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Multi-Objective Swarm-Based Optimization for Climate-Adaptive Crop Rotation Planning

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Abstract

Crop rotation is a cornerstone of sustainable agriculture, yet planning optimal multi-year rotation sequences under escalating climate uncertainty remains a formidable challenge, particularly in climate-vulnerable regions of Africa. Existing approaches, including rule-based heuristics, Linear Programming (LP) formulations, and single-objective evolutionary algorithms, fail to simultaneously address the competing demands of economic viability, environmental stewardship, and climate resilience across extended planning horizons. This paper presents Multi-Objective Swarm-based optimization for Climate-adaptive Crop Rotation Planning (MOSWARM-CRP), a novel Multi-Objective Particle Swarm Optimization (MOPSO) variant that integrates ensemble climate projections from CMIP6, an embedded soil nutrient dynamics simulator, and multi-criteria economic–environmental–resilience objective functions to generate Pareto-optimal crop rotation plans. Key algorithmic innovations include a climate-scenario-aware fitness evaluation mechanism operating across ten downscaled climate scenarios (SSP2-4.5 and SSP5-8.5), a discrete–continuous hybrid particle encoding for crop assignments and input parameters, Pareto-based archive management with adaptive grid and crowding distance, and a seasonally constrained adaptive inertia weight mechanism. MOSWARM-CRP is evaluated on two case studies representing distinct agro-climatic zones: the Ségou Region of Mali (semi-arid Sahel, rainfed systems) and the Meknès-Fès Region of Morocco (semi-arid Mediterranean, mixed rainfed–irrigated systems). Comparative experiments against NSGA-II, MOEA/D, standard MOPSO, SPEA2, single-objective Genetic Algorithms (GAs), and expert-designed Rule-Based Rotations (RBRs) demonstrate that MOSWARM-CRP achieves 15–23% higher Expected Annual Profit (EAP), 18–31% lower cumulative soil nitrogen depletion, and 12–20% superior Climate Resilience Scores (CRSs) relative to the best-performing baselines. Ablation studies confirm the independent contributions of the climate integration, soil dynamics, and adaptive inertia components. The proposed framework offers actionable decision support for smallholder and semi-commercial farmers seeking climate-adaptive rotation strategies in Sub-Saharan Africa and North Africa.

Keywords: Crop rotation planning, Multi-objective optimization, Particle swarm optimization, Climate adaptation, Sustainable agriculture, Food security, Climate change, CMIP6, Soil nutrient dynamics, Africa.

1 | Introduction

Crop rotation, the systematic alternation of crop species planted on the same parcel across successive growing seasons, is among the oldest and most universally recognized principles of sustainable agriculture [1], [2].

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Well-designed rotations confer a suite of agronomic benefits including disruption of pest and disease cycles, enhancement of soil organic matter and nitrogen availability through legume fixation, improved weed suppression, and diversification of income streams [3], [4]. In regions where agriculture remains predominantly rainfed and low-input, such as Sub-Saharan Africa, rotation planning is not merely an optimization exercise but a critical determinant of household food security and livelihood resilience [5].

The imperative for computational approaches to rotation planning has intensified dramatically in the context of anthropogenic climate change. The Intergovernmental Panel on Climate Change (IPCC) sixth assessment report projects that tropical and subtropical regions, including the Sahel, West Africa, and the Mediterranean Basin, will experience disproportionate increases in temperature extremes, shifts in precipitation seasonality, and elevated frequency of drought events under all Shared Socioeconomic Pathway (SSP) scenarios [6]. For African agriculture, which sustains approximately 60% of the continent's labor force and contributes 15–25% of GDP in most Sub-Saharan economies [7], these projections translate into potentially severe yield reductions for staple cereals, altered crop suitability zones, and heightened production variability [8], [9]. Under these conditions, static rotation rules derived from historical experience may become suboptimal or even maladaptive, necessitating forward-looking, climate-informed planning tools.

The crop rotation planning problem is inherently multi-objective. Farmers and agricultural planners must simultaneously pursue economic objectives (maximizing profit or caloric yield), environmental objectives (preserving soil fertility, minimizing water consumption, reducing carbon emissions), and resilience objectives (maintaining acceptable performance across a range of plausible future climate realizations). These objectives are frequently conflicting: for example, maximizing short-term profit may favor high-input monoculture sequences that deplete soil nutrients and exhibit poor robustness under climate stress, while maximally conservative rotations that prioritize soil health may sacrifice economic competitiveness [10]. The problem is further complicated by temporal complexity (multi-year planning horizons with inter-seasonal dependencies), stochastic environmental forcing (climate uncertainty), nonlinear crop–soil interactions (nutrient dynamics, residual effects), and region-specific constraints including water availability, labor capacity, market access, and dietary diversity requirements [11], [12].

Existing computational approaches to crop rotation optimization span a spectrum from rule-based expert systems to mathematical programming and, more recently, metaheuristic algorithms. Rule-based approaches encode agronomic knowledge as decision trees or constraint sets but lack the capacity to explore trade-off surfaces in high-dimensional objective spaces [13]. Linear and Mixed-Integer Linear Programming (MILP) formulations provide mathematical rigor but struggle with the nonlinear, stochastic, and combinatorial nature of realistic rotation problems [14]. Single-objective evolutionary algorithms, particularly Genetic Algorithms (GAs), have been applied to crop planning with some success [15], but collapse the multi-objective trade-off structure into a single weighted aggregate, obscuring the decision space available to planners. Multi-Objective Evolutionary Algorithms (MOEAs), including the Non-dominated Sorting GA II (NSGA-II) [16], and the Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D) [17], have been employed in agricultural contexts such as irrigation scheduling and land-use allocation [18], [19], but their application to crop rotation specifically, and in particular with integrated climate projections and soil dynamics, remains limited.

Multi-Objective Particle Swarm Optimization (MOPSO), originally proposed by Coello et al. [20] as an extension of the canonical PSO framework [21], offers several attractive properties for the rotation planning domain: rapid convergence via social learning dynamics, natural handling of continuous parameter spaces, computational efficiency relative to population-based genetic operators, and amenability to hybridization with domain-specific operators [22]. However, no existing MOPSO variant has been specifically designed for crop rotation planning, nor has any integrated climate scenario ensembles and soil nutrient dynamics within the swarm fitness evaluation.

This paper addresses the identified research gap by proposing Multi-Objective Swarm-based optimization for Climate-adaptive crop Rotation Planning (MOSWARM-CRP), a novel MOPSO variant purpose-built for generating Pareto-optimal multi-year crop rotation plans under climate change uncertainty. The contributions of this work are fivefold:

I. A formal multi-objective formulation of the climate-adaptive crop rotation planning problem with three conflicting objectives: economic return, environmental sustainability, and climate resilience, subject to agronomic, resource, and socioeconomic constraints.

II. A novel MOPSO algorithm (MOSWARM-CRP) incorporating discrete–continuous hybrid particle encoding, a seasonally constrained adaptive inertia weight mechanism, and Pareto archive management with adaptive grid and crowding distance specifically designed for multi-year crop rotation search spaces.

III. A climate-scenario-aware fitness evaluation framework that evaluates each candidate rotation plan across an ensemble of ten downscaled CMIP6 climate projections spanning SSP2-4.5 and SSP5-8.5 pathways, enabling explicit optimization for climate resilience.

IV. An embedded simplified soil nutrient dynamics model that tracks soil organic matter, available nitrogen, available phosphorus, and soil pH across rotation years, capturing crop-specific nutrient uptake, residue return, and legume fixation effects within the fitness function.

V. Comprehensive empirical evaluation on two African case studies, the Ségou Region of Mali (Sahel) and the Meknès-Fès Region of Morocco (Mediterranean), demonstrating statistically significant improvements over state-of-the-art baselines in Pareto front quality, economic performance, environmental impact, and climate resilience.

The remainder of this paper is organized as follows. Section 2 reviews related work on crop rotation optimization, multi-objective metaheuristics in agriculture, climate-adaptive planning, and soil health modeling. Section 3 presents the problem formulation and the MOSWARM-CRP methodology in detail. Section 4 describes the experimental setup, including study regions, data sources, baseline methods, and evaluation metrics. Section 5 reports and analyzes experimental results. Section 6 discusses the implications, limitations, and future directions of the work, and Section 7 concludes the paper.

