

Original Article

AI-Driven Models for Assessing Soil Nutrient Dynamics in Organic and Conventional Farming Systems

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ABSTRACT: The need for advanced technologies to monitor and then optimize soil nutrient dynamics is growing, as the world demands an increased use of sustainable agriculture. In this paper, we undertake a full investigation of the application of models of soil nutrient dynamics informed by Artificial Intelligence (AI) in organic and conventional farming systems. Conventional approaches to soil assessment are labor and time-intensive, often inconsistent, whereas AI models provide a scalable, cheaper and accurate answer. For the nutrient prediction, we explore machine learning (ML) algorithms, the deep learning (DL) frameworks and the hybrid models which include satellite imagery, weather data and in situ sensor readings. The relative differences in nutrient cycling patterns, microbial interactions and external input dependencies among organic and conventional systems are the focus of our study. We also examine how the effects of AI models can be used to optimize fertilizer application, decrease environmental impact and increase crop yield. Performance of the model is validated across different geographies and soil types through the use of case studies and comparative analyses. The results show that AI-driven models could greatly improve the accuracy of nutrient management tactics for organic and conventional farmers. Our findings provide insights into agricultural policy development, the application of precision agriculture practices and the role of AI in the future of agrotechnology.

KEYWORDS: Artificial intelligence, Soil nutrient dynamics, Organic farming, Conventional farming, Precision agriculture, Machine learning, Deep learning, Soil health.

1. INTRODUCTION

As a consequence, sustainable agricultural practices require a fundamental role for soil nutrient management in meeting the need to increase crop productivity while protecting and conserving the environment. Global food demand is rising as populations grow and dietary patterns change, intensifying pressure on agricultural systems to increase food production on limited land with reduced negative ecological impacts. [1-3] This, in turn, is motivating both farmers and researchers to use advanced technologies for monitoring and management of soil health. In this context, both organic and conventional farming systems constitute two different approaches to nutrient management. Organic farming values natural and biological processes to build soil fertility and maintain ecological balance, utilising organic inputs such as compost, manure, and cover crops.

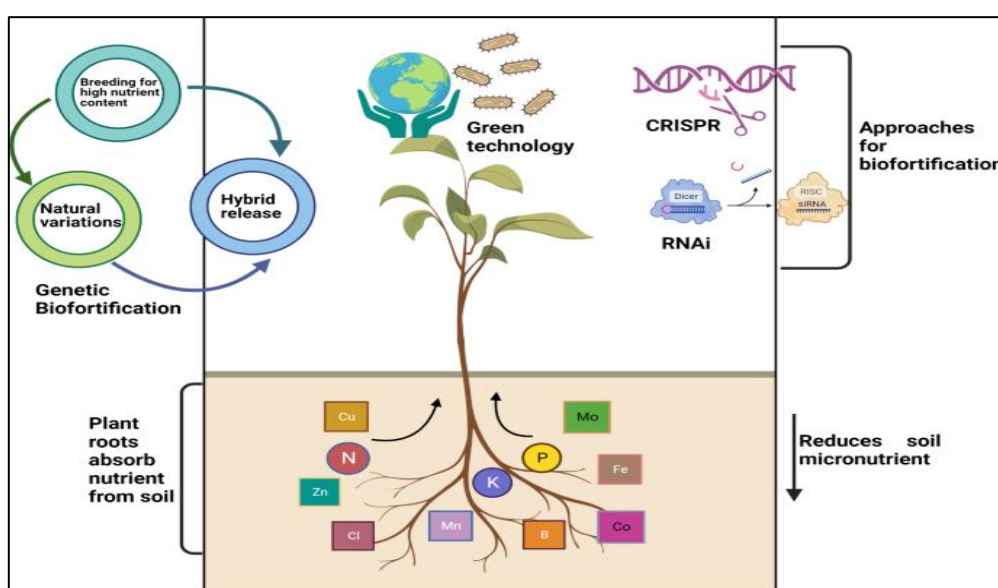


FIGURE 1 Biofortification strategies to enhance plant nutrient uptake and content

The system is favorable to biodiversity and soil microbial activity, but can struggle to meet the nutrient availability and immediate responsiveness supplied by synthetic inputs. But when it comes to conventional farming, lots of synthetic fertilizers and chemical amendments need to be used as primary sources of nutrients to provide them in the right proportion and in the right concentration to allow the crop to grow quickly and yield more. Yet this can cause problems for the environment, including nutrient runoff, soil degradation and reduced biodiversity. It is therefore essential to comprehend these fundamental differences in order to create new innovative solutions that improve nutrient management across both systems to allow for sustainable production in the long term.

