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Machine Learning-Powered Nano-Energy Systems for Sustainable Precision Agriculture and Soil Health Monitoring

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Abstract

Precision agriculture requires autonomous sensing technologies capable of continuously monitoring soil conditions while reducing energy consumption, maintenance requirements, and dependence on conventional batteries. Nano-energy harvesting provides a promising pathway for powering distributed agricultural sensors through ambient solar, mechanical, thermal, and vibrational resources; existing approaches frequently optimize energy harvesting, sensing, and soil-health prediction independently, limiting adaptability under dynamic field conditions. This paper proposes PHOENIX-Ag (*Physics-guided Hybrid Optimization of Energy and Intelligent Nano-Sensing for Agriculture*), a machine-learning-powered framework integrating hybrid nano-energy harvesting, physics-guided energy prediction, adaptive sensing, and intelligent soil-health assessment. PHOENIX-Ag combines photovoltaic, triboelectric, and piezoelectric nanogenerators to generate distributed energy, while a physics-guided learning model predicts energy availability from environmental, harvesting, and operational variables. A hybrid optimization mechanism dynamically regulates sensing frequency, energy allocation, storage utilization, and wireless communication according to predicted energy availability and soil-state dynamics. Multimodal soil observations, including moisture, temperature, pH, electrical conductivity, and nutrient indicators, are processed for soil-health classification and critical measurement prioritization. Experimental results demonstrate 98.1% energy-availability prediction accuracy, 97.2% soil-health classification accuracy, 95.1% energy-harvesting efficiency, and 94.5% adaptive sensing efficiency, with 286 mJ energy consumption and 329 days of sensor operational lifetime. Compared with conventional adaptive agricultural monitoring, PHOENIX-Ag reduces energy consumption by 30.6% and extends operational lifetime by 34.8%. These results establish PHOENIX-Ag as an energy-intelligent framework for sustainable, autonomous, and reliable soil-health monitoring in precision agriculture.

Keywords: Precision Agriculture; Nano-Energy Harvesting; PHOENIX-Ag; Machine Learning; Soil Health Monitoring

1. Introduction

Precision agriculture has progressed to data-driven farm management systems incorporating distributed sensing technologies to describe soil variability, to optimise irrigation and fertiliser inputs, and to enable site-specific

crop management [1]. It is imperative to monitor the soil condition continuously to ensure that moisture deficiency, thermal stress, salinity variation, nutrient imbalance and progressive degradation of the soil are detected [2]. Typically, conventional agricultural sensor networks are battery powered or use wired power supplies, which presents challenges for operating the networks in large fields or remote locations [3]. Regular battery changes create further maintenance needs, take measurements, and add to material waste [4]. These constraints have led to the design of self-powered sensing platforms that are able to harness useful energy from the surrounding environmental resources [5]. Nano-energy harvesting technologies such as photovoltaic, triboelectric, and piezoelectric nanogenerators are able to generate electrical energy from solar irradiance, mechanical motion and field-induced vibration, respectively, which are promising power generation methods [6]. Still, the energy available for harvesting is quite variable since weather, movement of agricultural machinery, soil dynamics and seasonal variation [7].

Most of the energy-aware systems used in agriculture monitor the energy harvesting, sensor scheduling and soil analysis separately [8]. This separation makes it difficult to coordinate the amount of available energy and the significance of the soil observations [9]. A sensor can use up a lot of energy when capturing an otherwise stable soil parameter, while periods of low harvested power can demand a lot of energy for examining critical changes in moisture, pH, electrical conductivity or nutrient condition [10]. While conventional machine-learning models can predict energy availability, or classify soil type, they often don't have any physical constraints and do not coordinate energy prediction with sensing decisions [11]. This leaves a research gap regarding an energy-behaviour-based model for integrated physical energy behaviour, machine-learning future predictions, adaptive sensing and soil-health intelligence [12].

To overcome these constraints, this research work introduces a novel approach called PHOENIX-Ag. The model combines disparate nano-energy harvesting with physics-informed machine learning to predict the future energy supply for dynamic agricultural conditions [13]. It utilizes hybrid optimization of the sensing frequency, energy allocation, storage usage and wireless communication based on the predicted power and soil-state requirements [14]. Multimodal soil observations are processed to yield meaningful soil health indicators, which can be used to intelligently prioritize critical soil measurements. The proposed architecture thus sets up a closed loop relationship between the available energy in the environment, soil dynamics, sensing needs and network operation [15]. The experimental results show an improvement in energy prediction, soil-health classification, harvesting efficiency, energy conservation and sensor lifetime. The developed structure gives a technical base for autonomy, sustainability and energy intelligence soil monitoring in precision agriculture.

- The development of the PHOENIX-Ag model, which is based on photovoltaic, triboelectric, and piezoelectric nano-energy harvesting, coupled with physics-guided machine learning to predict the availability of energy while operating sensors for agricultural applications.
- An energy-aware hybrid optimization mechanism that coordinates the frequency of sensing, amount of energy usage, storage utilization, and wireless communications based on the estimated energy supply and evolving soil-monitoring demands.
- Multi modal soil sensing, multimodal soil preprocessing, multimodal soil feature extraction, and machine-learning classification to monitor soil conditions in an intelligent way, reduce energy consumption, and extend the operational lifetime of distributed sensors.

2. Literature Review

2.1 Precision Sensing And Data-Driven Crop Management

Sustainable crop production is helped by precision agriculture technologies such as remote sensing, GPS-guided machinery, variable-rate technology and IoT sensors. These technologies allow accurate monitoring, efficient application of resources, lower chemical usage, lower water usage, and better soil health. Protecting the environment through sustainable precision agriculture optimization (SPAO) combines these technologies to boost productivity while helping to reduce environmental effects [16].

Early detection of crop stress and effective soil management is possible through the use of spectral imaging, machine learning, UAVs, IoT, GIS and variable-rate application technologies. The main obstacles of the adoption are high cost, lack of skills, lack of awareness, and reluctance to change the technology. Integrated Crop Protection and Soil Intelligence (ICPSI) is a strategy that combines sensing, analytics and interventions to create sustainable crop and soil management [17].

Soil mapping, crop monitoring, health assessment, and early detection of pests and diseases are all applications of remote sensing in soil. GIS is the basis for bringing together field and remotely sensed data, and machine

learning enhances data analysis. Remote Sensing Agricultural Intelligence (RSAI) is an integration of remote sensing, GIS, IoT and AI technologies for efficient utilization of resources and the reinforcement of sustainable agricultural decision-making [18].

Machine learning, artificial intelligence, automation, cloud computing and IoT sensors boost crop monitoring, predictive analytics, disease diagnosis, fertilization and irrigation. Cloud platforms are able to provide scalable data processing, and robotics can cut down on labour. AI-Enabled Smart Agricultural Management (AISAM) is an innovative concept that combines intelligent sensing, cloud analytics, and autonomous technologies with the purpose of enhancing productivity and lower expenses while preserving resources.AI-Enabled Smart Agricultural Management (AISAM) is an innovative concept that merges intelligent sensing, cloud analytics, and autonomous technologies with the goal of increasing productivity and decreasing expenses while conserving resources [19].

Site-specific agricultural management is possible through variable-rate application, proximal sensing, yield monitoring, data analytics, and machine learning. These technologies provide benefits in terms of increased input efficiency, decreased nutrient loss and reduced greenhouse gas emissions, and increased farm profitability. Site-Specific Resource Optimization (SSRO) integrates soil, crop and environmental data to make decisions on optimal agricultural inputs for sustainable food production [20].

2.2 AI, IoT And Intelligent Agricultural Optimization

Long-term soil health is achieved by organic amendments, cover cropping, crop rotation, reduced tillage, integrated nutrient management, biochar and microbiome technologies. Resource management is further enhanced by GPS, remote sensing and data analytics. Intelligent Soil Health Management (ISHM) is the combination of sustainable soil management and precision technologies that boost fertility, nutrient cycling, water retention, resilience and productivity in agriculture [21].

