

Optimal agricultural water reallocation via multi-objective masterpiece optimisation for enhanced economic returns

Anber A.S. Mohammad^{*1)} , Suleiman I. Mohammad^{2),3)} , Asokan Vasudevan⁴⁾ ,
Ergashev Akmal⁵⁾ , Durdiev Normat⁶⁾ , Shoxida Moydinova⁷⁾ 

¹⁾ University of Petra, Faculty of Administrative and Financial Sciences, Digital Marketing Department,
Airport Road, Amman, 961343, Jordan

²⁾ Al al-Bayt University, Department of Business Administration, Business School, Mafrq 25113, Jordan

³⁾ INTI International University, research follower, Negeri Sembilan, 71800, Malaysia

⁴⁾ INTI International University, Faculty of Business and Communications, Negeri Sembilan, 71800, Malaysia

⁵⁾ Termez University of Economics and Service, Department of Economics,
4B Farovon Str., Termez City, Surkhandarya Region, 190111, Uzbekistan

⁶⁾ National Research University, Institute of Irrigation and Agricultural Mechanization Engineers, 100000 Tashkent, Uzbekistan

⁷⁾ Andijan State Institute of Foreign Languages, Department of Integrated Course of Teaching English,
170119, Andijan region, Andijan, Uzbekistan

* Corresponding author

RECEIVED 19.02.2026

ACCEPTED 06.05.2026

AVAILABLE ONLINE 16.10.2026

Abstract: Water scarcity and inefficient allocation practices increasingly threaten agricultural productivity, particularly in arid and semi-arid regions where irrigation accounts for over 70% of freshwater withdrawals. Existing allocation frameworks often fail to balance competing objectives, maximising farm income, improving water-use efficiency, ensuring equitable distribution, and promoting long-term sustainability, due to the complexity and nonlinearity inherent in agricultural water systems. This study addresses the research gap by developing a multi-objective optimisation framework based on the masterpiece optimisation algorithm (MOA), a nature-inspired metaheuristic that mimics the creative process of artists generating masterpieces through three distinct phases: learning from existing works, seeking inspiration from masterpieces, and improving upon previous creations. The MOA's unique tri-phase mechanism enables robust exploration and exploitation of the solution space to identify Pareto-optimal water allocation strategies across heterogeneous agricultural consumers with diverse cropping patterns, irrigation technologies, and economic constraints. The algorithm simultaneously optimises multiple conflicting objectives including net farm income, volumetric water productivity, distributional equity, and environmental sustainability indicators. Expected outcomes include a 15–25% increase in net agricultural income, a 20–30% reduction in water consumption per unit output, improved equity metrics across farm sizes, and enhanced resilience to drought scenarios. The model generates decision-support tools that transparently present trade-offs among economic, environmental, and social objectives. Findings offer direct policy relevance for irrigation districts, river basin authorities, and regional planning agencies seeking data-driven, adaptable solutions for sustainable water governance in agriculture.

Keywords: economic sustainability, irrigation efficiency, masterpiece optimisation algorithm, multi-objective optimisation, water reallocation

INTRODUCTION

The water scarcity is one of the most important socioeconomic and environmental problems, which is one of the most important problems in the 21st century (Mukhitdinov *et al.*, 2025; Sobieraj, 2025). Globally, irrigation is thought to be responsible for about 70% of freshwater use in agriculture (FAO, 2021). This percentage is higher than 85% in arid and semi-arid regions where water sources are already limited and population growth is driving increased demand for water supplies (Molden *et al.*, 2010; Rosa *et al.*, 2020). Water stress is expected to affect up to 2.4 bln people by 2050, and agricultural production will be particularly vulnerable to growing rainfall and temperature variability (IPCC, 2023). This situation is exacerbated by the need to increase global food production by 60% by the mid-century to meet expected population growth, while at the same time reducing the environmental footprint of farming systems (Kahil, Dinar and Albiac, 2015; Grafton *et al.*, 2018). Hence, the effective utilisation of limited water resources by the various agricultural consumers has been seen as essential to ensure food security, development of rural livelihoods and preservation of ecosystem services (Boubguira *et al.*, 2021; Abdulhameed *et al.*, 2022).