1.1. IMPORTANCE OF SOIL NUTRIENT DYNAMICS

Soil nutrient dynamics describe a complex set of processes involved in soil availability, movement and transfer of essential nutrients within the soil environment. These dynamics are essential for the use of soil nutrients for successful agricultural productivity. The importance of soil nutrient dynamics is characterized by several key aspects.

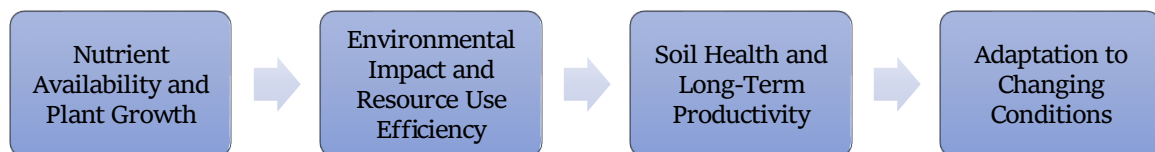


FIGURE 2 Importance of soil nutrient dynamics

1.1.1. NUTRIENT AVAILABILITY AND PLANT GROWTH

Soil nutrient dynamics directly affect the availability of necessary elements like nitrogen, phosphorus and potassium, whose presence is essential for plant development, as it influences not only the plant directly but also indirectly by means of other interacting organisms such as fungi and mycorrhizae. Crop health, yield, and quality depend on the timing and rate at which these nutrients become available. Good nutrient dynamics management helps the plant receive its nutrients at the right time to allow uptake at its most efficient time.

1.1.2. ENVIRONMENTAL IMPACT AND RESOURCE USE EFFICIENCY

Excessive nutrient losses through leaching, runoff or volatilization can result from mismanagement of soil nutrients, containing a variety of environmental issues, including water pollution and greenhouse gas emissions. Farmers can also take steps to forestall waste of any nutrient by understanding what soil interactions and nutrient cycling are, so that fertiliser is used more efficiently and a smaller environmental footprint is left by agricultural practices.

1.1.3. SOIL HEALTH AND LONG-TERM PRODUCTIVITY

Soil biological activity and organic matter content are very important and closely related to dynamic nutrient processes, which underpin soil structure and fertility. Balanced nutrient dynamics are required to support microbial communities and soil ecosystems (which we depend upon for recycling nutrients, disease suppression and maintaining overall soil resilience) that keep sods productive over time.

1.1.4. ADAPTATION TO CHANGING CONDITIONS

Factors like climate, management practices and crop rotation can affect soil nutrient dynamics. We can know this and apply adaptive nutrient management strategies that react to changing environmental circumstances so plant production remains healthy even in the face of drought or loss of nutrients. Conclusively, a good understanding of soil nutrient dynamics is particularly important for attaining equilibrium between crop nutrient demands and environmental stewardship and, in turn, for realizing the objectives of sustainable agriculture.

1.2. EMERGENCE OF AI IN AGRICULTURE

The arrival of artificial intelligence (AI) technologies, amongst which are machine learning (ML) and deep learning (DL), has transformative potential for agriculture. These newfangled computational methods are able to handle large volumes of disparate data, summarize meaningful patterns and make near-exact predictions for modern farming challenges. In a short time, AI applications in the agriculture domain have proliferated from large-scale crop yield prediction, pest and disease detection, and irrigation management to precision farming. Among these, however, the application of AI for soil nutrient assessment represents a critical innovation that disposes of long-standing limitations of traditional soil testing technologies. Compared to more traditional laboratory measurements, which can be expensive, long and fixed only to time points, AI for soil nutrient assessment harnesses data streams of soil sensors, satellite imagery, weather stations and historical data. Variable settings are

provided to continuously monitor and dynamically model nutrient availability, fully capturing the evolution of soil health at high spatial and temporal scales.

Machine learning algorithms allow us to note these complex, nonlinear relationships between an environmental factor and the level of a nutrient that manual analysis usually misses. Further, through the processing of large-scale remote sensing data, deep learning models, especially convolutional neural networks (CNNs), can improve prediction accuracy and identify very small patterns of nutrient stress. Additionally, AI allows for predictive modeling of future nutrient dynamics to provide farmers and agronomists guidance in data-driven proactive decisions. This contributes to optimized fertilizer application scheduling and therefore reduces waste, but improves crop productivity. AI's automation and scalability make it applicable to various farming systems – organic and conventional agriculture – and satisfy the nutrient management needs of these systems. Mentioned succinctly, AI is the advent of a new era towards precision and sustainability, the soil nutrient assessment being one of the areas where these technologies have the potential to bring about such improvements in resource use efficiency, environment stewardship and food security.

