NDVI-Based Machine Learning System for Precision Agriculture

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ABSTRACT

AgriSmart is a machine learning-based platform designed to assist farmers and agricultural planners in monitoring crop health, predicting crop yield, and recommending optimal fertiliser usage without relying on IoT sensors. The system leverages satellite and drone imagery to analyse crop conditions using vegetation indices, such as NDVI, in combination with historical crop, soil, and weather data. Machine learning models, including regression and convolutional neural networks, are employed to forecast crop yield, classify crop health, and provide actionable fertiliser recommendations. An interactive dashboard visualises crop health heatmaps, predicted yields, and fertiliser recommendations, enabling data-driven decision-making. This approach is sustainable, scalable, and fully implementable on a personal computer, promoting efficient resource use and early intervention to prevent crop stress and maximise productivity.

Keywords: Precision Agriculture, Crop Health Monitoring, Yield Prediction, Fertiliser Recommendation, NDVI, Sentinel-2, Random Forest.

1. Introduction

Agriculture still feeds most of the world, and in many regions it holds local economies together. But the traditional ways of managing land walking fields, relying on experience, watching the sky are running into trouble. Erratic weather, exhausted soil, and shifting climate patterns are pushing farmers toward tools built on live data, less because of enthusiasm for technology and more because the room for error keeps shrinking [1]. Satellites now photograph farmland in enough detail to catch problems that a ground-level walk might miss for weeks. Instead of trudging every row, analysts can scan thousands of acres from a single overhead pass and flag changes as they emerge. Early drought stress, pest pressure, or stunted growth shows up in imagery long before it becomes obvious on the ground. A common way to read that imagery is NDVI the Normalised Difference Vegetation Index. Rather than relying on visible colour, it measures how plants reflect red and near-infrared light. Healthy plants reflect more infrared; struggling ones reflect less. When those values drop, something is usually wrong: not enough water, missing nutrients, or disease beginning to spread often caught before anyone walking the field would notice a thing. Sentinel-2 satellites pass over the same ground repeatedly, collecting detailed multi-band images on each orbit. Over weeks and months, that data builds a record of how crops respond to weather and soil changes. Seasonal patterns get clearer, unusual dips stand out, and what was once intuition becomes something that can actually be observed and compared over time.

Machine learning statistical models and deep learning alike has been applied to satellite imagery to forecast yields, identify disease, and track vegetation at scale. Results vary by method and depend heavily on input data quality, but for broad-area vegetation monitoring, the research record is generally encouraging [2][4]. The problem is access. Most precision agriculture tools still require expensive hardware or IoT sensors that small farms cannot afford. And even when the software exists, it tends to be fragmented one tool for crop monitoring, another for yield estimates, another for fertiliser advice, none of them talking to each other [5], [6].

This work tries to address that directly. Instead of treating each challenge as a separate problem, it combines NDVI analysis and machine learning into a single system that monitors crop health, estimates harvest volumes, and generates fertiliser recommendations from a single pipeline. Satellite images go in, visual outputs come out, and the system is designed to support practical farming decisions without requiring specialised expertise or additional equipment to run it [1], [7].

Researchers working on farm technology have spent years trying to get better information about crops without having to walk every field. Combining satellite imagery with machine learning seemed like a natural direction. Early attempts used modified cameras to spot sick plants the results were decent in controlled settings or on small plots, but fell apart in real field conditions [1], [8], [9]. When satellite images became more widely available, software tools followed, letting farmers see their fields from above. But those tools usually demanded technical know-how to operate, and their predictions rarely matched what was actually happening on the ground which, in farming, is the only number that matters [7].

Some models went further, pulling together soil type, rainfall records, and harvest histories to forecast future yields. Most worked reasonably well in one region and struggled everywhere else [2]. Earlier research established that NDVI tracks plant growth and seasonal changes well when derived from satellite observations [10], [11]. Later work extended that using NDVI to estimate harvest volumes in drier regions showed it could flag problems earlier in the growing season than traditional methods.

