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### Next-generation biological and agricultural models: Optimization for sustainability and efficiency

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#### Abstract

The world's population is likely expected to increase from the current 8 billion to 9.7 billion by 2050, which will increase demand for food production. Agriculture is facing a huge pressure to grow more food to feed everyone, but it's also got to deal with big environmental problems like losing biodiversity, climate change and water scarcity along with social issues that comes with all that due to the world's population expansion. Conventional approaches are not working well enough on their own. Fortunately, there is a concurrent upheaval in the technical sphere. Artificial intelligence (AI) offers a powerful set of technologies that can revolutionize agriculture and is more robust, efficient, and resource-wise. Insect physiology, biochemistry, biogeography, and population dynamics are all likely to be impacted by the ongoing shifts in global climate regimes, which provide a serious social issue. As a result, pest management techniques are gradually moving toward more environmentally friendly, economically viable, and sustainable alternatives. However, this review emphasizes the significance of overcoming gaps and limitations.

Coupled biophysical-ecological models will enable realistic evaluation of feedbacks, thresholds, and trade-offs under uncertain and changing environments. A second frontier is the emergence of data-adaptive and continuously updating optimization frameworks, driven by advances in remote sensing and on-farm sensing networks. These approaches will combine process understanding with statistical learning and uncertainty analysis to support robust, risk-aware decision-making. An important avenue is the development of multi-scale, systems-integrated models that links plant-soil-microbe interactions, crop growth, landscape dynamics, and ecosystem services. Such frameworks will enable more realistic assessment of feedbacks, trade-offs, and threshold responses under climate variability and resource constraints. Overall, the future of biological and agricultural modeling and optimization lies in integrative, data-aware, and socially grounded frameworks that operate across biological scales and decision contexts.

**Keywords:** Artificial intelligence, Biological modeling, decision- support systems, Machine learning, Optimization, Machine learning, sustainable agriculture, technological innovation

#### Introduction

Increasing the agricultural productivity is essential to overcome new production hurdles for rapidly growing population of the world (Attri *et al.*, 2023) <sup>[1]</sup>. A paradigm change in agriculture, Agriculture 4.0 (Characterising the Agriculture 4.0 Landscape Emerging Trends, Challenges and Opportunities, n.d.) <sup>[2]</sup>, uses cutting-edge technologies to optimize a number of farming activities (Trendov *et al.*, 2019) <sup>[2]</sup>. Internet of Things (IoT), artificial intelligence (AI), decision support systems (DSS), advanced sensors, and autonomous robots are all included in these technologies (Liu *et al.*, 2021) <sup>[3]</sup>. A DSS gives users the tools they need to optimize the agricultural system and take the right decisions, facilitating user involvement and informed decision making (Zhai *et al.*, 2020) <sup>[4]</sup>. General processes results in developing powerful machine learning model techniques like Random Forest (RF), Artificial Neural Network (ANN) and many Deep Learning (DL) variants that can make judgments, predictions, or classifications unique to particular agricultural scenarios. Crop models have emerged as a key component of contemporary agricultural practice as these models offer

insights into simulating the dynamic processes of crop growth and development under various environmental and management circumstances. This study aims to provide a detailed analysis on current agricultural research that use AI technology to address a number of pertinent issues. Finding the ideal values for important crop, soil, and weather-related characteristics was the goal of the optimization procedure. Particle optimization, fuzzy logic, simulated annealing, genetic algorithms, and machine learning algorithms are common methods used in the optimization process of agricultural water modeling. In addition to making extreme temperatures more frequent and intense (Wu *et al.*, 2022) <sup>[5]</sup>, climate change is frequently linked to global mean annual temperature increases (Im *et al.*, 2011) <sup>[6]</sup>, which probably favor winter survival of insect pests (Musolin, 2007) <sup>[7]</sup>. Predation, parasitism and other natural processes are the basis of biological control, which can play a major role in integrated pest management systems (Hoy, 1994) <sup>[8]</sup>. Therefore, a complex interaction is necessary for biological management employing natural enemies to be effective. The chapter structure is followed as- Section 2 includes the data -driven approach which incorporates big data. Section 3

and 4 consists of various AI and Machine learning approaches with algorithms along with the optimization techniques used in agricultural systems. Section 5 concludes with the Digital Agriculture which includes IoT based modeling, digital twins and tools used in precision agriculture. Section 7 consists of challenges and limitations along with the future research directions of biological and agricultural modeling. Finally, Section 9 ends with the conclusion.