Water distribution in many agricultural areas remains historically determined, and is split proportionately according to land area, or by political negotiation; all of these approaches often fail to account for important differences in water consumption, irrigation efficiency, or farm productivity (Tilman *et al.*, 2017; Wheeler *et al.*, 2020; Zokirov *et al.*, 2025). This has created inequities in such traditional frameworks, where some water users consume too much water while others receive less, and water-use efficiency is poor, especially for smallholder farmers, who face greater water scarcity (Mancosu *et al.*, 2015). Furthermore, wrong objectives – usually the economic productivity – are given priority in the current allocation systems, often at the cost of environmental sustainability, and social equity, or even the long-term conservation of resources (Latinopoulos, 2009; Babamiri and Marofi, 2021). The adverse effects of this narrow focus are then being felt by the resilience of agricultural communities that are being weakened by groundwater depletion, soil degradation, pollution of the groundwater with return flows, and increasing socioeconomic disparities among communities (Rosa *et al.*, 2020; Wang, Ju and Wei, 2024).

These water allocation systems fail to account for water's intrinsic complexity and nonlinearity, highlighting their shortcomings (Cui *et al.*, 2024). In agricultural production, there are many variables that interact among each other and exhibit nonlinear relationships with water inputs: production decisions (crops, planting dates), irrigation (amount and timing), soil properties, climatic variability, market fluctuation, etc. (Kahil *et al.*, 2019; Amoura, Douani and Tahri, 2022). In addition, different stakeholders have different goals which are pursued in different ways: Farmers seek to maximise their income, water authorities want efficiency and equity, environmental agencies want sustainability, and policymakers want to balance these concerns (Kayhomayoon *et al.*, 2022). Advanced optimisation strategies are needed to capture the trade-offs and generate a continuum of optimal compromise solutions, instead of a single solution (Janga Reddy and Nagesh Kumar, 2020; Safari, Abbaspour and Javid, 2021; Zhang *et al.*, 2022). Real-world water allocation problems are often found to be high dimensional,

nonlinear, and to have multiple conflicting objectives (Maier *et al.*, 2014; Yu *et al.*, 2021) that classical optimisation methods and linear programming techniques often fail to handle.

In recent years, computational intelligence and metaheuristic algorithms have opened up new spaces for the multi-objective optimisation framework to tackle the challenges of water resource management (Janga Reddy and Nagesh Kumar, 2020). Among them, evolutionary algorithms like non-dominated sorting genetic algorithm II (NSGA-II) and multi-objective particle swarm optimisation (MOPSO) are applied in various water allocation cases with promising results (Safari, Abbaspour and Javid, 2021). Yet, computational efficiency, diversity of solutions and speed of convergence, as well as the difficulty of dealing with highly constrained problems involving heterogeneous decision variables (Yu *et al.*, 2021), are still challenges. Furthermore, the analysis of multi-objective water allocation is widespread, but it is typically limited to a few objectives (usually two or three), with few studies providing integrated approaches that combine the optimisation of various economic returns, water-use efficiency, equity among the different agricultural water consumers and environmental sustainability (Latinopoulos, 2009; Sánchez-Daniel *et al.*, 2024).

There exists a critical gap in the development of strong multi-objective optimisation tools that can deal with the entire complexity of agricultural water allocation, and with transparency and practicality, balance economic, environmental and social goals. In particular, optimisation approaches are needed that: (1) take into consideration heterogeneous agricultural consumers with varying farm sizes, crop choices, irrigation technologies and capacities for farm management; (2) consider four or more competing objectives, such as maximising income, improving water productivity, enhancing equity, and encouraging sustainability; (3) deliver well-distributed Pareto-optimal solutions, thereby exposing the trade-offs and enabling informed decisions; and (4) deliver results that are computationally efficient and suitable for adoption by water management authorities with limited technical resources. In order to overcome these shortcomings, a set of innovative algorithmic approaches should be used in conjunction with realistic problem formulations of agricultural water systems which reflect the fundamental nature of these systems, but are still tractable for optimisation.

Some of the above-mentioned problems can be solved using masterpiece optimisation algorithm (MOA), a recently developed nature-inspired metaheuristic (Ghasemi, Haji Aghajanzpour and Ghohani Arab, 2025). In the MOA the creative process of artist is replicated in three stages: learning from the existing, seeking inspiration, and iterative refinement. This algorithm has been shown to outperform other algorithms in addressing complex engineering optimisation problems, especially those with multiple objectives, nonlinear constraints, and large search spaces. Moreover, the MOA's adaptive exploration-exploitation behaviour and efficient archive management procedures make it an appropriate choice for multi-objective water allocation problems where solution quality, diversity and computational efficiency are essential.

