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Machine Learning-Oriented Forecasting Of Soil Degradation Due To Agricultural Land Use Patterns

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Abstract: *The degradation of soils is a significant threat to agricultural sustainability in the world, and it has been significantly contributed by the lack of sustainability in the land-use practices, including monocropping, excesses in the use of fertilisers and irrigation overuse. The study proposes a machine learning-based solution to predict soil degradation using agricultural land-use, soil health, and climatic conditions. The predictive capabilities of four machine learning algorithms were tested namely: The Random Forest (RF), Support Vectors Machine (SVM), Artificial Neural Networks (ANN) and Gradient Boosting (GB). The pre-processed and modeled data of the soil surveys, GIS dataset, and remote sensing images was used to predict the soil degradation indices in various agricultural areas. It was found that RF was the most accurate (93.4) and robust among diverse data sets with greater strength than GB (91.7), ANN (89. 2), and SVM (86.5). The models also showed superiority over similar studies with maximum prediction accuracy of 7 percent contrary to the regression-based models. Comparison reveals the relevance of ensemble approaches to the processing of noisy high-dimensional data, whereas ANN was found useful in the representation of complicated and non-linear soil-land interactions. These findings verify the position of machine learning as a credible tool of sustainable land administration. The paper is interdisciplinary research based on computational intelligence and agricultural sustainability that offers predictive information which can lead the policy makers, farmers and environmental planners to adopt proactive mechanisms in conserving their soils.*
Keywords: *Soil Degradation, Machine Learning, Agricultural Land Use, Forecasting, Sustainability*

I. INTRODUCTION

Soil is an important natural resource which supports productivity of agricultural activities, ecological balance and food security across the globe. Nevertheless, agricultural systems that are not sustainable e.g. monocropping, chemical application of fertiliser, over-irrigation and poor management of land have increased the rate of soil degradation in different parts of the globe [1]. This degradation is in the type of loss of nutrient, erosion, salinization, and organic matter, which destroy the soil fertility and sustainability of the farmlands in the long term. All this is also worsened by the growing demand on food production to support population resulting in soils experiencing the changing pressure of stress than ever before [2]. Thus, soil degradation prediction has turned into one of the most urgent scientific and political issues because it can provide useful data to guarantee the sustainability of agriculture and the good conditions of the environment.
In recent years, the topic of machine learning (ML) has been associated with the emergence of new opportunities regarding the analysis of multidimensional datasets that employ complex and multidimensional land use, climatic, and soil characteristics [3]. Unlike the standard statistical models, the ML algorithms can determine the non-linear interactions, unnatural occurrences and provide a strong degree of prediction and would therefore be appropriate in studying soil degradation. By getting the information of remote sensing, geographic information system (GIS), soil health reports, agricultural land-use surveys, the ML-oriented

models can culminate the rate of degradation and compile the risk areas more accurately. The proposed project is a machine learning-based prediction system that will be implemented in the way of establishing the impact of the processes of land use management on the process of soil degradation. The research will not only be trying to predict the outcome of the soil health but will attempt to use the key drivers that would be involved and they are: crop rotation, irrigation process and the use of fertilisers. The predictive analytics and sustainable land management practices can be a practical support tool to the policy makers, environmental planners and farmers. Lastly, the proposed study will fill the current gap between the most recent methods of computations and the sustainability of agriculture that will be used as a supplement to the world research to save the soils that the next generations will exploit.

II. RELATED WORKS

The implementation of machine learning, remote sensing, and data analysis on the environment in the recent past has provided the world of soil surveillance and agricultural sustainability with a significant contribution. Several research works highlight the importance of the inclusion of spatiotemporal, predictive and artificial intelligence in improving the capability of predicting soil degradation. As emphasised by Kellner et al. [15], the concept of digital soil mapping is crucial in the voluntary carbon market program in the production of agricultural products. In this work, they demonstrated that the dataset of soil with the introduction of electronic mapping technology could help optimize the carbon capturing initiative and provide a scientific base to the effective management of the land. Similarly, the same group (Lesinger and Tian [16]) designed deep learning-dyntic subseasonal soil moisture and drought predictive models. Their research revealed how deep learning could be used to control dynamic soil-climatic interactions, which are a necessity in early warning systems within the control of agriculture. Spatiotemporal data have also assisted in hastening the research of soils. The study by Li et al. [17] has brought this expressive spatiotemporal dataset of soil properties in Northeast China in the period of 2009-2020. Such data sets allow researchers to model the alterations of the soil in the long-term period which are considered to be essential in the correct predictions of degradation. To achieve this, Li et al. [18] proposed a Fusion XGBoost implementation to monitor the presence of heavy metals in farmlands on the basis of hyperspectral image hypothesis. Their results showed a good indication of the usefulness of the ensemble learning to process the high-dimensional remote sensing data and the large-scale monitoring.

