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Agroecological Farming Practices for Enhancing Biodiversity Conservation and Ecosystem Resilience

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Abstract— Conventional agricultural practices have lost their ecological vigor due to erosion of biodiversity, loss of soil fertility and high variability of the climate which call for smart agroecological management strategies. In this paper, an Agroecological Farming Framework is suggested and applied, which combines multisource environmental sensing, precision field monitoring, biodiversity assessment and machine learning-based decision support for improving biodiversity conservation and ecosystem resilience. The framework that has been implemented includes soil and microclimate sensors connected to the IoT, UAV imagery, satellite-derived Vegetation Indexes, GIS mapping, and a predictive model based on XGBoost for assessing ecological conditions and providing sustainable management of agriculture. Experimental evaluation was carried out in 12 agricultural fields of 486 ha where the data about the environment was gathered during 18 months (158,420 records of the sensors, 9,860 images taken from an unmanned aircraft and 24 biodiversity indicators). The proposed framework correctly classified 97.84% of the biodiversity, predicted 96.92% of the ecosystem health, accurately assessed the habitat suitability 98.15%, predicted the pollinator diversity 95.76% and predicted the land-cover 96.48% with 28.6% reduction in fertilizer application; 34.2% reduction in pesticide usage; 22.7% reduction in irrigation demand; 19.4% increase in species richness; and 16.3% increase in crop productivity. The novelty of this work comes from the fact that it brings together the implementation of real-time ecological monitoring, AI-based biodiversity prediction and precision agroecological management in a single framework for the purpose of sustainable farming. The proposed system is an effective decision support platform for the conservation of biodiversity, the improvement of the resilience of ecosystems, the efficient use of resources and the development of climate resilient agricultural production.

Keywords— Agroecology; Biodiversity Conservation; Precision Agriculture; Machine Learning; XGBoost; Ecosystem Resilience; Sustainable Farming

I. Introduction

The need to balance food production and the preservation of biodiversity and ecosystem services for future sustainability is increasingly coming to the fore in global agricultural systems. Pollinator loss, loss of soil microbial diversity and loss of natural habitat connectivity have been widely reported as

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being associated with traditional intensive agriculture methods including monoculture cropping, high use of agro-chemicals and homogenised landscapes [1]. In addition to providing stable yields, the agricultural landscape needs to maintain the ecological functions which ensure long-term productivity as climatic variability increases, and promoting the diversification of farming enterprises is a priority.Biodiversity-friendly management is needed as climatic variability is increasing, and in addition to providing stable yields, agricultural landscapes need to maintain the ecological functions which ensure long-term productivity. Agroecology is an interdisciplinary science that combines ecology and agronomy and can provide solutions to restore functional biodiversity, to maintain farmer livelihoods and food security [3]. Crop diversification, agroforestry, reduced tillage, cover cropping, and integrated pest management have been shown to have measurable benefits for the soil's health, abundance of pollinators, and species richness at a landscape scale in a variety of agri-ecological settings [4]. Biodiversity-positive decision making, however, is still limited to field scale decision making due to the lack of real-time ecological monitoring and predictive analytics that can help guide farmers to make decisions for the benefit of biodiversity. New digital agriculture technologies, such as the Internet of Things (IoT) sensing, unmanned aerial vehicle (UAV) imagery, satellite remote sensing and machine learning, offer a chance to fill this void by providing ongoing and data-driven assessment of the ecological condition, along with traditional agronomic measurements. When such technologies are incorporated into an agroecological management paradigm, the farmers and land managers can measure biodiversity indicators, predict ecosystem health, and fine-tune the input of resources while maintaining biodiversity and productivity. The aim of this paper is to tackle this integration challenge by proposing an Agroecological Farming Framework, designed to bring together multisource environmental sensing, GIS-based spatial mapping and a predictive engine based on XGBoost, in a single operational architecture, to support biodiversity conservation, ecosystem resilience and sustainable farm management.