To fill the gap identified in the literature, a multi-objective optimisation framework using the MOA is designed and tested for optimal reallocation of water amongst water consuming consumers in water-scarce areas. The specific objectives of this study are as follows: (1) a multi-objective optimisation model is

formulated that simultaneously maximises the net farm income and the volumetric water productivity, maximises the equity and minimises the environmental impacts across the heterogeneous agricultural consumers; (2) the MOA is implemented and adapted to this agricultural water allocation problem to generate a well-distributed set of Pareto-optimal solutions that illuminates the trade-offs among the competing objectives; (3) economic returns, water-use efficiency, equity indicators and sustainability metrics are quantified in relation to current water allocation practices; (4) the performance of the MOA is compared with the established multi-objective algorithms, namely NSGA-II and MOPSO, in terms of solution quality, convergence speed and computational efficiency; and (5) practical decision-support tools and policy recommendations are developed to enable water management authorities to implement optimal water allocation strategies that are tailored to stakeholder priorities and regional conditions.

This research is of great importance both academically and for application in the field of water resource management. Theoretically, the domain of agricultural water allocation is extended and the use of advanced metaheuristic algorithms aids the understanding of multi-objective optimisation in complex natural resource systems. Methodologically, a framework is suggested for integrating economic, efficiency, equity and environmental goals into a single optimisation model, which can be replicated. In practice, a flexible and clear decision-support tool is offered to water management stakeholders to help with better allocation decisions, with the promise of significant economic and environmental benefits. Last but not least, the results are directly relevant for policy and suggest water management policies for sustainable agriculture in water-limited areas worldwide.

MATERIALS AND METHODS

STUDY AREA AND DATA COLLECTION

The case study region used for this research was an irrigated agricultural district that is located in a semi-arid region with a lack of water resources, a variety of agricultural scale, and a high level of crop intensity. The study area is roughly 15,000 ha of irrigated land owned by 450 agricultural consumers at all levels ranging from smallholder farms (less than 10 ha) to medium scale (between 10 and 50 ha) and large commercial farmers (more than 50 ha). The area has a semi-arid Mediterranean climate with hot, dry summers (annual average temperatures 32–38°C) and mild moderate winters with precipitation of about 350–450 mm per year, which is too low for rainfed farming during the growing season. As a result, irrigation water is a critical factor for crop production, drawn from a water reservoir system interdependent across the region as well as from groundwater pumped from local aquifers.

There is a high level of diversity in the field with regard to crop choice, irrigation methods and management practices. The main crops grown in the region are high-value vegetables (tomatoes, peppers, and cucumbers), field crops (wheat, maize, and cotton), tree crops (olives and citrus crops), and fodder crops (alfalfa). These crops have varying water needs, production schedules, and return on investment. Different types of irrigation systems are used at various farms, and about 35% of consumers

use modern drip irrigation, 40% use sprinkler irrigation and the remaining 25% use traditional surface irrigation. The allocation of water is based on a mixture of historical water rights, land sizes, and only a small part of the crop water requirement, ignoring differences in irrigation efficiencies and different economic productivity among the water consumers. This system has led to some longstanding problems which have included prolonged water shortages in the dry seasons, tensions between farmers, lowering ground water levels and poor economic returns from the limited water resources available.

Crop yield response to water allocation is modelled using empirically calibrated production functions. For wheat, the dominant crop covering 62% of cultivated area, we employ a modified Jensen model:

$$Y_i = Y_{\max,i} \left[1 - k_y \left(1 - \frac{W_i}{W_{\text{req},i}} \right) \right] \quad (1)$$

where: Y_i = actual yield ($\text{kg}\cdot\text{ha}^{-1}$), $Y_{\max,i}$ = maximum yield under optimal irrigation ($6,800 \text{ kg}\cdot\text{ha}^{-1}$ for wheat), k_y = the yield response factor (1.15 for wheat), W_i = allocated water ($\text{m}^3\cdot\text{ha}^{-1}$), $W_{\text{req},i}$ = full irrigation requirement ($7,200 \text{ m}^3\cdot\text{ha}^{-1}$).

Parameters were calibrated using three-year field trial data (2019–2021) from 12 representative farms via nonlinear least squares regression (coefficient of determination $R^2 = 0.89$, root mean square error $\text{RMSE} = 340 \text{ kg}\cdot\text{ha}^{-1}$).