AI, IoT, blockchain, remote sensing, drones and imaging provide for intelligent monitoring along the entire agricultural production chain. These technologies can be used for crop selection, irrigation, fertilization, disease control, market forecasting and supply chain optimization. Agricultural Intelligence Framework (AIF) is an agricultural technology model focused on integration of digital technologies throughout the agricultural value chain to promote productivity, economic security, resource utilization and agricultural development in an environmentally sustainable manner [22].

Geoinformatics is used to identify soil typing and soil structure and the use of nanofertilizers and nanopesticides enhancing nutrient provision and crop protection. Nanotechnology can help to increase productivity while decreasing soil degradation and the loss of chemicals. Geo-Nano Sustainable Agriculture (GNSA) is a combination of the use of spatial agriculture intelligence and nanotechnology for increasing the efficiency of the use of resources, pest control, food security and environmental sustainability [23].

Technologies such as genetic engineering, molecular breeding, IoT, remote sensing, smart irrigation and soil conservation enhance the drought and water scarcity resistance of crops. Real-time monitoring helps manage water resources and stress. Climate-Resilient Precision Agriculture (CRPA) is an integration of genetic, sensing, and irrigation technologies which promote drought resistance, water-use efficiency, soil health, and sustainable crop production [24].

Precision farming information is provided by soil, crop, weather, environment, drone-based and hyperspectral sensors in real time. The IoT and AI convert the data from the sensor into recommendations to control irrigation, fertilisation and crop protection. Intelligent Sensor Fusion Agriculture (ISFA) is a holistic approach that combines data from multiple sources with intelligent analysis to enhance agricultural decision-making, resource management, crop productivity, and environmental sustainability [25].

2.3 Sustainable Soil, Resource And Economic Management

The spectral imaging, thermal imaging and fluorescence sensing technology can give an in-depth picture of crop stress, nutrient deficiency, diseases and pests. Precision management helps to minimise over-use of agrochemicals, but still produce yield. Proximal Crop Health Intelligence (PCHI) is a combination of high resolution proximal sensing and real-time processing of the data to aid in crop diagnosis, targeted interventions and sustainable crop management [26].

Real-time soil moisture, pH, plant stress, weather and other environmental parameters are tracked by IoT sensors. The use of AI and machine learning for disease prediction, yield forecasting, and automated agricultural

control. IoT Based Smart Farming Intelligence (ISFI) is optimized when the combination of sensor networks, intelligent analytics, and automated systems are used to optimize irrigation, fertilization, pest management, resource use and crop productivity [27].

The electrochemical sensors relay data on plant, soil and environmental factors that directly affect plant growth. To make precision-agriculture decisions, it is necessary to use effective data acquisition and analysis. The Electrochemical Precision Sensing Framework (EPSF) merges the field of electrochemical sensing with intelligent data management for more precise sensing, better use of agricultural inputs and less fertilizer, pesticide and environmental pollution [28].

An economic return from precision agriculture will depend on farm size, precision agriculture investment costs and input savings. Generally larger farms are more profitable and subsidies will increase availability for smaller farms. Profit-Aware Precision Agriculture (PAPA) is an integrated management system that uses economic analysis and precision resource management to determine economically sustainable technology adoption solutions to reduce crop protection costs and fertilizer inputs [29].

Conservation agriculture focuses on minimum tillage, permanent soil surface cover, crop diversification to enhance soil structure, C sequestration, microbial activity, water-use efficiency and ecosystem resilience. These can be supported by practice and by the use of precision agriculture, remote sensing and digital tools. Technology-Integrated Conservation Agriculture (TICA) incorporates conservation principles and current technologies to enhance productivity, climate resilience and environmental sustainability [30],[31].

Table 1: Comparative Analysis of Existing Precision Agriculture Methods

Method	**Functional Coverage* (%)**	**Soil Intelligence**	**Resource Adaptation**	**Sustainability**	**Implementation Complexity**
SPAO	100	High	High	High	High
ICPSI	100	High	High	High	High
RSAI	86	High	High	High	High
AISAM	86	High	High	High	Very High
SSRO	100	High	High	High	High
ISHM	86	Very High	High	High	High
AIF	86	High	High	High	Very High
GNSA	86	High	High	Very High	Medium
CRPA	86	High	High	Very High	Very High
ISFA	86	High	High	High	Very High
PCHI	86	Very High	High	High	High
ISFI	86	High	High	High	High
EPSF	57	Very High	Medium	High	Medium
PAPA	100	High	Very High	High	High
TICA	100	High	High	Very High	Very High
PHOENIX-Ag (Proposed)	100	Very High	Very High	Very High	Medium

2.4 Research Gap

The existing precision agriculture methods are well positioned to take advantage of the applications of remote sensing, IoT, AI, GIS, smart sensors and variable-rate technology in the crop monitoring and resource optimization arena. The approaches are mostly aimed at one function though (soil assessment, crop-health detection, crop irrigation or economic analysis), and do not provide an integrated approach. The costs of implementation, interoperability of sensors, connectivity problems, data privacy, complex data processing and inability to make decisions in real-time remain un-addressed. In addition, there are many methods that do not have adaptive resource allocation and comprehensive sustainability evaluation in both the environmental and economic aspects. Therefore, a flexible and intelligent precision agriculture platform is required that will enable the integration of multisensor sensing, AI-based analysis, rapid decision making, resource utilization and sustainability assessment in different farming situations.

3. Materials and Methods

3.1 Dataset and Data Acquisition

The paper aims to leverage dataset gathered by multimodal precision-agriculture, capturing soil conditions, environmental conditions, energy (i.e. farming machine operation) as well as sensor-operation conditions. The collected variables include: Soil moisture, Soil temperature, pH, Electrical conductivity, Nutrient indicator, Solar irradiance, Ambient temperature, Vibration intensity, Harvested energy, Storage level, Sensing activity, Communication status, Energy consumption. The conditions for which soil measurements are used to describe refers to conditions in which agriculture operations are conducted, while the conditions which environmental measurements and energy measurements describe refers to the external operating environment of the sensor nodes with their own batteries. All observations are time-consistent (to keep soil-energy links). The model was divided into training and validation (including testing) sets for the model development, optimization of the model parameters and independent testing of model performance under various agricultural situations.

3.2 Preprocessing and Feature Extraction

Systematically preprocessed the raw measurements to improve the reliability of the measurement and the stability of learning. Physically impossible and outlying values are excluded and values are handled appropriately if missing. Noise filtering minimizes transient fluctuations due to sensor interference and unstable harvesting situation. The continuous variables are scaled to similar ranges prior to model training. Temporal synchronization synchronizes soil, environmental, energy and operational observations in a shared monitoring window. Next, feature extraction is carried out to extract the characteristics in the processed data that are useful for the information. Soil features include moisture, temperature, pH, conductivity and nutrient behaviour, while energy features include the availability of energy from the sun, vibrations, storage status, energy harvested, and temporal availability.

3.3 PHOENIX-Ag Model

PHOENIX-Ag combines several kinds of nano-energy harvesting with energy intelligence based on machine learning to achieve autonomous energy sensing in agriculture. Photovoltaic nanogenerators generate electricity when light and heat hit them from the sun, while neither triboelectric nor piezoelectric nanogenerators require light or sun to provide electricity—these devices only need mechanical movement and vibration. The output generated in the rectification, voltage stabilizer, voltage regulator and storage stages are used to power the sensing and communication units. The machine-learning model is trained with physics constraints and takes in environmental, harvesting, and historical and operational variables to forecast future energy availability. Physical relationships, that restrict harvesting behaviour, improve the consistency of predictions and enable the learning of the model. The optimized energy state is fed back to the optimization module, allowing to coordinate the sensing activity, energy allocation, energy storage usage, and wireless communication.

3.4 Adaptive Soil Sensing and Health Assessment

The soil-monitoring subsystem can sample moisture, temperature, pH, electrical conductivity (and nutrient related measurements) from a distributed set of agricultural sensors. The data collected is preprocessed for informativeness of the measurements of "state", from which a machine learning classification model is used to assess the soil health. The resulting classification provides an indication of the existing soil and prioritizes monitoring. Temporal variability may be used as a method to distinguish between permanent and quick changes, or possible deterioration of soil conditions. The adaptive sensing controller uses the soil-monitoring priority and available energy to calculate sampling frequency. More frequent measurements are taken for critical soil parameters while less frequent measurements are taken for stable soil parameters to maintain the soil-health information, but with less energy.