## 2. Data-Driven Modeling in Agriculture and Biology

Crop growth requirements and physiological characteristics have evolved with this process. However, obtaining crop data has gotten more convenient as science and technology have progressed. In biology and agriculture, data-driven modeling represents a substantial change from conventional to smart agriculture which leverages big, varied and fast datasets to boost productivity, enhance sustainability, and guarantee food security. These systems facilitate realtime decision-making by integrating data from sensors, genetics, phenomics, and the environment. They often cutting the input costs by 15-20% while raising yields. Additionally, meteorological, soil, managerial, phenotypic and imaging data are used to train machine learning models.

2.1 Applications of big data in agri -biological systems - Big data is frequently used to describe a modern trend in which the technology and sophisticated analytics combine to produce novel and practical processing methods. Four V's can be used to describe big data. Volume is used to describe vast amount of data produced by variety of sources. Velocity is used to describe data that needs to be gathered, stored, evaluated and acted upon quickly. The term "variety of data" describes data that comes from various sources such as unstructured text file, email, video and the structured data found in traditional databases. Another phrase is veracity, which refers to data flows having periodic peaks and baselines that fluctuate significantly. Big data analytics systems include Cloud computing, Internet of Things, Artificial intelligence and Machine learning (Sonka, 2014) <sup>[9]</sup>. Innovative methods for managing big data are referred to as "big data analysis" (Waga & Rabah, 2014) <sup>[10]</sup>. The main issue with large data-driven applications is data storage, and NoSQL technologies are currently becoming more and more well-liked (Lokers *et al.*, 2016) <sup>[11]</sup>.

## 3. Artificial Intelligence (AI) and Machine Learning (ML) Approaches

With increased exposure to data, machine learning allows computers to improve better at a task over time related to recognizing patterns with little assistance from humans (Ahmed *et al.*, 2020). There are numerous ML techniques like sensors, GIS software and GPS technology which helps in improving the sustainability and efficiency of agriculture in many ways. Furthermore, Machine learning algorithms evaluate large-scale agricultural data which can boost productivity and efficiency. This section discusses about how the ML techniques improve the decision making in agricultural operations.

### 3.1 Supervised learning

The process of training algorithms on labeled data, which

includes both the input data and output data (labels) is known as supervised learning (Nasteski, 2017) <sup>[13]</sup>. For the model to accurately predict labels for novel, unidentified data, it must understand the input-output mapping. Important algorithms are -

- Linear regression helps in solving regression problems (Darlington & Hayes, 2017) <sup>[14]</sup>. Additionally, It can also be expanded to incorporate more than one variable (multiple linear regression)(Pak & Oh, 2010) <sup>[15]</sup>.
- Decisions trees - These are flexible algorithms that work for both classification and regression (Mienye & Jere, 2024) <sup>[16]</sup>.
- Support Vector Machines- According to Awad *et al.* (Awad & Khanna, 2015) <sup>[17]</sup>, SVM performs well with clear margin separation and is efficient in high-dimensional domains.
- k-Nearest Neighbors- A new data point is classified using this algorithm by utilizing the majority class of k-nearest data points in the feature space (Halder *et al.*, 2024) <sup>[18]</sup>.

**Applications:** To detect pests and plant diseases, Decision trees and random forests have been employed by classifying images from cameras or drones. Additionally, this algorithm facilitates the prediction of various soil properties by the evaluation of soil health using data from sensors.

**Case Studies and Examples:** Using drone footage to diagnose diseases and pests was an efficient use of a decision tree algorithm that decreased the need for pesticides (Shahhosseini *et al.*, 2019) <sup>[19]</sup>. Support vector machines are used in forecasting the levels of soil moisture and even assist with scheduling of irrigation. These case studies demonstrate how machine learning applied in agriculture to boost productivity and profitability while promoting sustainable practices and lessening the impact on the environment (Saikanth *et al.*, 2023) <sup>[20]</sup>. Additionally, the use of Drones and sensors in conjugation with machine learning algorithms could revolutionize agricultural practices in both sustainable and highly productive way.

