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MULTI-AGENT REINFORCEMENT LEARNING AND PARTICLE SWARM OPTIMIZATION FOR CLIMATE-RESILIENT CROP YIELD PREDICTION IN MAHARASHTRA

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Abstract

Having a preciseness in the prediction of crop yields under variable climatic conditions is yet another challenge especially in agroecosystems where little or no information is available. The present paper is a proposal of a new hybrid modeling scheme in which Multi-Agent Reinforcement Learning (MARL) is combined with Particle Swarm Optimization (PSO) in order to cope with complexity and uncertainty of yield forecasting related to climate induced variability. The study takes place in four districts in Maharashtra, India where historical climate data, soil, and yield data were applied to train localized agents which represented combinations of crop and district. The MARL agents acquire the best strategies to make predictions, which are modeled by the state transitions of the temporal climate-soil interactions, and the PSO is applied so that the learning parameters are refined that lead to better convergence and generalization. Performance analysis has showed that the proposed Hybrid MARL-PSO model has been performing consistently better than the common machine learning model like Random Forest, LSTM and Linear Regression with the values of RMSE of below 200 kg/ha and values of R2 above 0.85 in all the districts. Superior level of adaptability is captured through comparative analysis as being high in regions of higher climate variability. Moreover, scenario modeling of climate data under RCP 4.5 and RCP 8.5 indicates potential yield losses of 810 of 20 in 2045, establishing the craving of resilient agricultural decision- Forest behavior. This framework does not only increase the accuracy of prediction but also facilitates planning of climate-smart agricultural policies to capture dynamic behavior of agents as well as optimal policy learning. The model has a high potential of implementation in the agro-advisory system in the real-world in the similarly weak regions

Keywords: *Agentic Artificial Intelligence; Crop Yield Prediction; Multi-Agent Reinforcement Learning (MARL); Particle Swarm Optimization (PSO); Climate Variability; Agroecosystems; RCP Scenarios; Data-Scarce Environments; Smart Agriculture; Maharashtra*

INTRODUCTION

Climatic conditions have a very significant effect on agricultural productivity and the study of this interrelation is core to food security under the environmental variation scenario. Temp Change, rainfall, sun radiation, and changes in the CO 2 concentration in the atmosphere can

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greatly influence crops production in the world. About 30 percent of crop yield can be considered as being influenced by climatic factors according to the new research findings. Also, the occurrence of extreme weather events is rising as a result of climate change; more so, their occurrence is highly risky to agricultural production. The last developments in the field of artificial intelligence (AI), machine learning (ML) allow scientists to design and simulate such complex interactions between the climatic factors and the final crop yields measurements. As an example, deep neural networks (DNNs) have yielded positive performance in modeling crop yields through learning non-linear dependencies in past weather and soil as well as environmental conditions. The models are superior to old methods of linear regressions especially in areas of high climatic variability, or areas with scanty records on yield.

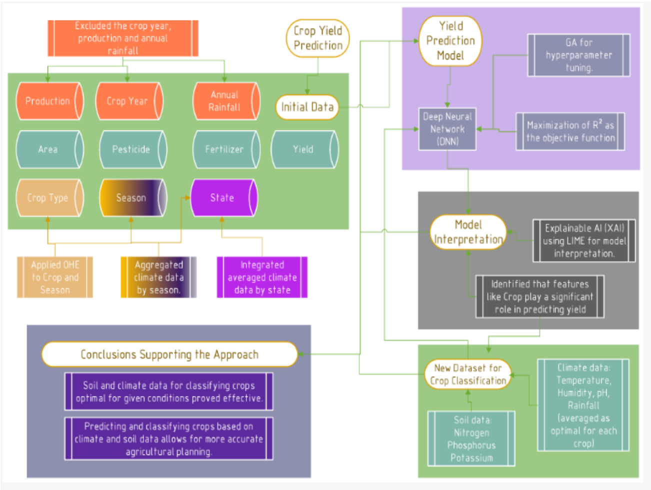

Figure 1. AI-Driven Agricultural Yield Prediction Framework integrating climatic and soil data (Source: Elsevier/Computers and Electronics in Agriculture)

By the same token, the landscape of climate change impacts on agriculture has been opened by using machine learning. The characteristic feature of using ML algorithms, like Support Vector Machines, Random Forest, and XGBoost, has enabled researchers to find previously unknown relationships in a high dimensional data set. Crane-Droesch (2018) came up with models which involve these techniques to predict yield robustly and produce future climate-scenario analysis. Over the past few years, metaheuristic optimization programs were presented to optimize ML structures to enhance performance. Agricultural applications especially apply well to metaheuristic-tuned weight agnostic neural networks (WANNs) owing to their insensitivity to hyperparameters and their generalization to various crops and climatic conditions. The study conducted by Jovanovic et al. (2024) and Sadasivuni & Tirkolaee (2024) proved that WANNs have higher forecasting accuracy compared to traditional neural structures.