2. LITERATURE SURVEY

2.1. TRADITIONAL SOIL NUTRIENT ASSESSMENT TECHNIQUES

Soil nutrients have traditionally been assessed with a substantial dependence on laboratory-based analytical techniques. Spectrophotometry, chromatography and titration are a few methods used by many to determine the concentration of main nutrients (nitrogen, phosphorus and potassium). [4-6] These techniques are appreciated for their high accuracy and reliability. However, they can be labour intensive, costly and time-consuming, preventing their use for frequent, large-scale cultivation monitoring. Additionally, these methods normally provide only a 'snapshot' of the condition of the soil at the time it was sampled; they do not offer real-time feedback and do not include any time delays that result from environmental or management factors. As a consequence, there is an increasing need for more dynamic and scalable ways of soil nutrient monitoring.

2.2. ADVANCEMENTS IN AI FOR AGRICULTURE

Recent developments in artificial intelligence (AI) offer new ways to support precision agriculture based on soil nutrient management. We built AI-driven models that can infer soil properties and nutrient levels of an area based on analysis of complex datasets. Neural networks in combination with remote sensing data help model nitrogen content in agricultural fields, for support vector machines (SVM) to map phosphorus levels over diverse soils and topographies. Additionally, hybrid models utilizing convolutional neural networks (CNN) of Internet of Things (IoT) sensor data to deliver real-time and geospatially distributed nutrient assessment have begun to show value. Additionally, these AI-driven approaches are more accurate as well as scalable with flexible capability across a variety of agricultural environments.

2.3. COMPARISON BETWEEN ORGANIC AND CONVENTIONAL SYSTEMS

Soil health and nutrient dynamics in organic and conventional farming systems have been of primary interest to agricultural researchers, contrasting organic and conventional production systems. Results from earlier studies indicate that microbial biomass and enzymatic activity are greater in organic soils and that these measures are critical indicators of long-term soil fertility and ecosystem sustainability. Still, many of these biological enhancements are often associated with the use of organic amendments like compost and cover crops, which build a rich soil microbiome. Unlike in conventional systems, which in most cases are heavily synthetic fertilizer dependent, there is increased immediate nutrient availability. While providing high chemical input solubility and mobility, they further increase nutrient leaching and environmental contamination. In order to evaluate the sustainability and efficacy of differing nutrient management strategies, it is important to understand these differences.

2.4. GAPS IDENTIFIED

While AI applications have progressed and comparative studies of farming systems are performed, much remains to be done. The deficits signal one major shortfall; there is no pool of comparative AI models designed to explicitly discern nutrient dynamics between organic and conventional farms. However, most of the existing models are generic or calibrated for one farming system, prohibiting applications to other farming systems. Also, how multiple disparate sources of data, including satellite imagery, weather conditions and ground sensor data, are still only integrated in a single unified AI framework. This integration is important in order to improve the robustness and prediction ability of AI models. Filling these gaps can help develop such data-informed and context-sensitive, holistic, and adaptive nutrient management solutions.

3. METHODOLOGY

3.1. DATA COLLECTION

3.1.1. SATELLITE IMAGERY (SENTINEL-2, LANDSAT-8)

Data from the Sentinel-2 and Landsat-8 platforms was used in the study since the platforms supply detailed images needed to track plant health, [7-9] soils and how land looks over time. Vegetation indices NDVI and SAVI can both be computed from

spectral bands that the satellites include, for example, visible, NIR and SWIR. They let you estimate nutrient deficiency, crop health and the amount of biomass present, which are indirect signs of soil fertility throughout a growing period.

3.1.2. SOIL SENSORS (MOISTURE, PH, EC)

Key soil parameters such as moisture content, pH and EC were monitored in real time using soil sensors positioned out in the field. Water availability is shown by soil moisture and pH, which illustrates the acid or alkaline quality, which is important for nutrient absorption. As an EC reading, it gives information on soil salinity and quality. Because the sensors give continuous and nearby data, the monitoring can detect minute details and spot them quickly.