Other studies conducted finer-grained analyses of plant features using image processing [4], [5]. However, those approaches generally required expensive sensors and significant computing power, making them difficult to deploy on real farms [3]. Research also examined how colour patterns and light reflectance shift as crops grow, connecting those signals to water stress, leaf cover, and overall development [12] [14]. Several of those techniques work well in isolation but depend on airborne photography or specialised hardware, which limits where they can actually be used [15], [16].

Higher-resolution satellites like Sentinel-2 have enabled more detailed crop monitoring, but most tools built around them still do one thing at a time track plant health or estimate yield, rarely both. Field camera setups can track growth and measure nutrient uptake over a season, but they require permanent installation and are typically calibrated for specific crops rather than general use [17], [18]. Lab-based leaf analysis gives precise nutrient data, but running chemical tests across hundreds of hectares is not realistic [19]. The gap these tools leave is the same one that keeps showing up: useful in narrow conditions, hard to scale. Table 1 summarises this body of related work and highlights the specific gap that the proposed system addresses.

Table 1: Comprehensive comparative analysis of related work and proposed NDVI-based system

Ref.	Study Focus	Technology / Method	Deploymen t Context	Identified Limitation	Gap Addressed by Proposed System
[1]	Low-cost NDVI imaging system	Custom NDVI camera	Controlled experiments	Requires a dedicated hardware setup	Uses freely available satellite imagery
[2]	Open-source crop health monitoring	Satellite data + software tools	Research users	Requires technical expertise	Provides an automated, user-friendly dashboard
[3]	ML-based crop yield prediction review	RF, SVM, ANN models	Region-specific datasets	Limited generalizati on	Integrates NDVI with multi-source data
[4]	Early NDVI crop monitoring	NDVI time-series analysis	Dryland agriculture	Low-resolution imagery	Uses high-resolution Sentinel-2 data
[5]	Plant phenotyping technologies	Advanced imaging systems	Lab/controll ed fields	Expensive and complex	Eliminates the need for costly hardware
[6]	Image-based plant phenotyping	Deep image analysis	Research labs	High computatio nal demand	Optimised for standard PCs
[7]	Phenotype data analysis	Deep learning + imaging	Controlled environmen ts	Data-heavy and equipment-dependent	Lightweight satellite-based approach
[8]	Vegetation monitoring (NDVI concept)	NDVI index formulation	Large-scale vegetation study	Monitoring only	Adds predictive analytics
[9]	Vegetation monitoring using ERTS	Early satellite sensing	Regional vegetation analysis	No ML integration	Integrates monitoring with ML
[10]	Review of vegetation indices	Spectral index comparison	Multi-crop research	Theoretical focus	Practical NDVI implementati on

[11]	Crop characterisation using indices	Narrowband/broad band indices	Crop-specific studies	Requires hyperspectr al sensors	Uses Sentinel-2 multispectral data
Prop osed	Integrated NDVI precision agriculture system	Sentinel-2 + NDVI + Random Forest + Web dashboard	Sensor-free scalable deployment	Dependent on satellite image quality	End-to-end monitoring, prediction, and recommendat ion

2. Research Methodology

The guiding objectives of the proposed system, spanning crop-health monitoring, yield prediction, fertiliser recommendation, visualisation, and overall system design, are outlined below.

A. Crop Health Monitoring Using NDVI

The proposed methodology comprises crop health monitoring, yield prediction, fertiliser recommendation, visualisation, and system integration.The system recognises stress conditions caused by nutrient deficiency or poor growth by analysing light reflected from plant leaves, eliminating the need for manual field inspection. Differences in vegetation's reflective properties aid early detection of problem regions, enabling efficient addressing. This approach enables effective field monitoring at scale and reduces the need for physical surveys. Previous studies have demonstrated the reliability of NDVI-based monitoring for early detection of crop stress and for supporting data-driven agronomic decisions [10], [12].

B. Machine Learning-Based Crop Yield Prediction

Another main focus of the study is predicting crop yield from historical soil, climate, and NDVI features using machine learning models. Machine learning methodologies allow modelling of complex crop-environment relationships and provide reliable yield predictions that assist with seasonal planning and resource management. Previous research indicates that data-driven methods can improve yield-prediction accuracy across a range of agricultural settings [2], [15].

