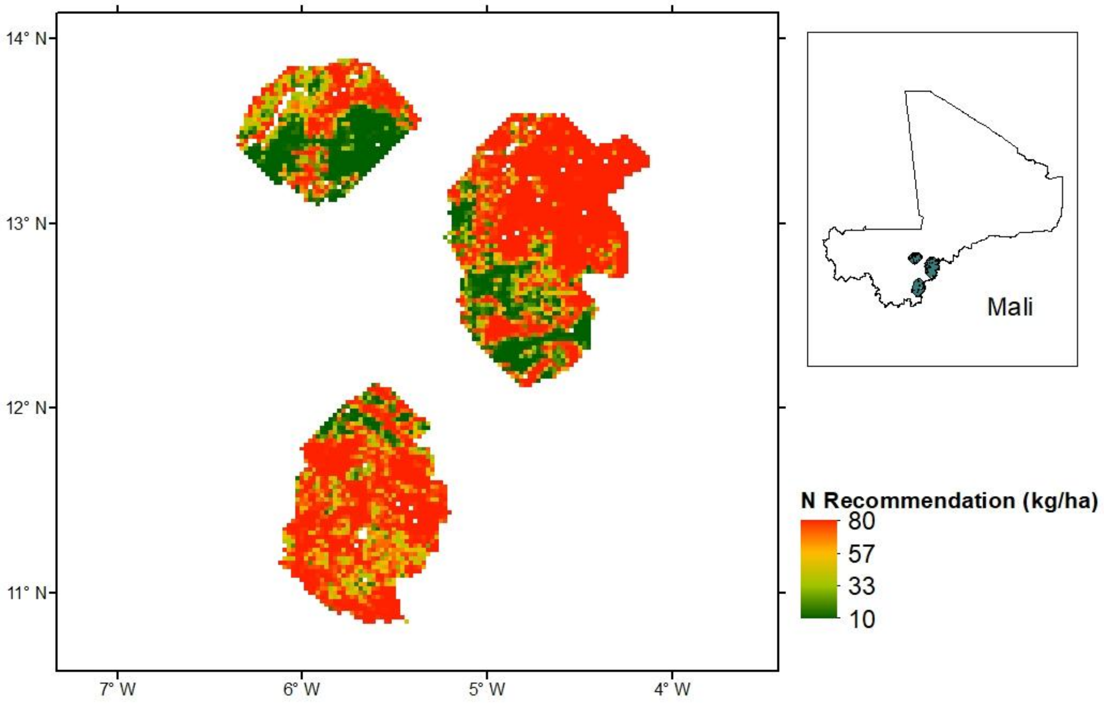

Figure 19*: V0 Nitrogen Recommendation Map for Rice of the Target Area, Mali.*

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***Figure 20**: V0 Phosphorus Recommendation Map for Rice of the Target Area, Mali.*

***Figure 21**: V0 Potassium Recommendation Map for Rice of the Target Area, Mali.*

Validation and performance of V0 using LLM crowdsourced systematic literature data

This study employed a novel validation approach, where a Gradient Boosting Model (GBM), previously trained on an independent dataset, was used to predict crop yields based solely on NPK values extracted from the literature (Figure 22). These predicted yields were then compared directly against the actual yields reported in those same literature sources. The results indicate that the method is a valid and effective way to estimate yields, as in some cases the model accurately predicted the yield. This was more prominent for Ghana, Nigeria but less so for Togo. Specifically for Ghana, there was a strong performance for rice and maize ($R^2 > 0.80$) (Figure 22).

Nigeria the model showed moderate model performance from R2 of 0.57-0.69. Togo, maize had low correlation of less than 0.5, due to fewer data to train V0 and fewer peer reviewed publications to extract data from. The V0 recommendations could not be validated for Sierra Loene and Liberia as there no peer reviewed publications to extract data from. This highlights the need to conduct nutrient omission trials to get more high-quality data to train and test models (Figure 22).