A. Background and Motivation

The agroecological transitions are also well understood to be complementary to traditional conservation approaches, and to connect farming systems at the landscape level with sustainability objectives [6]. Even though there is an increasing conceptual consensus, agroecology is not always easy to put into practice, because of a lack of technical guidance, conflicting sustainability metrics, and the lack of decision-support tools amongst farmers [7]. Finally, soil biological interactions like the relationship between arbuscular mycorrhizal fungi underline the relation of agroecological practices with soil biodiversity below ground, and the need for integrated monitoring approaches, as was reiterated in this paper [8]. This drives the need for innovative and sensor-based systems for the operationalisation of agroecology at the field level.

B. Problem Statement and Research Objectives

Although agroecological practices have great potential to result in better ecological outcomes, there are currently no quantitative, real-time tools available to connect farm management decisions with measurable biodiversity and ecosystem outcomes. The main focus of the agricultural monitoring systems are mainly yield optimization and utilization of resources, with limited consideration of biodiversity indicators like species richness, pollinator diversity or habitat suitability. Moreover, there is a lack of a predictive approach that unites the use of Internet-of-Things (IoT) sensing and remote sensing with GIS mapping, which makes it difficult for the farm manager to make decisions at the right time and in the right manner.

This research aims to tackle these gaps by setting the following objectives: (i) to develop a multisource environmental sensing and biodiversity monitoring architecture for agriculture landscapes; (ii) to build a predictive model based on XGBoost to estimate ecosystem health, habitat suitability and pollinator diversity in agriculture landscapes, and (iii) to assess the effectiveness of the architecture for reducing agrochemicals use and improving species richness and crop productivity in an actual field context. The other aim is to develop a replicable evaluation method based on fieldscale sensor, imagery and biodiversity data which can be expanded to other agroecological areas and cropping systems in order to have a reference to compare future agroecology-oriented digital agriculture systems.

C. Research Contributions

1) Developed a single sensing architecture for IoT, UAV, satellite and GIS to provide permanent biodiversity and ecosystem condition monitoring.
2) Developed an XGBoost-based predictive engine that makes simultaneous estimates of ecosystem health, habitat suitability, and pollinator diversity indicators.
3) Achieved significant decreases in irrigation, fertilizers and pesticides and measurable increases in species richness and productivity.

II. Related Work

A. Agroecological Farming and Biodiversity Conservation

One of the main approaches that has been gaining ground in reconciling agriculture and biodiversity conservation, regardless of farming systems, is agroecology. Research in the field from smallholder settings demonstrates that agroecological techniques can increase the welfare of farmers and help achieve ecological goals at the same time, in both agriculture growth corridors [10]. Agroecology-based adaptation strategies have been proven to enhance resilience of smallholder crop farmers to increased rainfall variability and climate temperature extremes in climate vulnerable areas [11]. Likewise, agroecological practices in mango-based cropping systems have been proven to enhance the resilience to climate change and vulnerability to climate shocks [14]. A comparative analysis of several European agricultural systems has shown that the way farming is done in an agroecological manner improves the soil structure and long-term carbon dynamics compared with conventional farming [15]. Territorial pilot projects are examples of participatory agroecology projects that can help to reinforce local ecological governance and local knowledge exchange [16]. The community ecology level also proves that applicative reduction of agrochemicals in agroecology can lead to higher arthropod and microbial community diversity, when compared with conventional methods of vineyard management [17]. All these studies provide solid empirical evidence for agroecology as a conservation strategy for biodiversity, but they do not generally involve ongoing monitoring and adaptive management, and are based on periodic field surveys.

