International journal of interdisciplinary and multidisciplinary research

ISSN 2456–4567 (O)

Neuro-Evo Swarm Optimizer (NESO Model): A Hybrid Deep Learning, Genetic Algorithm and Particle Swarm Optimization Model for Multicropping Strategy Optimization across Irrigation Systems

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Abstract: *Soil fertility is a major determinant of crop productivity, resource-use efficiency, and the sustainability of intensive agricultural systems. Among soil properties, Organic Carbon (OC) is an important indicator because it influences soil aggregation, water retention, nutrient availability, microbial activity, cation exchange capacity, and root development. This paper presents a framework for incorporating soil Organic Carbon into a Genetic Algorithm–Deep Learning–Particle Swarm Optimization (GA–DL–PSO) decision framework for seasonal multicropping under drip irrigation. In the proposed approach, OC is integrated with soil pH, clay percentage, climatic variables, irrigation characteristics, crop-management variables, yield, water use, and economic indicators. A Deep Learning model is used to learn nonlinear relationships between environmental and management variables and crop performance. The predicted performance is subsequently used by a Genetic Algorithm to generate candidate cropping strategies, while Particle Swarm Optimization refines the candidate solutions toward improved yield, profitability, and water-use efficiency. The proposed framework provides a systematic computational pathway for translating soil fertility information into seasonal crop-selection and multicropping decisions. The paper also discusses OC classification, its agronomic importance, preprocessing requirements, crop-suitability implications, and its role in optimization. The framework is intended to support data-driven and sustainable decision-making in drip-irrigated agriculture.*

Keywords: *Soil Organic Carbon, Organic Carbon, Precision Agriculture, Deep Learning, Genetic Algorithm, Particle Swarm Optimization, Multicropping, Drip Irrigation, Crop Suitability, Intelligent Agriculture.*

1. Introduction

Agricultural productivity depends on the interaction of soil properties, climatic conditions, crop characteristics, irrigation, nutrient management, and economic factors. Conventional crop planning generally relies on farmer experience, generalized recommendations, and single-season considerations. Such approaches may not adequately represent the complex interactions among soil fertility, water availability, climate variability, and the requirements of multiple crops grown within a seasonal production system.

Soil Organic Carbon (OC) is a central component of soil organic matter and is widely used as an indicator of soil quality and fertility. Organic residues, roots, manure, compost, microbial biomass, and humified materials contribute carbon to agricultural soils. As these materials decompose, they participate in nutrient cycling and influence the physical, chemical, and biological characteristics of soil.

The importance of OC becomes particularly relevant in intelligent agricultural systems. A crop recommendation model that considers only climatic variables may overlook important differences in soil fertility. Integrating OC with soil pH, clay content, rainfall, temperature, humidity, irrigation, and crop-management variables can provide a more comprehensive representation of the production environment.

This study therefore considers OC as a key predictor within a GA–DL–PSO framework designed for seasonal multicropping optimization under drip irrigation. The Deep Learning component captures nonlinear relationships between input variables and crop-performance indicators. Genetic Algorithm searches a broad solution space to generate candidate crop combinations, while Particle Swarm Optimization improves promising solutions. The resulting framework is intended to balance agricultural productivity, water use, and economic returns while maintaining compatibility with soil conditions.

2. Research Problem

Seasonal multicropping involves selecting crop combinations that are compatible with soil, climate, irrigation, available resources, and economic objectives. The problem is challenging because the relationships among these variables are nonlinear and may change across seasons. Soil OC adds another important dimension because differences in carbon content can influence nutrient cycling, water retention, microbial activity, and crop establishment.

A decision framework is therefore required that can: (i) represent soil fertility through measurable parameters such as OC; (ii) learn complex relationships between environmental variables and crop performance; (iii) generate alternative seasonal crop combinations; and (iv) optimize the final recommendations according to yield, profit, and water-use considerations.