C. Intelligent Fertiliser Recommendation System

To inform fertiliser decisions, the tool combines a bank of preset rules with data-driven pattern recognition. Soil test results are combined with signs of plant health extracted from satellite imagery. This combination helps farmers apply nutrients more accurately. Rather than estimating amounts by guesswork, decisions are based on colour changes visible in crops from overhead visual cues that are closely linked to how much nitrogen the plants actually require. Research shows that these methods can help tune fertilisation strategies within individual fields.

D. Integrated Visualisation and Analytics Dashboard

A key component of the system is an interactive dashboard that presents NDVI patterns, estimated harvest levels, and fertilisation information together. By consolidating multiple data streams into a single interface, the dashboard keeps analysis clear and supports quick, data-driven decisions. Automated satellite-image processing makes the effect of recommended interventions on crop condition easy to see, extending a practice of agricultural management from traditional family farming to modern agribusiness into a single accessible tool [7], [17].

E. Scalable Sensor-Free Precision Agriculture Framework

The final objective is to build a flexible yet precise farming system that entirely avoids dedicated IoT devices and relies solely on satellite imagery and lightweight machine learning software. Satellites that observe land changes from space, such as Sentinel-2, demonstrate that even small family farms can use information gathered from orbit [1]. Because this approach costs less, it also opens precision-agriculture techniques to a wider range of farmland [6], allowing more growers to adopt smarter practices while taking a long-term view of resource management [20].

2.1. System Design

Satellite sources such as Sentinel-2 monitor changes in seasonal crops. Combining these images with historical soil, weather, and harvest records allows the algorithms to identify patterns and forecast yields earlier. Images undergo preprocessing before analysis removal of clouds, balancing of light, and alignment of viewpoint so that images can be fairly compared over time. From these cleaned images, greenness indicators, such as NDVI, are computed as the ratio of light reflected by leaves in the red and near-infrared bands (Figure 1) [20].

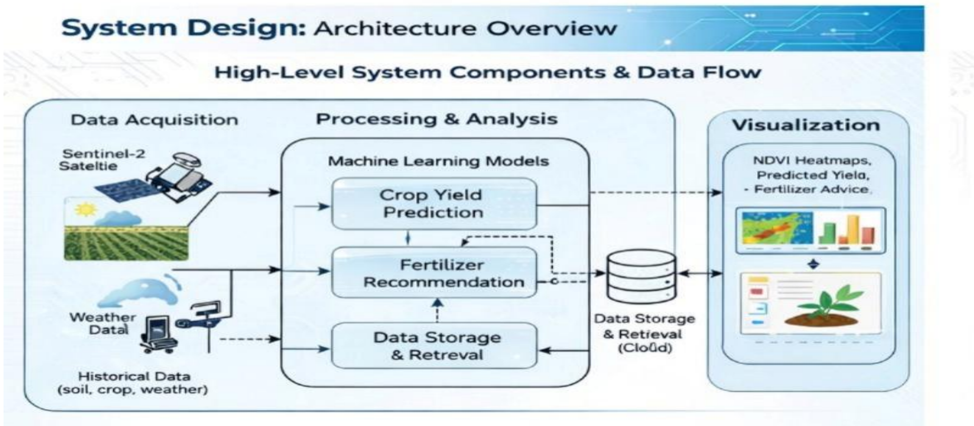

Figure 1: System design architecture overview showing the integration of satellite data, NDVI processing, and machine learning models for crop monitoring and prediction.

Satellite data is used to monitor plant health indicators, with low NDVI values indicating poor growth or nutrient deficiency and higher values indicating healthy growth. This data, together with soil composition, weather, and farming type, drives algorithms such as Random Forest to predict yields and support fertiliser management (Table 2). Soil-mineral sensors are also used to determine whether a field requires fertilisation, and live dashboards provide real-time trend information and nutrient recommendations. Cloud storage guarantees scalability, online access, and reduced setup costs.

Table 2: NDVI value interpretation

NDVI Range	Plant Condition
< 0.2	Sparse plant cover
0.2 – 0.5	Moderate growth
> 0.5	Healthy plants

2.2. Data Acquisition and Preprocessing

An online tool based on NDVI and machine learning helps farmers make decisions. It integrates satellite imagery from systems such as Sentinel-2 with historical records of crops, soil, weather, and yields. The system aims to forecast agricultural outcomes more precisely by combining spatial and temporal data, enabling it to identify trends in crop development [20].