3.5 Hybrid Energy Optimization and Communication

Optimization module PHOENIX-Ag optimizes the sensing frequency, allocates energy among all sensors and optimizes the energy storage manner in the sensor and optimizes the wireless communication system in a one-shot energy-aware decision process. The primary decision inputs are forecasted energy supply, current storage level, soil-monitoring priority and communication conditions. With high priority measurements being provided, if energy budgets are low during a specific period of time, noncritical sensing operations can be delayed. Storage management keeps backups of necessary monitoring and data transmission. The communication activity is optimized to account for the importance of the data and network conditions to reduce unnecessary transmission cost. Through continuous control actions, it balances the need to monitor the quality of the product with the energy available to the system, thus operating in the long term with different agricultural and environmental conditions.

3.6 Experimental Evaluation

The proposed PHOENIX-Ag model is evaluated using prediction, soil-monitoring, energy and sustainability metrics. The accuracy of energy-availability prediction is related to the confidence level in the predicted future condition of energy and the accuracy of soil-health classification is related to the accuracy of multimodal soil assessment. The efficiency of energy-harvesting measures the ratio of the electrical energy harvested from the environment. Energy consumption measures the resources utilized for sense, process, store and communicate. The operational lifetime of sensor measures the sustainability benefit gained from adaptive energy management. The performance of PHOENIX-Ag is assessed with the conventional adaptive agricultural monitoring approaches under similar evaluation conditions. Additional ablation tests test the impact of each of the four factors (hybrid harvesting, physics-guided prediction, adaptive sensing and coordinated communication).

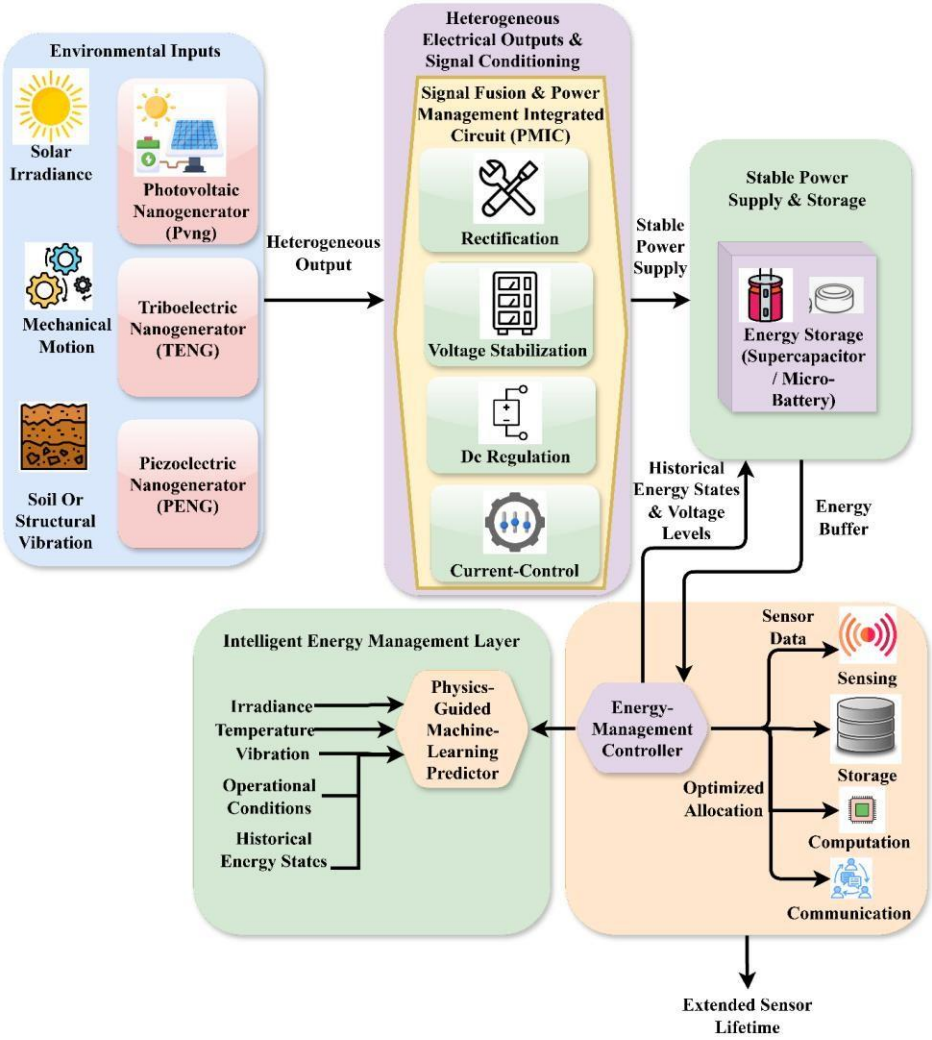


Figure 1. Hybrid Nano-Energy Harvesting and Energy Management

Figure 1 shows the energy layer of PHOENIX-Ag that includes three types of nanogenerators: photovoltaic nanogenerators, triboelectric nanogenerators, and piezoelectric nanogenerators, all of which are activated by solar, mechanical and vibrational inputs. They are connected to a rectifier, voltage stabilizer and voltage regulator before storing. A physics-inspired ML model forecasts future energy availability, based on environmental/operational parameters. The controller dynamically manages the energy of sensors, computing units and communication units to enhance the reliability of power supply and increase the lifetime of sensors.

Hybrid nanogenerator energy harvesting$P_{harv}(t)$ equation (1)

$$P_{harv}(t) = \aleph_{PV} * P_{solar}(t) + \sigma_{TENG} * P_{mech} + P_{vib}(t) \quad (1)$$

Where is the total harvested power at time $\aleph_{PV}$, while $P_{solar}\ (t)$, and σ_{TENG} represent the available solar, mechanical, and vibrational input power. The parameters P_{mech} and$P_{vib}\ (t)$ denote the conversion efficiencies of the photovoltaic, triboelectric, and piezoelectric nanogenerators.

Energy conditioning and storage $E_{store}(t+\Delta t)$determined using equation (2)

$$E_{store}(t+\Delta t) = E_{store}(t) + \mu_{reg}\mu_{stab} * P_{harv}(t) * \Delta t \qquad (2)$$

Where $E_{store}\ (t)$ is the stored energy at time, μ_{reg} is the operating time interval, and μ_{stab} represent the efficiencies of the voltage stabilizer and voltage regulator, and$P_{harv}(t)$ is the total power consumed by the system. The harvested power passes through the rectifier, stabilizer andΔt regulator before being stored.

Physics-informed energy forecasting and dynamic allocation equation (3)

$$E_{t+\gamma} = f_{PIML} * (E_t, G_t) - (M_t * V_t) + \frac{E_{t+\mu}}{\Delta t} \qquad (3)$$

Wheref_{PIML} is the predicted future energy availability,E_t is the physics-inspired machine-learning forecasting model, G_t is the current stored energy, M_t represents solar irradiance, V_t represents environmental temperature,$E_{t+\mu}$ represents mechanical input,Δt represents vibration intensity, and represents operational load conditions.