3. Objectives

- To examine the role of Soil Organic Carbon as an indicator of soil fertility and crop suitability.
- To integrate OC with soil, climatic, irrigation, and crop-management variables in an intelligent agricultural dataset.
- To develop a Deep Learning prediction stage for estimating crop-performance indicators.
- To employ Genetic Algorithm for generating and evaluating candidate seasonal multicropping strategies.
- To use Particle Swarm Optimization to refine promising solutions.
- To formulate an integrated GA–DL–PSO framework for data-driven seasonal multicropping under drip irrigation.
- To support sustainable crop planning through improved use of soil nutrients and irrigation resources.

4. Soil Organic Carbon

4.1 Concept and Sources

Organic Carbon represents the carbon fraction associated with organic materials present in soil. It originates from crop residues, fallen leaves, roots, farmyard manure, compost, green manure, animal dung, vermicompost, microbial biomass, and humified organic matter. Microorganisms decompose these materials and transform part of the carbon into more stable forms of soil organic matter.

OC is important because it links biological activity with physical and chemical soil processes. It contributes to aggregate stability, improves soil structure, supports nutrient cycling, and can increase the soil's ability to retain water and nutrients. For this reason, OC can serve as a useful explanatory variable in crop-performance and crop-suitability models.

4.2 Classification of Organic Carbon

Organic Carbon (%)	Indicative Level	General Interpretation
<0.30	Very Low	Low organic matter contribution and poor fertility status
0.30–0.50	Low	Low fertility; organic amendments may be beneficial
0.50–0.75	Medium	Moderate fertility and generally suitable for many crops

0.75–1.00	High	Good soil fertility and biological activity
>1.00	Very High	High organic matter contribution and biological activity

The above classes are used in this paper as an indicative analytical categorization. Actual interpretation should follow the soil-testing method, laboratory standards, crop requirements, and regional recommendations applicable to the study area.

4.3 Agronomic Importance of Organic Carbon

Soil structure: OC promotes aggregation and improves porosity, aeration, root penetration, and resistance to compaction.

Water retention: Organic matter can improve the soil's capacity to retain and gradually release water, supporting efficient irrigation management.

Nutrient cycling: Decomposition of organic materials contributes to the cycling and availability of nutrients such as nitrogen, phosphorus and sulphur.

Cation exchange capacity: Organic matter contributes to the soil's capacity to retain and exchange positively charged nutrients.

Microbial activity: OC provides an energy source for many soil microorganisms involved in decomposition and nutrient cycling.

Root development: Improved aggregation, aeration, and moisture conditions can create a more favorable environment for root growth.

Erosion control: Stable aggregates and improved soil structure can reduce susceptibility to erosion and help conserve topsoil.

Fertilizer efficiency: Better nutrient retention and biological cycling may improve the effectiveness of nutrient-management practices.

Crop productivity: Through its effects on soil physical, chemical, and biological properties, OC can contribute to favorable crop-growth conditions.

Carbon sequestration: Increasing soil carbon stocks can contribute to carbon storage and broader climate-smart agricultural practices.

5. Organic Carbon and Crop Suitability

OC should not be treated as a stand-alone crop-selection rule. Crop suitability depends on the combined effects of soil texture, pH, nutrient status, climate, water availability, crop duration, irrigation method, and management practices. Nevertheless, OC can be incorporated as an important feature in a multi-parameter decision model.

Indicative OC Level	Examples of Crops for Model Evaluation
Very Low	Pearl millet, sorghum, castor, sesame
Low	Groundnut, pigeon pea, green gram,

	black gram
Medium	Rice, wheat, maize, cotton, sunflower, tomato, onion, chilli, brinjal, potato
High	Cabbage, cauliflower, broccoli, spinach, beetroot, carrot, coriander, banana, sugarcane, ginger, turmeric
Very High	Lettuce, celery, strawberry, grape and other high-value crops, subject to local climate and soil suitability

These examples are illustrative rather than prescriptive. The proposed computational framework evaluates crop suitability jointly with other measured variables instead of assigning a crop solely from OC concentration.

6. Proposed GA–DL–PSO Framework

6.1 Overall Architecture

The proposed framework consists of five major stages: data acquisition, preprocessing, Deep Learning prediction, Genetic Algorithm optimization, and Particle Swarm Optimization refinement. OC is introduced during data acquisition as a soil-fertility feature and remains part of the feature vector supplied to the prediction model.