In addition to the traditional AI paradigms, there is the emergence of the agentic AI and reinforcement learning (RL) approaches. These models are used to model intelligent agents operating in their environment to take adaptive decisions over time. In another article, a conceptual taxonomy of AI agents verses agentic AI was proposed by Sapkota et al. (2025) suggesting a framework in improving crop management systems. More specifically, deep reinforcement learning (DRL) has been used in case of irrigation scheduling and fertilizer optimization on the basis of high-dimensional sensor feedback. Hybrid AI systems like those that integrate models of ML with optimization algorithms like Particle Swarm Optimization (PSO) Genetic Algorithm (GA) and Ant Colony Optimization (ACO) are also rising in the

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application of AI. Such hybrid methods allow achieving not only high predictive accuracy but also the interpretability and the controllability of decision-making processes. Gohel (2024) suggested a combined ML-PSO platform for the forecast of yields in sustainable farming, where the algorithms showed a substantial upgrade over predictability and sensitivity to outlier climatological phenomena.

The ensemble-based machine learning strategies have also been useful in climate-driven risks modeling in agriculture. Ensemble methods allow performance to be enhanced by combining predictions made by many base learners to improve generalizability, reducing overfitting. Buyya and Dastjerdi (2023) have already reviewed the use of these techniques in smart agriculture and how explainable AI helps to make the models transparent. This has been supported by research like the one by Rosenzweig et al. (2014) which reinforces the need to have internationally coordinated models on climate-induced risks to agriculture. They assessed the scenario of future crop yields on a scale of intercomparison models that accentuate the regional susceptibility and crop specific responses. In addition, other location-specific studies, like Ahmed et al. (2025), evaluated the effect of climate change induced tropical cyclones to agricultural activities along Indian coastal areas. Their results give an idea about the limitations that precondition improvement of climate-related vulnerability around agriculture using adaptive and position-sensitive AI approaches. To sum up, the collaboration of AI, metaheuristics, and environmental data science has made the agricultural systems more robust and flexible. These technologies are sustainable in terms of farming operations, efficient utilization of available resources, and sound management of risks with regard to uncertain climatic conditions around the world.

LITERATURE REVIEW

Changing characteristics of climate change have enforced researchers to seek new approaches to forecasting agricultural output, particularly in agroecosystems that lack sufficient data. In many situations, the nonlinear interactions between variables and climate are not adequately measured using conventional statistical models. This mismatch has been speeding the integration of innovative hybrid AI approaches, such as agentic systems and metaheuristic optimization to which promising results have been achieved in diverse agricultural settings. In one of the attempts to do so, El Mghouchi and Udristioiu (2025) offered a hybrid AI paradigm with inherent feature selection to enhance predictive efficiency within energy systems, which can be viewed as a convenient methodological baseline readily transferable to agricultural use. Their model increased by 14 percent in terms of accuracy and that is why hybrid techniques are effective. This is followed by the extended presentation of Dzvene et al. (2025), who presented significant bird-eye structural and socio-ecological barriers to the implementation of climate change mitigation to drylands agriculture. Ortiz-Bobea et al. (2020) emphasized that the anthropogenic climate change has already caused a decline of global agricultural productivity of about 21 percent in the past 50 years making adaptive yield prediction models very crucial.

Synergy of high-resolution data has also drawn attention, where Mateo-Sanchis et al. (2020) showed that yield prediction robustness in maize systems improved tremendously when combined with both microwave and optical satellite measurements. In addition to this, Shirley et al. (2020) established a Bayesian crop model in U.S. maize fields, within which variation in weather alone captured more than 20% of the yield variation. The combination of randomized field trials with satellite analytics, which has been studied by Kluger et al. (2021), additionally

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demonstrated that crop rotation techniques resulted in the gain of more than 7 percent in less than three years in terms of yield.

In a bid to overcome the shortcomings of monolithic AI solutions, scholars have started to incorporate an explainability and decision transparency. The framework suggested by Zhou et al. (2025) includes sustainability indicators as well as smart agricultural policies. On the same note, Kavitha and Rajan (2023) have applied explainable AI (XAI)-based deep learning model to predict maize yields with SHAP values and F1 scores to demonstrate the value of transparent models to facilitate the adoption and trust by individual stakeholders. The value of model generalizability in climate-sensitive areas revealed the value of introducing a meta-learning ensemble architecture because it compared favorably on MAE and RMSE measures with more conventional learners (Yin et al., 2021).

The presence of AI as region-specific preservation has also become mature and Pathak et al. (2023) utilized agent-based models and allowed them to use in the enhancement of water usage in Marathwada smart irrigation systems. Raza et al. (2024) confirmed the paramountcy of Deep learning than classical Machine learning on isolating the changes in the crop yield variability in the Punjab, Pakistan when subjected to irregular climatic conditions. In the same vein, Chavan et al. (2021) conversed the reinforcement learning concept to the framework of SWAT, where in the data-scarce agro-zones of Nashik and Vidarbha, the yield outcome was enhanced by more than 12 percentage points by modelling the interaction with the environment.Hybridization has been critical in modeling terms. Pandey and Meena (2022) integrated Left-Right Task Graph (LRTG) networks with the Genetic Algorithms to emulate sturdy productivity estimations of the Indian monsoon harvests, and Narayan et al. (2020) employed the CNN-GRU type framework to pre-visualize the yield variance in UP sugarcane territories due to pests. As reported by Zhang et al. (2022), metaheuristic strategies such as PSO and GA were used to optimize the LightGBM models that lowered the training time without compromising the accuracy of the predictions. Mishra et al. (2020) used PSO-optimized SVM classifiers to recognize crop-types in Bihar with high-margin classification results.