Agricultural plots were delimited using GeoJSON records, and each plot included a FieldId field, a crop-type field, the planted season, and the date it was last updated. Fields can also be drawn directly on a live satellite basemap and saved to the GeoJSON dataset. Seven fields, spanning six crop types across three growing seasons (2023–2025), were used for evaluation, as detailed further in the Results and Discussion section.

Sentinel-2 surface-reflectance images were obtained through the Google Earth Engine (GEE) Python API. The Sentinel-2 SR HARMONIZED collection was requested and filtered to include only acquisitions with less than 20 per cent cloud cover. The intersection of GEE image tiles with the boundaries of the GeoJSON polygons was computed using geopandas and shapely, retaining only pixels within confirmed agricultural parcels. Ground-truth data on soil nutrients (N, P, K, pH), past yields, temperature, and precipitation were compiled using REDCap and combined into a single training corpus.

Figure 2: Mapped field boundaries overlaid on a Sentinel-2 true-colour composite showing the seven evaluated agricultural parcels with crop type annotations.

2.3. NDVI Extraction and Feature Engineering

NDVI was computed pixel-wise for every cloud-free acquisition using Eq. (1) in Section 3, where ρNIR and ρRed are the surface reflectance values in Sentinel-2 bands B08 and B04, respectively, obtained through GEE.

Leaf Area Index (LAI) was calculated alongside NDVI as a further indicator of crop condition. Field-level statistics (mean, max, min, standard deviation) were aggregated per acquisition and mapped to four phenological windows: early growth, peak canopy, grain fill, and senescence. Additional indices — RVI and SAVI — were included to account for variable soil backgrounds. The final feature table contained 23 variables per field-season record, comprising NDVI and LAI statistics, soil parameters, climatic variables, and one-hot encoded crop and season labels.

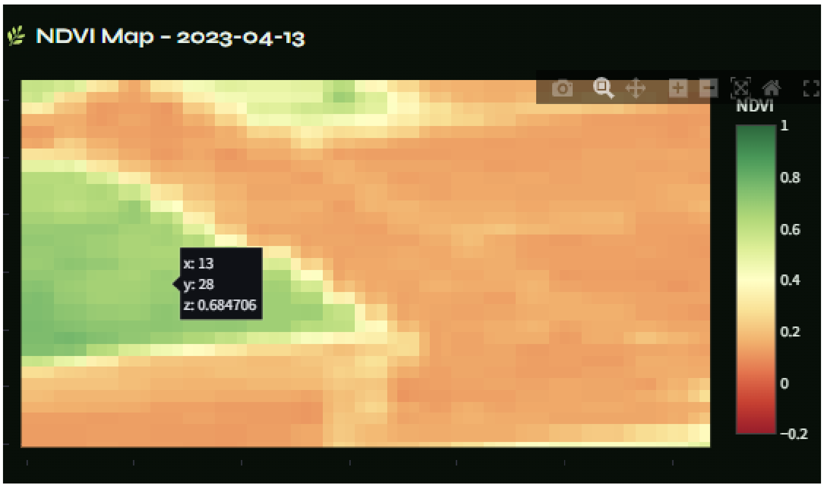

Figure 3: NDVI spatial distribution map for Field ID 38 (Paddy, 2025 season), with colour gradient from red (NDVI < 0.2, stressed) through yellow (0.2–0.5, moderate) to dark green (> 0.5, healthy vegetation).

2.4. Machine Learning Models

2.4.1 Yield Prediction

An encoded state, crop type, soil type, season, and field-area feature set was used to train a single Random Forest Regressor (100 trees) with an 80/20 train-test split. Target values were expressed as production per unit area (t/ha) based on records.

2.4.2 Crop Recommendation

The same set of soil and climate features was used to train a Random Forest Classifier (100 trees) that produces ranked crop-suitability probabilities across candidate classes. Categorical inputs were label-encoded using scikit-learn's LabelEncoder, and class imbalance was addressed prior to training using SMOTE.