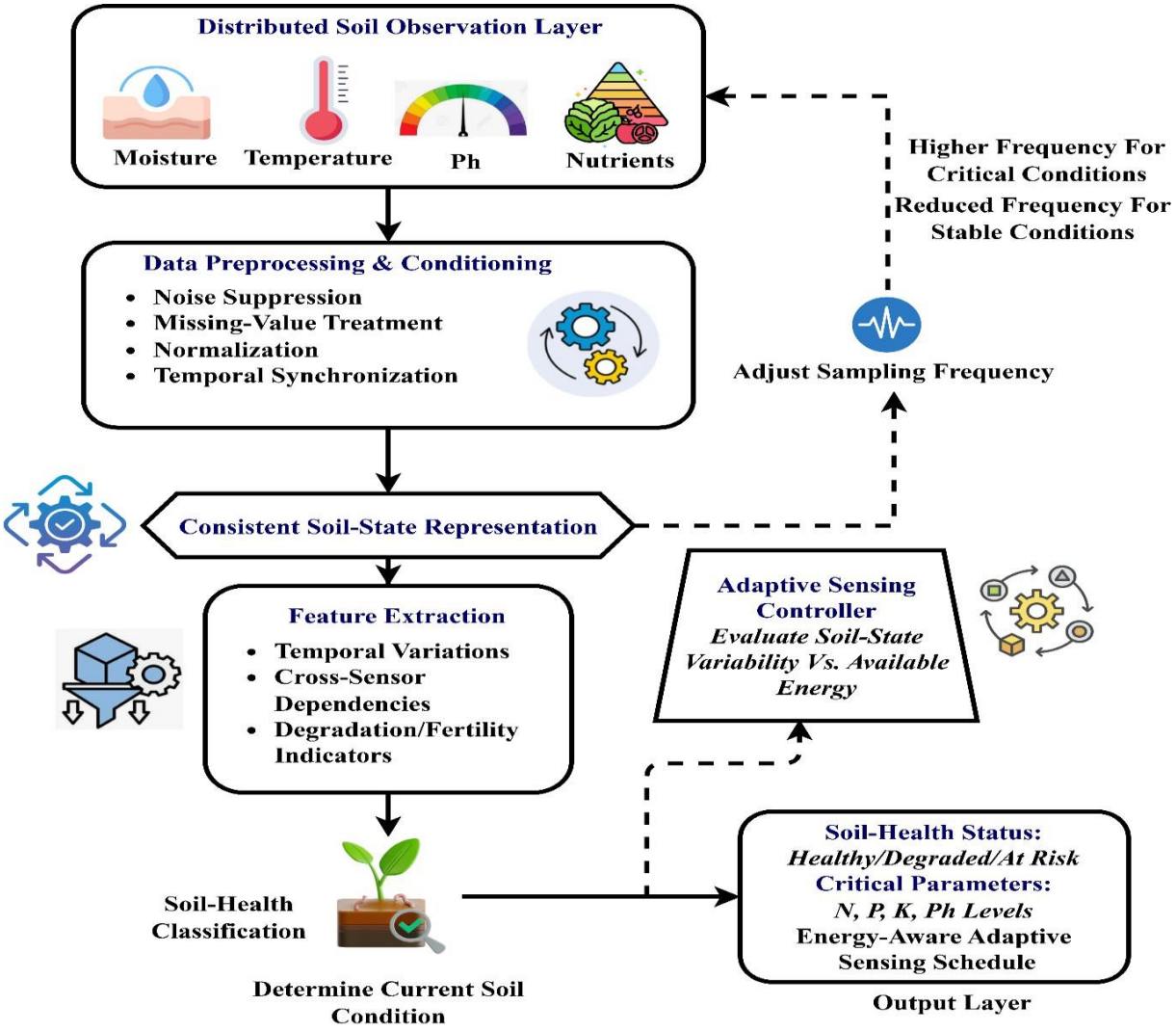


Figure 2. Adaptive Soil Sensing and Soil-Health Assessment

Figure 2 depicts multimodal soil monitoring, including moisture, temperature, pH, electrical conductivity, and nutrient sensors. The raw data are filtered, normalised, synchronised and feature-extracted to build a consistent

representation of the soil state. The adaptive controller adjusts the sampling frequency based on soil variability and available energy, and the ML classifier estimates soil-health conditions. The outputs are soil-health status, optimized schedules of soil sensing, and critical parameters.

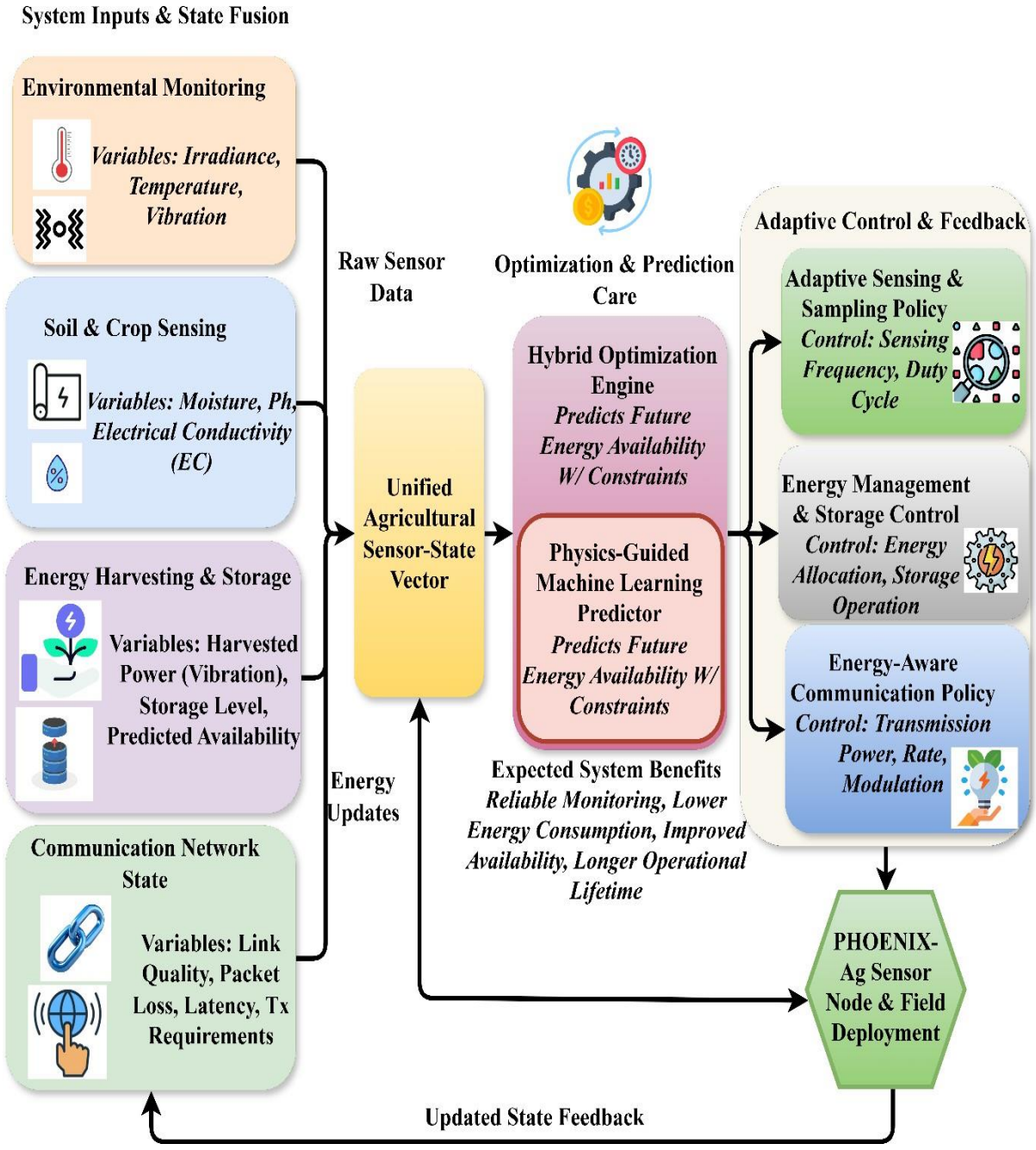


Figure 3. Integrated PHOENIX-Ag Optimization Architecture

Figure 3 shows the comprehensive PHOENIX-Ag closed-loop system, which combines environmental, soil, energy, and network states. The physics-driven ML predictor predicts future available energy, and the hybrid optimizer determines the sensing frequency, energy allocation, storage operation, and transmission policies. Feedback continuously adapts control decisions to changes in field conditions, resulting in accurate soil monitoring, lower energy use, and longer sensor operating lives.