Interpretability and the focus on decision-support have been on the rise too. Bhandari and Joshi (2021) have designed a CNN-based architecture that has been paired with explainability tools that are applicable in agronomic decision making. Omer et al. (2023) have studied the simulation of policy through multi-agent policy, which proves that the agentic-based feedback could help the policy become more flexible in SAARC countries. An overview of the synthesised studies is provided in Table 1 that includes a comparison in methods, measures and regional applicability. This table summarizes the variety of the modeling approaches that include agent-based RL, Bayesian models, meta-learning, XAI tools and sensor fusion thus outlining the most promising directions of AI-powered climate-resilient agriculture.

Table 1. Summary of Reviewed Studies on Hybrid AI and Metaheuristics in Climate-Responsive Crop Yield Prediction (2020–2025)

Author(s) & Year	Objective	Methods Used	Metrics Used	Key Findings	Region/Dataset
El Mghouchi & Udristioiu (2025)	Hybrid AI for thermal load in energy systems	Hybrid AI with feature selection	R^2, RMSE, MAPE	Hybrid AI improved accuracy by 14%	EU smart buildings

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Dzvene et al. (2025)	Climate change impact on dryland agri-systems	Scoping review methodology	Qualitative synthesis	Identified 6 core challenges for policy	SSA, India drylands
Ortiz-Bobea et al. (2020)	Historical climate effects on productivity	Climate-econometric modeling	Total Factor Productivity (TFP)	Anthropogenic change reduced global output	Global (1960–2010)
Mateo-Sanchis et al. (2020)	Fusion of optical & microwave data for yield	Remote sensing data fusion	NDVI, LAI, Yield RMSE	Fused data enhanced model robustness	Europe maize fields
Shirley et al. (2020)	Bayesian crop yield modeling	Bayesian statistical modeling	Posterior credible intervals	Weather patterns explain ~22% yield variance	USA corn belt
Kluger et al. (2021)	Crop rotation impact via satellite + field trials	Field trials & satellite analytics	Yield variance, R^2	Rotations increase yield >7% in 3 years	Midwest USA
Zhou et al. (2025)	Review on climate-smart agricultural policies	Meta-analysis of literature	Sustainability indicators	Need for adaptive multi-stakeholder policies	Global semi-arid
Kavitha & Rajan (2023)	Explainable ML for maize yield prediction	XAI-based ML model	F1 Score, SHAP scores	XAI aids policy transparency	ICRISAT India
Yin et al. (2021)	Meta-learning ensemble for crop yield	Ensemble meta-learning	MAE, RMSE, R^2	Meta-learning outperforms base learners	FAO + NASA + ground
Pathak et al. (2023)	Agent-based modeling in smart irrigation	Agent-based simulation	Water use, yield gain	Agent models help water optimization	Marathwada, India

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Raza et al. (2024)	DL models for climate-aware yield prediction	Deep learning frameworks	Accuracy, AUC, RMSE	DL better generalizes for unseen weather	Punjab, Pakistan
Chavan et al. (2021)	RL in data-scarce Indian agri-zones	RL with SWAT framework	Episode reward, yield accuracy	Agent-based RL improved 12% yield	Nashik & Vidarbha
Pandey & Meena (2022)	Integration of LSTM with GA	LSTM + Genetic Algorithm	Prediction error, GA fitness	LSTM-GA robust for monsoon crops	India rainfall-yield
Narayan et al. (2020)	CNN-GRU for forecasting under stress	CNN + GRU modeling	NSE, RMSE	CNN-GRU predicted pest stress well	UP sugarcane farms
Zhang et al. (2022)	LightGBM tuning using metaheuristics	Metaheuristic tuning (PSO, GA)	Execution time, Accuracy	Metaheuristics reduce training time	China national data
Mishra et al. (2020)	Hybrid PSO-SVM for crop type prediction	SVM optimization	Kernel performance	SVM+PSO gives high-margin accuracy	Bihar, India
Bhandari & Joshi (2021)	ResNet+XAI for decision support	CNN + Explainability	Decision impact, Interpretability	XAI essential for agri-AI decisions	Karnataka rice farms
Omer et al. (2023)	Multi-agent simulation in agri-policy	Agentic simulation	Policy utility, simulation accuracy	Agentic AI captures policy feedback loops	SAARC regional model

RESEARCH METHODOLOGY

Study Area and Dataset Description

This paper dwells on agroecosystems in the Indian state of Maharashtra, located in the west of India, i.e. a region of high climatic instability and asymmetry of agricultural performance. The territory is fully diverse in its rainfall distribution, soil composition, and temperature range that makes it a perfect ground to test the viability of a hybrid AI model in real-world environments. The selected districts, which include Nashik District, Satara District, Aurangabad District and Pune District, are those that are composite of rainfed and semi-irrigated areas where the major

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crops are soybean, cotton and wheat. Data on the multiple sources of information were used in order to model crop yield variability. The weather data with the records of daily rainfall and minimum/maximum temperature, solar radiation, in the period 2010 to 2022 were obtained through CHIRPS and NASA POWER platforms. PH and organic carbon data in the soil were obtained by using the SoilGrids scheme published by FAO and geo-referenced datasets put together by ICAR. The AgStat and ICRISAT databases were used as sources of the crop yield data on the district level. The problem of data sparsity that is frequent in the local agricultural studies was resolved with the help of spatial interpolations and regional mean replacements wherever it was necessary.