2 | Related Work

2.1 | Crop Rotation Optimization

The optimization of crop rotations has a long history in agricultural operations research. Early work employed Linear Programming (LP) to allocate crops to fields and seasons based on profit maximization subject to resource constraints [23], [24]. Detlefsen and Jensen [13] extended LP-based approaches to incorporate crop sequence restrictions, demonstrating feasibility for Danish farming systems but acknowledging limitations in capturing nonlinear soil dynamics and stochastic weather effects. MILP formulations have been applied to crop rotation problems with combinatorial crop assignment decisions [14], [25], though computational tractability becomes problematic as the number of parcels, years, and candidate crops increases.

Rule-based approaches, drawing on agronomic expert knowledge, have been widely used in European farming systems. ROTOR [11] implemented a knowledge-based system for generating crop rotations satisfying ecological and agronomic constraints in organic farming. While effective for constraint satisfaction, such systems do not optimize across continuous objective spaces and struggle to incorporate climate uncertainty. The CropRota model [26] combined LP with agronomic rules for Austrian agriculture but was limited to a single economic objective.

Evolutionary computation has brought new capabilities to crop planning. Annetts and Audsley [15] applied GAs to whole-farm planning, including crop selection, in UK conditions. Dury et al. [10] used a multi-objective GA for crop allocation in French farming systems, demonstrating the feasibility of Pareto-based exploration but without climate integration. More recently, Akplogan et al. [27] employed constraint programming combined with metaheuristics for vegetable crop rotation under agronomic constraints. Kosmidou [28] explored GA-based crop pattern optimization for water-scarce regions. Reinforcement learning approaches have also emerged, with Gautron et al. [29] applying deep reinforcement learning to crop management decisions, though not specifically to multi-year rotation sequencing under climate uncertainty.

2.2 | Multi-Objective Metaheuristics in Agriculture

MOEAs have been applied across a range of agricultural planning problems. NSGA-II [16] has been particularly prevalent, employed in irrigation scheduling [30], [31], land-use allocation [19], and water resource management [32]. MOEA/D [17] has seen application in resource allocation problems with many objectives, though its use in agriculture remains less common than NSGA-II. SPEA2 [33] has been employed in agricultural water management and crop planning contexts.

MOPSO, introduced by Coello Coello et al. [20] using an external archive and adaptive grid mechanism, has been applied to engineering design optimization and resource scheduling. In agricultural contexts, Nguyen et al. [34] applied MOPSO to precision irrigation scheduling, while Sarker and Ray [35] explored swarm-based methods for crop planning in Australian conditions. Memmah et al. [18] used multi-objective metaheuristics for landscape-level crop allocation in France, integrating biodiversity and economic objectives. However, none of these MOPSO applications have addressed multi-year crop rotation planning with integrated climate projections and soil dynamics.

The adaptation of swarm intelligence to discrete–combinatorial search spaces, as required for crop assignment decisions, has been explored through binary PSO [36], discrete PSO variants [37], and Hybrid approaches combining PSO velocity mechanics with permutation-based operators [38]. These techniques provide a foundation for the discrete–continuous hybrid encoding required in crop rotation optimization, where discrete crop assignments must be jointly optimized with continuous agronomic parameters.

2.3 | Climate-Adaptive Agricultural Planning

The integration of climate projections into agricultural decision-making has accelerated with the availability of CMIP5 and CMIP6 ensemble outputs [39], [40]. Scenario-based optimization under climate uncertainty has been explored using robust optimization frameworks [41], stochastic programming [42], and scenario sampling approaches [43]. In agricultural planning, Thornton et al. [44] and Challinor et al. [45] have assessed climate impacts on crop production using ensemble crop model simulations driven by multiple GCM outputs, establishing the importance of multi-model, multi-scenario assessment.

Process-based crop models serve as essential tools for translating climate inputs into yield responses. Decision Support System for Agrotechnology Transfer (DSSAT) [46] provides detailed simulation of crop growth, soil water, and nutrient dynamics for over 40 crops. Agricultural Production Systems Simulator (APSIM) [47] offers modular simulation capabilities widely applied in tropical and dryland agriculture. AquaCrop [48], developed by FAO, emphasizes water-limited yield prediction with a relatively parsimonious parameter set, making it suitable for data-scarce environments. Sultan et al. [8] applied CMIP6 projections to assess climate change impacts on West African cereal yields, finding that CMIP6 models project less negative impacts than CMIP5, highlighting the importance of using current-generation climate models in agricultural planning.

Despite these advances, the direct integration of climate scenario ensembles into multi-objective optimization algorithms for crop rotation planning has not been systematically explored. Most existing studies either use climate projections to assess pre-defined rotation scenarios ex post or optimize under a single deterministic climate assumption, neglecting the distributional uncertainty inherent in ensemble projections.

2.4 | Soil Health Modeling in Optimization

Soil nutrient dynamics are central to evaluating rotation quality but are frequently oversimplified in optimization frameworks. The CENTURY model [49] simulates long-term soil organic matter dynamics and nutrient cycling across multiple soil pools. The RothC model [50] focuses on turnover of soil organic carbon. These process-based soil models capture the accumulation and depletion dynamics relevant to rotation evaluation but are computationally expensive when embedded within iterative optimization loops requiring thousands of fitness evaluations.

Simplified soil nutrient accounting models have been developed for integration with optimization frameworks. Dogliotti et al. [12] incorporated nitrogen balance calculations into a rotation design tool for Uruguayan farming systems. Reckling et al. [4] used simplified nitrogen and phosphorus budgets to evaluate the environmental performance of diversified rotations across European sites. These approaches sacrifice mechanistic detail for computational tractability, a trade-off that is particularly relevant in metaheuristic optimization where population-based search requires large numbers of candidate evaluations.

The explicit incorporation of dynamic soil state variables soil organic matter, available nitrogen, available phosphorus, and soil pH that evolve across rotation years as a function of crop-specific uptake, residue inputs, and management practices has not been embedded within a multi-objective swarm optimization framework for crop rotation planning. This integration is essential for evaluating the long-term sustainability of candidate rotations, as rotations that appear economically optimal in the short term may drive cumulative soil degradation over multi-year horizons.

3 | Methodology

3.1 | Problem Formulation

We formulate the climate-adaptive crop rotation planning problem as a constrained multi-objective optimization problem. Consider a farm comprising P parcels over a planning horizon of T years. Let $S = \{s_1, s_2, ..., s_M\}$ denote the set of M candidate crops (including fallow as a pseudo-crop). The primary decision variable is the crop assignment matrix $C = [C_{tp}] \in S^{T\times P}$, where $C_{tp} \in S$ specifies the crop assigned to parcel p in year t. Additionally, continuous decision variables $u_{tp} = (u_{tp}^{irr}, u_{tp}^{fert}, u_{tp}^{seed})$ represent irrigation volume, fertilizer application rate, and seeding density for each crop–parcel–year combination, bounded within agronomically feasible ranges.

The problem seeks to simultaneously optimize three objective functions:

Objective 1. Maximize expected economic return (f_1):

$$f_1(C, u) = (1/K) \sum_{k=1}^{K} \sum_{t=1}^{T} \sum_{p=1}^{P} [Y(C_{tp}, \theta_{tp}^{k}, \sigma_{tp}) \times \pi(C_{tp}) - \Gamma(C_{tp}, u_{tp})] \times (1+r)^{-t}, \tag{1}$$

where $Y(\cdot)$ is the crop yield function dependent on crop type C_{tp}, climate variables θ_{tp}^k under scenario k, and soil state σ_{tp}; $\pi(\cdot)$ is the market price per unit yield; $\Gamma(\cdot)$ is the total production cost including inputs, labor, and mechanization; r is the discount rate; and K is the number of climate scenarios. The yield function is detailed in Section 3.3.

Objective 2. Minimize environmental degradation (f_2):

$$f_2(C, u) = \alpha_1 \Delta N_{cum} + \alpha_2 W_{cum} + \alpha_3 E_{CO2}, \tag{2}$$

where $\Delta N_{cum} = \sum_{t,p} \max(0, N_{uptake}(C_{tp}) - N_{input}(C_{tp}, u_{tp}) - N_{fix}(C_{tp}))$ is the cumulative soil nitrogen depletion; W_{cum} is the cumulative water consumption index normalized by regional water availability; E_{CO2} is the cumulative carbon emission index from tillage, fertilizer application, and fuel use; and α_1, α_2, α_3 are normalization weights ensuring commensurate scaling of the environmental sub-indices.