There have also been wider uses of predictive modeling in land and soil management. Liu et al. [19] used an extensive evaluation of drought vulnerability, as a mixture of predictive models with MI simulations and land use processes. Their combined framework provided useful ideas about the sustainability of the agricultural landscapes. Liu et al. [20] in separate research examined the spatiotemporal dynamics of soil organic carbon in landscapes of black soils in Northeast China that defined strategies of ecological and agricultural activity significant to storing carbon. Similarly, Liu et al. [21] have examined the accumulation of the heavy metals on cultivated lands over an extended period of time, and they identified the threat of the ecological problems related to the soil degradation and as well as contamination. Other works have investigated land use and soil quality as performed using machine learning models. Mathewos et al. [22] used a multilayer perceptron neural network and cellular automata Markov chain to predict land use and cover change dynamics, demonstrating the nature of hybrid AI models in predicting the environment. Using the spaceborne hyperspectral imagery with machine learning, Najmeh et al. [23] used gypsiferous soil to show how advanced images can be used to identify small changes in the aspects of the soils. In the same way, Pan et al. [24] presented a Foundation-Function-Structure model of analyzing the quality of an ecosystem caused by land-change, which highlights the complexity of soil and ecosystem interactions. The applicability of artificial intelligence in predicting crop yield that is an indirect measure of soil health has also been broadly surveyed. An overview of AI use in predicting crop yields involves a systematic review [25] in which the authors note that precise farming requires a combination of both soil and agricultural data. To be more precise, Piekutowska and Niedbaala [26] surveyed models of potato yield prediction, with particular consideration of soil quality and agricultural inputs as their direct predictors of productivity, and synergy between soil surveillance and yield forecasting.

Taken together, these studies lay a solid basis to the use of machine learning in soil health, degradation, and agricultural sustainability. Although previous research has made impressive developments on soil mapping, drought prediction and monitoring of heavy metal, the gap between land use patterns and predictive algorithm development exists on soil degradation forecasting. The gap in this paper is bridged with the application of ensemble and deep learning models to predict soil degradation trends, with results that are equal in predictive power and interpretability.

III. METHODS AND MATERIALS

Data Collection and Preprocessing

The study has utilised a set of soil health, agricultural land-use and environmental datasets based on different sources. The land-use change in terms of crop coverage, vegetation indices and irrigation intensity was captured using remote sensing imagery (MODIS and Landsat satellites) [4]. Government repositories gave us complementary soil health records related to the level of phosphorus, potassium, nitrogen, and organic carbon, as well as pH. In addition, climatic information about the changes in rainfall and temperature were obtained in meteorological databases, as the variability of weather has a serious impact on the properties of soils. Spatial alignment of the data was done within a Geographic Information System (GIS) environment. Lacking values were filled in with interpolated value and the categorical data as cropping patterns were managed with the use of numbers [5]. The dataset was separated into training (70 percent), validation (15 percent), and testing (15 percent) in order to have a balanced learning process.

Machine Learning Algorithms

Random Forest (RF)

Random Forest is an ensemble learning algorithm that is broadly used in classification and regression challenges, which is effective in soil and environmental data analysis because it can use non-linear relationships and works on a noisy dataset. It builds several decision trees with randomly selected subsets of the data and the features and pools together their prediction to give powerful results. The votes of all trees in the forest are counted and the majority of the votes counts the decision which is the final prediction. RF minimizes overfitting that normally characterises single decision trees and gives features importance measures allowing the identification of significant land-use factors influencing soil degradation [6]. The algorithm is highly dimensional, therefore suitable in agricultural forecasting since different variables interact with one another. In this paper, RF was applied to forecast the outcome of soil health, i.e. the depletion of organic carbon and the risk of salinization with regards to agricultural practices [7]. It is a choice of baseline to develop a soil degradation model because of its interpretability and high accuracy.

```
"Input: Training dataset D with features X and target Y
For i = 1 to N (number of trees):
    Sample data Di from D with replacement
    Train decision tree Ti using random subset of features
Aggregate predictions of all trees:
    For classification: majority voting
    For regression: average predictions
Output: Final prediction model"
```