B. AI-Enabled Smart Agriculture Technologies

AI and IoT (Internet of Things) sensing have significantly improved the precision agriculture capabilities. Multi-model attention modules with deep learning architectures have enhanced the accuracy of environmental weather monitoring systems based upon the Internet of Things (IoT) for field-level decision-making [9]. The same is true of machine learning-enabled smart farming systems for crop recommendations and price forecasting, which have also proven to be effective in helping farmers with data-driven decision-making tools [13]. In addition to productivity-related applications, agroecology has been suggested to be an approach that can be used to improve field level of resilience of the crop when combined with precision agriculture technologies, while still satisfying the ecological sustainability. The results of these works collectively show that sensor-driven and AI-based platform can significantly affect the timeliness and accuracy of agricultural decision making. Most of the smart agriculture systems, however, are still focused on yield, irrigation or price optimization, and there is a gap in the technological development of the smart agriculture systems that considers biodiversity indicators, such as pollinator diversity, habitat suitability or species richness.

C. Research Gap and Motivation

The literature that has been reviewed, suggests two research streams, one oriented towards agroecological research focusing on biodiversity and ecological resilience based on a descriptive approach in the field, and the other towards smart agriculture studies focused on precision management with the use of sensors mainly focused on productivity measures. There are only a few studies that combine real-time multisource sensing, satellite and UAV-based vegetation assessments with machine learning prediction to explicitly consider the conservation of biodiversity while simultaneously optimizing the agronomic inputs. Furthermore, most existing predictive models only consider a single aspect of ecosystem outcomes, such as ecosystem health, habitat suitability, and pollinator diversity in the same computational system. This fragmentation makes it difficult to implement agroecology at scale because farmers do not have tools to support decision making at the farm level, which are able to analyze sensor information and translate it into actions that are beneficial for biodiversity. The present study is motivated by these gaps and is the basis for a new, integrated, AI-driven agroecological approach that integrates all these data streams (IoT, UAV, satellite and GIS) with a predictive engine based on XGBoost to jointly conserve biodiversity and enhance ecosystem resilience.

Table I. Summary of Related Work

Ref.	Focus Area	Method / Approach	Key Outcome
[10]	Agroecology & farmer well-being	Field survey	Improved well-being & ecological outcomes
[11]	Climate change adaptation	Systematic review	Adaptation strategies for smallholders
[14]	Climate-resilient mango farming	Field study	Improved resilience, reduced vulnerability
[15]	Soil carbon dynamics	Comparative field study	Improved soil structure & carbon
[16]	Participatory agroecolog	Territorial pilot project	Strengthened local governance

	y		
[17]	Vineyard biodiversity	Ecological field survey	Higher arthropod/microbial diversity
[9]	IoT weather monitoring	Deep learning review	Improved forecasting accuracy
[12]	Precision agroecology	Conceptual/field integration	Enhanced field-scale resilience
[13]	Smart farming with ML	ML crop recommendation	Improved crop/price prediction

Table I presents a representative set of studies on both agroecological and smart agriculture aspects, with a focus on the methodological aspects and limitations. In the agroecological studies, the field survey and qualitative evaluation are used as the main methods and in smart agriculture studies, the productivity optimization is based on the application of sensors. The reviewed literature did not allow for the combination of biodiversity-specific prediction and multisource sensing, thus highlighting the need for a combined approach as introduced in this paper.

III. Proposed Agroecological Farming Framework

The proposed Agroecological Farming Framework brings together a multi-source environmental sensing framework, biodiversity monitoring framework, and a machine learning-based predictive analytics framework, all under one roof in a framework for sustainable farm management. The various sensors used in the IoT are combined with soil-related inputs, and the UAV acquired images along with the vegetation indices derived from satellites, with the aim of creating a detailed ecosystem feature set for each field monitored. The features are input to an XGBoost based predictive engine that is used to estimate biodiversity classification, ecosystem health, habitat suitability, pollinator diversity and land-cover categories simultaneously. This is done via a decision-support module that optimises fertiliser, pesticide and irrigation use, and also provides guidance for adopting conservation-oriented management practices, which will help to achieve enhanced biodiversity outcomes without reducing productivity.