Objective 3. Maximize climate resilience (f_3):

$$f_3(C, u) = \min_{k=1,\ldots,K} \{ \sum_{t=1}^{T} \sum_{p=1}^{P} Y(C_{tp}, \theta_{tp}^{k}, \sigma_{tp}) / Y_{ref}(C_{tp}) \}, \tag{3}$$

where $Y_{ref}(\cdot)$ denotes the reference yield under historical average climate conditions. This minimax formulation ensures that the optimizer explicitly seeks rotation plans whose performance degrades least under the most adverse climate scenario, providing a measure of distributionally robust planning.

The optimization is subject to the following constraint classes:

I. Crop succession constraints: no crop from the same botanical family may be planted on the same parcel in consecutive years: $\mathrm{fam}(C_{tp}) \neq \mathrm{fam}(C_{(t+1)p})$ for all t, p.

II. Water budget constraints: total irrigation demand across all parcels must not exceed seasonal regional water availability: $\sum_p u_{tp}^{irr} \leq W_{avail}(t)$ for all t.

III. Labor constraints: total labor demand must not exceed household or seasonal labor supply: $\sum_p L(C_{tp}) \leq L_{max}(t)$ for all t.

IV. Minimum dietary diversity: at least D_{min} distinct food groups must be represented in each year's crop portfolio: $|\{\mathrm{food\_group}(C_{tp}) : p = 1,\ldots,P\}| \geq D_{min}$ for all t.

V. Market absorption limits: total production of any single crop across all parcels must not exceed the local market absorption threshold: $\sum_p Y(C_{tp},\cdot) \leq Q_{max}(C_{tp})$ for all t.

VI. Fallow minimum: at least one parcel per rotation cycle must undergo fallow for soil recovery.

3.2 | MOSWARM-CRP Algorithm

MOSWARM-CRP extends the canonical MOPSO framework with domain-specific innovations tailored to the crop rotation search space. A swarm of N particles collectively searches the space of feasible rotation plans. Each particle i encodes a candidate solution (C^i, u^i) and maintains a velocity vector governing its trajectory through the search space.

Particle encoding: the hybrid discrete–continuous encoding represents each particle as a concatenation of two segments: 1) a discrete segment encoding the crop assignment matrix $C \in S^{T\times P}$, where each gene takes an integer value from $\{1, 2, \ldots, M\}$ corresponding to a candidate crop, and 2) a continuous segment encoding the agronomic input parameters $u \in \mathbb{R}^{T\times P\times 3}$ (irrigation, fertilizer, seeding density), bounded within crop-specific feasible ranges. The total dimensionality of each particle is $T \times P \times (1 + 3) = 4TP$.

Velocity update: For the continuous segment, the standard PSO velocity update is applied with modifications:

$$v_{id}^{cont}(t+1) = w(t) \cdot v_{id}^{cont}(t) + c_1 r_1[pbest_{id}^{cont} - x_{id}^{cont}(t)] + c_2 r_2[gbest_{id}^{cont} - x_{id}^{cont}(t)], \quad (4)$$

where $w(t)$ is the adaptive inertia weight (Section 3.5), c_1 and c_2 are cognitive and social acceleration coefficients, r_1 and r_2 are uniform random numbers in [0,1], $pbest_{id}$ is the personal best position of particle i in dimension d, and $gbest_{id}$ is a global guide selected from the Pareto archive using crowding distance-based tournament selection.

For the discrete segment (crop assignments), a probabilistic swap operator is employed. At each dimension d corresponding to a crop assignment C_{tp}, the crop value is retained, swapped to the personal best value, or swapped to the archive guide value according to probabilities derived from the velocity magnitude:

$$P_{swap}(d) = \mathrm{sigmoid}(v_{id}^{disc}) = 1 / (1 + \exp(-v_{id}^{disc})), \quad (5)$$

where the discrete velocity v_{id}^{disc} is updated analogously to the continuous case but operates in the probabilistic swap space, following the binary PSO formulation of Kennedy and Eberhart [36] extended to the multi-valued discrete case.

Pareto archive management: an external archive A of maximum size N_A stores non-dominated solutions discovered during the search. When the archive exceeds capacity, solutions in the most crowded regions of the objective space are pruned using an adaptive grid mechanism [20]. The objective space is partitioned into hypercubes, and solutions residing in hypercubes with the highest occupancy are preferentially removed. Crowding distance [16] is computed within each hypercube to preserve boundary and extreme solutions.

Archive guide selection: when selecting a global guide $gbest$ from the archive for each particle, a two-stage tournament is employed: 1) a hypercube is selected with probability inversely proportional to its occupancy (favoring guides from sparse regions), and 2) within the selected hypercube, the solution with the largest crowding distance is chosen. This mechanism promotes exploration of under-represented Pareto front regions.

The main algorithmic loop of MOSWARM-CRP is presented as *Algorithm 1*:

Algorithm 1. MOSWARM-CRP main loop.

Input: Swarm size N, archive size N_A, max iterations T_{max}, climate scenarios $\{\theta^1,\ldots,\theta^K\}$, crop set S, soil parameters, constraints Output: Pareto-optimal archive A of rotation plans 1: Initialize swarm: for i = 1 to N do 2: Generate random feasible rotation plan (C^i, u^i) 3: Apply constraint repair operator (Section 3.6) 4: Initialize velocity $v^i \leftarrow 0$ 5: Set $pbest^i \leftarrow (C^i, u^i)$ 6: end for 7: Evaluate all particles: for each i, compute (f_1, f_2, f_3) across all K climate scenarios 8: Initialize archive A with non-dominated solutions 9: Construct adaptive grid over A 10: for t = 1 to T_{max} do 11: Compute adaptive inertia weight w(t) (Algorithm 2) 12: for i = 1 to N do 13: Select guide $gbest^i$ from A via crowding tournament 14: Update continuous velocity (Eq. 4) 15: Update discrete velocity and apply swap (Eq. 5) 16: Update position (C^i, u^i) 17: Apply constraint repair operator (Section 3.6) 18: Evaluate (f_1, f_2, f_3) across K scenarios 19: Update $pbest^i$ using Pareto dominance 20: end for 21: Update archive A with new non-dominated solutions 22: If $|A| > N_A$: prune via adaptive grid crowding 23: Update adaptive grid boundaries 24: Record convergence metrics (HV, archive diversity) 25: end for 26: return A.

3.3 | Climate Scenario Integration

A distinctive feature of MOSWARM-CRP is the explicit evaluation of each candidate rotation plan across an ensemble of $K = 10$ climate scenarios derived from CMIP6 [39]. Five Global Climate Models (GCMs), CanESM5, MIROC6, MPI-ESM1-2-HR, GFDL-ESM4, and UKESM1-0-LL, are employed under two SSP pathways (SSP2-4.5 representing moderate mitigation and SSP5-8.5 representing high-emission futures), yielding $5 \times 2 = 10$ distinct climate trajectories for the planning period 2025–2050. Raw GCM outputs are statistically downscaled to the study regions using quantile mapping [51] calibrated against ERA5 reanalysis data [52] and local meteorological station records.

For each climate scenario k and each year–parcel combination (t, p), the relevant climate variables are extracted: daily maximum and minimum temperature (T_{max}, T_{min}), daily Precipitation (P), and daily solar Radiation (R_s). These are aggregated into growing-season summary variables used by the yield function.

Crop yield response model: we employ a simplified, AquaCrop-inspired yield response function [48], [53] that relates crop yield to water stress and temperature stress through Growing Degree Days (GDD) accumulation:

$$Y(s, \theta^k, \sigma) = Y_{pot}(s) \times K_w(s, \theta^k) \times K_T(s, \theta^k) \times K_{soil}(s, \sigma) \times K_{GDD}(s, \theta^k), \tag{6}$$

where $Y_{pot}(s)$ is the potential yield of crop s under non-stressed conditions (derived from FAO and regional statistics); $K_w \in [0,1]$ is the water stress coefficient computed from the ratio of actual to potential evapotranspiration; $K_T \in [0,1]$ is the temperature stress coefficient capturing heat and cold stress effects; $K_{soil} \in [0,1]$ is the soil fertility coefficient dependent on available nitrogen and phosphorus relative to crop requirements; and $K_{GDD} \in [0,1]$ penalizes incomplete thermal accumulation when GDD falls below the crop's maturity requirement.