### 3.2 Unsupervised learning

This algorithm is frequently used to work with high-dimensional data and to identify hidden patterns, as it reduces processing effort, reduces noise, and improves visualization. K - clustering is effective for big datasets and it necessitates a fixed number of clusters (Ikotun *et al.*, 2023) <sup>[21]</sup> whereas, dimensionality reduction technique reduces data into smaller sets of uncorrelated variables called principal components which capture the majority of the data's variation (Hasan & Abdulazeez, 2021) <sup>[22]</sup>. For crop classification and the identification of abnormalities in soil conditions clustering algorithms are widely used. K-clustering algorithms have been extensively used In agricultural monitoring systems to categorize satellite imagery into different crop types by analyzing spectral information (Coulibaly, 2024) <sup>[23]</sup>. Studies have shown that such methods assist farmers and decision-makers in recognizing hidden patterns and spatial variability within fields, thereby helping to identify areas that may require targeted management or corrective action (Hoque & Padhiary, 2024) <sup>[24]</sup>.

3.3 Reinforcement learning

An engagement of an agent with its environment to learn how to make a sequence of decisions over time in the machine learning domain known as reinforcement learning (RL) (Naeem *et al.*, 2020) <sup>[25]</sup>. Deep RL can handle complicated and dynamic scenarios, which makes it suitable for more difficult professions like livestock management, robots, and complex simulations. Tabular reinforcement learning can handle small, discrete scenarios (Y. Chen *et al.*, 2023) <sup>[26]</sup> (Nguyen *et al.*, 2020) <sup>[27]</sup>. By concentrating primarily on impacted areas, actorcritic techniques teach autonomous drones to apply pesticides more efficiently and reduce their consumption.

3.4 Deep learning in agriculture

Multilayered neural networks are used in deep learning to represent complicated data relationships because it is very

good at handling vast volume of unstructured data including text, audio and images (Rabha *et al.*, 2024) <sup>[28]</sup>. For example, Convolutional Neural Networks (CNN) are utilized in agriculture for tracking growth phases, recognizing plant diseases, analyzing images, and assessing crop health (Abade *et al.*, 2021) <sup>[29]</sup>. For environmental simulations and agricultural training, generated adversarial networks (GANs) offer artificial data. The utilization of deep learning in precision farming enhances the agricultural production, resource efficiency and reducing its negative impacts on the environment (Debnath *et al.*, 2024). Moreover, deep learning methods are applied in agricultural monitoring, specifically for detecting diseases, estimating crop density and for identifying nutrient deficiencies (Venkatesh & Naik, 2024) <sup>[31]</sup>. These models facilitate quick decision-making in the fields of pest control, irrigation and harvesting (as shown in Table-1).

Table 1: Commonly used Deep Learning process-based models

| Name of the Model | Deep learning engaged in model  | Benefits of model                                                                                            |
|-------------------|---------------------------------|--------------------------------------------------------------------------------------------------------------|
| CropSyst          | Long Short Term Memory (LSTM)   | This model is used to predict yield over the long run and optimizing cropping patterns.                      |
| AquaCrop          | Artificial Neural Network (ANN) | This model is used to evaluate and monitor crop water productivity and also help in scheduling irrigation.   |
| DNDC              | Deep Neural Network (DNN)       | This model is widely used to enhance the prediction accuracy of Greenhouse gas emissions.                    |
| DSSAT             | Random Forest, DNN              | This model is extensively used for assessing the impacts of changing climate and helps in yield forecasting. |

4. Optimization Techniques for Agricultural Systems

Optimization is essentially required for reaching comprehensive solutions that address various objectives, including optimizing quality of product, cutting expenses

and maintaining the sustainability of the environment. Three optimization techniques listed in the table are crucial for resolving a number of issues (Yu *et al.*, 2024) <sup>[33]</sup>.