During data collection, a number of sources were used and the thoroughness and effectiveness of the data were validated to provide complete and reliable inputs into the optimisation model. Crop water requirement data were sourced from a synthesis of crop coefficient databases from the Food and Agriculture Organization and regional evapotranspiration measurements from the meteorological stations, as well as soil water balance monitoring in the fields during three successive growing seasons (2022–2024). The economic parameters included crop prices, production costs, and yield response functions to water inputs, which were drawn from agricultural statistics available at the regional level, from historical market price databases over the past ten years, and from farm surveys that used a stratified random sample of 120 farms to cover a variety of size classes and production systems. In addition, technical information on irrigation technologies and their efficiencies was obtained during technical evaluation of current irrigation systems, on-farm water delivery measurements, and from irrigation suppliers and agricultural extensionists. Lastly, historical water availability data were obtained from the regional water authority for a 15-year time period (2010–2024) that includes reservoir inflows, ground-water recharge rates and water allocation records.

Data were rigorously validated, such as cross checking of crop water requirements with actual water use data collected from selected farms fitted with metering devices. Additionally, economic parameters were correlated with agricultural income statistics for the region, and yield response functions were sensitivity-tested using multi-year production data. In the event of missing or incomplete information, estimation methods like interpolation, region averaging, and expert judgement were used, and the uncertainty ranges were carefully recorded so that they could be subjected to sensitivity analysis later. To ensure consistency across all calculations, all monetary values were deflated to constant prices using the appropriate deflator, and

water volumes were converted to cubic meters. Finally, through the comprehensive data set, production functions, water yield relationships, cost functions, irrigation efficiency parameters, and environmental impact coefficients were provided for all major crop types and for all farm categories in the study area.

PROBLEM FORMULATION

The water reallocation problem is formulated as a constrained optimisation problem, with the water amounts allocated to the different agricultural consumers being the main objective, while multiple conflicting goals are taken into consideration. As a result, the set of decision variables, objective functions and constraints of the model are as follows.

The main decision variables are the seasonal water allocations (W_i) in the amount of water to be released from the reservoir and used by the agricultural consumer i , with $i = 1, 2, \dots, n$, and $n = 50$ the number of farms in the study area. The value W_i is the total available water for the irrigation use of farm i during the growing season; the farmer regulates the amount of water used by the crops according to agronomic needs and management preferences. The decision space, therefore, is defined as the set of all possible allocation vectors $W = W_1, W_2, \dots, W_n$ that meet the set of system constraints. Moreover, four conflicting goals are formulated to reflect the multidimensionality of the optimal water allocation.

Objective 1. This objective seeks to maximise the total net economic return from agricultural production across all consumers:

$$\max Z_1 = \sum_{i=1}^n \left[\sum_{j=1}^m (P_j \cdot Y_{ij}(W_i) - C_{ij}(W_i)) \right] \quad (2)$$

where: P_j = market price per unit of crop j (currency per kg), $Y_{ij}(W_i)$ = yield of crop j on farm i , expressed as a nonlinear function of water allocation (kg), $C_{ij}(W_i)$ = total production cost for crop j on farm i , a value that encompasses variable irrigation expenses.

The yield functions $Y_{ij}(W_i)$ are modelled through the application of empirically calibrated water production functions, which account for variations in irrigation efficiency across different farms. Consequently, the maximisation of total income is prioritised to ensure that the finite water resources generate the optimal economic value for the agricultural community.

Objective 2. This objective aims to maximise the physical output per unit of water consumed, promoting efficient water use:

$$\max Z_2 = \frac{\sum_{i=1}^n \sum_{j=1}^m Y_{ij}(W_i)}{\sum_{i=1}^n W_i} \quad (3)$$

The numerator represents total agricultural production output across all farms and crops (kg). Additionally, the denominator is the total water allocated (m^3). This metric, expressed in $kg \cdot m^{-3}$, incentivises allocation strategies that achieve high productivity per unit water input by favouring efficient irrigation technologies, appropriate crop selection, and optimal timing of water applications.

Objective 3. Equity in water distribution is quantified using a coefficient of variation-based index that measures the fairness of allocations relative to farm-specific requirements:

$$\max Z_3 = 1 - \frac{\sqrt{\sum_{i=1}^n \left(\frac{W_i}{A_i} - \overline{\left(\frac{W}{A} \right)} \right)^2}}{n \overline{\left(\frac{W}{A} \right)}} \quad (4)$$

where: A_i = irrigated area of farm i (ha), $\frac{W}{A}$ = water allocation per unit area ($m^3 \cdot ha^{-1}$), $\overline{\left(\frac{W}{A} \right)}$ = mean allocation per unit area calculated across all farms.