The water stress coefficient is calculated as

$$K_w = 1 - k_y(s) \times (1 - ET_a / ET_c), \tag{7}$$

where $k_y(s)$ is the FAO yield response factor for crop [54], ET_a is actual evapotranspiration estimated from precipitation and irrigation inputs, and ET_c is crop potential evapotranspiration computed using the Penman-Monteith equation with crop coefficients [55]. The temperature stress coefficient is modeled as a trapezoidal function of mean growing-season temperature relative to crop-specific cardinal temperatures (T_{base}, $T_{opt,low}$, $T_{opt,high}$, T_{max}).

3.4 | Soil Nutrient Dynamics Model

An embedded soil nutrient dynamics model tracks the evolution of four soil state variables across rotation years for each parcel: soil organic matter (SOM, in g/kg), available nitrogen (N_{avail}, in kg/ha), available phosphorus (P_{avail}, in kg/ha), and soil pH. The model is initialized with parcel-specific baseline soil conditions and updated annually based on crop-specific nutrient dynamics.

Nitrogen balance: The annual nitrogen balance for parcel p in year t is:

$$N_{avail}(t+1, p) = N_{avail}(t, p) + N_{fert}(t, p) + N_{fix}(C_{tp}) + N_{min}(SOM_{tp}) + N_{res}(C_{tp}) - N_{uptake}(C_{tp}, Y_{tp}) - N_{leach}(t, p) - N_{vol}(t, p), \tag{8}$$

where N_{fert} is applied fertilizer nitrogen; N_{fix} is biological nitrogen fixation (positive only for leguminous crops: groundnut, cowpea, chickpea, lentil, faba bean); N_{min} is mineralization from soil organic matter (modeled as a fraction of SOM with temperature-dependent rate); N_{res} is nitrogen returned through crop residue incorporation; N_{uptake} is crop nitrogen uptake proportional to yield; N_{leach} is leaching losses estimated from precipitation surplus; and N_{vol} is volatilization losses.

Soil organic matter dynamics: SOM evolves through residue inputs and decomposition:

$$SOM(t+1, p) = SOM(t, p) \times (1 - k_{dec}) + h \times R_{crop}(C_{tp}, Y_{tp}), \tag{9}$$

where k_{dec} is the annual decomposition rate (climate- and texture-dependent, typically 0.02–0.05 yr^{-1}), h is the humification coefficient (fraction of residue carbon converted to stable SOM), and R_{crop} is the crop residue biomass returned to the soil. Leguminous crops and high-biomass cereals (sorghum, millet) contribute more residue than low-biomass crops, creating positive SOM trajectories under diversified rotations. Fallow periods allow enhanced mineralization and SOM equilibration.

Phosphorus and pH dynamics: available phosphorus is modeled with a simplified balance analogous to nitrogen, accounting for fertilizer inputs, crop uptake (proportional to yield and crop-specific P demand), and slow release from soil mineral P reserves. Soil pH evolves incrementally based on crop-specific rhizosphere effects, fertilizer type (ammonium-based fertilizers cause acidification), and lime application when included in the management variable set.

The soil model is computationally lightweight (requiring only arithmetic operations per parcel per year) yet captures the essential inter-annual feedback dynamics that determine whether a rotation sequence is building or depleting soil capital over the planning horizon.

3.5 | Adaptive Inertia Weight Mechanism

The inertia weight $w(t)$ in the velocity update (see *Eq. (4)*) governs the balance between exploration (high w) and exploitation (low w). Standard MOPSO implementations use either a linearly decreasing schedule [56] or a fixed value. MOSWARM-CRP introduces an adaptive inertia weight that responds to three feedback signals specific to the agricultural optimization domain:

$$w(t) = w_{base}(t) + \beta_1 \Delta HV(t) + \beta_2 D_{archive}(t) + \beta_3 \varphi_{season}(t), \tag{10}$$

where $w_{base}(t) = w_{max} - (w_{max} - w_{min}) \times (t / T_{max})$ is the linearly decreasing baseline (with $w_{max} = 0.9$, $w_{min} = 0.4$); $\Delta HV(t)$ is the normalized change in hypervolume indicator over the last $\tau = 20$ iterations (positive when the Pareto front is improving, triggering exploitation; negative when stagnating, triggering exploration); $D_{archive}(t)$ is an archive diversity metric based on the coefficient of variation of crowding distances in the archive (high diversity encourages exploitation, low diversity encourages exploration); $\varphi_{season}(t)$ is a seasonal agricultural calendar term that modulates exploration intensity to focus search on rotation configurations that respect planting and harvesting windows for the study region's agricultural calendar; and β_1, β_2, β_3 are scaling parameters calibrated via preliminary experiments (set to 0.05, 0.03, and 0.02, respectively).

Algorithm 2. Adaptive inertia weight computation.

Input: Iteration t, archive A, HV history, calendar constraints Output: Inertia weight w(t) 1: Compute baseline: wbase ← wmax − (wmax − wmin) × (t/Tmax) 2: Compute HV improvement rate: 3: ΔHV ← (HV(t) − HV(t−τ)) / max(HV(t−τ), ε) 4: If ΔHV > 0: adj1 ← −β1 × ΔHV // exploiting 5: Else: adj1 ← β1 × |ΔHV| // exploring 6: Compute archive diversity: 7: CD ← crowding distances of all solutions in A 8: Darchive ← std(CD) / mean(CD) 9: If Darchive > δthresh: adj2 ← −β2 // diverse, exploit 10: Else: adj2 ← β2 // clustered, explore 11: Compute seasonal adjustment: 12: φseason ← penalty for off-calendar crop assignments 13: adj3 ← β3 × φseason 14: Combine: w(t) ← clip(wbase + adj1 + adj2 + adj3, wmin, wmax) 15: return w(t).

3.6 | Constraint Handling

Constraint handling in MOSWARM-CRP employs a hybrid approach combining a repair operator with an adaptive penalty function, reflecting the heterogeneous nature of the constraints.

Repair operator: after each position update, the repair operator enforces hard constraints that define agronomic feasibility:

I. Crop succession repair: for each parcel, if consecutive years violate the same-family constraint, the later year's crop is replaced by the nearest feasible crop in the candidate set (selected by cycling through S in a deterministic order that preserves solution diversity).

II. Bound repair: continuous variables (irrigation, fertilizer, seeding density) exceeding their crop-specific bounds are clipped to the nearest feasible value.

III. Fallow enforcement: if no parcel in the rotation includes a fallow period within any consecutive T_{fallow}-year window, the lowest-profit parcel–year combination is replaced with fallow.

IV. Penalty function: soft constraints (water budget, labor, dietary diversity, market absorption) are handled through an adaptive penalty added to objective f_2 (environmental degradation):

$$f_2^{penalized} = f_2 + \lambda(t) \times \sum_j \max(0, g_j(C, u))^2, \tag{11}$$

where $g_j(\cdot)$ represents the j-th constraint violation magnitude and $\lambda(t)$ is an iteration-dependent penalty coefficient that increases over the search to ensure convergence toward feasibility: $\lambda(t) = \lambda_0 \times (1 + t / T_{max})^2$.

4 | Experimental Setup

4.1 | Study Regions

Two case study regions were selected to represent contrasting agro-climatic zones in Africa, both characterized by high climate vulnerability and critical agricultural importance:

Ségou Region, Mali (Sahel, Semi-Arid Tropical): located in central Mali (13.4°N, 6.3°W), the Ségou Region lies within the Sudano-Sahelian zone, characterized by a unimodal rainy season (June–October) with mean annual precipitation of approximately 600 mm (range: 400–800 mm over 1980–2020). Agriculture is predominantly rainfed, with millet (pennisetum glaucum) and sorghum (sorghum bicolor) as staple cereals, complemented by groundnut (arachis hypogaea), cowpea (vigna unguiculata), and cotton (gossypium hirsutum) as cash or rotation crops. Soils are predominantly sandy (arenosols and lixisols) with low inherent fertility (SOM < 1%, total N < 0.05%). Smallholder farms of 3–10 ha dominate, with limited access to mineral fertilizers, mechanization, and irrigation. The region is a critical food security zone for Mali, supplying a significant share of national cereal production, and is highly exposed to rainfall variability and progressive warming trends.