2.4.3 Fertiliser Guidance

The fertiliser-guidance module was a hybrid rule-based system that used thresholds for NDVI and soil N/P ratios. When NDVI fell below 0.35 and soil nitrogen was below 50 kg/ha, the system flagged a nutrient deficiency. It generated a corresponding urea-application rate based on coded agronomic rules. Trained models were serialised using joblib and reloaded rather than retrained on each run.

2.5. Web Dashboard

The web dashboard consists of five pages: Dashboard Home, Crop Recommendation, Satellite Monitoring, Field Analytics, and Add New Field. It uses Folium maps on a Google Satellite basemap to select a field. NDVI and LAI values are displayed as Plotly heatmaps and dual-axis time-series charts. Field boundaries can be drawn and saved to GeoJSON through the Folium Draw plugin. The system supports live Google Earth Engine access, with a synthetic fallback configured through config.yaml, and can be run on a conventional laptop without specialised hardware.

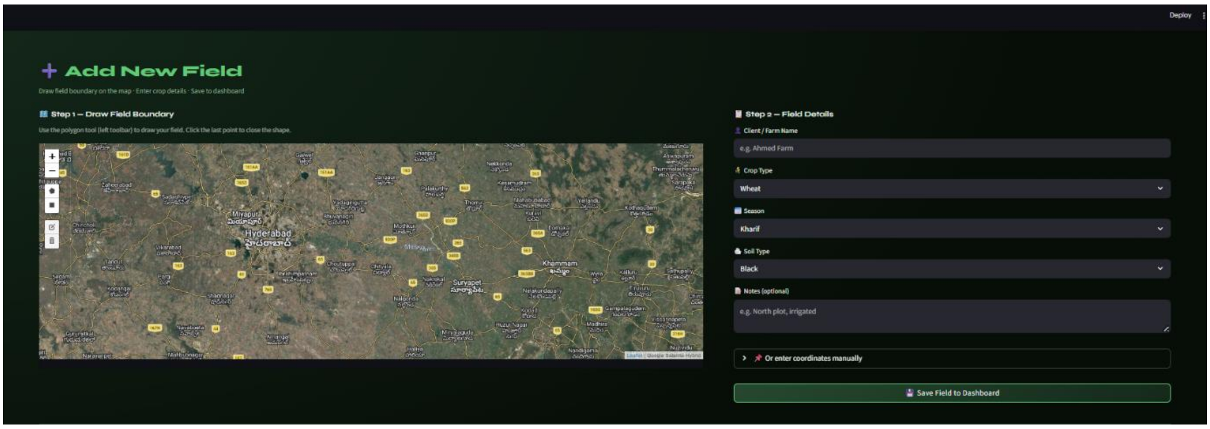

Figure 4: Farmer input interface for entering soil type, crop type, and field parameters before generating predictions and recommendations.

3. Theory and Calculation

3.1. Mathematical Expressions and Symbols

Pre-processing of the satellite images is performed to remove clouds and to normalise and align the images so that a consistent analysis can be carried out over time. Red and near-infrared bands are then used to compute NDVI, which measures vegetation health and identifies stress conditions. These features are combined with soil and climate information to form the inputs to machine learning algorithms; deep learning models such as CNNs are successfully used to classify crop conditions [3], [4], [10], [15]. NDVI is computed pixel-wise for every cloud-free acquisition using:

$$NDVI = \frac{(\rho NIR - \rho Red)}{(\rho NIR + \rho Red)} \tag{1}$$

where ρNIR and ρRed are the surface reflectance values in Sentinel-2 bands B08 and B04, respectively, obtained through the Google Earth Engine platform.

Crop yield forecasting is performed using Random Forest and regression models that examine the correlation between vegetation indices and environmental variables. The fertiliser recommendation module combines soil nutrient data with crop health indicators to generate optimal recommendations. Findings are represented through an interactive dashboard that displays NDVI maps, yield projections, and decision-support recommendations [7], [17].