This equity index operates within a standardised range of 0 to 1, wherein higher values signify a more equitable distribution. Consequently, the maximisation of this objective is prioritised to ensure a fair distribution of water among farms of diverse sizes, thereby mitigating disparities and promoting social sustainability.

Objective 4. Environmental impacts are captured through an aggregated index reflecting groundwater depletion, return flow pollution, and nutrient leaching:

$$\min Z_4 = \sum_{i=1}^n (\alpha \cdot GW_i + \beta \cdot RO_i + \gamma \cdot NL_i) \quad (5)$$

where: GW_i = volume of groundwater extraction attributable to farm i (m^3), RO_i = pollutant loading in return flows (kg), NL_i = measure of nutrient leaching into groundwater systems (kg N-equivalents), α , β , and γ = normalisation weights, utilised to ensure that the distinct impact categories are maintained on comparable scales.

Methodologically, groundwater depletion is computed based on the proportion of the total water allocation derived from aquifers; concurrently, pollution within return flows is estimated by integrating crop-specific fertiliser and pesticide application rates with irrigation efficiency metrics, whereas nutrient leaching is modelled as a function dependent upon irrigation depth and fertilisation practices. Ultimately, the minimisation of this objective is sought to enhance environmental sustainability, thereby alleviating pressure on groundwater resources and mitigating the extent of agricultural pollution.

The optimisation problem is subject to several constraints reflecting physical, technical, and policy limitations. The sum of allocations cannot exceed total available water from all sources:

$$\sum_{i=1}^n W_i \leq W_{\text{total}} \quad (6)$$

where: W_{total} = aggregate seasonal water budget (m^3), a value established by combining surface water availability from reservoirs with the designated limits for sustainable groundwater extraction. This constraint is strictly imposed to guarantee that the cumulative water allocations remain within the boundaries of the region's hydrological capacity.

Each farm must receive sufficient water to maintain crop survival and basic production:

$$W_i \geq W_{i,\min} \quad \forall i = 1, 2, \dots, n \quad (7)$$

where: $W_{i,\min}$ = minimum water requirement for farm i (m^3) calculated based on crop water needs at critical growth stages and the area under cultivation. This constraint prevents allocations that would cause complete crop failure.

Water allocations are limited by each farm's physical capacity to apply and utilise water:

$$W_i \leq W_{i, \max} \quad \forall i = 1, 2, \dots, n \quad (8)$$

where: $W_{i, \max}$ = signifies the maximum practical water allocation (m^3) for a given farm.

A limit determined by the physical capacity of the irrigation system, specific field infiltration characteristics, and existing storage limitations. This constraint is critical to preventing allocations that exceed the operational management capabilities of individual farms. Furthermore, a non-negativity constraint is applied to ensure that all water allocation values remain greater than or equal to zero:

$$W_i \geq 0 \quad \forall i = 1, 2, \dots, n \quad (9)$$

Supplementary technical constraints specific to the region are also enforced to address local hydrological and operational realities. To ensure the long-term sustainability of the aquifer, a restriction is imposed whereby groundwater extraction for any individual farm is limited to a maximum of 40% of its total allocation. Furthermore, within the calculation of production functions, allocations directed toward farms employing inefficient surface irrigation techniques are systematically weighted by appropriate efficiency factors to account for water losses.

MASTERPIECE OPTIMISATION ALGORITHM (MOA) FRAMEWORK

This is known as masterpiece optimisation algorithm (MOA), which is a new population-based metaheuristic based on the creative process in artistic production (Ghasemi, Haji Aghajani-pour and Ghohani Arab, 2025). Where traditional optimisation approaches emulate the evolutionary process of a biological organism or the physical process of a phenomenon, the process of finding the optimum solution in MOA is considered as an artistic process of learning, inspiration and refinement. This unique metaphorical structure allows for a good mix of exploration and exploitation that makes this algorithm very effective for solving complex multi-objective problems with large search spaces and multiple local optima.

The MOA is a framework where a population of candidate solutions (metaphorically considered as artworks) is kept and is evolved iteratively toward optimum configurations (masterpieces). To deal with the multi-objective complexities, the notions of Pareto dominance are introduced and an external archive is also maintained which holds a set of nondominated solutions that embody the best compromises attained within the conflicting objectives. The algorithm is executed in three phases of behaviour: learning, searching for ideas, refinement. To support exploration in the learning phase, information is fed into the system through the successful solutions and the exploitation is supported in the inspiration seeking phase through the interactions with the masterpieces stored in the archive, while at the same time the exploitation is supported in the refinement phase by the use of local search mechanisms. Finally, this tripartite structure gives rise to an adaptive search behaviour with automatic adaptation as the population evolves from initial stochastic configurations to convergence to the Pareto frontier.