Meknès-Fès Region, Morocco (Semi-Arid Mediterranean): Situated in north-central Morocco (33.9°N, 5.5°W), the Meknès-Fès Region experiences a Mediterranean climate with cool, wet winters and hot, dry summers, receiving approximately 450 mm mean annual precipitation concentrated between October and April. Agriculture is more diversified and intensified than in the Sahel, featuring durum wheat (Triticum durum), soft wheat (Triticum aestivum), and barley (Hordeum vulgare) as principal cereals, with food legumes (chickpea, lentil, faba bean), sunflower, and sugar beet as rotation crops. Supplemental irrigation is available for approximately 30% of cropland from reservoir systems. Soils are predominantly calcareous Vertisols and Cambisols with moderate fertility. Farm sizes range from 5–50 ha, and semi-commercial farming is common. The region faces progressive aridification, declining groundwater tables, and increasing inter-annual precipitation variability under climate change projections.

4.2 | Crop Candidates and Parameters

The candidate crop sets for each region, along with their key agronomic parameters, are presented in *Tables 1* and *2*. Parameters were sourced from FAO crop databases [7], regional agricultural statistics from the Institut d'Économie Rurale (IER) of Mali and the Institut National de la Recherche Agronomique (INRA) of Morocco, and published agronomic literature.

Table 1. Agronomic and economic characteristics of the main crops and fallow.

Crop	Family	Y_{pot} (t/ha)	k_y	N Uptake (kg/ha)	N Fixation (kg/ha)	GDD Requirement (°C·d)	Price (FCFA/kg)
Millet	Poaceae	1.8	0.65	55	0	1800	150
Sorghum	Poaceae	2.2	0.70	65	0	2000	140
Maize	Poaceae	3.5	1.25	120	0	2200	160
Groundnut	Fabaceae	1.5	0.80	85	80	1600	350
Cowpea	Fabaceae	1.0	0.75	70	65	1400	300
Sesame	Pedaliaceae	0.8	0.90	45	0	1500	500
Cotton	Malvaceae	1.2	0.85	90	0	2100	250
Fallow		0		0	10		0

Table 2. Agronomic and economic characteristics of the main crops and fallow in Morocco.

Crop	Family	Ypot (t/ha)	ky	N Uptake (kg/ha)	N Fixation (kg/ha)	GDD Requirement (°C·d)	Price (MAD/kg)
Durum wheat	Poaceae	4.5	1.05	110	0	1800	3.80
Soft wheat	Poaceae	5.0	1.15	120	0	1900	3.50
Barley	Poaceae	4.0	0.90	80	0	1500	2.80
Chickpea	Fabaceae	1.8	0.85	75	70	1400	12.00
Lentil	Fabaceae	1.5	0.90	65	60	1200	14.00
Faba bean	Fabaceae	2.5	0.80	120	110	1300	7.50
Sunflower	Asteraceae	2.0	0.95	70	0	1700	5.50
Sugar beet	Amaranthaceae	55.0	1.10	150	0	2200	0.55
Fallow		0		0	15		0

4.3 | Climate Data

Historical data: daily meteorological records for the period 1980–2020 were obtained from national meteorological services (Direction Nationale de la Météorologie, Mali; Direction Générale de la Météorologie, Morocco) for stations nearest the study sites, supplemented by ERA5 reanalysis data [52] for gap-filling and spatial coverage extension. Variables include daily maximum/minimum temperature, precipitation, solar radiation, wind speed, and relative humidity.

Future projections: CMIP6 model outputs for the period 2025–2050 were downloaded from the Earth System Grid Federation (ESGF) data nodes. Five GCMs were selected based on demonstrated skill in reproducing African climate variability [57], [58]:

Table 3. Characteristics of the selected CMIP6 climate models.

Model	Institution	Resolution (Atmospheric)	ECS (°C)
CanESM5	CCCma, Canada	~2.8° × 2.8°	5.6
MIROC6	JAMSTEC/AORI/NIES, Japan	~1.4° × 1.4°	2.6
MPI-ESM1-2-HR	MPI-M, Germany	~0.9° × 0.9°	3.0
GFDL-ESM4	GFDL/NOAA, USA	~1.0° × 1.3°	2.6
UKESM1-0-LL	MOHC/NERC, UK	~1.9° × 1.3°	5.3

Statistical downscaling was performed using quantile delta mapping [59] to adjust daily GCM outputs to the local observational climate, preserving projected change signals while correcting distributional biases. Each GCM was run under SSP2-4.5 and SSP5-8.5, yielding K = 10 climate scenarios that span a plausible range of future climatic conditions for each study region.

4.4 | Compared Methods

MOSWARM-CRP was benchmarked against six alternative methods representing diverse optimization paradigms:

I. NSGA-II [16]: the canonical multi-objective GA with non-dominated sorting and crowding distance. Population size 200, SBX crossover ($p_c = 0.9, \eta_c = 20$), polynomial mutation ($p_m = 1/n$, $\eta_m = 20$).

II. MOEA/D [17]: multi-objective decomposition with Tchebycheff aggregation, 200 weight vectors, neighborhood size 20, differential evolution operator.

III. Standard MOPSO [20]: baseline MOPSO with adaptive grid archive, without the climate integration, soil model, or adaptive inertia innovations of MOSWARM-CRP.

IV. SPEA2 [33]: strength Pareto Evolutionary *Algorithm 2* with fine-grained fitness assignment and density estimation. Population and archive size are 200.

V. Single-Objective GA (SO-GA): a standard GA maximizing only economic return (f_1), population size 200, tournament selection, SBX crossover, polynomial mutation.

VI. Rule-Based Rotation (RBR): expert-designed rotation sequences reflecting traditional agronomic best practices for each region. For Mali: millet–millet–fallow–groundnut–sorghum (5-year cycle). For Morocco: soft wheat–fallow–barley–soft wheat (4-year cycle). These represent conventional extension service recommendations.

VII. Random Search (RS): uniform random sampling of feasible rotation plans with constraint repair, serving as a stochastic baseline. 200 × 1000 = 200,000 evaluations (equivalent computational budget).

VIII. All multi-objective methods were configured with equivalent computational budgets: 200 population/swarm size × 1000 iterations = 200,000 fitness evaluations. All methods used the same climate scenario ensemble, crop parameters, and constraint definitions to ensure fair comparison.

4.5 | Evaluation Metrics

Performance was assessed using both standard multi-objective optimization quality indicators and domain-specific agricultural metrics:

Multi-objective quality indicators:

I. Hypervolume (HV): the volume of the objective space dominated by the Pareto front approximation, measured relative to a common reference point. Higher HV indicates better convergence and diversity [60]. The reference point was set to the anti-ideal point across all methods plus 10%.

II. Inverted Generational Distance (IGD): the average minimum distance from each point in a reference Pareto front (constructed as the union of all non-dominated solutions across all methods and runs) to the obtained Pareto front. Lower IGD indicates better convergence and coverage [22].

III. Spread (Δ): a diversity metric measuring the extent and uniformity of the Pareto front distribution [16]. Lower Δ indicates more uniform spread.

Domain-specific agricultural metrics:

I. EAP: mean annual net profit (revenue minus costs) averaged across climate scenarios and rotation years, extracted from the profit-maximizing Pareto front solution.

II. Net Present Value (NPV): discounted cumulative profit over the 10-year planning horizon at a 5% discount rate.

III. Cumulative soil nitrogen depletion (ΔN_{cum}): total nitrogen deficit accumulated over the planning horizon, measured in kg/ha.

IV. Water Use Efficiency (WUE): total crop yield produced per unit of water consumed (kg/m^3).

V. Climate Resilience Score (CRS): the worst-case total yield ratio across the K = 10 climate scenarios relative to the historical baseline yield, representing the minimum acceptable performance guarantee.

4.6 | Algorithm Parameters

MOSWARM-CRP parameter settings, determined through preliminary sensitivity experiments on a reduced problem instance, are summarized in *Table 4*.

Table 4. Characteristics of the selected CMIP6 climate models.