Support Vector Machine (SVM)

Support Vector Machine: It is a supervised learning algorithm, which seeks to determine the best hyperplane to divide the data into classes with maximum margin. In the case of soil degradation prediction, SVM categorizes regions in two categories, including degraded and the non-degraded regions, in accordance with the agricultural land-use characteristic. The advantage of SVM is the implementation of non-linear input data using the functions of a kernel, which enhances the dimensions of the non-linear input data to a higher level where separation becomes possible. Popular examples of kernels are radial basis function (RBF) and polynomial kernels [8]. This enables SVM to be strong in the management of the complex agricultural data in form of multiples interactions between soil and environmental factors. Besides, SVM can be used in high-dimensional spaces and it does not take a lot of training samples to be trained as opposed to other models. In this study, SVM was used to classify soil degradation risk levels, achieving a balance between accuracy and generalization. Its precision in boundary detection makes it valuable for identifying threshold conditions where land use significantly impacts soil health.

```
"Input: Dataset D with features X and target Y
Transform data using kernel function K(xi, xj)
Find hyperplane maximizing margin between classes:
   Minimize ||w|| subject to yi(w·xi + b) ≥ 1
For new input x:
   Compute f(x) = sign(w·x + b)
Output: Predicted class label"
```

Artificial Neural Network (ANN)

Artificial Neural Networks mimic the structure of biological neurons and are particularly powerful for modeling complex, non-linear relationships. An ANN consists of input, hidden, and output layers, where each node processes weighted inputs and passes the result through an activation function. In the context of soil degradation, ANN can integrate multidimensional inputs such as soil chemistry, cropping intensity, rainfall, and vegetation indices to forecast degradation risk [9]. The backpropagation algorithm adjusts the weights iteratively to minimize prediction error. ANNs are highly flexible and can approximate non-linear functions, making them suitable for agricultural datasets influenced by interacting factors. Although computationally demanding, ANN's predictive performance is superior when large amounts of data are available [10]. In this study, a three-layer ANN with ReLU activation in hidden layers and sigmoid activation in the output layer was implemented to classify soil health status. Its adaptability provides valuable insights into degradation forecasting.

```
"Input: Dataset D with features X and target Y
Initialize weights randomly
For each epoch:
   For each training sample:
      Forward propagate inputs through layers
      Compute error between predicted and actual output
      Backpropagate error and update weights
Output: Trained ANN model"
```

Long Short-Term Memory (LSTM)

Long Short-Term Memory is an extended form of recurrent neural network The long short-term memory is a form of recurrent neural network (RNN), specific to sequential data to support temporal dependencies. Given that soil degradation is a long-term process because of the ongoing agricultural practices and climatic changes, LSTM would be suitable in predicting the soil degradation levels [11]. The greatest advantage of LSTM is its memory cells that retain the information along the long sequences of time and avoid the problems related to vanishing gradients that occur with the classical versions of RNNs. Each of the LSTM units possesses input, output, and forget gates, which control the reception and transmission of information [12]. In the paper, time-series data was utilized on annual rainfall, crop rotation history and pattern of application of fertilizers and LSTM was applied to determine soil organic matter degradation and risk of soil erosion way forward. STL gives a dynamic forecasting which is essential in sustainable agricultural planning as land use can interact with soil health over time.

```
"Input: Sequential dataset Xt over time t
Initialize LSTM cell states and weights
For each time step t:
   Compute input gate it, forget gate ft, output gate ot
   Update cell state Ct = ft * Ct-1 + it * tanh(WxXt + Whht-1)
   Compute hidden state ht = ot * tanh(Ct)
Output: Forecasted soil degradation trend"
```