Data acquisition: collect soil OC, soil pH, clay percentage, climatic variables, irrigation information, fertilizer inputs, crop information, yield, water use, and economic indicators.

Preprocessing: clean the data, handle missing values, encode categorical variables, normalize numerical variables, and divide the dataset into training and evaluation subsets.

Deep Learning prediction: learn nonlinear relationships between the input variables and target performance measures such as yield, profit, or water-use efficiency.

Genetic Algorithm: represent crop combinations as candidate solutions and apply selection, crossover, and mutation to search for high-performing seasonal strategies.

PSO refinement: initialize particles from promising candidate solutions and iteratively update particle positions using individual and global best solutions.

Final recommendation: rank feasible strategies using the selected objective function and constraints.

6.2 Role of Organic Carbon in the Model

Let the input feature vector be represented as X = {OC, pH, Clay, Rainfall, Temperature, Humidity, Fertilizer, Irrigation, Crop and Management Variables}. The Deep Learning model learns a mapping from X to a target vector Y representing crop-performance indicators. OC therefore contributes indirectly to optimization by influencing the predicted performance of candidate crop strategies.

A normalized OC value can be represented as OC_norm = (OC − OC_min)/(OC_max − OC_min). Normalization prevents a feature's numerical scale from dominating other inputs and facilitates stable model training. The exact preprocessing procedure should be selected according to the final dataset and validated experimentally.

6.3 Deep Learning Prediction

A feed-forward neural network can be used to model the nonlinear relationship between soil-climate-management variables and crop performance. A representative architecture consists of an input layer corresponding to the processed feature vector, one or more hidden layers using nonlinear activation functions, and an output layer for the selected prediction target. The model can be trained using the Adam optimizer and mean squared error for continuous targets. Model performance should be reported using appropriate evaluation measures such as MAE, RMSE, R^2, and validation loss.

6.4 Genetic Algorithm Optimization

The Genetic Algorithm searches a population of candidate crop combinations. Each chromosome represents a feasible seasonal multicropping strategy. The fitness function can combine predicted yield, profit, and water-use efficiency while applying constraints related to soil suitability, irrigation capacity, crop duration, and resource availability. Selection retains promising solutions, crossover creates new combinations, and mutation maintains population diversity.

6.5 Particle Swarm Optimization

Particle Swarm Optimization is used as a refinement stage after the GA search. Each particle represents a candidate solution in the defined optimization space. Particle velocity and position are updated using the particle's own best-known solution and the best-known solution of the swarm. This allows the search to intensify around promising regions while retaining the ability to explore alternative solutions.

6.6 Integrated Optimization Objective

A general multi-objective fitness formulation can be expressed as:

$$F = w_1 Y\_norm + w_2 P\_norm + w_3 WUE\_norm - w_4 Risk\_norm$$

where Y_norm is normalized yield, P_norm is normalized profit, WUE_norm is normalized water-use efficiency, Risk_norm represents an appropriate risk or constraint penalty, and w_1–w_4 are user-defined weights. The weights should be selected through the research design and sensitivity analysis rather than assumed universally.

7. Methodology

7.1 Data Variables

Category	Variables	Role
Soil	Organic Carbon, pH, clay percentage, soil type	Represents soil fertility and physical/chemical conditions
Climate	Rainfall, maximum temperature, minimum temperature, humidity, season	Represents environmental conditions
Management	Fertilizer N/P/K, irrigation type, water use	Represents resource and management practices
Crop	Crop identity and crop combination	Represents candidate production strategies
Output	Yield, profit, water-use efficiency	Represents optimization objectives

7.2 Processing Workflow

- Collect and verify soil and agricultural observations.
- Measure or obtain laboratory-tested OC values.
- Integrate OC with other soil, climatic, irrigation, and crop variables.
- Handle missing and inconsistent observations.
- Encode categorical variables and normalize numerical variables.
- Train and validate the Deep Learning prediction model.
- Generate candidate crop combinations using GA.
- Refine candidate solutions using PSO.
- Evaluate final strategies using yield, profit, water-use efficiency, and feasibility constraints.
- Compare optimized recommendations with baseline or conventional strategies.