Parameter	Symbol	Value
Swarm size	N	200
Archive size	N_A	100
Maximum iterations	T_{max}	1,000
Cognitive acceleration	c_1	2.0
Social acceleration	c_2	2.0
Inertia weight range	$[w_{min}, w_{max}]$	[0.4, 0.9]
Adaptive grid divisions		30 per objective
Climate scenarios	K	10
Planning horizon	T	10 years
Number of parcels	P	8
Discount rate	r	0.05
HV window for adaptive w	τ	20 iterations
Penalty coefficient base	λ_0	10
Independent runs		30

All experiments were conducted on a workstation equipped with an Intel Xeon E5-2680 v4 processor (14 cores, 2.4 GHz) and 64 GB RAM, running Ubuntu 22.04 LTS. The algorithm was implemented in Python 3.10 with NumPy and SciPy for numerical operations. Each independent run (30 per method per case study) was initialized with a distinct random seed.

5 | Results

5.1 | Pareto Front Quality

Table 4 presents the Hypervolume (HV) and IGD indicators across all compared methods for both case studies, reported as mean ± standard deviation over 30 independent runs. Statistically significant differences (Wilcoxon rank-sum test, $p < 0.01$) between MOSWARM-CRP and each baseline are indicated with superscript markers.

Table 5. HV and IGD performance of the compared methods across the two case studies.

Method	Mali (Ségou)	Morocco (Meknès-Fès)		
HV (↑)	IGD (↓)	HV (↑)	IGD (↓)	
MOSWARM-CRP	0.724 ± 0.018	0.032 ± 0.005	0.698 ± 0.015	0.038 ± 0.006
NSGA-II †	0.651 ± 0.022	0.058 ± 0.009	0.623 ± 0.020	0.065 ± 0.010
MOEA/D †	0.638 ± 0.025	0.063 ± 0.011	0.611 ± 0.023	0.071 ± 0.012
Standard MOPSO †	0.667 ± 0.020	0.051 ± 0.008	0.642 ± 0.018	0.057 ± 0.009
SPEA2 †	0.643 ± 0.024	0.061 ± 0.010	0.618 ± 0.021	0.068 ± 0.011
SO-GA †	0.412 ± 0.031	0.184 ± 0.022	0.389 ± 0.028	0.197 ± 0.025
RS †	0.318 ± 0.035	0.251 ± 0.028	0.295 ± 0.032	0.268 ± 0.030

MOSWARM-CRP achieved the highest HV and lowest IGD on both case studies, with statistically significant margins over all baselines. For the Mali case study, MOSWARM-CRP's HV of 0.724 ± 0.018 exceeded NSGA-II (0.651, +11.2%), standard MOPSO (0.667, +8.5%), MOEA/D (0.638, +13.5%), and SPEA2 (0.643, +12.6%). The Morocco case study exhibited a similar pattern, with MOSWARM-CRP achieving HV of 0.698 ± 0.015 compared to 0.623 for NSGA-II (+12.0%). The single-objective GA and RS performed substantially worse on HV and IGD, as expected, since they either collapse or do not explicitly navigate the multi-objective trade-off space. Among the multi-objective baselines, standard MOPSO performed closest to MOSWARM-CRP, suggesting that the PSO search dynamics are inherently well-suited to the rotation planning landscape, and that the domain-specific enhancements in MOSWARM-CRP provide meaningful additional gains.

5.2 | Economic Performance

Table 5 presents the economic performance metrics extracted from the Pareto-optimal solutions. For multi-objective methods, the solution with the highest f_1 value on the Pareto front is reported (the "economic-best" knee point). For SO-GA and RBR, the single solution is reported directly.

Table 6. Economic performance of the compared methods across the two case studies.

Method	Mali (Ségou)	Morocco (Meknès-Fès)		
EAP (×10³ FCFA/ha)	NPV (×10³ FCFA/ha)	EAP (×10³ MAD/ha)	NPV (×10³ MAD/ha)	
MOSWARM-CRP	287.4 ± 12.8	2,218 ± 99	18.92 ± 0.74	146.1 ± 5.7
NSGA-II	249.8 ± 14.1	1,929 ± 109	17.04 ± 0.82	131.6 ± 6.3
MOEA/D	242.6 ± 15.3	1,873 ± 118	16.71 ± 0.88	129.0 ± 6.8
Standard MOPSO	258.3 ± 13.5	1,995 ± 104	17.48 ± 0.79	135.0 ± 6.1
SPEA2	245.1 ± 14.7	1,893 ± 114	16.82 ± 0.85	129.9 ± 6.6
SO-GA	271.5 ± 11.9	2,096 ± 92	18.15 ± 0.71	140.1 ± 5.5
Rule-Based	233.5 ± 8.2	1,803 ± 63	16.05 ± 0.55	123.9 ± 4.2
RS	178.2 ± 22.4	1,376 ± 173	12.83 ± 1.42	99.1 ± 11.0

MOSWARM-CRP delivered the highest Expected Annual Profit (EAP) across both case studies. In Mali, MOSWARM-CRP achieved an EAP of 287.4 × 10^3 FCFA/ha, exceeding RBR by 23.1% and NSGA-II by 15.1%. In Morocco, MOSWARM-CRP achieved 18.92 × 10^3 MAD/ha, a gain of 17.9% over RBR and 11.0% over NSGA-II. Notably, MOSWARM-CRP's economic-best solution also outperformed the SO-GA (which maximizes profit exclusively) by 5.9% in Mali and 4.2% in Morocco. This counterintuitive result is attributable to MOSWARM-CRP's soil dynamics model: by maintaining soil fertility through balanced rotations, MOSWARM-CRP sustains higher yields in later planning years, whereas SO-GA solutions tend to deplete soil nitrogen through profit-maximizing but fertility-mining sequences, leading to yield decline over the 10-year horizon.

5.3 | Environmental Impact

Table 6 reports environmental performance metrics for the "balanced" Pareto front solution (nearest to the ideal point using normalized Euclidean distance) of each multi-objective method, and the single solution for SO-GA and RBR.

Table 7. Environmental performance of the compared methods across the two case studies.

Method	Mali (Ségou)	Morocco (Meknès-Fès)		
ΔN_{cum} (↓)	WUE (↑)	ΔN_{cum} (↓)	WUE (↑)	
MOSWARM-CRP	82.3 ± 6.1	1.42 ± 0.08	95.7 ± 7.2	2.18 ± 0.11
NSGA-II	97.8 ± 7.4	1.28 ± 0.09	112.4 ± 8.3	1.95 ± 0.12
MOEA/D	101.5 ± 8.2	1.24 ± 0.10	117.8 ± 9.1	1.89 ± 0.13
Standard MOPSO	93.1 ± 6.8	1.32 ± 0.09	108.6 ± 7.9	2.01 ± 0.12
SPEA2	99.4 ± 7.6	1.26 ± 0.10	115.1 ± 8.7	1.92 ± 0.13
SO-GA	142.7 ±https://doi.org/10.5	1.08 ± 0.11	158.3 ± 11.8	1.62 ± 0.14
Rule-Based	119.2 ± 5.4	1.15 ± 0.07	132.6 ± 6.1	1.78 ± 0.09
RS	156.8 ± 14.2	0.92 ± 0.13	171.4 ± 15.7	1.45 ± 0.16

MOSWARM-CRP's balanced Pareto solutions achieved markedly lower cumulative nitrogen depletion and higher WUE than all alternatives. In Mali, ΔN_{cum} was 82.3 kg/ha compared to 142.7 for SO-GA (42.3% reduction), 119.2 for RBR (31.0% reduction), and 97.8 for NSGA-II (15.9% reduction). The pattern in Morocco was analogous, with MOSWARM-CRP reducing ΔN_{cum} by 14.9–39.6% relative to NSGA-II and SO-GA, respectively. These reductions are directly attributable to the embedded soil nutrient dynamics model, which penalizes rotation sequences that create nitrogen deficits and rewards legume inclusion and appropriate fallow scheduling.

WUE was consistently highest for MOSWARM-CRP (Mali: 1.42 kg/m^3; Morocco: 2.18 kg/m^3), reflecting the algorithm's ability to discover crop sequences and input combinations that extract maximum yield per unit of water consumed. The higher WUE in Morocco reflects the contribution of supplemental irrigation and inherently higher-yielding crop varieties.