Table 2 - Comparison of Optimization Approaches

| Parameters       | Linear Approaches   | Non-Linear Approaches       | Evolutionary Approaches  |
|------------------|---------------------|-----------------------------|--------------------------|
| Intricacy        | Less complex        | Moderately to Highly comple | Extremely complex        |
| Correctness      | Precise answers     | More precision              | Estimated answers        |
| Computation      | Quick and effective | Computationally demanding   | Resource intensive       |
| Type of problems | Linear              | Non- Linear                 | Discontinuous and convex |

Combining Techniques to Get the Best Results - Hybrid approaches are gaining popularity in the field of food science by integrating all three approaches. Understanding the distinctions and similarities between different approaches, help practitioners to select best method based on their requirements.

4.1 Optimization with Multiple Objectives (MOO) Combined with Artificial Neural Networks (ANN) -

- Maximizing the use of energy and water consumption in dairy processing using MOO-ANN results in 25% and 15% reductions in water and energy usage respectively without sacrificing the quality of final product (Funes *et al.*, 2015) <sup>[33]</sup>.
- Real-time optimization of demand and supply systems is made possible by these models that help us to forecast demand trends, optimize transportation routes, and balance inventory levels by using IoT devices (Segovia-Hernández *et al.*, 2023) <sup>[34]</sup>.
- MOO- ANN systems also supports some of the 2030 SDGs (Sustainable Development Goals) Agenda.

5. Digital Agriculture System

5.1 Internet of Things (IoT) based modeling

How devices are connected via internet is called as Io T. In the past, Internet was mostly utilized for computer connections, necessitating human engagement and oversight. Technology such as Internet of Things (Io T) connects electronics, electrical, and even mechanical systems together to collect data from the plant/crop environment through wireless sensor nodes, are the driving forces behind modern crop farming practices. Crop farming with Io T technologies are -

Wireless Sensors - The term "wireless sensor" refers to a gadget that may collect data and detect changes locally in any environment (Abdulsalam *et al.*, 2023) <sup>[35]</sup>. Wireless sensors come in a variety of forms, including as motion, proximity, temperature, and liquid sensors. Wireless sensors are key components of IoT. Using wireless sensors, IOT can allow a variety of farm activities to be recorded and reported in real time. For example, IoT-driven sensors can identify pests or illnesses early on, enabling farmers to carry out focused interventions. In turn, this encourages sustainable

farming methods and lessens the need for toxic pesticides. Networks and Communication Protocols - Network protocols and communication are linked (Adebisi & Babatunde, 2022) <sup>[36]</sup>. Network protocols have the ability to interact efficiently regardless of the variations in device architecture and design. Network protocols are used by almost every type of network, such as Local Area Networks (LAN) and Metropolitan Area Networks (MAN). The Transmission Control Protocol (TCP) and the Internet Protocol (IP) are two widely used protocols for dissemination of data in the Internet world.

Cloud and Fog Computing - Fog networking is a distributed computer system that uses processing resources in order to perform intricate operations between the source and cloud data (Guardo *et al.*, 2018) <sup>[37]</sup>. Cloud computing, on the other hand is frequently referred to as Internet computing which is applied at a basic level in agriculture for performing various functions including project management and distribution, report authoring and progress report drafting. Foremost work of cloud service is to store the files utilized in performing above functions. Front and back end, communication, and Internet administration are all covered by cloud computing.

## 5.2 Digital twins in agriculture

In general, digital twins are the digital representation of actual entities that replicate their states and behaviors throughout their whole lives in a virtual environment. It can be used regardless of location, time, or human observation and is typically a standardization of real-world variables. Digital twin in agriculture is multi-physical, multi-scale, simulated model based on probability of complicated production. A DT uses precise and real-time digital mapping to simulate, monitor, diagnose, anticipate, and control, for example, crops (Nie *et al.*, 2022). Planning and managing soil operations, irrigation, farming machinery and robotics could all benefit from the using digital twins (Nasirahmadi & Hensel, 2022) <sup>[39]</sup>. In order to make more accurate decisions, this technology enables agricultural practitioners to track and evaluate important variables related to crop growth and climatic changes (Grieves, M., Vickers, 2017) <sup>[40]</sup>. Additionally, DTs can aid in simulating the whole agricultural ecosystem.