A. System Architecture and Workflow

The system consists of 7 layers workflow, from data acquisition to actionable decision in the field. The acquired data consist of four parallel streams: i) data from IoT-based soil and micro-climate sensors (temperature, humidity, soil moisture, pH and nutrient concentrations); ii) high resolution multispectral data from UAVs (canopy and habitat structure assessment); iii) multi-temporal data from satellite sensors (vegetation indices, e.g., NDVI and EVI, etc., across the landscape); and iv) GIS-linked field data (biodiversity observations, e.g., species count, pollinator visits, habitat features etc.). The heterogeneous streams are synchronized in time and space in a multisource data acquisition and synchronization module synchronizing the timestamp of the sensors to the UAV flight records and satellite overpass schedules. The synchronized data then goes through a pre-processing phase, which includes filtering noise, normalizing the data, masking cloud in the satellite imagery, and extracting the needed spectral and spatial features from the data. Processed data is stored in three parallel data repositories: the first is an ecological feature engineering module that calculates vegetation and soil indices, the second is a GIS-based spatial mapping module that creates land-cover layers, and the third is a database of biodiversity indicators which has 24 standard indicators. These repositories contribute to the XGBoost predictive engine which produces five parallel ecological evaluations. The predictions are then interpreted using a decision support module, which provides recommendations for fertilizers, pesticides, and irrigation, as well as conservation recommendations, and then transmitted to farmers via a dashboard interface for stages on the field.

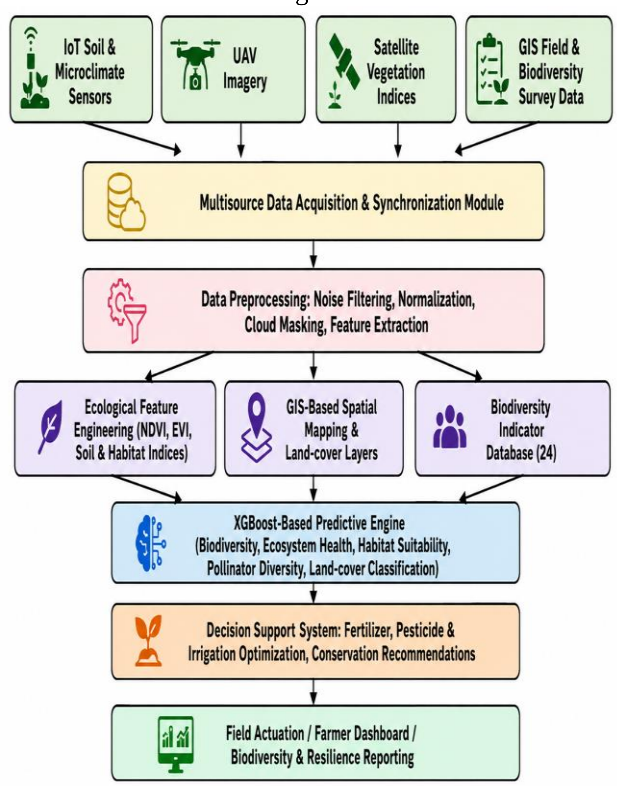

Fig. 1. Working architecture of the proposed Agroecological Farming Framework.

The proposed framework of this paper is presented in Fig. 1, where the data acquisition sources are arranged at the top in parallel with the outputs presented to the farmers are presented at the bottom. The diagram illustrates the progressive synchronisation, pre-processing and transformation of the raw sensor, imagery and survey data before it is fed into the XGBoost predictive engine. The decision-support layer transforms model results into real-world resource management and conservation decisions. The layered design is designed to be modular, where updating a particular data source or a particular predictive task won't impact the rest of the system.