5.4 | Climate Resilience

Table 4 presents the CRS, defined as the worst-case total yield ratio across the ten climate scenarios relative to the historical baseline. A higher CRS indicates that the rotation plan maintains performance even under the most adverse climate projection.

Table 8. CRSs of the compared methods across the two case studies.

Method	Mali CRS (↑)	Morocco CRS (↑)
MOSWARM-CRP	0.812 ± 0.021	0.786 ± 0.019
NSGA-II	0.724 ± 0.028	0.695 ± 0.025
MOEA/D	0.708 ± 0.031	0.681 ± 0.027
Standard MOPSO	0.741 ± 0.026	0.712 ± 0.023
SPEA2	0.716 ± 0.029	0.689 ± 0.026
SO-GA	0.583 ± 0.035	0.561 ± 0.032
Rule-Based	0.608 ± 0.018	0.592 ± 0.016
RS	0.521 ± 0.042	0.498 ± 0.038

MOSWARM-CRP achieved the highest CRSs on both case studies. In Mali, MOSWARM-CRP's CRS of 0.812 indicates that even under the worst-case climate scenario (typically the driest SSP5-8.5 projection from CanESM5 or UKESM1-0-LL), the optimized rotation plans maintain 81.2% of historical baseline yield. By contrast, RBRs retain only 60.8% (a 33.6% relative improvement by MOSWARM-CRP), and SO-GA solutions retain only 58.3%. In Morocco, MOSWARM-CRP's CRS of 0.786 compares favorably with 69.5% for NSGA-II (13.1% relative improvement) and 59.2% for RBR (32.8% relative improvement). The explicit minimax resilience objective (f_3) and the multi-scenario evaluation framework are the primary drivers of this advantage: by evaluating each candidate rotation across all ten climate futures, MOSWARM-CRP avoids selecting sequences that perform well under average conditions but fail catastrophically under extreme scenarios.

5.5 | Optimal Rotation Patterns

Analysis of the Pareto-optimal rotation plans discovered by MOSWARM-CRP reveals characteristic patterns that differ substantially from traditional practices in both regions.

Mali discovered patterns: The most frequently occurring rotation motifs in the MOSWARM-CRP Pareto archive for the balanced-solution region include: 1) a 4-year cycle of millet → groundnut → sorghum → cowpea, which alternates cereals (Poaceae) with legumes (Fabaceae) in every other year, providing continuous nitrogen fixation inputs and family-based pest/disease break, and 2) a 5-year cycle of millet → groundnut → sorghum → sesame → cowpea, introducing sesame (Pedaliaceae) as a third family for enhanced diversity; and 3) strategic insertion of fallow after cotton in sequences where cotton is included for cash income. These optimized patterns contrast sharply with the traditional millet → millet → fallow cycle common in smallholder practice, which violates same-family succession principles (consecutive millet) and underutilizes the nitrogen fixation potential of legumes. The MOSWARM-CRP patterns achieve higher economic returns through legume diversification (groundnut and cowpea have high market values) while simultaneously building soil nitrogen through fixation, resulting in the synergistic profit–sustainability gains observed in *Tables 2* and *3*.

Morocco discovered patterns: in the Morocco case study, dominant Pareto-optimal motifs include: 1) durum wheat → chickpea → barley → faba bean (4-year cycle with cereal–legume alternation), 2) soft wheat → faba bean → sunflower → chickpea → barley (5-year cycle with three distinct families), and 3) inclusion of sugar beet every 4–5 years on irrigated parcels for high cash returns, followed by legumes to restore nitrogen. These patterns outperform the traditional wheat → fallow → wheat or wheat → barley → wheat sequences by replacing unproductive fallow years with nitrogen-fixing legumes and by introducing non-cereal crops (sunflower, sugar beet) to diversify both agronomically and economically. The cereals-only traditional rotations, while simple and low-risk, forfeit significant profit from high-value legume and industrial crops and fail to exploit biological nitrogen fixation, resulting in higher fertilizer dependency and greater vulnerability to nitrogen price volatility.

5.6 | Ablation Study

To quantify the individual contributions of MOSWARM-CRP's key innovations, we conducted an ablation study removing each component in isolation. *Table 8* reports HV and domain-specific metrics for the Mali case study (results for Morocco follow the same pattern).

Table 9. Ablation analysis of MOSWARM-CRP components for the Mali case study.

Variant	HV (↑)	EAP (×103 FCFA/ha)	ΔNcum (kg/ha) (↓)	CRS (↑)
Full MOSWARM-CRP	0.724 ± 0.018	287.4 ± 12.8	82.3 ± 6.1	0.812 ± 0.021
Without climate integration (single avg. scenario)	0.681 ± 0.020	276.2 ± 13.5	86.9 ± 6.8	0.698 ± 0.029
Without soil dynamics model (static soil)	0.692 ± 0.019	268.5 ± 14.2	108.4 ± 8.3	0.795 ± 0.023
Without adaptive inertia (linear decrease only)	0.706 ± 0.019	281.1 ± 13.1	84.7 ± 6.4	0.802 ± 0.022
Without all three (standard MOPSO baseline)	0.667 ± 0.020	258.3 ± 13.5	93.1 ± 6.8	0.741 ± 0.026

The ablation results reveal that each component contributes meaningfully but addresses different performance dimensions. Removing the climate scenario integration causes the largest drop in CRS (from 0.812 to 0.698, a 14.0% reduction), confirming that multi-scenario evaluation is critical for resilience optimization. Without the soil dynamics model, ΔN_{cum} increases by 31.7% (from 82.3 to 108.4 kg/ha), and EAP decreases by 6.6%, demonstrating that accurate soil state tracking is essential for both environmental and long-term economic objectives. Rotations that appear profitable under static soil assumptions lead to yield decline as soil nitrogen is depleted. The adaptive inertia mechanism provides the most modest individual improvement (HV: 0.706 vs. 0.724 for the full model), but contributes to faster convergence and better spread, with particular benefit in the early optimization phases. The combined effect of all three components (full MOSWARM-CRP vs. standard MOPSO) yields a synergistic HV improvement of 8.5%, confirming that the innovations are complementary rather than redundant.

5.7 | Computational Cost and Convergence

Table 9 reports the mean computational runtime per independent run and the iteration at which 95% of the final HV is achieved (convergence iteration) for each method.

Table 10.

Method	Runtime Per Run (Min)	Convergence Iteration (95% HV)
MOSWARM-CRP	34.7	612
NSGA-II	31.2	721
MOEA/D	28.5	685
Standard MOPSO	22.4	643
SPEA2	33.8	738
SO-GA	18.6	415
RS	20.1	

Computational runtime and convergence performance of the compared methods.

MOSWARM-CRP's runtime of approximately 35 minutes is modestly higher than baselines (11.2% more than NSGA-II, 54.9% more than standard MOPSO), primarily due to the multi-scenario fitness evaluation (each particle is evaluated across $K = 10$ climate scenarios) and the soil dynamics simulation within the fitness function. However, this overhead is modest in absolute terms; 35 minutes is well within the practical tolerance for a strategic planning tool applied once per growing season or planning cycle. Importantly, MOSWARM-CRP converges to 95% of its final HV by iteration 612, substantially faster than NSGA-II (721), MOEA/D (685), and SPEA2 (738), indicating that the adaptive inertia mechanism and PSO social learning dynamics accelerate early convergence despite the higher per-iteration computational cost.

6 | Discussion

The experimental results consistently demonstrate MOSWARM-CRP's superiority across all evaluation dimensions Pareto front quality, economic performance, environmental sustainability, and climate resilience for both case studies representing distinct agro-climatic contexts in Africa. Several factors underpin these advantages, and their analysis provides insights relevant to both the optimization and agricultural planning communities.

Why MOSWARM-CRP outperforms multi-objective baselines: the performance advantage of MOSWARM-CRP over NSGA-II, MOEA/D, and SPEA2 is attributable to two complementary mechanisms, 1) the PSO search dynamics particularly the social learning from archive guides via crowding distance-based tournament selection enable rapid convergence toward promising regions of the Pareto front while maintaining diversity through the exploration–exploitation balance governed by the adaptive inertia weight, and 2) more importantly, the integration of climate scenarios and soil dynamics within the fitness function transforms the search landscape in ways that reward genuinely superior rotation designs. Without the soil model, all methods operate on a fitness landscape where soil fertility is treated as an inexhaustible constant, leading to overvaluation of extractive rotation sequences. MOSWARM-CRP's embedded soil dynamics create a more realistic fitness landscape where long-term soil capital maintenance is rewarded, aligning the optimization surface with agronomic reality.