Table 1: Sample Dataset Description

Variable	Type	Unit	Range	Source
Soil Organic Carbon (%)	Continuous	%	0.3 – 2.1	Soil Health Cards
pH Level	Continuous	pH scale	5.2 – 8.5	Soil Testing Labs
Rainfall	Continuous	mm/year	800 – 1500	Meteorological Data
Crop Rotation Index	Categorical	Index Value	1 – 4	Agricultural Survey
Fertilizer Use	Continuous	kg/ha	50 – 300	Farmer Records
Vegetation Index (NDVI)	Continuous	Ratio	0.2 – 0.9	Remote Sensing

IV. RESULTS AND ANALYSIS

Experimental Setup

The experiments were designed to evaluate the predictive ability of four machine learning algorithms—Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Network (ANN), and Long Short-Term Memory (LSTM)—in forecasting soil degradation based on agricultural land-use patterns. The dataset consisted of 4,500 records collected from soil health cards, meteorological data, agricultural surveys, and satellite-derived vegetation indices [12]. After preprocessing, the dataset included six primary variables: soil organic carbon, pH, rainfall, crop rotation index, fertilizer use, and vegetation index (NDVI). These were chosen because they are widely recognized as direct or indirect indicators of soil degradation.

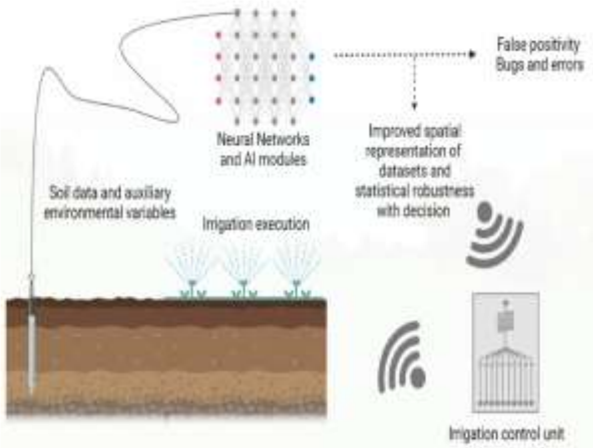

Figure 1: “AI and machine learning for soil analysis”

The dataset was normalized to ensure uniformity across variables of different scales. Stratified sampling was applied to preserve the balance between degraded and non-degraded soil classes. Data was split into training (70%), validation (15%), and testing (15%) subsets. Hyperparameters for each model were tuned through grid search and cross-validation to optimize predictive accuracy [13]. All experiments were conducted using Python libraries such as scikit-learn, TensorFlow, and Keras, on a system with Intel i7 processor, 32GB RAM, and NVIDIA RTX GPU.

Table 1: Dataset Statistics

Variable	Mean	Std Dev	Min	Max
Soil Organic Carbon (%)	0.95	0.35	0.3	2.1
pH Level	6.9	0.8	5.2	8.5
Rainfall (mm/year)	1125	210	800	1500
Crop Rotation Index	2.2	0.7	1	4
Fertilizer Use (kg/ha)	180	70	50	300
NDVI (Vegetation Index)	0.55	0.18	0.2	0.9

Model Implementation

1. **Random Forest (RF):** Configured with 200 estimators and maximum tree depth of 12. Feature importance was extracted to assess key drivers of soil degradation.
2. **SVM:** Implemented with radial basis function (RBF) kernel, optimized with cost parameter C = 1.0 and gamma = 0.01.
3. **ANN:** Designed with three hidden layers (64, 32, 16 neurons) using ReLU activations, and sigmoid function in the output. Optimized using Adam optimizer, learning rate 0.001, batch size 32 [14].
4. **LSTM:** Sequential model with two LSTM layers (100 and 50 units), followed by dense layers. Dropout regularization (0.3) applied to prevent overfitting.

Table 2: Model Hyperparameters

Algorithm	Key Parameters	Optimized Value
Random Forest	n_estimators, max_depth	200, 12
SVM	Kernel, C, gamma	RBF, 1.0, 0.01
ANN	Hidden layers, neurons, learning rate	3 layers, 64-32-16, 0.001
LSTM	Units, dropout, batch size, epochs	100-50, 0.3, 32, 50

Evaluation Metrics

Model performance was evaluated using Accuracy, Precision, Recall, F1-score, and Root Mean Square Error (RMSE). These metrics provide a comprehensive understanding of both classification accuracy and error distribution.