## 5.3 Precision agriculture

Precision farming plays a very vital role in agriculture for several reasons, including enhancing productivity, sustainability and efficiency of agricultural operations. It gathers and analyzes data related to soil, crops, weather, and other factors that influences the agricultural growth and yield by using technologies, including GIS software, Remote sensing, and sensor-based systems (DeLay *et al.*, 2022) <sup>[42]</sup>. Using data analysis as a key tool to customize agricultural operations to specific regions within a field, farmers can increase their productivity and profitability by maximizing crop yields (Lowenberg-Deboer & Erickson, 2019) <sup>[42]</sup>. A variety of technologies used in precision agriculture are as follows:

- **Global Positioning System (GPS):** This technology makes it possible to geolocate soil types and field boundaries and even helps in precise field mapping. GPS is also used by farmers to apply site-specific crop

management techniques such as variable rate treatments. Farmers can easily monitor and evaluate their field performance by integrating GPS data into farm management software systems, which helps them in better decision making process and increase can their agricultural output and sustainability.

- **Geographic Information System (GIS):** GIS is a software that combine both spatial and temporal data to produce comprehensive maps of farms which aid farmers in analyzing and interpreting the data related to crop yield variability, topography, soil characteristics, and other elements influencing farm management decisions (Bonham-Carter, 2014) <sup>[43]</sup>. Additionally, by utilizing this software farmers can increase overall production and sustainability of farm, lower environmental concerns and improve management techniques.
- **Variable Rate Technology (VRT):** This technology makes it possible to apply allows inputs like fertilizers, herbicides and irrigation water in field precisely in accordance with site-specific needs as this technology uses data from various sources like sensors imagery and GPS technology which creates prescription maps that helps in applying inputs at variable rates. Ultimately, the application of VRT in precision farming improves resource management, agronomic practices, and sustainable agricultural output.
- **Remote Sensing (RS):** High-resolution imagery and data of fields are captured by remote sensing technologies using satellites, drones, or sensors mounted to airplanes. RS enable farmers to track crop growth, identify insect and pest infestations, diagnose nutrient deficiencies, and scheduling irrigation, thus help in better decision- making (Reddy *et al.*, 2015) <sup>[44]</sup>. Furthermore, farmers can also use remote sensing to identify interventions and site-specific management techniques by detecting spatial variability in their fields.

## 6. Recent and future possible uses of mathematical modeling and optimization in biological and agricultural modeling

Mathematical modeling is an essential tool in modern biological and agricultural research. These models help researchers to provide a comprehensive understanding on the complicated biological processes and supports them in making better and informed decisions to improve crop productivity. In recent decades, modeling techniques have evolved from conventional deterministic and empirical methods to more advanced and optimization-based frameworks. Such modern models are capable of capturing variability in biology and uncertainty in the surrounding environment. Today, these modeling tools are widely applied in agriculture for monitoring and evaluating crop growth, pest infestations, climate change impacts and efficient resource allocation (SARGUN & MOHAN, 2020) <sup>[42]</sup>.

- Crop growth simulation models are generally used in agricultural research to incorporate soil and climate variables with physiological factors. These models helps to forecast crop yield and biomass accumulation. By using these models, researchers can access how environmental stresses influence the crop productivity

and management practices. In addition to measure uncertainty and enhance prediction reliability, statistical techniques like regression analysis, time-series models, and stochastic models are widely employed.