The critical role of climate scenario integration: the ablation study unambiguously demonstrates that multi-scenario climate evaluation is the single most impactful innovation for resilience optimization (Section 5.6). When rotations are optimized against a single average climate trajectory, the resulting plans are "brittle"; they perform well under modal conditions but fail disproportionately under extreme scenarios, particularly the high-emission SSP5-8.5 projections from high-ECS models (CanESM5, UKESM1-0-LL). By explicitly incorporating the minimax resilience objective across ten climate scenarios, MOSWARM-CRP steers the search toward rotation configurations that are inherently robust: Crops with broader thermal tolerance ranges, drought-tolerant varieties in the candidate set, and sequences that maintain yield stability through diversification. This finding resonates with the robust optimization literature [41] and suggests that climate-explicit evaluation should become a standard feature of agricultural optimization tools.

Practical implications for smallholder farmers: the rotation patterns discovered by MOSWARM-CRP are not merely theoretical optima; they represent actionable, agronomically sensible strategies. The cereal–legume alternation patterns dominant in both case studies align with well-established agronomic principles [61], [62] but go further by quantifying the economic and environmental returns of specific sequences and parameterizing input levels (fertilizer, seeding density) for each crop–year combination. For Malian smallholders currently practicing millet monoculture or millet–fallow sequences, the transition to a millet–groundnut–sorghum–cowpea rotation represents a feasible intensification pathway that increases income through high-value legume crops while reducing nitrogen fertilizer dependency through biological fixation. The Moroccan results similarly suggest that replacing wheat–fallow with wheat–legume–cereal–legume sequences can unlock substantial economic and environmental co-benefits, consistent with the "green morocco plan" policy emphasis on crop diversification and legume promotion [63].

Policy relevance for food security and climate adaptation: the results have direct relevance to national and regional food security policy in Africa. The African Union's Comprehensive Africa Agriculture Development Programme (CAADP) and the Malabo Declaration call for evidence-based agricultural transformation strategies that simultaneously improve productivity, resilience, and sustainability [64]. MOSWARM-CRP provides a quantitative framework for identifying rotation strategies that advance all three goals simultaneously, offering policymakers a tool for evaluating the productivity–resilience–sustainability trade-off surface and selecting strategies aligned with national priorities. The 12–20% climate resilience improvement is particularly significant given the projected intensification of drought frequency in the Sahel [65] and progressive aridification of North Africa [66].

Limitations and caveats: Several limitations of the current work should be acknowledged: 1) the crop yield response model, while inspired by AquaCrop [48], [53], is substantially simplified and does not capture all physiological processes (e.g., crop phenology, pest/disease pressure, nutrient toxicity). Integration with full process-based crop models (DSSAT, APSIM) would enhance yield prediction accuracy but at significant computational cost, 2) pest and disease dynamics which are strongly influenced by rotation patterns are not explicitly modeled; their inclusion would require additional state variables and interaction terms, 3) socioeconomic factors including market price volatility, labor migration, input supply chain disruptions, and household preference heterogeneity are treated deterministically or omitted, whereas in practice these factors introduce substantial additional uncertainty, 4) the crop parameter calibration relies on literature values and regional averages; site-specific calibration with local trial data would improve prediction accuracy but requires field-level data that may not be available in data-scarce African contexts, and 5) the CMIP6 ensemble, while spanning a range of climate sensitivities, does not fully characterize deep uncertainty in climate projections; expansion to larger ensembles or alternative scenario frameworks (e.g., storyline approaches) could provide additional robustness.

Comparison with mathematical programming approaches: Linear and mixed-integer programming approaches to crop rotation [14], [25] offer guaranteed global optimality for their specific formulations but require linearization of the yield response, soil dynamics, and climate uncertainty components that are intrinsically nonlinear. MOSWARM-CRP sacrifices global optimality guarantees in favor of handling the full nonlinear, stochastic, multi-objective problem structure without approximation. For practical planning purposes, the high-quality Pareto front approximations delivered by MOSWARM-CRP (with HV values exceeding 0.70) provide sufficient decision support, particularly given that the inherent uncertainty in crop parameters and climate projections renders the distinction between "globally optimal" and "high-quality approximate" solutions largely moot.

Future directions: Several promising research directions emerge from this work: 1) integration with full process-based crop simulation models (DSSAT [46], APSIM [47]) via surrogate modeling or model emulation could enhance yield prediction accuracy while maintaining computational tractability, 2) participatory optimization approaches that incorporate farmer preferences, indigenous knowledge, and risk attitudes through interactive Pareto front navigation could enhance adoption and relevance, 3) extension to additional agro-climatic regions beyond Sub-Saharan and North Africa including South Asia, Southeast Asia, and Central America would test the algorithm's generalizability, 4) real-time seasonal re-optimization using within-season weather observations and updated short-term forecasts could transform the tool from a strategic planning instrument to a tactical decision support system, and 5) integration of market price forecasting models (e.g., using time-series machine learning methods) as a source of economic uncertainty, complementing the climate uncertainty already captured, would provide more realistic profit distributions. Sixth, multi-farm, landscape-level optimization incorporating spatial interactions (pollination services, pest corridors, collective market impacts) represents an important scaling challenge.

7 | Conclusion

This paper has presented MOSWARM-CRP, a novel MOPSO algorithm for climate-adaptive crop rotation planning that integrates ensemble climate projections, embedded soil nutrient dynamics, and a three-objective optimization framework targeting economic return, environmental sustainability, and climate resilience. The algorithm introduces four key innovations: climate-scenario-aware fitness evaluation across CMIP6 ensembles, a discrete–continuous hybrid particle encoding tailored to the rotation search space, Pareto archive management with adaptive grid and crowding distance for effective three-objective trade-off surface approximation, and a seasonally constrained adaptive inertia weight mechanism that balances exploration and exploitation throughout the search.

Comprehensive empirical evaluation on two African case studies, the Ségou Region of Mali (semi-arid Sahel) and the Meknès-Fès Region of Morocco (semi-arid Mediterranean), demonstrates that MOSWARM-CRP significantly outperforms state-of-the-art MOEAs (NSGA-II, MOEA/D, SPEA2, standard MOPSO), a single-objective GA, and expert-designed RBRs across all evaluation dimensions. The algorithm achieves 15–23% higher EAP, 18–31% lower cumulative soil nitrogen depletion, and 12–20% superior CRSs relative to the best baselines, with statistically significant margins confirmed over 30 independent runs. Ablation studies confirm the complementary contributions of climate integration (critical for resilience), soil dynamics modeling (critical for environmental sustainability and long-term economic performance), and the adaptive inertia mechanism (beneficial for convergence speed and solution diversity).

The rotation patterns discovered by MOSWARM-CRP, particularly cereal–legume alternation cycles with strategic fallow insertion, are agronomically sound, economically attractive, and climatically robust, offering actionable recommendations for smallholder and semi-commercial farmers in climate-vulnerable African regions. The algorithm's computational cost (approximately 35 minutes per run on standard hardware) is practical for seasonal planning applications. As climate change intensifies the challenges facing African agriculture, computational tools like MOSWARM-CRP that can navigate the complex trade-offs between productivity, sustainability, and resilience will become increasingly essential for evidence-based agricultural transformation. Future work will pursue integration with process-based crop models, participatory optimization frameworks, and extension to additional agro-climatic regions and landscape-level planning scales.

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Author Contributions

M. T.; conceptualization, methodology, software, writing original draft, supervision.

F. Z. B.; formal analysis, validation, data curation, writing review & editing, visualization.

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Data Availability

The CMIP6 climate projection data used in this study are publicly available from the ESGF data nodes[1]. Historical climate data were obtained from the direction Nationale de la Météorologie of Mali and the Direction Générale de la Météorologie of Morocco under data-sharing agreements. ERA5 reanalysis data are available from the Copernicus Climate Data Store. Crop parameters were sourced from FAO public databases and published literature as cited. The MOSWARM-CRP source code and experiment scripts are available[2].

Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Consent for Publication

The author confirms consent for the publication of this work.

Ethics Approval and Consent to Participate

This article does not contain any studies with human participants performed by the author.

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