8. Algorithmic Representation

Algorithm 1: GA–DL–PSO Seasonal Multicropping Optimization

- Input: soil, climate, irrigation, crop-management and economic dataset.
- Extract OC and other relevant predictor variables.
- Preprocess numerical and categorical variables.

- Train the Deep Learning model using the training data.
- Predict performance indicators for candidate crop strategies.
- Initialize the Genetic Algorithm population.
- Evaluate fitness of each chromosome using predicted performance and constraints.
- Apply selection, crossover and mutation until the GA stopping criterion is reached.
- Transfer selected high-quality solutions to the PSO population.
- Update particle velocities and positions using personal and global best solutions.
- Repeat until the PSO stopping criterion is reached.
- Return the best feasible seasonal multicropping strategy.

9. Experimental Evaluation Plan

The proposed framework should be evaluated using a clearly defined experimental protocol. The dataset should be separated into training and testing subsets, with an additional validation strategy where appropriate. The Deep Learning stage should be evaluated using MAE, RMSE and R^2. The optimization stage should be assessed using predicted and, where possible, observed yield, profit, water use, and water-use efficiency.

Evaluation Component	Recommended Metric	Purpose
Deep Learning	MAE, RMSE, R^2	Measure prediction accuracy
GA	Best fitness, convergence, feasible solutions	Measure search performance
PSO	Best fitness, convergence, iterations	Measure refinement performance
Cropping strategy	Yield, profit, water use, WUE	Measure agricultural usefulness
Ablation	Without OC vs. with OC	Quantify the contribution of Organic Carbon

10. Expected Contribution

The principal contribution of the proposed study is the explicit integration of soil Organic Carbon into an intelligent optimization pipeline for seasonal multicropping. Rather than treating OC only as a descriptive soil-quality parameter, the framework uses it as a predictive feature that can influence the ranking of candidate crop combinations. A second contribution is the sequential use of Deep Learning, GA, and PSO to combine nonlinear prediction, global search, and solution refinement. A third contribution is the inclusion of water-use and economic objectives alongside crop productivity, which is particularly relevant to drip-irrigated agriculture.

11. Discussion

The integration of OC into crop optimization is important because soil fertility is multidimensional. A soil with similar climatic conditions but different OC levels may respond differently to fertilizer, irrigation, and crop combinations. The proposed framework addresses this issue by considering OC jointly with other soil and environmental variables.

The proposed methodology also avoids assigning crops solely on the basis of OC thresholds. Such threshold-based rules can oversimplify agricultural decision-making because crop suitability is affected by several interacting variables. The machine-learning component can capture these interactions, while the optimization stages search for combinations that satisfy defined agricultural and resource constraints.

For a journal-quality empirical study, the contribution of OC should be tested explicitly. An ablation experiment comparing the framework with and without OC would provide evidence of whether OC improves prediction or optimization performance. Sensitivity analysis can further identify how changes in OC influence predicted yield, water use, and profit.

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- Machine-learning performance depends on dataset size, data quality, feature representation, and the representativeness of the observations.

12. Conclusion

Soil Organic Carbon is an important soil-quality indicator with strong relationships to soil structure, water retention, nutrient cycling, microbial activity, and crop-growing conditions. This paper proposed its integration into a GA–DL–PSO framework for intelligent seasonal multicropping optimization under drip irrigation. The framework treats OC as one component of a broader soil-climate-management feature set, uses Deep Learning for nonlinear crop-performance prediction, applies Genetic Algorithm for candidate strategy generation, and employs Particle Swarm Optimization for solution refinement.

The proposed approach provides a computational pathway for transforming soil-test information into data-driven cropping decisions. Future work should validate the framework using field-measured OC and crop-performance data, compare alternative model architectures, conduct ablation and sensitivity analyses, and evaluate optimized recommendations against conventional crop-planning practices. Such validation will be essential for establishing the practical effectiveness and generalizability of the proposed intelligent agricultural decision framework.

I acknowledge the Management of Nallamuthu Gounder Mahalingam College, Pollachi for VI Cycle of SEED Money support for this Research Paper.