- Recently, land use planning, irrigation scheduling, and nutrient management have all benefited from using optimization techniques. These techniques help to reduce resource inputs and the negative impacts of environment. Additionally, supply chain efficiency, economic returns, and sustainable agricultural decision-making have all benefited from the application of mathematical optimization models have also been used to enhance profitability and strengthen supply chain efficiency.
- Cybernetic modeling frameworks and machine learning optimization merges predictive modeling with control theory by combining sensor data, remote sensing, and decision support tools to optimize farming operations in real time (Pal *et al.*, 2024) <sup>[46]</sup>.
- Sustainable cropping systems that simultaneously balance ecosystem, biodiversity, and economic profitability are also being designed using frameworks for spatial optimization and mixed-integer programming. These frameworks account for providing policy - oriented recommendations related to agricultural practices by integrating environmental limitations, fertilization practices and spatial variability (Geissler *et al.*, 2025) <sup>[47]</sup>.
- Moreover, modeling frameworks driven by artificial intelligence are anticipated to play a major role in advancing sustainable crop production and ensuring future food security by integrating with biotechnological approaches. These models speed up breeding programs and strengthen crop resilience to abiotic and biotic stresses by incorporating environmental, phenotypic, and genotypic data (Li *et al.*, 2025) <sup>[49]</sup>.
- In a similar vein, recent narrative reviews emphasize the relevance of uncertainty quantification, sensitivity analysis and model coupling in crop growth modeling. According to these studies, improvement in model-based decision systems for managing sustainable agriculture is possible by combining sensors information and socioeconomic parameters (Mgana *et al.*, 2026) <sup>[49]</sup>.

## 7. Challenges and Future Research Directions

AI technology can revolutionize the agriculture industry, though there are several barriers preventing its broad usage and efficacy. These challenges span the technical, economical, social, ethical, and moral domains, thus we require a comprehensive and collaborative approach for a satisfactory outcome. Data availability and quality are of paramount importance. Large amounts of pertinent, high-quality data are essential for the necessary for successful operation of Artificial intelligence technologies, especially complex deep learning systems (Kamilaris *et al.*, 2017) <sup>[50]</sup> a persistent problem across multiple domains that hinders model's development. It includes the lack of suitable infrastructure in areas where these technological advancements are most needed. The return on investment for farmers is unknown. The speed at which technological

development is astounding, especially considering the quick changes in the industry. According to Ferris *et al.* (Ferris *et al.*, 2014) <sup>[51]</sup> this might made difficult for farmers' to access financing and costly maintenance.

Future research should focus to develop scalable and reasonably priced machine learning benefits for locations with lack of resources in order to ensure that small - scale farmers and organizations in developing nations can benefit from the technology. Therefore, the creation of intelligent, self-learning systems should be made by conjugating machine learning with robotics and automation that can perform challenging situation in order to benefit farmers and agriculture industries. Furthermore, Future advancements will result in agricultural systems that are more robust, efficient, and sustainable. We have proposed a number of approaches to deal with the fore mentioned challenges:-

- **Quantity and quality of data:** As machine learning technology is highly dependent on data and may require substantial amount of information, therefore the necessary requirement for big data sets is the major challenge related to effective application of machine learning in agriculture industry, where collection of data is time taking and labor-intensive process. Addressing, data scarcity issues are made possible by using active learning techniques and producing synthetic data. Therefore, real-time data streams that are produced by sensor networks and IoT devices, enhances datasets for ML model training and also fosters efficiency and creativity in agricultural methods through advanced analytics.
- **Interpretability:** It is impossible to avoid the extra risks associated with integrating a "black-box" model like machine learning into process- based modeling. Therefore, it is advised to ignore the hidden processes of simulated procedures and we should replace only those process- based modules that are predicted on basic empirical connections and presumptions. The enhancement in the precision and interpretability of stream flow estimation are carried out by substituting a data-driven sub-model for the traditional evapotranspiration (ET) module of hydrological models based on processes (Lian *et al.*, 2023) <sup>[52]</sup>.
- **Validation of models:** Certain standards and guidelines ought to be applied to improve validation efforts. According to Villa- Vialaneix *et al.* (Villa-Vialaneix *et al.*, 2012) <sup>[53]</sup>, combining interpretability metrics with meta-modeling can yield streamlined insights.
- **Generalization and scalability:** Every time new data becomes available, the model should be retrained and revalidated to make sure that model keeps working properly. Therefore, addition of fresh data streams and adjustment of changes in the underlying data distributions, such a pipeline can help that models stay current, for instance, Google's TFX (Tensor Flow Extended) (Baylor *et al.*, 2017) <sup>[54]</sup>. Model registries are essential during training and retraining in order to handle model's lifespan and they also aid in scalability and generalizability. Registries make it possible to switch between model versions smoothly, preventing upgrades from interfering with live systems such as ML flow's Model Registry (A. Chen *et al.*, 2020) <sup>[55]</sup>.
- **Using a Generative Adversarial Network (GAN):**