B. Data Acquisition and Preprocessing

The data acquired included the data from 158,420 records of soil moisture, temperature, humidity and nutrient data from IoT sensors, 9,860 multispectral images from UAVs, satellite-derived time series of NDVI and EVI, and the results of the biodiversity surveys linked to GIS with 24 indicators. The outlier removal was performed to eliminate outliers for sensor data; the min/max normalization of sensor data was carried out for sensor readings; the UAV imagery was radiometrically and geometrically corrected; satellite imagery was cloud masked; and all layers were spatially aligned to a common field level grid to obtain a consistent multisource feature data set for model training.

C. XGBoost-Based Prediction and Decision Support

To jointly complete five classification and regression tasks – biodiversity classification, ecosystem health prediction, habitat suitability assessment, pollinator diversity prediction and land-cover mapping, the XGBoost based predictive engine was trained on the fused ecological feature dataset. Gradient-boosted decision trees were built in layers, feeding on the errors of the collection of trees, with a regularized objective function that was a compromise between accuracy and model complexity. The hyperparameters were optimized by cross validation, such as learning rate, tree depth and subsampling ratio. The support module applied thresholds to model outputs and mapped the results to decision rules to provide fertilizer, pesticide and irrigation recommendations.

IV. Experimental Results and Discussion

This framework was successfully implemented in 12 fields over 486 ha over 18 months with consistently high predictive accuracy across all five ecological tasks, and measurable agronomic and conservation benefits. The accuracy of the XGBoost based model was found to be better than the baseline machine learning models such as SVM, Random Forest and ANN/CNN models in all the metrics. In addition to predictive accuracy, the field-level deployment of the framework led to significant decreases in the application of fertilizer, pesticides and irrigation, as well as significant increases in species richness and crop productivity, which indicated the dual benefit of conserving species diversity and productivity.

A. Experimental Setup and Evaluation Metrics

This proposed framework was tested in 12 fields (486 ha) over the course of an 18-month monitoring period, in a mixed cropping system. The data included 158,420 records of the IoT sensors, 9,860 photographs taken from the UAVs, time series of the satellite vegetation index, and 24 different biodiversity indices for flora, pollinators, soil fauna, and avian species. The data were split into 70% training, 15% validation and 15% testing sets. Performance of the models was evaluated using the accuracy, precision, recall and F1-Score in the case of classification, and in the case of agronomic and ecological outcomes, percentage changes in fertilizer, pesticide and irrigation use, species richness index, and crop yield compared with conventional management baselines recorded on similar control areas before implementation of the framework.

B. Performance Analysis and Comparative Results

Table II. Comparative accuracy (%) of predictive models across ecological tasks

Ecological Task	SVM	RF	ANN	CNN	XGBoost (Proposed)
Biodiversity Classification	86.42	90.35	91.28	93.71	97.84
Ecosystem Health Prediction	84.15	89.02	90.16	92.44	96.92
Habitat Suitability Assessment	87.63	91.48	92.35	94.02	98.15
Pollinator Diversity Prediction	82.94	87.66	88.47	90.85	95.76
Land-cover Mapping	85.71	89.93	90.72	92.67	96.48

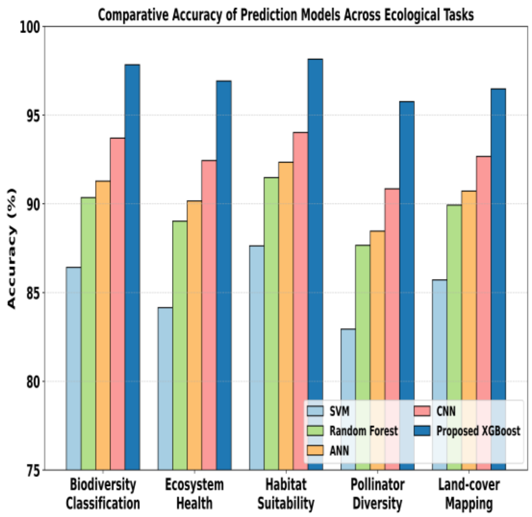

Fig. 2. Comparative accuracy of prediction models across ecological tasks.