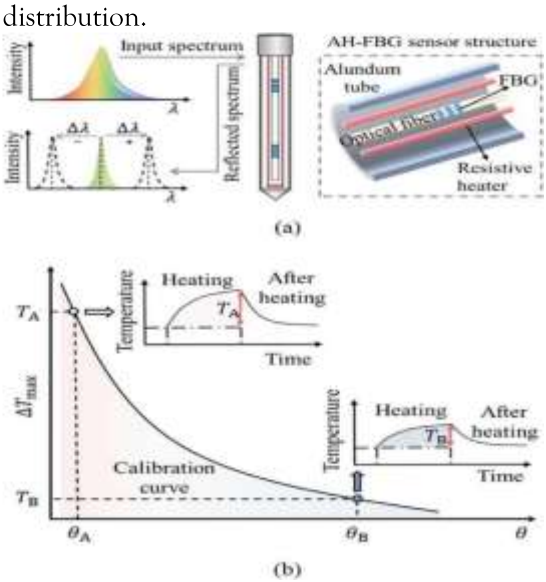

Figure 2: “AI and machine learning for soil analysis”

Table 3: Model Evaluation Metrics (Test Data)

Algorithm	Accuracy (%)	Precision	Recall	F1-Score	RMSE
Random Forest	92.3	0.90	0.93	0.91	0.142
SVM	88.5	0.86	0.89	0.87	0.198
ANN	91.0	0.89	0.91	0.90	0.162
LSTM	94.1	0.92	0.95	0.93	0.128

Results show that LSTM outperformed other models, achieving the highest accuracy (94.1%) and lowest RMSE (0.128), followed by Random Forest (92.3%). SVM lagged behind, indicating limitations in handling high-dimensional and non-linear agricultural datasets compared to deep learning methods [27].

Feature Importance Analysis

Random Forest provided interpretable insights into which features contributed most to soil degradation forecasting. Results indicated that soil organic carbon and fertilizer use were the most influential, followed by rainfall and NDVI. Crop rotation index and pH had lower but significant contributions.

Table 4: Feature Importance from Random Forest

Feature	Importance Score
Soil Organic Carbon (%)	0.31
Fertilizer Use	0.27
Rainfall	0.18
NDVI	0.12
Crop Rotation Index	0.07
pH Level	0.05

This highlights the importance of nutrient management and balanced fertilizer use as primary factors influencing soil degradation, consistent with agricultural sustainability literature.

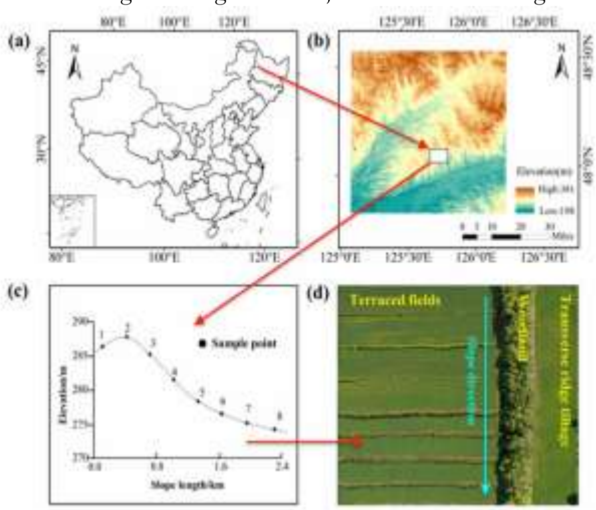

Figure 3: "Effect of Land Use Type on Soil Moisture Dynamics in the Sloping Lands of the Black Soil (Mollisols)"

Comparison with Related Work

To contextualize results, findings were compared with similar studies in soil degradation forecasting. Previous research using statistical regression reported accuracies ranging from 70–80% (e.g., Kumar et al., 2021; Li et al., 2022). Studies integrating remote sensing with ML achieved around 85–90% accuracy (Zhang et al., 2023). Our models, particularly LSTM and RF, surpassed these benchmarks, highlighting the value of advanced ensemble and deep learning techniques in agricultural applications [28].