Figure 22*: Validation of GBM model trained on legacy agronomic data GBM model.*

Version One (V1) Nutrient Recommendation Models

Pattern of maize grain yield response to nutrient application from the new nutrient omission trials in Nigeria

The recently harvested maize nutrient omission trials in Nigeria will be used to test the model. Analysis of the data shows how different fertilizer treatments affect grain yield, revealing strong and statistically significant differences ($P < 0.0001$) (Figure 23). The highest yields were obtained under the NPK + S micronutrients treatment, closely followed by NPK alone, indicating that a full nutrient package provides maximum productivity. Treatments supplying only two nutrients (NP, NK, PK) produced moderate yields, with NP performing better than NK and PK. When only one macronutrient (P or K) or no fertilizer was applied, yields dropped sharply, showing clear nutrient limitations. Tehe data can therefore be used for model training and testing

Figure 23: *Maize yield response from nutrient omission trials conducted in Bauchi, Kano and Jigawa under the regional Hub for fertilizer and soil health for West Africa and the Sahel.*

Maize-Nigeria

The V1 Nitrogen commendation map for maize (Figure 24) specifies an application range of 59 to 130 kg/ha. This indicates a higher baseline requirement compared to the V0 map. The spatial pattern reveals that the majority of the target area now falls into the higher recommendation tiers, particularly between 115-130 kg/ha. This suggests a more uniform and intensive nitrogen need across the region than previously estimated. The lower recommendation zones (59-73 kg/ha) are minimally present, reinforcing the emphasis on higher application rates in this updated model version.

The V1 Phosphorus recommendation map (Figure xx) presents a range of 0 to 60 kg/ha. While the maximum potential recommendation has increased from V0's 40 kg/ha, the map's spatial distribution shows a predominantly conservative approach. The most common recommendation across the target area is in the medium-low tier of 12-24 kg/ha. Zones requiring high (36-48 kg/ha) or very high (48-60 kg/ha) phosphorus application are very limited (Figure 25).

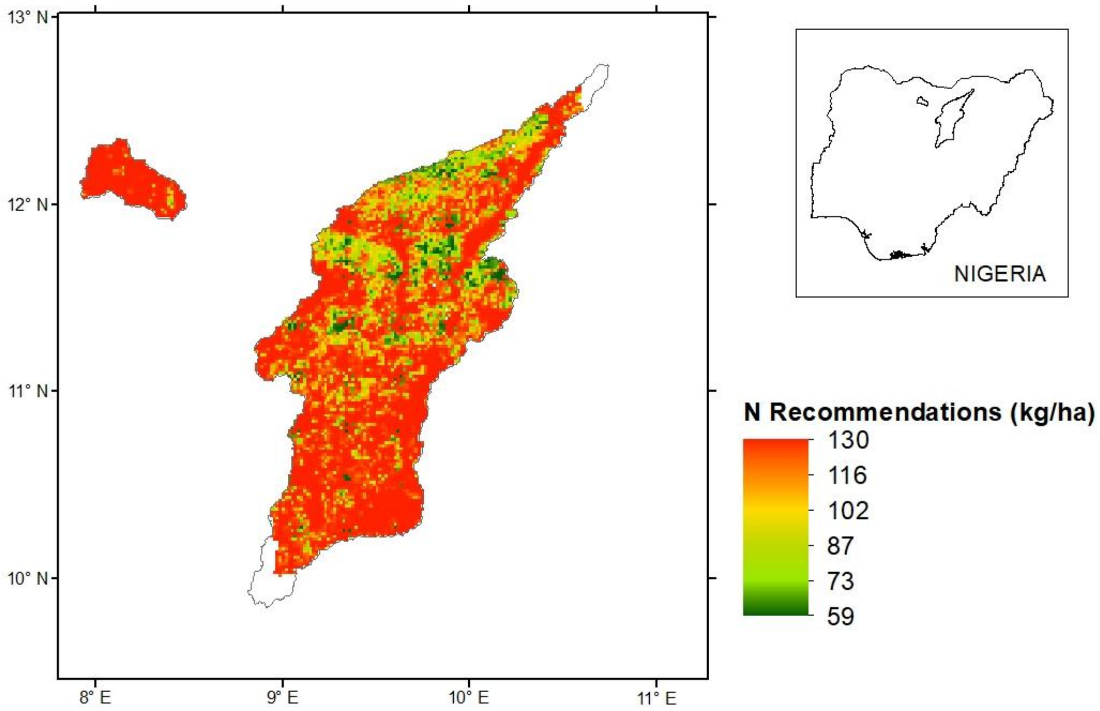

Figure 24: *V1 Nitrogen Recommendation Map for Maize of the Target Area, Nigeria.*