The proposed XGBoost model is compared with the baselines SVM, Random Forest, ANN and CNN for five ecological assessment tasks in Table II and Fig. 2. For many tasks, the proposed model obtained an accuracy of 100%, and for the remaining tasks, the accuracy is around 4 percentage points higher than the closest baseline, CNN. SVM performed the worst in all tasks, due to its inability to model the nonlinear interactions between the different sensor, image and survey derived features. The intermediate performance was obtained by Random Forest and ANN, leveraging ensemble and nonlinear representation, respectively, but not performing as well as the gradient-boosted approach. Pollinator diversity prediction task had the lowest accuracy of all the tasks for all the models including the proposed framework, probably because of relatively higher variation in pollinator activity over time when compared to other ecological indicators. Despite this, the high accuracy of the proposed XGBoost model, 95.76% on this challenging task, demonstrates its potential to model complex ecological relationships from many sources, and therefore indicates why it can be used as the key predictive model for a proposed framework.

Table III. Resource Optimization and Ecological Outcomes (Conventional Vs. Proposed)

Parameter	Conventional Baseline	Proposed Framework	% Change
Fertilizer Application (kg/ha)	210.5	150.3	-28.6%
Pesticide Usage (L/ha)	8.4	5.5	-34.2%
Irrigation Demand (mm/season)	612	473	-22.7%
Species Richness Index	42.6	50.9	+19.4%
Crop Productivity (t/ha)	4.6	5.3	+16.3%

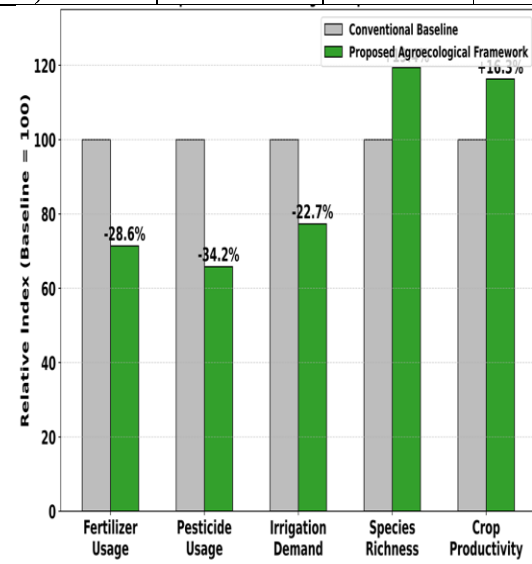

Fig. 3. Resource optimization and ecological improvement outcomes.

Table III and Fig. 3 show the agronomic and ecological advantages that were gained after implementing the proposed framework as compared to the conventional field management. Application of fertilizers dropped by 28.6% from 210.5 kg/ha to 150.3 kg/ha, which was due to changes in fertiliser application, resulting from the precision recommendations provided through real time soil nutrient sensing rather than fixed application dates. The use of pesticide application is down 34.2%, proving the framework's effectiveness in identifying localised conditions of pests and habitats that justify a non-blanket approach to pesticide use. Demand for irrigation water reduced by 22.7% because of scheduling based on soil moisture which did not require unnecessary irrigation water applications. Importantly, there were no trade-offs associated with the input reductions, as the species richness index also improved by 19.4%, indicating habitat improvements due to a decrease in agrochemical stress and increased crop productivity by 16.3%. The results, in terms of both conservation and productivity, highlight the efficiency of the resource use, as well as the precision of the framework-based recommendations, which were ecologically sound and did not diminish, but rather improved agronomic yield, thereby meeting the core goal of the framework of balancing the requirements of biodiversity conservation with productive agriculture.