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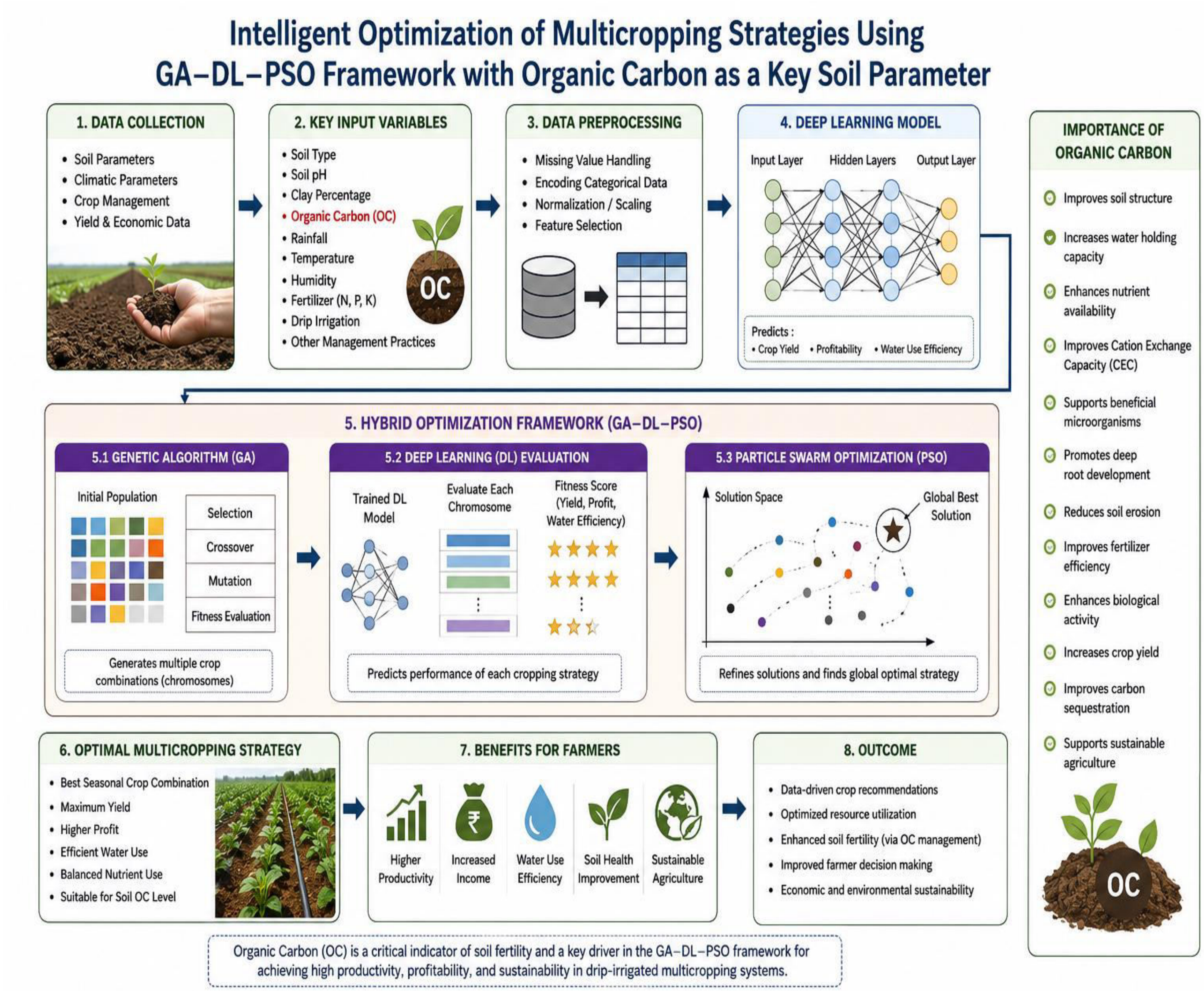

Figure 1. Proposed GA–DL–PSO Framework for Multicropping Strategy Optimization Using Organic Carbon as a Key Soil Parameter.

doi.org/10.54121/2021111527