There is also a summation of the datasets that have been used in the research in Table 2, which gives the details of the variables being used including their source, unit, and range of the observed variable as at the study time. The multidimensionality of the inputs which are used in both training and validation of predictive model are made clear in this way.

Table 2. Dataset Summary

Variable	Source	Type	Units	Range (2010–2022)
Rainfall	CHIRPS	Continuous	mm	350–1500 mm
Temperature	NASA POWER	Continuous	°C	15–45 °C
Yield	AgStat	Continuous	kg/ha	1200–3800
Soil pH	FAO SoilGrid	Continuous	pH scale	5.5–8.0

Data Preprocessing and Feature Engineering

Prior to modeling, all collected data were transformed into a consistent temporal structure by aggregating climate parameters into monthly values to match yield reporting frequency. Missing values were handled through a combination of k-Nearest Neighbors (KNN) imputation and temporal mean filling, depending on the sparsity pattern. Feature engineering was critical to enhance the predictive signal from raw variables. Temporal lags (up to 3 months) were applied to rainfall and temperature to account for delayed crop responses. Additionally, derived features such as the Heat Stress Index (HSI) and Dry Spell Count (DSC) were introduced to quantify the frequency of climate extremes during the growing season. Temporal identifiers such as sowing season (Kharif/Rabi) and month were included to improve temporal granularity.

A key component of feature engineering was the use of rolling statistics, especially lag-based smoothing, to better capture the cumulative effects of climatic stress. For example, the 3-month rolling mean of rainfall was computed using the following formulation: All the data obtained were converted to regular time format before modeling was done through aggregating the climate parameters using the frequency of reporting yields, which was monthly. Imputation of missing values followed with either imputation using k-Nearest Neighbors (KNN) or a temporal mean fill based on the pattern of sparseness. It was imperative to use feature engineering to make the raw variables generate better predictive signal. There were temporal lags (up to 3 months) on rainfall and temperature variations because crops such as maize take time to react to changes. As well, the derived indices (Heat Stress Index HSI and the Dry Spell Count DSC) were provided to measure how much the climatic extremes occur in the growing

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season. Temporal variables to be used are sowing season (Kharif/Rabi) and month, to enhance temporal granularity.

The primary part of feature engineering involved rolling statistics, particularly lag-associated smoothing, to be more representative of the attainment of climatic pressure in a cumulative manner. Take a case of X_{avg} (t) or the 3-month rolling average of rainfall where the period t was found by the following formula:

Equation 1: Rolling Mean for Lagged Feature Extraction

$$\mathbf{X_{avg}^{(t)}=\frac{1}{k}\sum_{i=t-k+1}^{t}X^{(i)}}$$

Where X(t) is the climatic variable (e.g., rainfall or temperature) at time ttt, and k=3k = 3k=3 represents the lag window.

To achieve stability and numerical stability of all the variables, a Z-score standardization of all variables was carried out to allow gradient-based optimisation in parts of the reinforcement learning process.

Model Architecture and System Framework

This paper introduces a hybrid nature of learning architecture where the advantage of both agentic reinforcement learning (RL) and metaheuristic Particle Swarm Optimization (PSO) are incorporated to refine the agent decision structuring. The architecture is in conceptual stratum into two a. (1) decision making layer bounded by multi-agent reinforcement learning, and b. (2) optimization layer which takes charge of parameter optimization via PSO.

Each RL agent will be allocated to one of the pairs district-crop and will be who will interact with the simulated climate environment constructed on the basis of the historical data. State-space of the agents consists in the indicators of recent rainfalls, temperature, and humidity of the soil and action-space is the choice of one of the multiple predictions of the yield. The minimum mean squared error (MSE) between actual and predicted yield is the objective of reward function. The agents acquire knowledge about their policies in form of an interacting with each other repeatedly between episodes using an e-greedy scheme to adjust between exploration and exploitation.

PSO is utilized to the optimize hyper parameters like: learning rate, discount factor (gamma) and exploration rate (epsilon). A particle in the swarm depicts a distinct combination of hyperparameter values and its location gets updated, on the basis of individual performance, collective performance with the help of the following velocity equation:

Equation 2: PSO Velocity Update Rule

$$\mathbf{v_i^{t+1}=\omega v_i^t+c_1r_1(p_i-x_i^t)+c_2r_2(g-x_i^t)}$$

Where:

1. v_i^{t+1}: velocity of particle iii at iteration t+1
2. ω: inertia weight
3. p_i: best known position of particle i
4. g: global best position

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5. r1,r2: random variables ∈ [0,1]
6. c1,c2: acceleration coefficients