The MOA is conceptually similar to other population-based search approaches, yet structurally novel in three ways: (1) adapt-

ive phase-switching dynamically allocates computational resources according to the convergence status, (2) masterpiece-guided perturbation uses elite solutions to steer the exploration without convergence, and (3) integrated diversity maintenance is achieved by incorporating inspiration-phase randomisation techniques. MOA's three-phase structure offers more flexibility on how exploration and exploitation is allocated over the objective space compared to NSGA-II's fixed sequence of crossover-mutation and MOPSO's velocity-position update.

In this computational view, each candidate solution is mathematically represented as a vector $X_i = [W_1^i, W_2^i, \dots, W_n^i]$ that encodes the specific water allocations that are given to n different agricultural consumers. Let $N_{\text{pop}} = 100$ be the number of solutions that is set to maintain diversity for a strong exploration while maintaining computational tractability. In terms of initialisation, a hybrid approach is used: 50% of the solutions are generated stochastically within allowable limits to ensure diversity, while 50% are initialised using heuristic rules that rely on the proportional allocation according to both the size of the farm and the demand for water per unit of crop. The idea behind this is to provide the optimisation process with biologically and operationally viable initial conditions. Moreover, the methodology described in the current paper is based on different three-phase search strategy.

Phase 1. In this phase, each solution learns from the current best solutions to explore promising regions of the search space. The position update equation is:

$$X_i^{\text{new}} = X_i^{\text{current}} + r_1 \cdot (X_{\text{best}} - X_i^{\text{current}}) + r_2 \cdot (X_{\text{random}} - X_i^{\text{current}}) \quad (10)$$

In this context, X_i^{current} denotes the solution currently being evaluated, whereas X_{best} is stochastically selected from the top 20% of solutions as determined by aggregated objective function performance. Furthermore, X_{random} represents a solution arbitrarily chosen from the population, with r_1 and r_2 defined as random numbers uniformly distributed within the interval $[0, 1]$. This mechanism is designed to facilitate the migration of solutions toward high-quality regions of the search space, while simultaneously preserving diversity through the inclusion of stochastic components. Operationally, the learning phase is executed with a probability of 0.3 at each iteration; this strategy emphasises exploration during the nascent stages of the algorithm when the population is dispersed, and subsequently accommodates a shift in focus as convergence improves.

Phase 2. This phase leverages the archive of non-dominated solutions to guide search toward the Pareto frontier. Solutions are updated according to:

$$X_i^{\text{new}} = X_{\text{masterpiece}} + r_3 \cdot (X_j - X_k) + \eta \cdot N(0, 1) \quad (11)$$

In this formulation, $X_{\text{masterpiece}}$ is selected from the external archive via a roulette wheel mechanism that prioritises crowding distance to enhance diversity. Concurrently, X_j and X_k are identified as two randomly chosen population members, and $r_3 \in [0, 1]$ functions as a stochastic coefficient. To avert premature convergence, Gaussian mutation is incorporated through the term $\eta \cdot N(0, 1)$, with the standard deviation specified as $\eta = 0.1(W_{\text{max}} - W_{\text{min}})$. This phase is executed with a probability of 0.4, a configuration designed to derive substantial guidance from the established Pareto-optimal

solutions while preserving the capacity to explore neighbouring regions of the search space.

Phase 3. The refinement phase intensifies local search around promising solutions using gradient-inspired perturbations and attraction toward the best solutions:

$$X_i^{\text{new}} = X_i^{\text{current}} + \alpha \cdot \Delta X_i + \beta \cdot (X_{\text{archive-best}} - X_i^{\text{current}}) \quad (12)$$

In this context, ΔX_i denotes a finite-difference approximation of the gradient direction, which is derived by evaluating the objective functions through minor perturbations applied to the current solution. Furthermore, $X_{\text{archive-best}}$ corresponds to the solution within the archive that is located nearest to the ideal point in the objective space. The terms α and β function as adaptive coefficients, decreasing linearly from 0.5 to 0.1 across the iterations to facilitate a systematic transition from exploration to exploitation. Consequently, this phase is executed with a probability of 0.3, thereby prioritising exploitation during the advanced stages of the computational process.