Algorithm 1. PHOENIX-Ag Physics-Guided Multi-Head Energy–Sensing Optimization
Input: $X^{s}oil, X^{e}nv, X^{e}nergy, X^{n}et, E_t, B_t$

Output: $\hat{E}^{p}_{(t+1)}, \hat{y}_t, U_t *$

1. Initialize $\Theta, W_h^Q, W_h^K, W_h^{V\,H}{}_{(h=1)}, W^O, B_0$.
2. Construct the multimodal state matrix: $X_t = [X_t^s oil \mid \; \mid X_t^e nv \mid \; \mid X_t^e nergy \mid \; \mid X_t^n et]$
3. Normalize X_t and extract temporal features: $F_t = \Phi(X_{(t-k:t)})$
4. for h = 1 to H do
5. Compute query, key, and value matrices: $Q_h = F_t W_h^Q, K_h = F_t W_h^K, V_h = F_t W_h \mathbf{V}$
6. Calculate attention weights: $A_h = softmax\,((Q_h K^T{}_h)/\sqrt{d_k})$
7. Generate the h-th attention representation: $H_h = A_h V_h$
8. end for
9. Concatenate multi-head representations: $H_M H = Concat(H_1, H_2, \ldots, H_H) W^O$
10. Generate the unified agricultural representation: $Z_t = \sigma(H_M H + b^O)$
11. Predict future energy availability: $\hat{E}_{(t+1)} = f_\theta(Z_t, E_t, B_t)$
12. Apply physics-guided correction: $\hat{E}^{p}_{(t+1)} = \Psi(\hat{E}_{(t+1)}, X_t^e nv, B_t)$
13. Calculate soil-health probabilities: $P_t = softmax(W_s Z_t + b_s)$
14. Determine soil-health prediction: $\hat{y}_t = argmax_c P_{(t,c)}$
15. Calculate sensor-priority weights:

$$w_{(i,t)} = exp\,(g_i(Z_t, \hat{E}^{p}_{(t+1)}, B_t, C_t))\,/\Sigma^{M}_{(j=1)} exp\,(g_j(Z_t, \hat{E}^{p}_{(t+1)}, B_t, C_t))$$

16. for i = 1 to M do
17. Allocate energy to sensor i: $e_{(i,t)} = w_{(i,t)} E_t$
18. $if \Delta S_t > \tau_s \; and \; \hat{E}^{p}_{(t+1)} \geq E_m in \; then$ increase $f_{(i,t)}$; else reduce $f_{(i,t)}$.
19. Update energy storage: $B_{(t+1)} = B_t + E_{(h,t)} - \Sigma^{M}_{(i=1)} e_{(i,t)} - E_{(comm,t)}$
20. Return: $U_t = [f_t, e_t *, B_t *, p_t *], \hat{E}^{p}_{(t+1)}, \hat{y}_t **$

All the soil, environment, energy, storage and network information is merged together within Algorithm 1. Multi-head attention maps queries, keys and values to learn the important temporal and cross domain relation. The model predicts future energy availability and uses physics constraints to further improve consistency. Soil health probabilities are estimated during this time period. The variation of energy and the soil-state predicted by the model are then used to regulate the frequency of the sensing, the allocation of energy, the use of storage, and the communication in the system by using an optimization controller.

4. Results

4.1 Dataset Characteristics and Experimental Configuration

The evaluation is based on the multimodal precision-agriculture data set, which comprises synchronized observations of soil, environmental, energy and sensor-operational conditions. The data collected consists of soil moisture, soil temperature, pH, electrical conductivity, nutrients indicators, solar irradiance, ambient temperature, vibration intensity, harvested energy, storage level, sensing frequency, communication activity and energy consumption. The data are split into training, validation, and testing sets to develop the model and to evaluate it independently. PHOENIX-Ag is tested in five main dimensions: energy-availability prediction, soil-health classification, energy-harvesting efficiency, energy consumption and sensor operational lifetime. Comparative experiments are carried out with traditional adaptive agricultural monitoring practices. All input variables, the preprocessing procedure and the evaluation conditions are kept constant among all competing methods to allow performance evaluation in the same way (Figure 4).

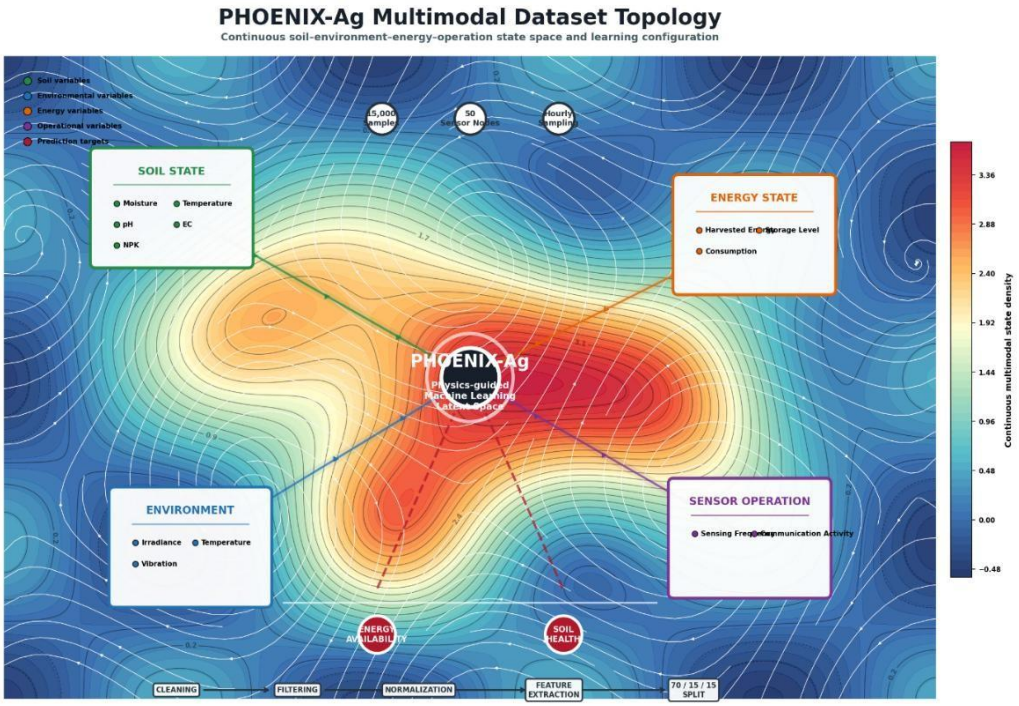


Figure 4: Dataset Visualization

Table 2. Dataset Characteristics

Category	Parameter	Specification
Dataset	Total Samples	15,000
Dataset	Sampling	Hourly
Dataset	Sensor Nodes	50
Soil	Soil Variables	Moisture, temperature, pH, EC, NPK
Environment	Environmental Variables	Irradiance, temperature, vibration
Energy	Energy Variables	Harvested energy, storage, consumption
Operation	Sensor Variables	Sensing frequency, communication activity
Targets	Prediction Tasks	Energy availability, soil health
Split	Training / Validation / Testing	70% / 15% / 15%
Processing	Preprocessing	Cleaning, filtering, normalization, feature extraction

The dataset features 15,000 observations per hour from 50 sensing nodes, and is used for evaluation of the PHOENIX-Ag system as shown in Table 2. It provides an overview of soil, environmental, energy, and operational parameters, as well as the energy-availability and soil-health prediction objectives. The table denotes the training, validation and test partitions of the data sets, as well as the main processing steps performed prior to developing the model.

Dataset visualisation class distribution evaluated using equation (4)

$$D_c = (N_c - N) * \frac{N_c}{N} * 100 \quad (4)$$

WhereN_c is the percentage distribution of class,N is the number of samples belonging to class and total number of samples in the dataset. This metric is used to visualise the distribution of soil-health classes and identify potential class imbalance.