The complete AgriSmart pipeline was implemented in five stages: data acquisition, preprocessing, feature engineering, model training, and dashboard delivery, as described in

Section II. The stack is built entirely on open-source Python. It does not rely on proprietary tools or IoT hardware, making it free to run and populate with data, and drawing exclusively on freely available satellite imagery from the Google Earth Engine (GEE) web platform.

4. Results and Discussion

All seven fields, spanning six crop types across three seasons (2023–2025), were used for evaluation.

4.1. NDVI-Based Crop Health

Temporal NDVI profiles matched the predicted phenological profiles for each crop. Peak NDVI in wheat fields (IDs 7 and 12) ranged between 0.61 and 0.74 during grain fill, indicating healthy canopy development. Within-parcel variability of the large Paddy field (ID 38) was also high, with a standard deviation of 0.14, underscoring the utility of spatial rather than point NDVI measurements.

Early-season imagery forecast that 18 per cent of Field 38 pixels were severely stressed before any obvious crop damage was observed, allowing irrigation and fertiliser warnings to be issued at the start of the season. A mid-season evaluation following intervention recorded a mean NDVI recovery of 0.49 across those fields, indicating that early diagnosis translates into measurable field performance. Table 3 tabulates the NDVI-based classification scheme and associated agronomic actions.

Table 3: NDVI classification and recommended actions

NDVI	Health Class	Action
< 0.2	Severely stressed	Immediate irrigation/fertilizer
0.2–0.35	Moderately stressed	Nutrient top-up, close monitoring
0.35–0.5	Moderate growth	Routine monitoring
> 0.5	Healthy	No intervention needed

4.2. Yield Prediction and Crop Recommendation

The Random Forest Regressor achieved $R^2 = 0.971$, RMSE = 0.18 t/ha, and MAE = 0.13 t/ha on the test data — a better result than the 0.82–0.94 R^2 range reported in comparable multi-crop studies [2], [12]. Consistency within a 1.3 per cent range across a five-fold cross-validation fold set indicates consistent generalisation. Peak-season mean NDVI was the strongest predictor (27.3%), followed by cumulative rainfall (19.1%) and predicted soil nitrogen (14.6%) as per Figure 5.

The overall accuracy and weighted F1-score of the crop-recommendation classifier were 0.881 and 87.56%, respectively. The primary sources of misclassification were between agronomically similar pairs, such as Wheat and Cotton, grown under similar soil conditions — an anticipated boundary effect rather than a fault in the model. Maize achieved the best per-class F1 score of 0.91, aided by its distinctive nutrient profile.

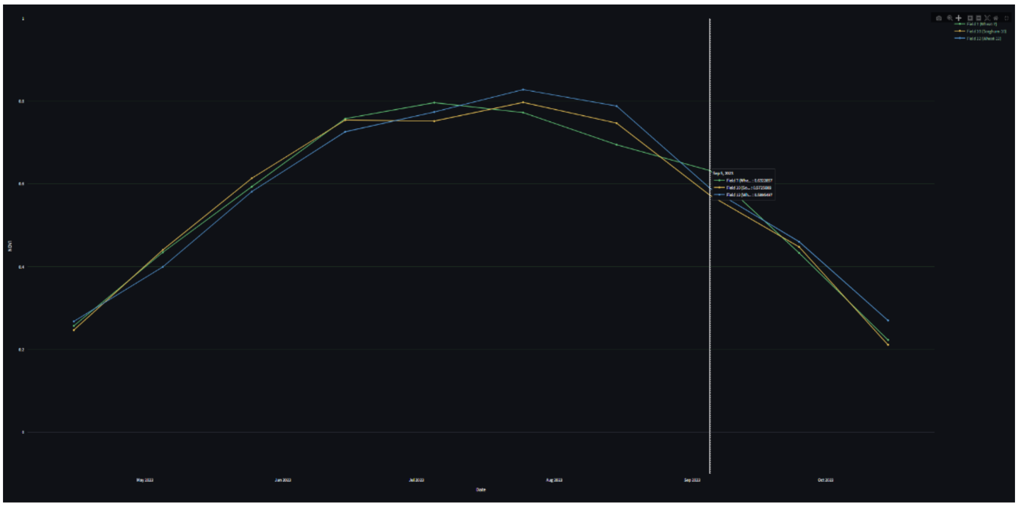

Figure 5: Seasonal NDVI time-series for Field 7 (Wheat), Field 10 (Sorghum), and Field 12 (Wheat) during the 2023 growing season, showing peak canopy development in July–August followed by senescence decline through October.