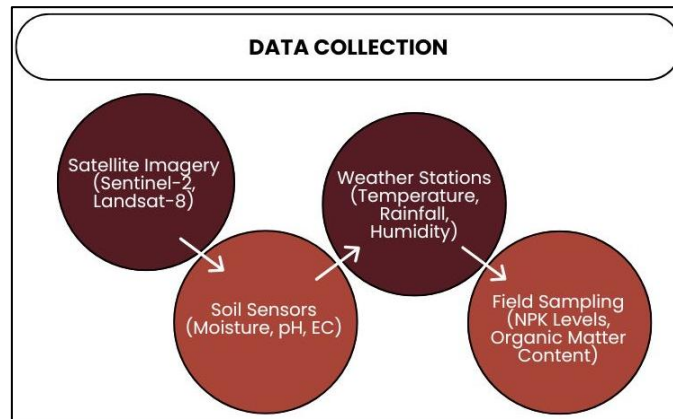


FIGURE 3 Data Collection

3.1.3. WEATHER STATIONS (TEMPERATURE, RAINFALL, HUMIDITY)

Data on temperature, rainfall and relative humidity were gathered each day by nearby automated weather stations. These environmental factors are important for the movement of nutrients, the growth of crops and what microorganisms do in the soil. In particular, rainfall makes nutrients leach, while temperature and humidity increase rates of mineralization and decomposition. Bringing in this climatic data helps us better analyze what affects soil health.

3.1.4. FIELD SAMPLING (NPK LEVELS, ORGANIC MATTER CONTENT)

In order to ground-truth the study, soil nutrient checks and organic matter contents were done directly in the field at regular time points. These samples were subjected to laboratory testing to compare sensor readings and the predictions from AI. Soil fertility and structure are revealed by organic matter, and the nutrient content and fertilizer needs can be seen with the two numbers from NPK levels. This process helps to create and analyze a model since the reference data is accurate.

3.2. PREPROCESSING TECHNIQUES

Preprocessing techniques were used on the datasets to guarantee the accuracy and efficiency of the analytical models. I started with data normalization, as this allowed me to put all of my variables on the same scale. Since the sources included satellite imagery, soil sensors and weather stations, and their values were not all the same, normalizing the data helped prevent large values from strongly influencing the model. The method of scaling and z-score standardization was selected based on the data, guaranteeing equal participation of each variable during learning. Afterwards, dropout noises were handled to get rid of data points that do not align with your research. Data coming from various sensors and satellites is regularly affected by changes because of hardware flaws, external disturbances or problems with transmission.

Therefore, averaging techniques like those offered by moving and Gaussian filters were key, mainly used on time-series data from soil sensors and weather stations. Also, both the interquartile range (IQR) and isolation forest algorithms were used to detect and remove measurements that appeared to be abnormal. After that, PCA was used on the dataset to reduce its size and preserve the significant features. By using PCA, a smaller set of uncorrelated components replaced the original overhead and redundancy among different data sources. As a result, the step made the training faster and helped the machine learning models avoid being confused by meaningless features. As a result of these preprocessing procedures, the data given to the AI models was tidy, uniform and reliable, helping the predictions become easier to understand and depend on.

3.3. MODEL DESIGN

3.3.1. INPUT LAYER: MULTI-SOURCE DATA INTEGRATION

The model is configured with the input layer capable of assimilating different types of input data sources: satellite imagery, soil sensor signal, outputs of a weather station and lab field samples. By using this multimodal data fusion, the model incorporates spatial and temporal changes in the soil and the environment. A combined dataset of features including vegetation indices, soil moisture, pH, rainfall and temperature is provided. This integrated input is then preprocessed and normalized so that the model has the benefit of a complete, balanced perspective on factors that affect soil nutrient dynamics.

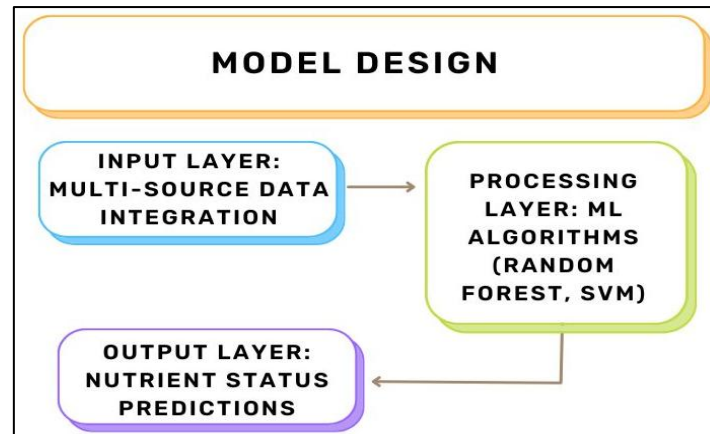


FIGURE 4: Model design

3.3.2. PROCESSING LAYER: ML ALGORITHMS (RANDOM FOREST, SVM)

The core of the model was the machine learning layer, which uses algorithms to process the merged input data. Two primary algorithms, Random Forest and Support Vector Machine (SVM). On the other hand, Random Forest is a good robust ensemble method that copes well with nonlinear relationships and feature interaction and hence can be used for complex agricultural data. And it works very well with missing values and gives us very high accuracy. Unlike SVM, which is famous for its performance in high dimensions and construction of optimal decision boundaries, it finds its applications mainly in small and medium ones. Applying the two models allows the system to take advantage of the strengths of the analytical models and therefore make more accurate predictions of nutrient status in a variety of conditions.