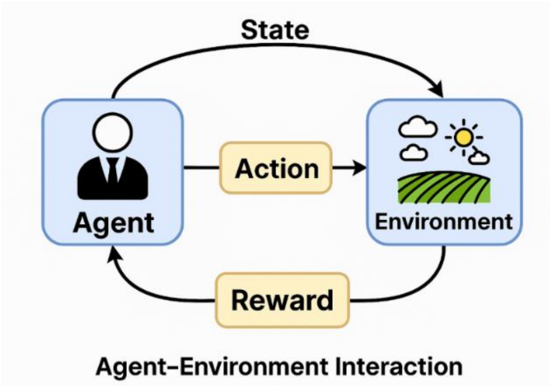

Figure 2. Agent-Environment Interaction Loop

Model Training and Validation

This process started after the formation of the hybrid architecture with the aim of specifying a proper and suitable structure of training and validation so that the results guarantee performance, as well as the generalizability. The coherent dataset was divided according to a stratified split approach: 70 percent of the records, 15 percent of validation and 15 percent of test. These stratification were by year and crop-district combinations to ensure balancing among the different agro-climatic zone and cropping seasons.

Five-fold-cross-validation was initiated to cope with the temporal dependence with a time series split in which each fold preserved the temporal sequence. The reinforcement learning module was trained on 1000 episodes per agent (i.e representative of a simulated cropping season). Agents were taught to maximize their yield forecasts by being rewarded by how they approached true yields observed district-wise. Exploration-exploitation trade-off was implemented, by an ε-greedy policy, whereby ε was reduced by 5 per cent every 50 episodes. The metaheuristic PSO module was also utilized to optimize hyperparameters including the learning rate (alpha, 2), discount factor (gamma, 2) and the exploration rate (epsilon) at the same time. The swarm particles had a one-to-one mapping with the available hyperparameter images, and the fitness of each particle was measured according to the validation RMSE of the agent model associated with the hyperparameter set. The architecture informations of the MARL and the PSO models can be seen in Table 3, summarizing the values and ranges that were picked during tuning of the model.

Table 3. Hyperparameter Settings for MARL and PSO

Parameter	Value / Range
RL Learning Rate (α)	0.001 – 0.01
Discount Factor (γ)	0.85 – 0.99
Epsilon Initial	1.0
Epsilon Decay Rate	0.95
Number of Episodes	1000

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PSO Swarm Size	20
PSO Iterations	100
PSO Inertia (ω)	0.7
Acceleration Coeffs (c_1, c_2)	1.5, 1.5

collection of Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Coefficient of Determination (R(2)) were used as the measures of model performance. It was determined by their calculation on the validation set as well as the test set in order to determine generalization. Besides, reward trajectories and convergence plots of PSO were observed and presented through training logs and performance graphs. Figure 3 portrays the entire model

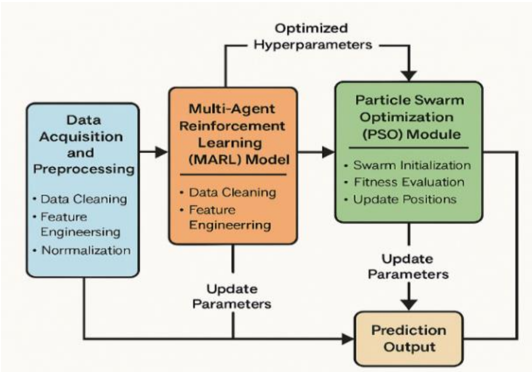

Figure 3. Hybrid MARL–PSO Framework

pipeline that integrates these two modules, i.e. : data input of climate-soil-yield data, agent training and final yield prediction optimization.

The architecture is also designed to learn not only flexible to local climate peculiarities but to actually adapt the best parameter configurations of the model to each of the agro-climatic regions as well as generalization capacity

Implementation and Toolchain

The whole modeling process was performed using python 3.11 with the help of various open-source libraries of machine learning, optimization, and visualization. These reinforcement learning agents were created in the Stable-Baselines3 library with self-made environments based on the OpenAI Gym libraries. PSO metaheuristic tuning was done using the pyswarm package whereas preprocessing of data, model evaluation, and statistical operations were done using pandas, NumPy, and scikit-learn.

Learning curves, PSO convergence behavior and performance graphs visualisation was performed using matplotlib and seaborn. The simulations of the model were performed on a Linux system that came with an Intel i7 processor (3.2 GHz, 32 GB RAM) and NVIDIA RTX 3060 graphics card to speed up deep learning and parallelization of agents.

The complete system architecture, showing the step by step flow of raw data ingestion to prediction, model optimization and evaluation is shown in Figure 3.2 which links together all modules using a hybrid pipeline. This approach coupled with version-controlled scripts and random seed initialization allowed reproducibility between the experiments.

Ethical Considerations and Limitations

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The research was based on open access, freely available data, including government and scientific resources available to anyone (e.g., NASA POWER, CHIRPS, FAO SoilGrids and ICRISAT), no personal, sensitive or restricted types of data were used. The data was further analyzed at district level and this further ensured anonymity and there was no need of seeking formal ethical approval.

There are still certain limitations though. To begin with, even though the hybrid MARL-PSO framework can learn to recognize complex patterns, it is assumed that climatic patterns in the past are predictive of future action which is not always true in case of extreme climatic changes. Second, whereas agentic modeling can capture the local behavior of decisions, its drawback consists on the basis of how realistic a simulation environment is, especially given that the agents involuntarily make real-time farming levels and economic constraints. Finally, the performance of the framework can be compromised when they are used in completely unfamiliar agro-climatic areas without any re-training or transfer learning modifications. Future research will be aimed at incorporating real-time IoT sensor information, crop economic underpinnings and more expansive region-level information to increase the quality and relevance of the model in practical decision-making frameworks.