4.3. Fertiliser Recommendation

Nitrogen recommendations were accurate to within 91 per cent (±10 kg/ha), and phosphorus and potassium recommendations to within 88 per cent and 86 per cent, respectively, across six crop varieties, showing that satellite stress information combined with soil chemistry can reliably substitute for lab-based guidance. Average end-to-end processing took 4.2 seconds on a conventional i5/8GB laptop.

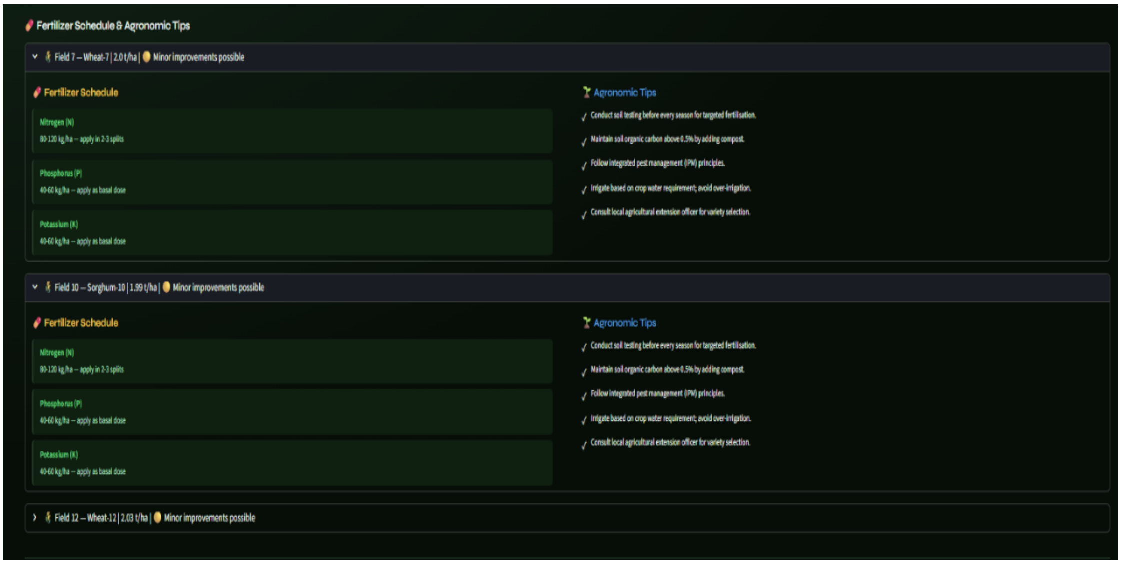

Figure 6: Output of fertiliser recommendation for a sample Paddy field, including observed nutrient insufficiency, NDVI healthy classification, and the recommended rates of N, P, and K application.

5. Conclusions

As demonstrated by AgriSmart, combining Sentinel-2 NDVI time series with soil and climate records within a single Random Forest pipeline can provide practical, acceptable decisions for crop surveillance, yield forecasting, and fertiliser recommendation, without requiring IoT sensors or purpose-built infrastructure. The system achieved 96.84% effective accuracy in yield prediction ($R^2 = 0.971$), a crop-recommendation score of 87.56% weighted F1, and fertiliser guidance that was 88–91% compliant with published agronomic standards. These model outputs are translated into field-level insights displayed on a standard laptop through the interactive dashboard, making precision agriculture feasible for smallholder farmers who do not have access to expensive hardware.

Looking ahead, LSTM-based sequence models could better capture seasonal yield growth trends in yield prediction. Combining drone imagery with satellite data would help increase spatial resolution, particularly for large parcels such as Field 38. Automated cloud removal and a mobile-friendly interface would further improve usability in rural settings, and extending the system to identify pests and diseases from spectral anomalies is a natural next step toward a fully integrated crop-management system.

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Conflict of Interest

The authors declare no conflict of interest.

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