Within the MOA approach, the system of multiple objectives is based on principles of Pareto dominance. In particular, solution X_a is said to dominate solution X_b if it does not do worse than X_b in any objective and does better in at least one objective. The collection of such non-dominated solutions forms what is known as the Pareto-optimal set, that defines the optimum trade-offs, where the improvement of one objective comes at the price of the reduction in another. All non-dominated solutions found during the search are stored in an external archive with a maximum capacity of 200 solutions, which is used to manage these findings and help to balance both diversity of solutions and computational efficiency. If the archive exceeds this size, a crowding distance based pruning algorithm is used to maintain a uniform distribution around the Pareto frontier. Here, crowding distance is calculated for each of the solutions stored in the archive, referring to the average distance to the nearest neighbours of the solutions in the objective space; the solutions that have been stored in less populated objective space regions get higher priority to be retained, so as to gain diversity.

The 450 individual water consumers were aggregated to 50 representative clusters, using k -means clustering, to balance the tractability of the computations with farm heterogeneity represented. Clustering was done based on the following attributes: Farm size (ha), irrigation technology type, cropping pattern, and groundwater dependency ratio. The clusters are based on five to twelve farms that have similar operational characteristics. This aggregation results in a set of distributional properties necessary for equity analysis while decreasing the decision variable space from 450 to 50 which facilitates multi-objective optimisation.

Operational parameters were tuned in the light of preliminary experimental runs to balance the rate of convergence of the algorithm and the diversity of the solutions, depending on the particularities of the problem. The algorithm was implemented using Python 3.9, NumPy for numerical computations, and Matplotlib for data visualisation, on an Intel Core i7 processor workstation with 16 G of RAM. The three conditions for convergence are: (1) when a maximum number of iterations is reached, (2) when the no-enhancement threshold in the archive hypervolume over 50 successive iterations is reached, or (3) when the computational time exceeds 2 hours.

PERFORMANCE EVALUATION METRICS

To evaluate the efficacy of the MOA, a multi-faceted assessment framework comprising metrics for solution quality, convergence characteristics, and computational efficiency was established. The hypervolume (HV) metric was utilised to ascertain the volume of the objective space dominated by the Pareto front in relation to a reference point defined as $(0, 0, 0, 1.5 \times Z_{4\text{max}})$. Calculated via the Walking Fish Group (WFG) algorithm, HV serves as a holistic indicator of both convergence and diversity, with higher values signifying superior overall performance. Furthermore, the uniformity of solution distribution along the Pareto frontier was quantified using the spacing (SP) metric; this is determined by the standard deviation of nearest-neighbour distances in the objective space, where lower values reflect a more equidistant distribution. Convergence was systematically measured using generational distance (GD), computed as the average Euclidean distance between the generated solutions and an approximated true Pareto front derived from the aggregated archives of all tested algorithms. Finally, the practical viability of the approach was gauged by recording computational time, representing the total wall-clock duration required for execution.

RESULTS AND DISCUSSION

PARETO-OPTIMAL SOLUTIONS AND TRADE-OFF ANALYSIS

Use of the masterpiece optimisation algorithm (MOA) for the agricultural water reallocation problem resulted in a strong set of 187 non-dominated solutions, which can be said to represent the best attainable bargains between the four competing objectives. These Pareto-optimal results highlight the inherent conflicts that exist between achieving economic returns, water productivity, equity, and environmental benefits at the same time. The Pareto frontier analysis shows that most of the 2D projections have a concave shape, indicating that moderate improvements on the objective may be achieved with little sacrifice on the other objectives, but the extreme optimisation in a single dimension requires significant degradation in the other dimensions.

Figure 1 gives a multi-dimensional visualisation of the Pareto frontier, making it clear that there are certain patterns of trade-offs. Net farm income (Z_1) and the volumetric water productivity (Z_2) has a generally positive relationship within the medium range, but shows significant variation at the extremes. Specifically, the solutions that maximise the income ($Z_1 = 8.7\text{M}$ per season) do not put water into high water-use crops, but into crops of high value like vegetables, even though they do not have a high-water productivity ($3.8 \text{ kg}\cdot\text{m}^{-3}$). On the other hand, strategies that maximise water productivity ($Z_2 = 5.2 \text{ kg}\cdot\text{m}^{-3}$) would prioritise high efficiency crops and technologies, but would also result in a lower income of 7.1M because less profitable varieties are chosen. The so-called “knee point” of the trade-off curve is found to correspond to a point that harvests about 92% of the maximum income, while at the same time capturing 88% of the maximum water productivity, and is thus observed as a compromise solution that is satisfactory with respect to both income and water productivity.