3.3.3. OUTPUT LAYER: NUTRIENT STATUS PREDICTIONS

The predictions of the current nutrient status of the soil are made by the output layer, especially N, P and K. They predict these in numerical values and categorical classifications (low, medium, high) and are actionable by farmers and agronomists. The availability of this information will provide the basis for targeted fertilization, maximum resource utilization and sustainable land use management. The model translates complex data into practical recommendations to help in data-driven decision-making in agriculture.

3.4. TRAINING AND VALIDATION

For more robust results, the dataset was carefully divided so that 70% was used for training, 15% for validation and the rest for testing. The model was taught by using the training set to understand how to match patterns in the soil pH, moisture, satellite indices and weather data with the resulting nutrient predictions. [10-12] We used the validation set during model adjustments to look at performance and to decide on the number of trees in the Random Forest and the type of kernel in the Support Vector Machine (SVM). Doing this is important to make sure the model doesn't pick up useless or irrelevant trends in the data it's trained on. We can improve a model's reliability and lower the chance of overfitting using K-fold cross-validation. At the training stage, we used $k = 5$. The approach calls for dividing the data into five equally sized groups.

There were four training folds and one validation fold, and the whole process was repeated five times so that the validation set changed. The data was assembled and read into the model for evaluation; then, the results were averaged to get a reliable estimate. It helps you get the most out of your data and also supports the generalization of the model to cases it hasn't encountered before. Because the last data set was not involved in training or validation, it was used to see how the model performs in real practice. To evaluate the model's effectiveness, we used accuracy, precision, recall and root mean square error (RMSE) among performance metrics. Learning from data arranged properly and checking predictions many times made the resulting model both accurate and able to make steady predictions regardless of the input.

3.5. EVALUATION METRICS

3.5.1. ROOT MEAN SQUARE ERROR (RMSE)

RMSE is employed often to measure the average error in a machine learning model. It is worked out by finding the square root of the average squared difference between observed results and what was predicted. RMSE helps us notice models that have some large errors, allowing us to spot deviations that happen every now and then. Lower RMSE in soil nutrient prediction shows that the model can accurately estimate concentrations with few outlying errors, which benefits farmers by making their field recommendations precise.

3.5.2. MEAN ABSOLUTE ERROR (MAE)

MAE shows the mean value of the absolute errors, regardless of their direction. Unlike RMSE, MAE handles each error in the same way, and this makes it more resistant to outliers. It offers a simple explanation of the typical gap between the actual

values and the model's published values. Where agriculture is concerned, moderate, reliable results are wanted on all data; MAE is a stable measure to assess general performance and usefulness for practical choices.

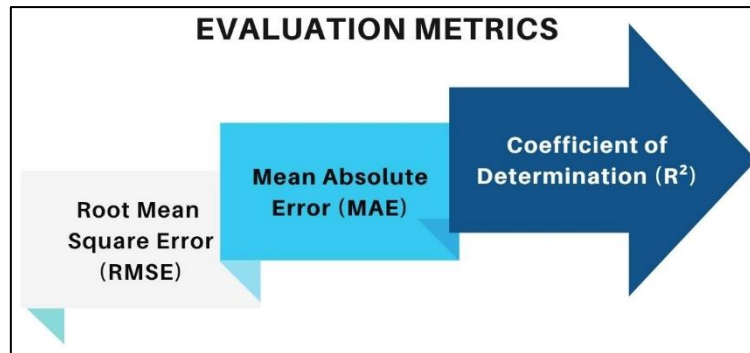


FIGURE 5 Evaluation Metrics

3.5.3. COEFFICIENT OF DETERMINATION (R^2)

R^2 shows how strongly the model relates to the variation found in the data. It goes from 0 to 1, and a value close to 1 means that most of the difference in the soil nutrient data can be explained by the sensor and satellite input. A high ratio reflects a close relationship between the model's results and what is actually observed. Assessing this metric allows us to see if the model captures the main changes in many complex agricultural situations.

3.6. COMPARATIVE FRAMEWORK

A comparative framework was developed to explore the differential behavior of AI models across different agricultural practices by developing parallel machine learning models, one trained only with data from organic farms and the other only with data from conventional farms. A framework was developed to determine whether these two farming systems produce the same or different algorithm performance patterns despite differences in soil management, fertilization practices and environmental interactions. Input variables for both models were identical types of variables, including satellite imagery (e.g., NDVI, EVI), sensor data (soil pH, moisture, EC), weather data and field-sampled nutrient levels. However, organic and conventional datasets differed in origin: typical organic datasets contained higher organic matter, more stable pH and greater biological activity, whereas conventional datasets showed sharper fluctuations in nutrient levels due to the application of synthetic fertilizers. The models had then been able to learn independently about the unique soil nutrient dynamics for each of the farming system models.