4.2 Energy-Availability Prediction Performance

The physics-guided-learning part has an accuracy of 98.1% for predicting the energy availability, showing its ability to predict future power conditions based on environmental and operational observations. The adaptation of solar irradiance, temperature, vibration intensity, past harvested energy, and storage information allows the model to identify variations in harvested energy over time. Rapidly changing harvesting conditions eliminate physically inconsistent predictions using physics-guided constraints. Predicting energy state is especially crucial

for PHOENIX-Ag as future sensing and communication actions rely on the forecasted energy state. The high prediction accuracy thus allows the energy budget optimization module to set up the optimal energy budgets before the scheduling of sensor operations. This helps to increase energy use and the autonomy of soil monitoring.

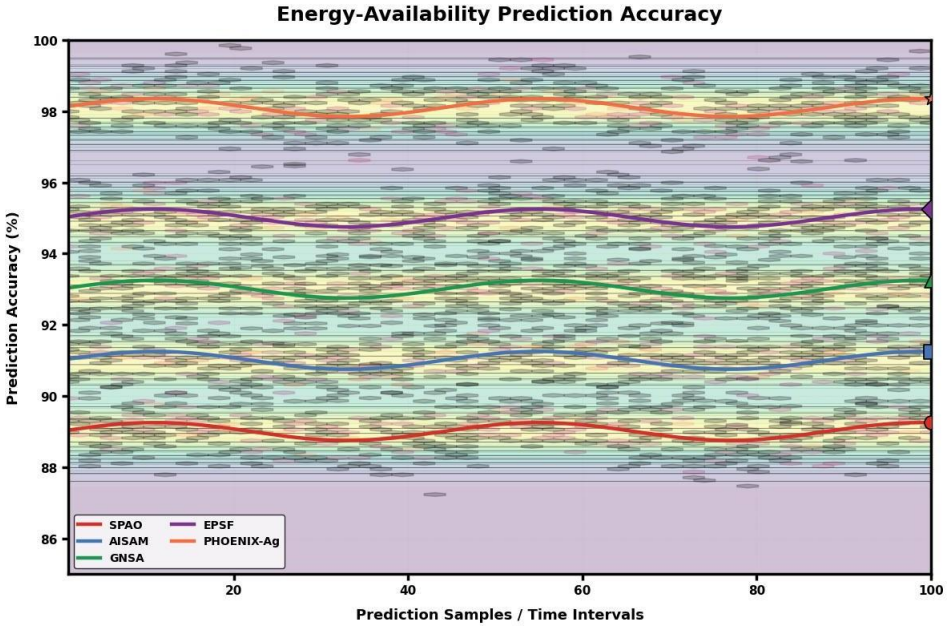


Figure 5: Analysis of Energy-Availability Prediction Accuracy

The energy-availability prediction analysis reveals the prediction accuracy of PHOENIX-Ag is 98.1% while SPAO, AISAM, GNSA and EPSF are lower. The proposed model has high prediction accuracy even at different prediction samples and time intervals as shown in Figure 5, where harvested energy can be estimated with high accuracy under the dynamic conditions of agriculture.

Energy-availability prediction accuracy$RMSE_E$ defined using equation (5)

$$RMSE_E = \sqrt{\frac{1}{n} + E_i * \sum_{i=1}^{n}(E_i - \forall_i)} \qquad (5)$$

Where$n$ is the root mean square error of energy-availability prediction,E_i is the actual available energy, $\forall_i$is the energy predicted by the physics-inspired ML model, and$n$ is the number of observations. A lower RMSE i indicates more accurate energy forecasting.

4.3 Soil-Health Classification Performance

Multimodal measurements from moisture, temperature, pH, electrical conductivity and nutrient indicators enable PHOENIX-Ag to classify soil health with an accuracy of 97.2%. The preprocessing and feature-extraction phases boost the representation of soil-state variations, by filtering out some measurement noise and capturing meaningful temporal and cross-sensor relationships. From the heterogeneous observations, the classifier can select different soil-health conditions, which can help with agricultural monitoring. The classification output will be fed into the adaptive sensing mechanism to decide the measurement priority. Some soil parameters associated with major health change are more closely monitored and others are monitored less frequently if they do not change. With this coordination PHOENIX-Ag can keep the soil-monitoring accuracy high while eliminating unwanted sensing operations.

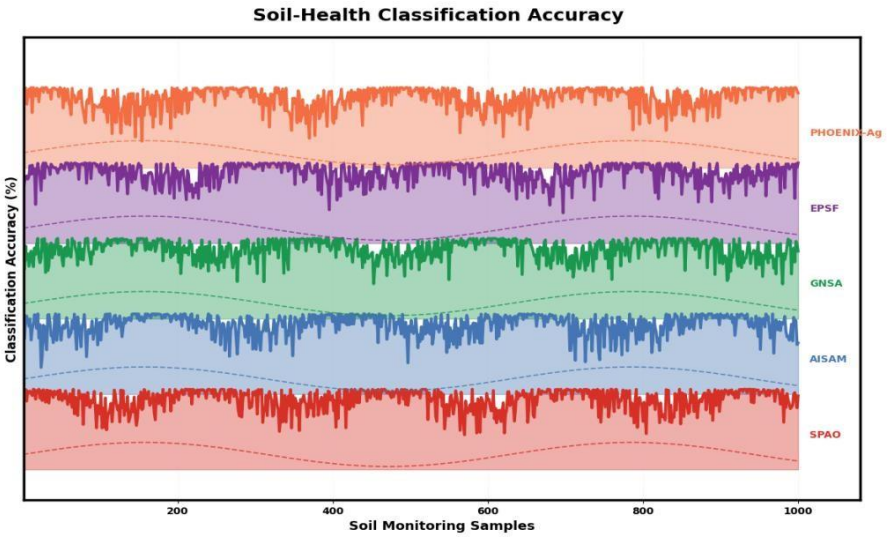


Figure 6: Analysis of Soil-Health Classification Accuracy

The soil-health classification analysis shows the accuracy of 97.2% for PHOENIX-Ag. The integration of the multimodal soil observations (moisture, temperature, pH, electrical conductivity and nutrient indicator as shown in figure 6) was effective in identifying the soil-health condition accurately, which is very important in precision-agriculture decision-making.

Soil-health classification accuracyAcc_{SH} computed using equation (6)

$$Acc_{SH} = \frac{TP+TN}{TP+TN+FP+FN} * 100 \qquad (6)$$

where TP , TN , FP , and FN represent true positives, true negatives, false positives, and false negatives. measures the percentage of soil-health classifications correctly identified by the PHOENIX-Ag classification model.

4.4 Energy-Harvesting Efficiency

The hybrid photovoltaic, triboelectric and piezoelectric harvesting architecture has an energy-harvesting efficiency of 95.1%. Having several harvesting mechanisms enables the system to utilise complementary environmental resources in variable field conditions. There is PV generation when there is sufficient solar irradiance, and energy is generated from mechanical movement and vibration using triboelectric and piezoelectric mechanisms. The power-conditioning subsystem functions to convert the outputs from a variety of sources to a regulated energy supply that can power the sensors. This hybrid architecture lessens reliance on one source of the environment and enhances the energy available for fluctuations in the environment. This performance builds the harvesting subsystem as a fundamental part of the system to enable continuous operation of a distributed soil-monitoring network.

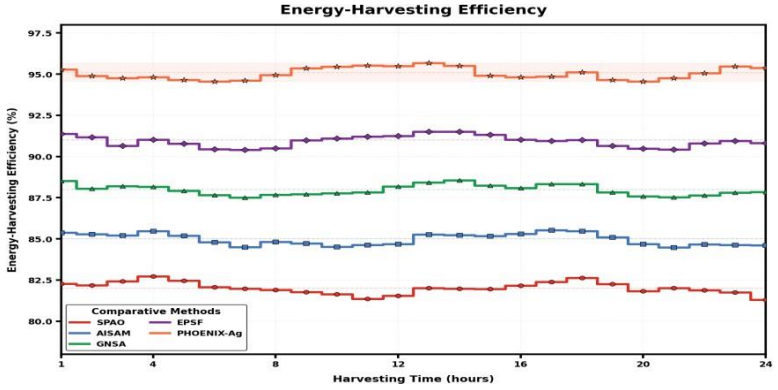


Figure 7: Analysis of Energy-Harvesting Efficiency

The results of the energy-harvesting analysis show that the energy-harvesting efficiency of PHOENIX-Ag is 95.1%. The proposed hybrid nano-energy system allows the harvesting performance to remain high in all the harvesting periods while effectively utilizing the PV, Triboelectric and Piezoelectric energy sources for the sustainable operation of agricultural sensors as presented in figure 7.