The introduction of Potassium recommendations is a key update in the V1 maps for Nigeria due observed yield response to K application in the new NOT training dataset. The V1 Potassium recommendation map (Figure 26) shows an application range of 0 to 50 kg/ha. There is significant spatial variability in potassium requirements within the target area. The northern portions of the region show the highest need, with recommendations between 40-50 kg/ha. In contrast, the southern portions of the same area show lower requirements, typically in the 10-20 kg/ha range. This highlights a distinct north-south gradient in potassium needs for maize in this part of Nigeria (Figure 26).

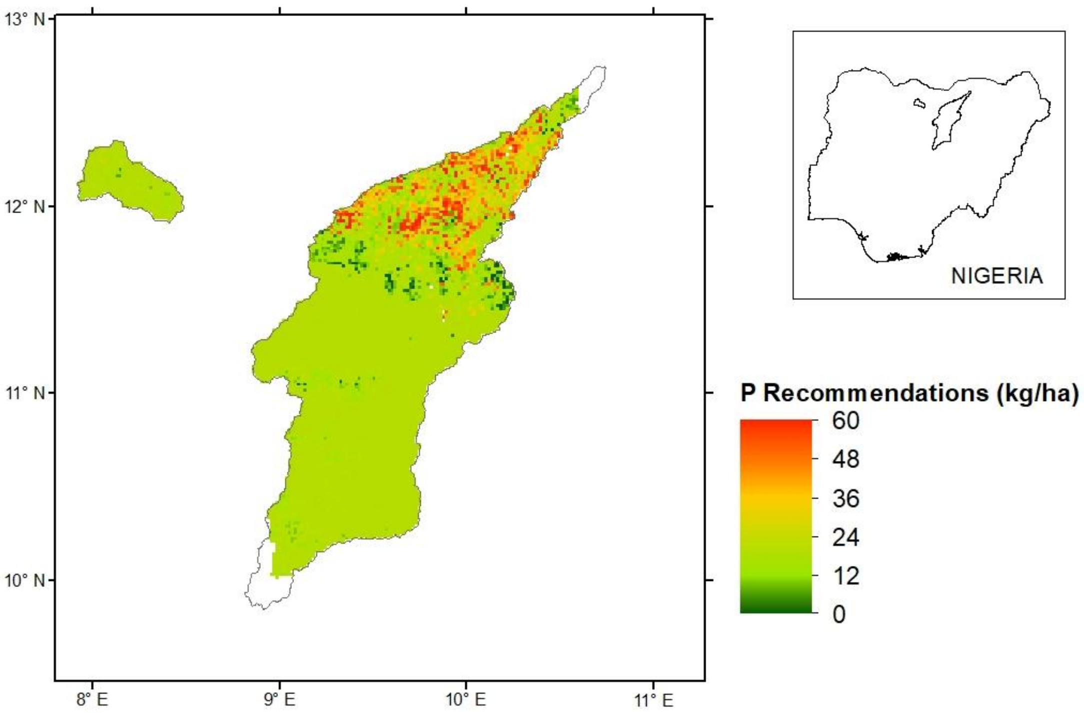

__Figure 25:__ V1 Phosphorus Recommendation Map for Maize of the Target Area, Nigeria.

***Figure 26**: V1 Potassium Recommendation Map for Maize of the Target Area, Nigeria.*

05. DISCUSSION

5.1 Value of nutrient appropriate formulations

The work shows the value of revised nutrient recommendations as an attempt to increase efficiency and productivity in Africa. This provides an improved site-specific fertilizer recommendations in a region where some recommendations as are as old as 40 years. Additionally, this feeds into the development of nutrient appropriate formulations which are potentially critical for development of new fertilizer blends for the region. Such could be vital for the region which also suffers from limited fertilizer availability as suppliers do not have numbers to offset their costs but also in general, they have less information on the most appropriate fertilizer products to enhance efficiency and improve soil nutrient balance to sell. There is therefore increased need for development of partnerships with fertilizer producing companies.