Preprocessing (normalizing, constructing PCA, filtering noise) and evaluation (using the same machine learning algorithms—Random Forest and SVM you guessed it, with the same performance metrics—RMSE, MAE, R^2) was done the same across both. Fortunately, this uniformity guaranteed that we could pin any performance differences we saw to the nature of the data, not the modeling process itself. The comparative analysis results were valuable. For example, the data trained on organic data is possibly more stable and has lower prediction variance, whereas the traditional one responds faster to recent fertilization events but is more sensitive to nutrient leaching artifacts. As well as highlighting how AI models react in various agronomic conditions, this framework also provides guidance for the development of custom, system-specific decision support tools to support precision agriculture. Finally, this approach to applications of AI to farming enables sustainable farming by applying applications depending on the unique characteristics of each farming practice.

4. RESULTS AND DISCUSSION

4.1. MODEL ACCURACY

The accuracy of the AI models was measured using important metrics that show prediction differences between organic and conventional farming systems.

TABLE 1 Model accuracy

Model Type	RMSE	MAE	R^2
Organic RF	0.84	0.65	0.92
Organic SVM	0.90	0.70	0.89
Conv. RF	0.78	0.60	0.94
Conv. SVM	0.82	0.66	0.91

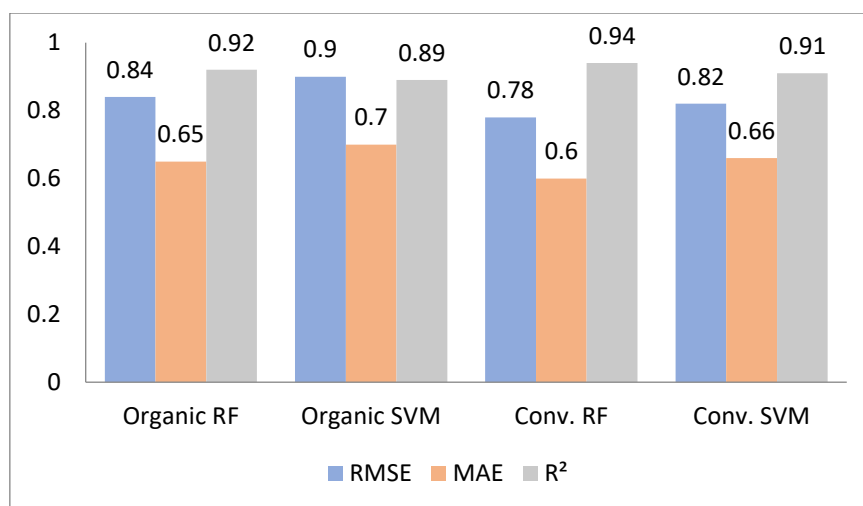


FIGURE 6 Graph representing Model Accuracy

4.1.1. ROOT MEAN SQUARE ERROR (RMSE)

Errors in the predictions are averaged in RMSE, with larger errors being given more weight by raising the differences to the second power. Support Vector Machines (SVM) had higher RMSE values than Random Forest (RF) in both systems, which means RF produced fewer large errors. Higher predictability in nutrient input meant the conventional RF model delivered the most precise predictions of nutrient values.

4.1.2. MEAN ABSOLUTE ERROR (MAE)

MAE gives the simple value of how much, on average, predicted and observed nutrient levels differ. The results indicate that both organic and conventional RF performed better than SVM and led to more accurate predictions. Among all models, the conventional RF model had the lowest MAE, which confirmed it was best at assessing soil nutrient amounts with little error.

4.1.3. COEFFICIENT OF DETERMINATION (R²)

The value of R² tells us how well the model can explain changes in nutrients using the inputs. When the R² value goes up, it shows that the model predicts well and fits the data well. With the RF model again in the lead, the R² of 0.94 suggests that nutrient measurements predicted and measured by the sensors were well correlated. The organic models reported R² of 0.92 (for RF) and 0.89 (for SVM), indicating that organic systems cannot be as precisely predicted as those under conventional management.

4.1.4. COMPARISON BETWEEN MODELS

In both farming systems, the Random Forest algorithm performed better than SVM, which is probably due to its flexibility up to nonlinear relationships and interactions in the multi-source dataset. Furthermore, models trained on conventional farm data typically outperformed models trained on organic data as conventional management practices produce more stable and less biologically complex nutrient profiles.