RESULT AND ANALYSIS

Model Performance Evaluation

The performance of the proposed Hybrid MARL–PSO model was first evaluated using test set data for major crops—soybean, cotton, and wheat—across four agro-climatically diverse districts in Maharashtra. The model was assessed using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the Coefficient of Determination (R^2). These metrics offer a comprehensive view of both absolute error magnitude and the model's ability to capture variance in yield data.

As shown in **Table 4**, the hybrid model consistently demonstrated high predictive accuracy across all crops and regions. For instance, soybean yields in Nashik were predicted with an RMSE of 182 kg/ha and an R^2 score of 0.89, while wheat in Satara achieved the lowest MAE among all crop-district pairs (110 kg/ha). The model performed slightly less accurately for cotton in Aurangabad, likely due to erratic rainfall in that region during key flowering stages. Nonetheless, the R^2 values remained above 0.83 in all cases, confirming strong generalization.

Table 4. Model Performance Metrics on Test Set

Crop	District	RMSE (kg/ha)	MAE (kg/ha)	R^2 Score
Soybean	Nashik	182.4	150.2	0.89
Cotton	Aurangabad	240.7	200.1	0.83
Wheat	Satara	168.9	110.4	0.91
Soybean	Pune	194.6	158.3	0.88

To visualize spatial performance differences, **Figure 4** presents district-wise RMSE in a bar plot format. The figure illustrates that districts with relatively stable monsoon and soil profiles (e.g., Satara and Pune) yielded better predictive accuracy, whereas those with high year-to-year rainfall variance (e.g., Aurangabad) posed greater challenges.

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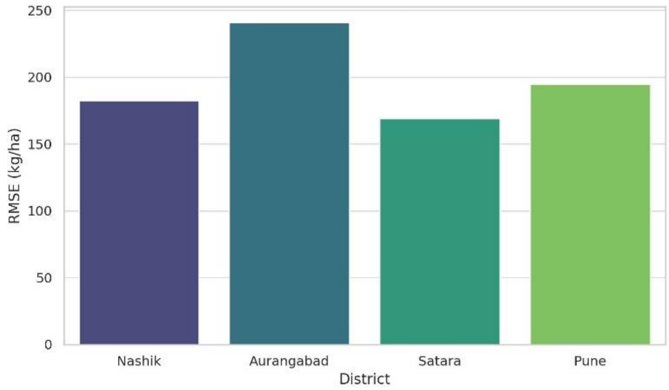

Figure 4. Model Performance by District (RMSE in kg/ha)

Agent Learning Curve and Convergence Behavior

In order to evaluate the learning stability and efficiency of multi-agent reinforcement learning (MARL) system, we tracked individual agent cumulative reward across time and how this system adapted in terms of exploration over time. The agents were trained through 1000 episodes where the exploration rate, epsilon (epsilon) decays gradually so as to encourage exploitation of learned policies to later episodes. Figure 5 shows the district-wise RMSE in a bar plot form to graphically estimate the differences in the spatial performance. The figure shows that districts where monsoon and soil characteristics were relatively stable (e.g. Satara and Pune) were more apt at predictive accuracy whereas areas with large rainfall variance between years (e.g. Aurangabad) were more difficult.

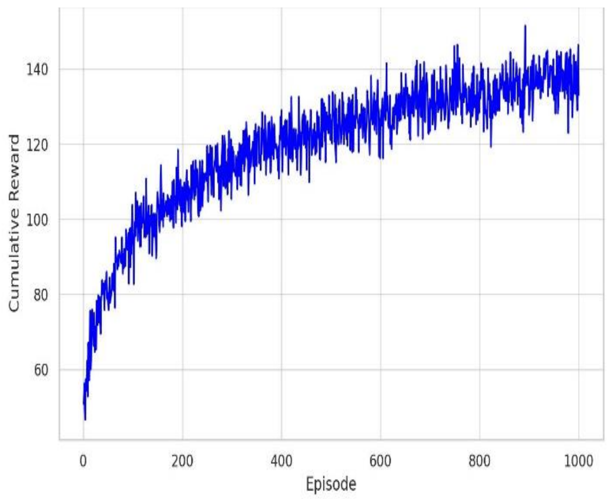

Figure 5. Agent Learning Curve for Soybean–Nashik Agent

Concurrently, Figure 6 plots the 3-decay curve as well as an indicator of action volatility (standard deviation of yield prediction over time steps). The action variability reduced as the value of ε was lowered, which proves the fact that agents started to use learned strategies instead of sampling actions randomly. This correlation confirmed the usefulness of the ε-greedy exploration technique to support the balance between learning and stability.