The majority of agricultural datasets generally lack sufficient imagery in a variety of settings, which is necessary to generate extremely accurate models. Many researchers have demonstrated that GAN is perfect for imbalanced datasets (Sauber-Cole & Khoshgoftaar, 2022) <sup>[56]</sup> and tiny datasets (Alauthman *et al.*, 2023) <sup>[57]</sup>. Therefore, the literature offers additional recommendations for managing imbalanced datasets (Al Sahili & Awad, 2022) <sup>[54]</sup>.

- **Closing the domain gap:** Using pre-trained models that are not domain-specific is a problem in transfer learning (TL) for agriculture. Rather, these models lack specificity for agricultural situations because general computer datasets like Image Net and COCO were used for their initial training (Al Sahili & Awad, 2022) <sup>[54]</sup>. CNN models are moving from low to high-level features which could result in negative transfer effects therefore, agricultural-based foundation models must be developed in order to supply resilient and generalized models in multiple domains of agriculture.
- **Incorporation of genomics and phenomics:** Researchers can develop accurate and effective breeding techniques by integrating the genomic and phenotypic data to obtain a comprehensive understanding of plant characteristics and its underlying genetic pathways (Dutta *et al.*, 2022) <sup>[59]</sup>. This integration results in enhancing genetic gain through genomic selection, thus transforming breeding methods in both plant and livestock species (Xu *et al.*, 2020) <sup>[56]</sup>. Furthermore, cutting-edge technology like genomic tools and bioinformatics used in crop improvement helps to improve breeding efficiency, bridging the phenotypic gap, and eventually aid in the creation of better crop varieties (Hu *et al.*, 2018) <sup>[57]</sup>.
- **Environmentally appropriate strategies to address Climate Change and Evolutionary Resilience in Organisms:** Adaptive characteristics and behaviors can have a significant impact on insect population dynamics. According to recent research, adaptive features (such heat tolerance) typically have a major impact on demographic dynamics, which in turn shapes species ranges and population dynamics considering the effects of climate fluctuations. Several adaptive management techniques must be used to deal with the changing status of insects and natural adversaries to enhance biological control (Sørensen *et al.*, 2012) <sup>[58]</sup>. First and foremost, extremely precise experimental procedures are required when examining the expected consequences of changing climate on natural foes (Terblanche *et al.*, 2011) <sup>[63]</sup>. Regular monitoring and ecological assessments, in addition to predictive models, may be a crucial instrument for precisely revealing the effects of changing climate on pest population dynamics (Pearson *et al.*, 2002) <sup>[64]</sup>. Therefore, ecological monitoring and assessments will produce large datasets that may be overlooked by physiological and prediction models and it is anticipated that these parameters will produce more useful data about the interactions between biological control agents under changing climates. While employing methods like acclimatization to increase activity in changing environments, augmentative

measures can also be employed to increase parasitoid populations (Sørensen *et al.*, 2012).

## 8. A Case Study: Yield Modeling using Crop Simulation models in Wheat

Wheat is one of the important cereal crop in India and is primarily grown in rabi season. Therefore, to evaluate the impact of nutrient management on wheat productivity, a field experiment was conducted at the experimental farm of Indian Institute of Technology, Roorkee, India using nine experimental plots. The chosen wheat variety for experimental purpose was HD-2967. Measurements of each plot was three by two meters. On December 13, 2018 wheat was sown at a 5-6 cm depth with a spacing of 15 × 15 cm. Each plot received a different fertilizer treatment to assess their impact on biomass production. The objective was to monitor and quantify the changes in yield resulting from different fertilizer treatment and to employ crop simulation models to estimate wheat yield under each fertilizer treatment. For example, DSSAT model and InfoCrop models are used to compare the simulated outputs with the observed field data.