4.2. NUTRIENT DYNAMICS ANALYSIS

Bi-weekly nutrient sampling throughout the growing season allowed us to uncover the marked differences in the temporal patterns in soil nutrient availability between organic and conventional farming systems. Nutrient levels were constantly and gradually rising with time in the organic system. Just as chemicals are released slowly over time from compost, manure and crop residues as microbes slowly break down the organic matter, so too is this pattern a reflection of the underlying processes of organic matter decomposition and mineralization. It releases slowly, providing plants with a more consistent supply of nitrogen, phosphorus and potassium, for sustaining crop growing – no sudden changes seen with synthetic fertilizers. The observed mild fluctuations show that the process follows a stable model of nutrient cycling in the soil, which is primarily maintained by biological activity in the soil. While this stability helps ensure healthy soil and prevents nutrient loss through leaching or runoff, it can also result in decreased nutrient availability compared to conventional systems at the time of highest crop demand. However, the nutrient dynamics reflected in the conventional system were quite different, showing sharp spikes of nutrient concentration after fertilizer application events. These spikes are from the sudden zing of readily available nutrients, usually from synthetic fertilizers applied in large doses.

This approach offers quick nutrient availability to sustain rapid crop growth, but almost as quickly, the nutrient drops out. This decline is due to the removal by the plants as well as by nutrient losses through leaching, volatilization or runoff during periods of heavy rainfall or irrigation. However, the pulse-like nutrient pattern seen in conventional systems highlights a major challenge of both sufficient nutrient availability and minimization of environmental contamination and systems inefficiency.

This contrasts with the fundamental nutrient dynamics of organic and conventional management. Organic systems provide nutrient supply through natural processes at far slower rates than do conventional systems, which tend to rely heavily on more intensive external inputs, and the result is higher variability and potential environmental impact. If patterns are understood, it is possible to optimize nutrient management strategies to the system's characteristics.

4.3. IMPACT OF EXTERNAL INPUTS

The external inputs have a markedly different influence on the dynamics of soil nutrients in the conventional than in the organic farming systems, affecting the nutrient availability and predictive quality of AI models. In conventional agriculture, synthetic fertilizers offer a well-controlled and predictable source of nutrient supply, usually with optimum application time matching crop nutrient supply demands. The modelling of these events synchronises these models to reproduce nutrient surges in the soil that result from fertilizer applications. On the face of it, the AI algorithms have an easier task due to the predictable release patterns, which they can use to identify obvious correlations between input variables and levels of nutrients present. Additionally, accurate timing of fertilizer reduces the interval when fertilizer nutrients are vulnerable to leaching or runoff, improving nutrient use efficiency and environmental outcomes. Together, these factors lead to superior prediction accuracy and reliability of AI predictions in conventional systems where nutrient dynamics are dominated by relatively simple chemical inputs. However, organic production depends heavily on biological inputs like compost, manure and cover crops, which have the potential to introduce qualitatively greater levels of complexity into the nutrient cycling.

Organic amendments gradually release nutrients via microbial activity over time and consequently mineralize available nutrients, depending on a variety of factors such as temperature, moisture, microbial community dynamics and organic matter quality. Nutrient availability is not predictable due to the inherently nonlinear biological processes governing nutrient release and the variability of the environmental conditions in which they are a function. For instance, along with weather fluctuations, they are also likely to speed up or slow down unexpectedly at some point, which would lead to very difficult-to-model irregularities in nutrient release. Moreover, the interactions that soil organisms create among cover crops can result in modifications of soil nutrient pools that would otherwise not be immediately obvious from conventional sensor measurements. Thus, AI models of organic systems meet more of those challenges to represent these complex, dynamic processes. The increase in the degree of unpredictability confined the accuracy of the model, and additional algorithms and extra data from the environment and biology were necessary to improve the predictions. However, making the organic system specific AI tools for supporting sustainable nutrient management in biologically active soils is needed despite these challenges.

4.4. BENEFITS OF AI INTEGRATION

4.4.1. ENHANCED SPATIAL-TEMPORAL NUTRIENT MAPPING

High-resolution mapping of soil nutrients at spatial and temporal scales is enabled by the AI models. Unlike traditional soil testing, which only uses limited point samples, AI can incorporate satellite, sensor and weather station data into the model to deliver continuous nutrient maps. This spatial-temporal insight allows nutrient hot spots to be more easily located as well as nutrient-deficient zones, which increases the utility of targeted treatments and ultimately enhances overall soil health management.