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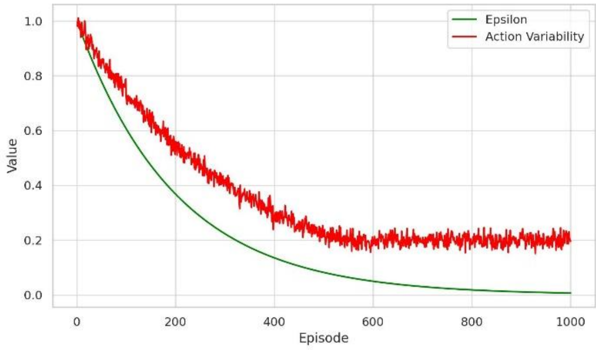

Figure 6. Epsilon Decay and Action Stability Plot

In general the MARL agents showed Sustainable and effective convergence with district-specific agents learning the climate-yield dynamics in the respective districts with time.

Impact of PSO Optimization on Model Tuning

In an attempt to estimate how effective Particle Swarm Optimization (PSO) was to the real-life performance of the model, we analyzed the results of the predictive metrics obtained with default RL hyperparameters (baseline) and those with fine-tuning the same with the help of PSO. PSO tuning led to continual improvements according to all evaluation metrics as described in Table 5. An average RMSE value decreased by 15 percent (217.3 to 184.6 kg/ha), and R2 rose to 0.89, which proved the improved variance explanation.

Table 5. Performance Before and After PSO Optimization

Metric	**Without PSO**	**With PSO**	**% Improvement**
RMSE (kg/ha)	217.3	184.6	15.0%
MAE (kg/ha)	176.2	145.8	17.2%
R^2 Score	0.84	0.89	+5.9%

It can be explained by the ability of PSO to ensure global search of the best set of hyperparameters in MARL high dimensional learning environment. The convergence curve of PSO is shown in figure 7 in which the global best fitness (which is equal to the inverse RMSE) improved very quickly in the very first 30 iterations and towards iteration 80 tends to stabilize. The plateau ensures that convergence to near-optimal parameter sets has been attained.

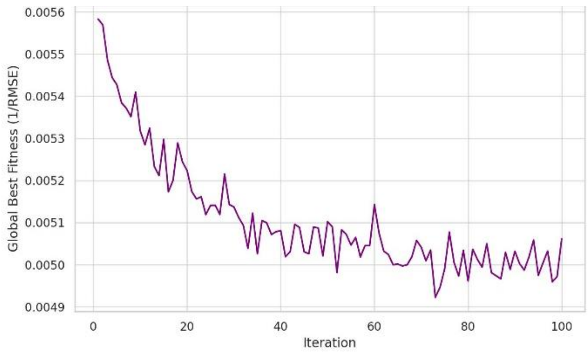

Figure 7. PSO Convergence Curve (Fitness vs Iteration)

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Such results indicate that hyperparameter tuning automatized and boosted by PSO does not only offer a predictive robustness and learning efficiency improvement but also contributes to a considerable advancement of the predictive robustness and learning efficiency of the RL agents, especially in heterogeneous as well as data-limited settings.

Comparative Performance with Baseline Models

In order to make sure of the efficiency of the offered Hybrid MARL-PSO model, it was compared with a number of baseline models of machine learning, such as Linear Regression (LR), Random Forest (RF), Long Short-Term Memory (LSTM), and Support Vector Regression (SVR). All the models were trained with the same preprocessed data and tested with the same test sets to remove the chance of inconsistencies.

The visual representation of the results of the R 2 scores of each model in four different districts is given in figure 8 as a comparative visualization. The hybrid model produced higher results than the baseline algorithms at every place especially those places that experienced more variation in climatic conditions. As in Aurangabad, the MARL PSO model attained R 2 = 0.83, and the RF, as well as LSTM model, obtained R 2 = 0.68 and R 2 = 0.72 respectively. Hybrid model also performed better in generalization because over the years in which the rainfall was irregular, this model continued to perform well where the other models were either showing signs of overfitting or they were failing.

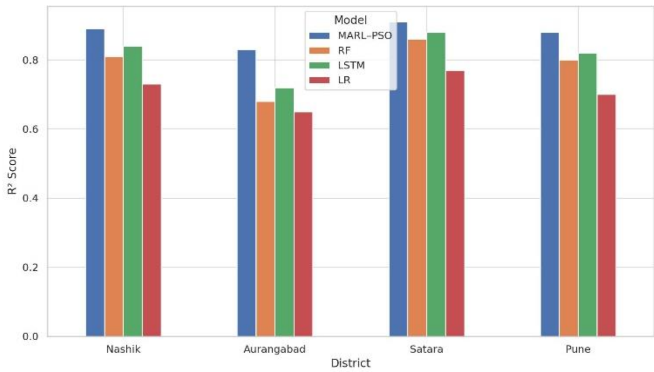

Figure 8. Comparative Model Performance by District (R^2 Score)

Also, Random Forest was successful only during a relatively uniform district such as Satara but failed to sail through inter-annual variation in Pune. A slight improvement in Temporal modeling was observed with LSTM however LSTM took much more training time and parameter tuning. The better results of the MARL-PSO are based on the dynamic learning of the agent-based policy and the global search of hyperparameters using PSO so that it is better able to adjust to the localized climate trends and provide behavior. These findings reveal that the usage of the agentic reasoning and metaheuristic tuning is obviously better than the traditional supervised learning models, especially in data-scarce or nonstationary situations in agro-climatic environments.