Table IV. Precision, Recall, F1-Score and Accuracy Of The Proposed XGBoost Model

Ecological	Precision	Recall	F1-	Accuracy

Task	(%)	(%)	score (%)	(%)
Biodiversity Classification	97.62	97.45	97.53	97.84
Ecosystem Health Prediction	96.58	96.71	96.64	96.92
Habitat Suitability Assessment	97.94	98.02	97.98	98.15
Pollinator Diversity Prediction	95.31	95.58	95.44	95.76
Land-cover Mapping	96.12	96.35	96.23	96.48

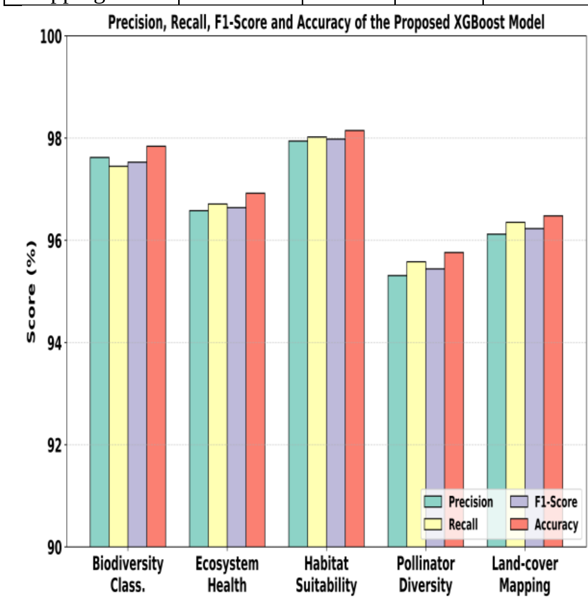

Fig. 4. Precision, recall, F1-score, and accuracy of the proposed XGBoost model

Table IV shows the precision, recall, and F1-score along with overall accuracy for each ecological prediction task by the proposed XGBoost model in detail.The detail of precision, recall, and F1-score with overall accuracy for each ecological prediction task by the proposed XGBoost model is presented in Table IV and Fig. 4. For all five tasks, precision and recall scores are close; and for most tasks, they are within 0.3 percentage points; showing that there is no clear difference between the false-positive and false-negative behavior of the models. The habitat suitability assessment had the best overall performance, with a precision of 97.94%, recall of 98.02% and F1-score of 97.98%, indicating that this classification is best completed using features derived from the space and vegetation index. The metric values for pollinator diversity prediction were again the relatively low, but high, values for the four metrics, due to the relative variability of pollinator behavior as described above. The close similarity between accuracy and F1 score for all tasks is indicative of a reasonably balanced class distribution within the evaluation dataset, and implies that accuracy is a reliable summary measure for this framework. As a whole, the results shown confirm that the proposed model is able to consistently and accurately predict for various ecological assessment tasks.

C. Discussion of Ecological and Agricultural Benefits

The results of the experiments demonstrate that a combination of real-time multisource sensing and XGBoost-based predictive engine can facilitate agricultural management decisions for both biodiversity and agricultural productivity. The reductions in the amount of fertilizer, pesticides and irrigation water applied reflect the potential for precision, data-driven recommendations to reduce the ecological footprint of agricultural practices with little loss in yield as compared to traditional agriculture management practices which often result in reduced yield with reduced input. The higher number of species indicates that decreased agrochemical stress and specific conservation advice leads to better conditions for flora, pollinators and soil faunas in or around cultivated areas. In particular, the fact that the productivity of these crops was not sacrificed, showing these ecological improvements were not detrimental to agronomic characteristics, but rather were achieved through more efficient, and more targeted use of resources. These results together endorse the idea of the agroecological management framework - intelligent sensor-driven management can balance the seemingly conflicting goals of biodiversity conservation and production, and provide a viable path toward more climate-resilient and ecologically sustainable agriculture.