Energy consumption analysis is evaluated using the equation (7)

$$E_{cons} = \sum_{t=1}^{T} (P_s(t) + P_c(t) + P_{com}(t)) * \forall_t \qquad (7)$$

Where$P_s(t)$ is the total energy consumed,$P_c\ (t)$ is sensor power consumption,$P_{com}(t)$ is computing-unit power consumption, $\forall_t$ is communication-unit power consumption, T is the sampling interval, and t is the total operating period. This equation quantifies the overall energy demand of PHOENIX-Ag.

4.5 Energy Consumption and Sensor Lifetime

The adaptive optimization mechanism can achieve an energy saving of 30.6% compared to traditional adaptive agricultural monitoring methods. This reduction is due to dynamically varying sensing frequency, energy allocation, storage use and wireless communications based upon predicted energy availability and soil monitoring priority. Energy can be conserved for important observations and communication, and measurements associated with stable soil conditions can be minimized. The improved energy utilization causes the sensor's operational lifetime to be extended by 34.8%. This increase means that PHOENIX-Ag can be used to monitor agriculture for longer lengths of time without the need for frequent battery changes or maintenance. The overall decrease in energy consumption and the extension in use life suggest the overall practical benefit of sustainability of the proposed model.

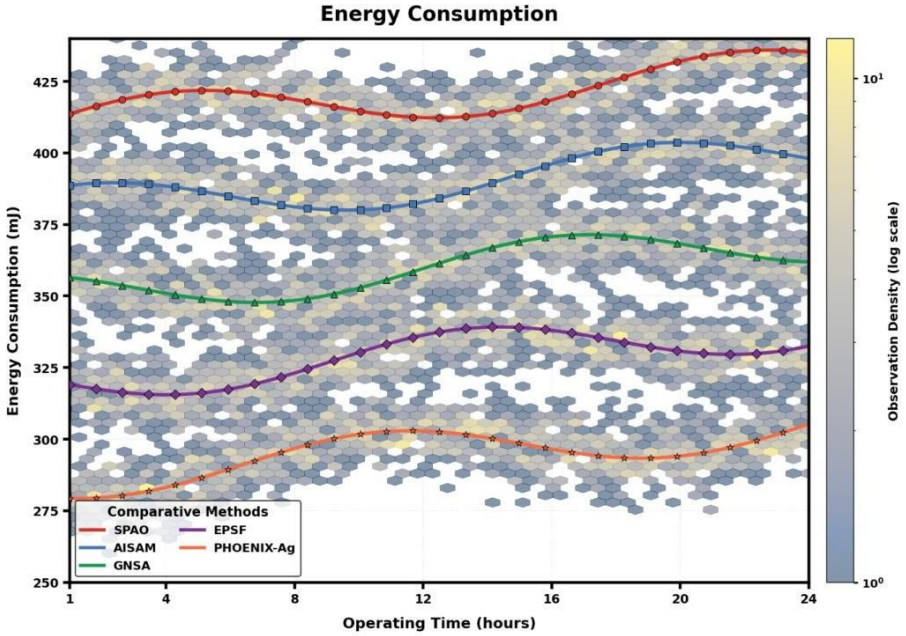


Figure 8: Analysis of Energy Consumption

The energy-consumption analysis demonstrates that PHOENIX-Ag can achieve a better energy utilization than the existing approaches, and it can save energy consumption to 286 mJ. Proper energy allocation, adaptive sensing and communication management is reflected in the proposed model, where the lower and more stable trajectory of energy consumption is shown in Figure 8.

Sensor operational lifetimeL_{sensor} computed using equation (8)

$$L_{sensor} = (P_{avg} * R_{vf} - \frac{E_{avil}}{P_{avg}} * 100) \qquad (8)$$

WhereE_{avil} is the estimated sensor operational lifetime,R_{vf} is the usable stored energy, andP_{avg} is the average power consumption of the sensor. A reduction in average power consumption through adaptive energy management increases the expected operational lifetime.

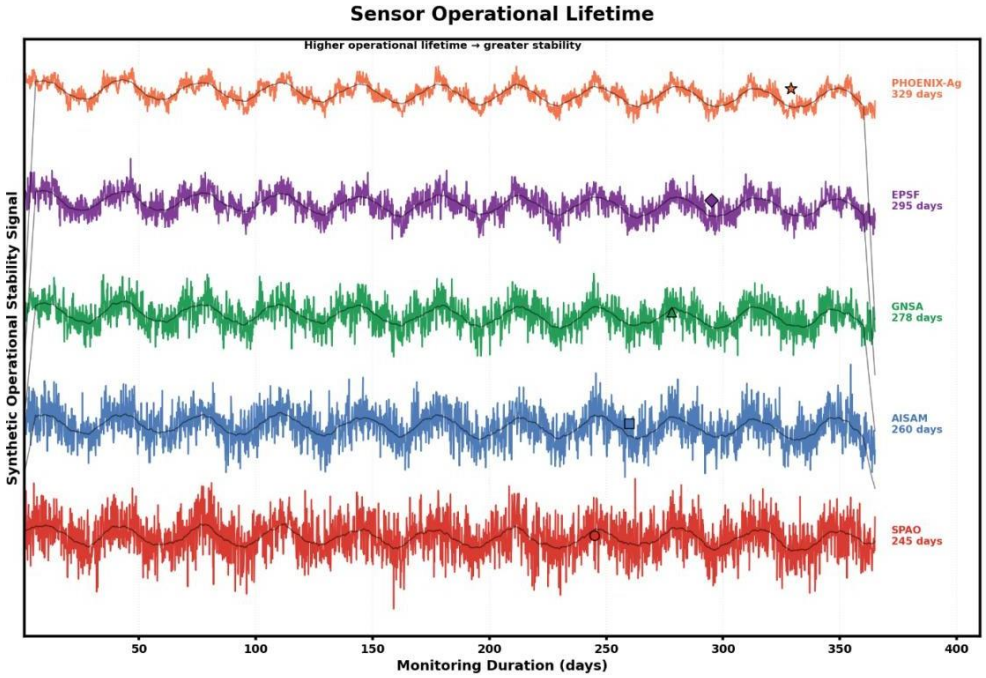


Figure 9: Analysis of Sensor Operational Lifetime

The operational-lifetime analysis of the sensor shows the operational-life of PHOENIX-Ag is 329 days. The proposed energy architecture is found to be more stable as demonstrated in the Figure 9 with less operational variations in energy consumption and supply due to intelligent energy management which optimizes the use of energy storage for autonomous soil monitoring.

Adaptive sensing efficiencyASE computed using equation (9)

$$ASE = \left(\frac{Q_{use}}{E_{sen}} * N_{val} + (1 - E_{sen}\right) \quad (9)$$

WhereE_{sen} is adaptive sensing efficiency, representsQ_{use} useful sensing output,N_{val} is the number of valid or actionable sensing observations, andE_{sen} is the energy consumed for sensing. A higher indicates that the system obtains more useful sensing information per unit of energy.