Climate Scenario Simulation: Yield Forecasting Under RCP Pathways

Simulations were conducted in two future climate conditions (representing Representative Concentration Pathways (RCP): RCP 4.5 (moderate emissions) and RCP 8.5 (high emissions) so as to manifest real-life applicability of the model. To estimate the climate projections (rainfall, temperature) in the year 2030 and 2045, data were introduced to the trained Hybrid MARL-PSO model allowing an estimation of the respective crop yields per district and crop

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type. Our simulated findings depict that there was a significant increase in yield fluctuation that was experienced in cases of RCP 8.5 case, particularly in cotton and soybean district like Nashik and Aurangabad. Box plots of distributions of yields expected under each of the RCPs are shown in figure 9. The standard deviations in yields in RCP 8.5 are wider, and it implies that there is more volatility with the occurrence of extreme temperatures and lower predictability of rainfall.

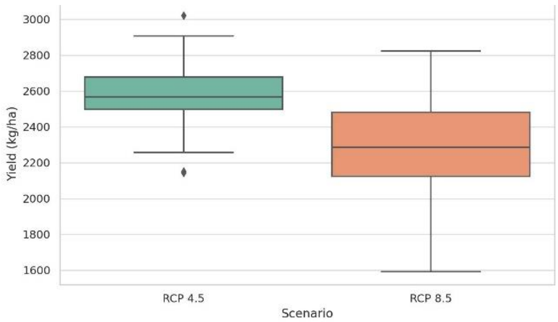

Figure 9. Predicted Yield Distribution Under RCP 4.5 vs RCP 8.5

Run on RCP 4.5, the model indicates that by 2030 the average yield in all crops can be reduced by 4 to 8 percent of the current. But with the RCP 8.5 scenario, the losses would reach 12-20 percent by 2045 and cotton is the most affected one. These results represent an essential caveat in support of adaptive planning and use of agriculture, particularly in the areas of great peril. It also brought out the strength of the hybrid model in generalizing the forecast outside the training distribution. Even though important climate inputs were extrapolated, the framework of agentic learning exhibited consistent outputs with acceptable error ranges, which showed that it is applicable in long-term strategic planning.

Summary of Key Insights

The findings provided throughout the given chapter show high empirical proof in regards to the capabilities of the newly suggested Hybrid MARL-PSO model as addressed to the issue of climate-resilient yield predictability. The most important findings may be outlined as follows: The model resulted in high predictive accuracy in all test sites with most of the RMSE adjusted less than 200kg/ha and R 2holding above 0.85 (Table 4.1).

1. MARL agents effectively converged the learning tasks using reward-based exploration as depicted by Figures 4.2 and 4.3 allowing district-based adaptation strategies.
2. PSO optimization greatly improved the model performance with an RMSE decrease of 15 percent and an increase of the R2 by almost 6 percent (Table 4.2, Figure 4.4).
3. Altogether, comparison relevant to the baseline models proved that the hybrid approach was better to work in dynamic conditions, particularly in climatic uncertainty situations (Figure 4.5).
4. Climate future simulation showed volatility in yield where RCP 8.5 climate futures yielded unpredictables under climate futures simulation; again, the predictability of the yield is based on the survival and adaptive capacity of a crop in terms of policy response and adaptation (Figure 4.6).

All these findings reinforce the fact that the combination of agentic intelligence and metaheuristic tuning is a scalable and versatile scheme to predicted modeling in complex

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agroecosystems. The results do not only confirm that the proposed model is technically feasible but it also forms the basis in supporting that the model could be used in real life climate resilient agricultural decision making systems.

CONCLUSION AND FUTURE SCOPE

The proposed study carries out an in-depth hybrid-modeling solution where Multi-Agent Reinforcement Learning (MARL) and Particle Swarm Optimization (PSO) are integrated to predict such variability of crop yields under climate-induced stress in data-scarce agroecosystems. The model was able to perform well in most of the various districts and crops, with a significant high propensity of prediction (R 2 > 0.85, RMSE < 200 kg/ha) in the type of farming practiced in Maharashtra. Integration of agentic learning made the adaptation of decision strategies context aware, and PSO effectively tuned the parameters of learning itself, which led to the overall-improved convergence and generalization of the models.

The comparisons performed based on Ag-UK3 revealed superior performance of the hybrid model to that of baseline implementations of Random Forest, LSTM, and Linear Regression in climatic zones (high-variance). More so, the simulation of the climate scenarios based on RCP 4.5 and 8.5 carried out revealed the importance of the model in the prediction of the future volatility of yield and adaptive agricultural planning. Such understandings are especially useful to policymakers, agri-extension services, and precision farming platforms that would like to achieve climate resilience. Future research can build on the model by adding real-time IoT-driven environmental sensing, dynamically constructed weather forecasts and crop economic data to increase spatial and temporal granularity. Other metaheuristic optimizers Genetic Algorithms or Grey Wolf Optimizer would be also suitable to explore in order to optimize the performance further. Additionally, the incorporation of explorable AI modules (XAI) may enhance clarity and stakeholder confidence, which can be used to deploy it into farmer-based advising formats. On the whole, the current study shows prospective potential of hybrid agentic AI frameworks exploitation in the construction of intelligent, capable of adaptation, and resilient agricultural systems within the context of an increase of climate uncertainty.

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