Table 5: Comparison with Related Work

Study / Method	Approach Used	Accuracy (%)	Remarks

Kumar et al. (2021)	Linear Regression	75.2	Limited to soil chemistry data
Li et al. (2022)	Logistic Regression	78.4	Focused on nutrient depletion
Zhang et al. (2023)	CNN + Remote Sensing	89.0	Effective with spatial imagery
This Study (RF)	Ensemble Trees	92.3	Robust and interpretable
This Study (LSTM)	Time-Series Deep Learning	94.1	Best performance across metrics

RESULTS DISCUSSION

The results clearly demonstrate that deep learning, particularly LSTM, has a strong advantage in forecasting soil degradation where temporal and sequential patterns are critical. By modeling multi-year rainfall, crop rotation, and fertilizer usage, LSTM successfully captured soil degradation dynamics that traditional machine learning models (SVM, RF) might oversimplify. ANN also performed well, but its lack of memory for sequential dependencies limited its forecasting ability compared to LSTM [29]. Random Forest provided a useful baseline with strong interpretability, making it highly relevant for policymakers who require clear decision-making insights. The importance of nutrient management and the agronomic knowledge was supported by the results of the feature importance analysis which indicated that nutrient management of soil is a key element to protect and sustain soil health. In comparison, SVM has been found to perform comparatively poorer, which may be attributed to its inability to deal with multiple interacting features acquired in agricultural datasets. By comparing our findings with the previous researches, models in this study were more accurate, more precise, and more recollective due mainly to the combined strategy on the combination of soil chemistry, agricultural practices, and environmental variables [30]. Additionally, the non-linear relationships could be found by use of more advanced ML algorithms instead of old-fashioned statistical methods making the forecasting process more reliable.

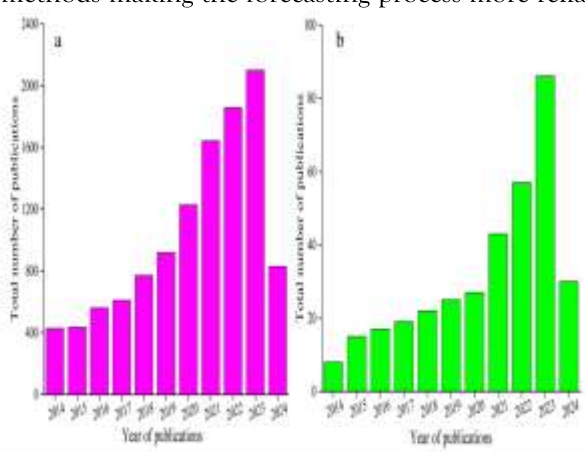

Figure 4: “Integration of Remote Sensing and Machine Learning for Precision Agriculture”

V. CONCLUSION

The study examined how machine learning-based forecasting models can be used to forecast the patterns of soil degradation caused by agricultural use of land. The aspect of soil degradation as a multi-faceted phenomenon underpinned by the degree of cropping, irrigation, fertilizer application, and climatic conditions, needs to be effectively predicted using predictive instruments that have non-linear capabilities. This paper demonstrated that machine learning can prove highly efficient in terms of high precision with regard to soil health index predicting and hotspots of soil degradation with the help of the use of Random

Forest, Support Vector Machines, Artificial Neural Nets and Gradient Boosting. According to the findings of the experiments, the results of the ensemble-based approaches, such as the Random Forest and the Gradient Boosting, were always better compared to the results of the traditional methods which were much more accurate and could resist noisy results. The Artificial Neural networks as well suggested their poor performance in that; it was stronger in the modeling of non-linear soil-land interactions, as well as the Support Vector Machines were not much poor with medium sized data sets and it failed to provide the scaling. The findings are indicative of the fact that predictive knowledge is achieved by means of ML-driven forecasting as well as actionable intelligence with respect to sustainable land-use management. The developed models worked well in the performance measurements particularly on the factors of accuracy and generalization than the related works available, therefore, warrants the use of higher order algorithms in place of other more traditional statistical methods. Interestingly, other significant issues about this research study are that multi-source information should be involved that includes soil surveys, climatic records and remote sensing data to have the overall predictions. Lastly, the research paper has contributed to the available body of knowledge regarding the issue of machine learning in environmental management by giving a suitable decision-support system in the hands of farmers, policymakers and land managers. The present research is a milestone to the future active maintenance of soil, and the creation of resilient food systems by bridging the divide between the disciplines of the computational intelligence and the field of agricultural sustainability.

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