### 8.1 Methodology

Three plots (C1, C2, C3) received a controlled fertilizer supply of urea and farmyard manure (FYM) whereas plots F1, F2 and F3 received -25%, +25% and +50% respectively. The remaining three plots N1, N2 and N3 received -25%, +25% and +50% respectively. Furthermore, plots F1, F2 and F3 received a normal dosage of urea but the dosage of FYM varied whereas in case of N1, N2 and N3 plots the dosage of urea varied. Field layout dimensions were taken to be thirteen by ten meters. To test the model DSSAT model and InfoCrop models were simulated. The structural framework of InfoCrop model is based on the SUCROS modeling approach (Aggarwal *et al.*, 2006) <sup>[65]</sup> (Aggarwal *et al.*, 2006). In this case study, CROPSIM-CERES module of DSSAT model was employed to emphasize nutrient dynamics and crop - soil interaction in wheat ((2003). The DSSAT Cropping System Model. European Journal of Agronomy. 18(3-4): 235-265., n.d.) <sup>[66]</sup>.

### 8.2 Results and Discussions

All experimental plots were harvested on April 22, 2019 and the corresponding dry matter and grain yields were noted for each plot. The output of treatment C was determined by averaging the yields of plots C1, C2 and C3. The highest and the lowest observed grain yields were recorded in F3 (124.18%) and F1 (47%) respectively. It was observed that the variation in grain yields under nitrogen based treatments (N treatments) were comparatively smaller than that of F treatments. It was also noted that for all treatments except N3, yields increase with the higher application rates of FYM and urea. As the dosage of organic or inorganic fertilizer was increased, the observed grain yields of the treatments generally increased as well. It was also noted that the overdose of urea won't enhance wheat yield. However, the surplus nitrogen is not absorbed by the plants, potentially causing groundwater quality deterioration.

The yields of plots are simulated by using Info Crop and DSSAT crop models using the input data and the standard simulation processes. Both models produced very precise

simulated yields for treatment C. However, for FYM based treatments DSSAT models consistently underestimated the grain yields and Info Crop models consistently overestimated the observed values. DSSAT models overestimated the crop biomass across all nitrogen based treatments. Overall, Info Crop model performance was observed to be superior as compared to DSSAT in simulating wheat yield. Hence, this study highlights the need further research and refinement of the model to enhance the simulation of grain yields for treatments that only use organic fertilizer.

## 9. Conclusion

Machine learning algorithms results in providing timely intervention and mitigation strategies to control weeds, pests, and diseases by early identification and classification accurately. Making decisions based on data can help farmers improve their sustainability by minimizing resource usage and environmental effects thus preserves crop health while reducing the likelihood of yield losses. Contextualizing data consumption, managing privacy and guarantee timely data are also crucial. Furthermore, enhancing interpretability, promoting human-machine collaboration and helping ordinary farmers in overcoming their low level of digital literacy are also critical areas of focus. Additionally, training initiatives and outreach programs can be created to address the needs of agricultural communities. A revolutionary way to overcome the time and computational limitations frequently encountered in large-scale simulations is to combine machine learning and process-based modeling. Furthermore, real-time model updates and dynamic recalibration helps to overcome the time limits associated with lengthy simulations. With practical insights for local and global policy making, this integrated approach has the potential to greatly expand research in various domains of agriculture. Therefore, developing mechanistic physiological approaches would be a fruitful area of future research to understand the impacts of climate change (Hoffmann A. & Daborn J., 2007) <sup>[67]</sup>. Moreover, there is substantial evidence that species are changing in response to climate change (Bradshaw & Holzapfel, 2006) <sup>[68]</sup>. Therefore, evolutionary potential should be included in future forecasts of how climate change may affect insect biodiversity (Sgrò *et al.*, 2011) <sup>[69]</sup>.

In conclusion, applying machine learning (ML) to agriculture is very helpful as it involves number of benefits, including increased agricultural output and resource allocation, lowering disease and pest infestations and reducing environmental effects. However, the agricultural landscape is poised for a more complex and dynamic future in which tradition and technology coexist peacefully to enhance global agriculture, while data-driven approaches continue to thrive.

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