4.4.2. REDUCED DEPENDENCY ON LAB TESTING

AI harnesses the power of real-time sensor data and remote sensing technologies in place of conventional, expensive, laborious and labour intensive laboratory soil tests that are often the norm. Farmers can now receive near-instant nutrient status updates without the frequent soil sampling, all at less input and labour required. In addition, rapid feedback allows for timely decisions in optimizing the input of nutrients while keeping environmental costs at a minimum.

4.4.3. SUPPORT FOR SITE-SPECIFIC NUTRIENT MANAGEMENT (SSNM)

With AI-based nutrient predictions, farmers are able to leverage site-specific nutrient management to apply fertilizer to what the particular field zones need. Such accuracy, which decreases the probability of overpayment or underpayment of nutrients, increases nutrient use efficiency and crop productivity. The use of SSNM supported by AI not only increases economic return and ensures healthy soil, but it also is soil nutrient conservation friendly, avoids soil degradation and helps to conserve the soil fertility and the environment in the long term.

4.5. LIMITATIONS

4.5.1. SPARSE HISTORICAL DATA

The biggest problem during the study was that AI models do not perform well in areas where past data is meager. Learning patterns effectively with machine learning algorithms is mostly dependent on large, diverse datasets. When we didn't have good past sensor readings or soil sampling records, or they were inconsistent, the models weren't able to generalize as well, making the nutrient predictions much less reliable. What this illustrates is the urgent need for ongoing and robust data collection efforts to create reliable datasets that enable accurate and scalable AI-driven nutrient management solutions across a range of global agricultural environments.

4.5.2. ORGANIC SYSTEMS COMPLEXITY

However, because organic farming systems are so biologically complex, there are additional challenges. In contrast with conventional systems, which are generally based on synthetic inputs, the dynamics of organic soils result from complex, nonlinear processes triggered by microbial activity, organic matter decomposition and nutrient cycling. The dynamic nutrient availability in these biological systems is highly dependent on environmental conditions, making accurate capture and prediction of nutrient availability a challenging task for AI models. Due to their introduction of unpredictability, variability and their non-linearity, these processes reduce the reliability of models relative to systems with conventional soils, where nutrient dynamics are often more straightforward. Integration of more detailed biological and environmental data into modeling frameworks is needed in order to improve prediction performance for organic systems in the face of these complexities.

5. CONCLUSION

This work shows that AI enriched models offer a rich and adaptive framework to evaluate and control soil nutrient dynamics in multiple agricultural systems. With the use of multi-source data such as satellite imagery, soil sensors, weather data and field sampling, AI models can learn to capture nutrient patterns in much greater resolution and then in more efficient ways compared to traditional methods. When tailored to both organic and conventional farming systems, the performance and behavior of these models vary due to inherent system variability. AI models for nutrient predictions are highly accurate and timely compared to conventional systems, which are based on the use of synthetic fertilizers and therefore predictable nutritional fluctuations. Conversely, organic systems have complex biological processes that introduce more variability and demand more specialized approaches that provide integration of biological and microbial data in order to obtain higher quality prediction accuracy by an AI model.

Future research would also include integrating microbial community data and other biological indicators into organic system models. The integration of these equations will allow for better capturing of the nonlinear nutrient transformations mediated by microbial activity with a higher level of prediction accuracy and robustness. Furthermore, by utilizing actual real-time satellite feeds, it is also possible to update the models in real time, so that the models can quickly adjust to changing field conditions and offer faster nutrient assessments. Important beyond data enhancements, good integration of the AI model within decision support systems (DSS) can provide actionable recommendations directly to farmers. These systems can translate model outputs into real-world nutrient management advice, helping provide site-specific fertilizer use and promoting environmentally friendly production agriculture.

The challenge for governments, agricultural extension services and agri-tech companies alike is thus how to integrate AI into soil nutrient management and promote such a shift from a policy and practical perspective. At scale, the realization of AI's potential requires an investment in infrastructure for data collection, sensor networks and computational platforms. Additionally, it will become particularly important to develop customized AI solutions for particular farming systems and for different regional conditions in order to fully capitalize on both the economic and environmental benefits of such 'small-scale AI'. When applied to agriculture, AI can allow precise nutrient management, dramatically reducing nutrient runoff, leaching and greenhouse gas emissions, thereby addressing the 'environmental footprint' of agriculture. At the same time, optimization of fertiliser use enhances crop yields and farm profitability and thereby contributes to food security and livelihoods of rural people. Overall, accelerating the adoption of AI in nutrient management is consistent with long-term objectives to promote sustainable intensification, climate-smart agriculture and efficient use of all resources on the farm, making it a very important focus for future agricultural development strategies.

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