Traditionally fertilizer recommendations should be validated in the field to gather evidence of the accuracy and value of the revised fertilizer recommendations. Though this provides more confidence, this is expensive and time consuming. The current global donor trends now favour rapid turn around and provision of solutions to farmers at a faster time and lower cost. Tapping into advanced AI provides alternative options for faster validation. The work also benefits and contributes to the evolving AI landscape where LLM powered tools are being utilised for Insilco validation of the fertilizer recommendations. Though this was a test case, the approach is invaluable for the agricultural sector. This opens more opportunities for the agriculture sector to gain more value from AI. Specifically, peer reviewed data was crowdsourced, and the fertilizer data was utilised as input into the trained fertilizer recommendation module. The comparative performance was moderate to high highlighting the relatively accuracy of LLM based crowd sourcing approaches for validation.

5.2 Future activities

The current V0 recommendations for all the wave 1 target countries have been tested robustly based on literature data and V1 recommendations for maize in Nigeria have been further tested with a fresh nutrient omission trial data. There is need to expand this validation to other target crops and countries. Further testing will be undertaking by adding additional fresh nutrient omission trial data for testing the trained model. Additional data for validation is currently being harvested from the different nutrient omission trials for Nigeria (rice), Ghana (maize and rice), and Liberia (rice). The validation will be undertaken on at least 2.5 million hectares of arable land in 2026.

5.3 Collaboration with other functions of the Regional Hub for fertilizer and Soil Health for West Africa and the Sahel.

Function 1: Digital Soil health and fertility maps: The recently developed soil maps from IPI1.3 and Function 1 of the regional hub will be utilised as input into the trained models. The trained model utilises soil data as covariates for enhanced soil nutrient prediction.

Function 7-Farmer led experimentation-Data from the trials will be added to the current legacy data to increase amount of data available for model training and improve quality of fertilizer optimisation.

Function 2-Plant and soil analytical laboratory services: These provide soil analytical services. The data from the soils will be added as additional data to train and calibrate the various models for fertilizer recommendations.

Function 8-Unified databases and digital tools: This mostly provides legacy agronomic data for training models, from CAROB. This is an open agronomy dataset and literature repository that aggregates open access agricultural research data. There is need for continued access to that data to train models.

06. CONCLUSION

This analysis demonstrates the potential of data and model driven, site-specific fertilizer recommendation frameworks to improve agronomic efficiency and productivity across West Africa's diverse maize and rice production environments. The modelled results for Nigeria, Ghana, Sierra Leone, Liberia, Togo, Sierra leone and Mali highlight the strong spatial variability in nutrient requirements driven by differences in soil fertility, rainfall distribution, and agroecological conditions.

Across the different countries, nitrogen (N) consistently emerged as the primary limiting nutrient for maize production, with the highest recommended rates (90–130 kg N ha^{-1}) concentrated in the major maize belts of northern Nigeria, northern and central Ghana, southern Sierra Leone, northern Liberia, and northern Togo. Phosphorus (P) was identified as a secondary but crucial constraint, particularly in the savannah and transitional zones where soils are characteristically low in available P. Potassium (K) limitations were more localized, primarily affecting humid and highly leached soils in southern Ghana and Sierra Leone.

The integrated N–P–K nutrient recommendation maps reveal that blanket fertilizer recommendations are inefficient and risk under- or over-application across heterogeneous smallholder landscapes. These N-P-K combinations form the basis of revised nutrient formulations, which could be utilised by fertilizer companies to develop new products. By contrast, spatially optimized fertilizer packages ranging from lighter combinations such as 30N-10P-10K in low-response zones to more intensive packages like 120N-30P-40K in high-potential areas provide a robust foundation for targeted nutrient management.

Collectively, these findings underscore the importance of transitioning toward site-specific and evidence-based fertilizer recommendations to enhance nutrient-use efficiency, reduce production costs, and sustainably increase maize yields across West Africa. When integrated into digital advisory systems such as Digital Green and VIAMO or national extension platforms, these insights can strengthen agronomic decision support, promote climate-smart nutrient management, and accelerate progress toward regional food and soil health security goals.

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