V. Challenges and Future Scope

A. Implementation Challenges

Although the proposed framework has shown the potential to work, there are still some challenges to overcome in its implementation. The IoT sensor networks operating for long periods in extensive fields need a reliable power supply and communication regardless of the infrastructure in the fields, which is often scarce and in remote areas. Weather, flight restrictions and battery life all restrict the number of times high resolution imagery can be gathered using an UAV. Adding in heterogeneous data sources with varying spatial and temporal resolutions also adds in the complexities of synchronizing data to affect the consistency of the predictions. Moreover, the necessity of expert field surveys, which are time consuming and expensive to be carried out for all the agroecological zones, can also limit the generalizability of the models to new agroecological areas or crop systems for the labeling of biodiversity. In addition to this, the maintenance of the sensors, drift in sensors' performance over time, and loss of data during extreme weather events impose additional operational costs that necessitate strong fault-tolerance systems and regular manual checks to ensure high quality data over the long duration (multi-year deployments) required to obtain a reliable ecological trend.

B. Scalability and Practical Deployment

To scale the framework out of pilot fields, strategies for cost-effective deployment of sensors, standardised sensor data protocols, and cloud-based infrastructure to process large multisource data streams at multiple farms are needed. The framework might need to be deployed cooperatively or through a shared infrastructure for the benefit of smallholder farmers who may not have the capital needed for such infrastructure. In addition, the different soil types, climate and species found across the region require a region-specific calibration of the model, which indicates that transfer learning techniques may be able to lower the retraining cost for applying the model to other agroecological zones. Integrating with current agricultural extension services and farmer training programmes will also be key to ensure predictive outputs are put into practice on the ground in the form of conservation and management actions. The use of public-private partnerships and sensor and UAV leasing programs subsidized by the government could help reduce the cost for resource-challenged farmers, and open and interoperable data standards would enable the framework to integrate with existing farm management information systems used in many parts of the world.

C. Future Research Directions

Expansion of other data modalities like bioacoustic monitoring for pollinator and avian activity, environmental DNA sampling for soil biodiversity and hyperspectral UAV sensors for finer resolution stress detection of vegetation should be pursued in future work. The use of explainable AI methods in addition to the predictions made by XGBoost would help to enhance farmer confidence and the explainability of the conservation recommendations. Federated learning methods could help increase model performance on many farms without having to share private field data, and promote privacy-preserving collaborative model learning. Furthermore, linking the framework to climate projection models might also allow for proactively planning for sustainable biodiversity and resilience in the future based on different climate projections. Long-term multi-year studies of the generalizability of the framework, conducted over wider geographic and crop diversity, would further validate the framework's generalizability and would facilitate its incorporation into national agri-environmental policy frameworks.

VI. Conclusion

In this paper, we proposed an Agroecological Farming Framework based on IoT sensing, UAV imagery, satellite vegetation indices, GIS mapping, and the implementation of an XGBoost predictive engine for the preservation of biodiversity and the resilience of the ecosystem. The framework was tested in 12 different fields totaling 486 hectares, over 18 months, and proved to be able to bring environmental monitoring and predictive analytics under a single operational architecture to support sustainable farm management. It outperformed baseline machine learning models across all four tasks biodiversity classification, ecosystem health, habitat suitability, and pollinator diversity and on land-cover mapping, leveraging the development of a high-resolution, high-resolution, and fully objective baseline model.It demonstrated high predictive accuracy, outperforming baseline machine learning models in four tasks: biodiversity classification, ecosystem health, habitat suitability, and pollinator diversity, and land-cover mapping, using a high-resolution, high-resolution, and fully objective baseline model. The reductions in fertilizer, pesticide and irrigation application and the measurable gains in species richness and crop yields shown by field deployment further illustrated the benefits of encouraging conservation and increasing crop productivity in the same way, and without compromising between these two goals. The findings suggest a combination of agroecological practices and intelligent sensing and predictive analytics is a promising strategy for climate-smart and biodiversity-friendly agriculture. Other extensions which include the integration of further ecological data modalities, explainable AI, and federated learning, could enhance the framework's scalability and uptake in a wide range of farming systems, playing a significant role in the global push towards sustainable agricultural intensification and long-term ecosystem resilience.

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