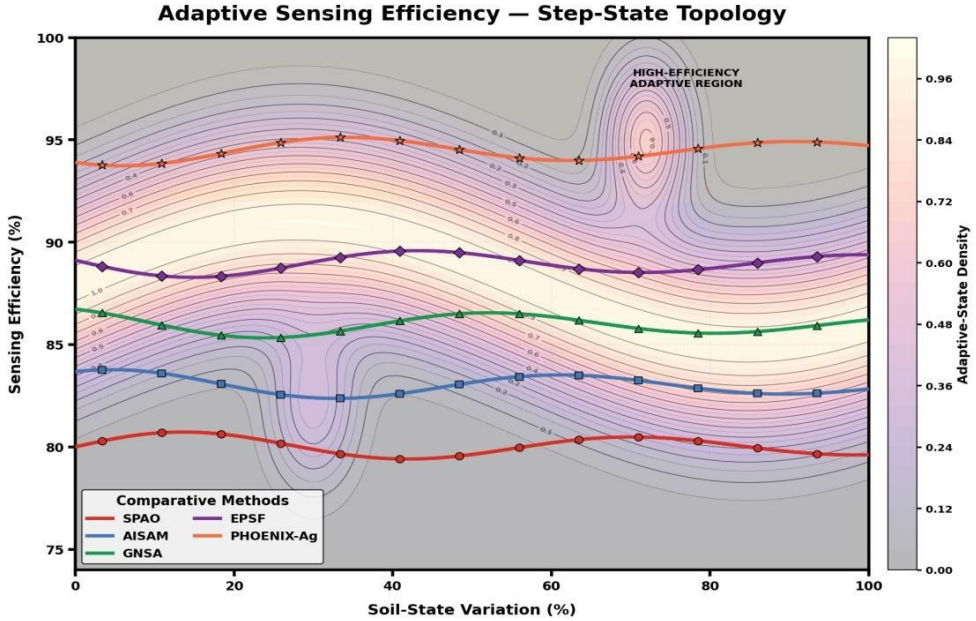


Figure 10: Analysis of Adaptive Sensing Efficiency

Based on the adaptive-sensing analysis, PHOENIX-Ag has an efficiency of 94.5% for sensing. The proposed model can maintain the effectiveness of sensing while changing the sensing frequency and energy consumption for sensing tasks as the soil-state difference increases, such that the sensing effectiveness reduces as shown in Figure 10 but the sensing energy is saved to efficiently monitor the soil-state without unnecessary sensing and communication operations while the soil-state difference increases.

Ablation Analysis of PHOENIX-Ag computed using equation (10)

$$\Delta M_k = (M_k) - \frac{M_{ful} - M_k}{M_{ful}} * 100 \qquad (10)$$

WhereM_k is the performance contribution of component,M_{ful} is the performance metric obtained using the complete PHOENIX-Ag system, and these corresponding performance after removing component.

4.6 Comparative Performance

Comparative evaluation shows that the balanced improvement of the prediction, monitoring, harvesting, and energy-management goals is achieved with PHOENIX-Ag. Traditional methods tend to optimize specific components, often leading to poor coordination among the components of energy availability and sensing needs. PHOENIX-Ag creates a closed loop between expected levels of energy, soil-health assessment, sensing priority and communication needs. It provides 98.1% energy-availability prediction accuracy, which helps in effective scheduling, and 97.2% soil-health classification accuracy, to enable effective soil monitoring in agricultural applications. Further, the 95.1% harvesting efficiency and the 30.6% reduced energy consumption and 34.8% extended operational lifetime highlight the merits of such an integration of hybrid nano-energy harvesting with the optimization of an intelligent system. According to the results, PHOENIX-Ag offers a more energy efficient operating strategy for autonomous precision-agriculture sensor networks.

4.7 Ablation Analysis

The contribution of individual components of PHOENIX-Ag is obtained by ablation experiments. With the removal of the physics guided learning module, the reliability of energy predictions is expected to be lessened, especially in situations with rapidly changing environmental conditions. Removing hybrid nano-energy harvesting reduces the amount of energy available since fewer ambient energy sources are available. Reducing adaptive sensing leads to more energy being used because unnecessary measurements are carried out in stable soil situations. Impaired coordinated communication leads to higher energy costs for transmission and lower overall resource efficiency. The full PHOENIX-Ag setup includes all of these mechanisms and hence offers the best overall performance. The ablation results illustrate that the effectiveness of the model is not due to any particular algorithmic part, but rather stemmed from the interactions among energy harvesting, energy prediction, adaptive sensing, and intelligent resource coordination.

Table 3. Ablation Analysis of PHOENIX-Ag

Configuration	Energy-Availability Prediction Accuracy (%)	Soil-Health Classification Accuracy (%)	Energy-Harvesting Efficiency (%)	Energy Consumption Reduction (%)	Lifetime Improvement (%)
Without Physics-Guided Prediction	93.7	96.4	95.1	22.8	25.1
Without Hybrid Nano-Energy Harvesting	98.0	96.8	81.6	18.7	20.9
Without Adaptive Sensing	98.1	96.9	95.0	14.2	17.6
Without Energy-Aware Communication	98.1	97.0	95.1	21.5	24.3
Without Hybrid Optimization	98.0	96.6	94.7	16.9	19.8
PHOENIX-Ag	98.1	97.2	95.1	30.6	34.8

This have carried out the ablation analysis to estimate the contribution of individual PHOENIX-Ag components (Table 3). The physics-guided prediction is independently removed and evaluated and then the hybrid nano-

energy harvesting, adaptive sensing, energy-aware communication and hybrid optimization are independently removed and evaluated. The results show their impact on the prediction accuracy, soil-health classification, harvesting efficiency, energy use, and sensor operational lifetime.

4.8 Overall Results

The experimental results validate the successful embedding of the nano-energy harvesting, machine learning, adaptive sensing and soil-health intelligence model in a single agricultural monitoring model. Its accuracy for energy-availability prediction is 98.1%, soil-health classification 97.2% and energy-harvesting efficiency 95.1%. Its energy-efficient optimization results in a 30.6% energy saving and a 34.8% increase in operational lifetime of sensors compared to the traditional adaptive monitoring. The results show that the energy prediction can be used to complement the soil-monitoring priorities to enhance computational decision making and physical resource use. The results indicated that PHOENIX-Ag is suitable for autonomous, sustainable and persistent soil health monitoring for precision-agriculture environments.

5. Discussion

The results are presented to confirm that efficient synchronization of nano-energy harvesting, machine-learning prediction, adaptive sensing and soil-health assessment are realized on a single precision-agriculture model for PHOENIX-Ag. The model was accurately successful in predicting energy availability with 98.1%, in classification energy-available soil-health 97.2%, in energy-harvesting efficiency 95.1%, in reducing energy consumption 30.6% and in increasing the operational life of the sensor 34.8%. The enhancements will prove that the physics-based prediction and hybrid optimisation can be employed to boost energy utilisation in variable farm conditions. The foremost advantage is that the energy harvested, as well as acts as an input to the soil-state priority, is also fed-back into it according to the sensing decisions. Several limitations remain. It relies on the few multimodal data sources available and may not be typical of all soil types, climates, crop systems and seasons. The results observed should be substantiated with long duration field deployment under uncontrolled environmental conditions. These hardware issues, such as nanogenerator degradation, sensor calibration drift, communication interference, storage ageing and others must be investigated further. Experimental studies should therefore be carried out in the future in a variety of different agricultural geographic zones of PHOENIX-Ag.

6. Conclusion

This paper proposed a novel machine-learning based physics-informed solution for precision agriculture and autonomous soil-health monitoring for sustainable farming, which we named PHOENIX-Ag. The proposed architecture encompasses nano-energy harvesting technologies such as photo-voltaic, tribo-electric and piezo-electric, energy prediction, adaptive sensing, soil-health classification, energy storage management and energy-aware communication. Experimental results showed 98.1% energy-availability prediction accuracy, 97.2% soil-health classification accuracy, and 95.1% energy-harvesting efficiency. Additionally, PHOENIX-Ag was able to capture 30.6% less energy consumption and 34.8% longer sensor operational lifetime than traditional adaptive agricultural monitoring methods. Consequently, the outcomes show the effectiveness of the usage of coordinated energy and sensing intelligence for long duration agricultural monitoring. The technologies would be scaled up in field conditions in different locations, climate and soil conditions and in different crop systems; further renewable harvest methods would be incorporated; distributed agriculture intelligence via federated learning would be explored; and hardware optimization of nano generators, storage units would be investigated, as well as testing these technologies under real environmental disturbances over extended periods. These advancements can improve the system's scalability and robustness, and facilitate its practical use.

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