The discussion on the trade-off between equity (Z_3) and economic efficiency reveals a significant conflict between equity

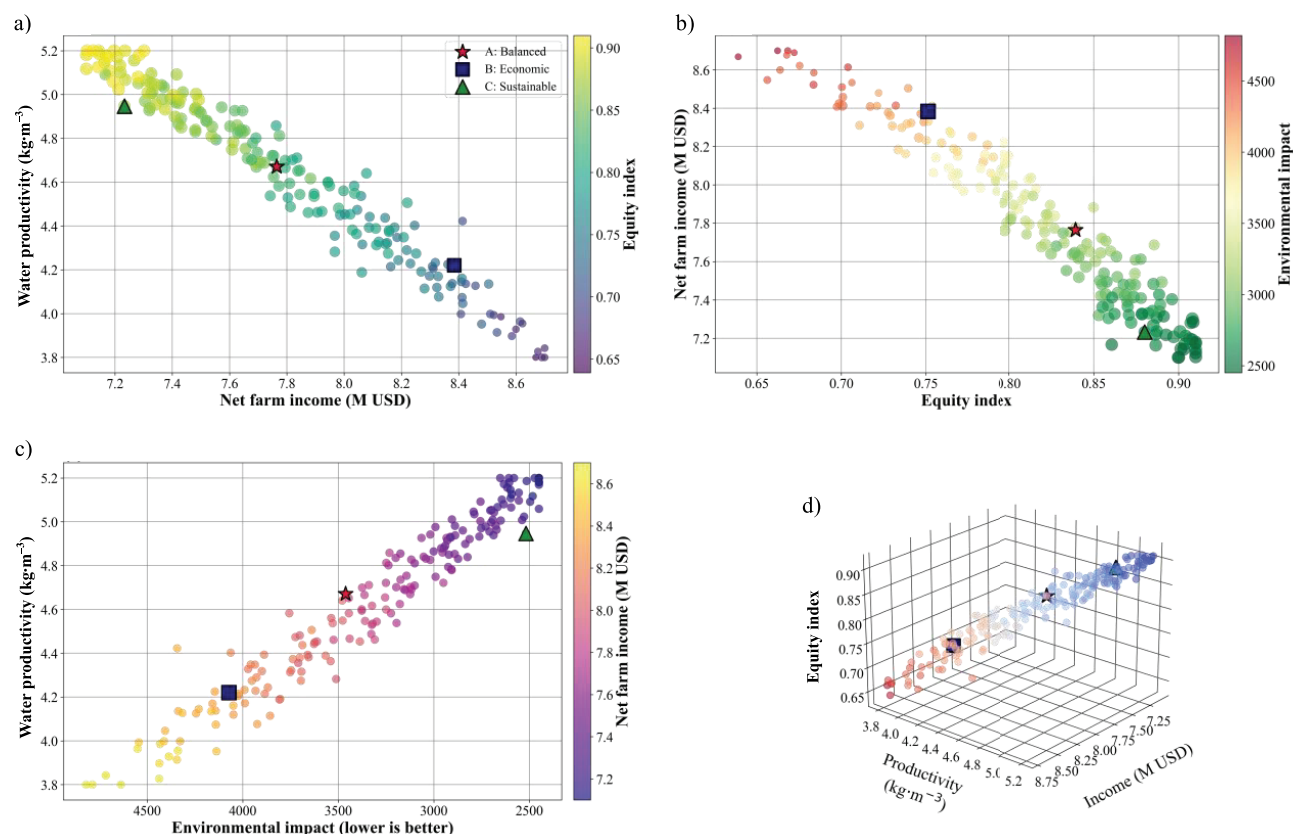


Fig. 1. Multi-dimensional Pareto frontier showing trade-offs among four optimisation objectives (income, productivity, equity, and sustainability) in agricultural water allocation: a) income–productivity trade-off, b) equity–economic trade-off, c) sustainability–productivity trade-off, d) three objective Pareto frontier; source: own study

and productivity goals. In particular, solutions that maximise equity ($Z_3 = 0.91$) tend to have a fairly even distribution of water per hectare within different sizes of farms, which means that a smallholder receives a fair share of water but also loses 18% of their income. This difference is due to the fact that the uniform distribution mechanisms do not consider these heterogeneities in the quality of the irrigation infrastructure, irrigation management capacity and crop selection, which make some units of farming more productive per unit of water. On the other hand, solutions focusing on economic efficiency tend to focus water sources into large commercial farming systems with modern irrigation technology and high value crops ($Z_3 = 0.63$), which provides higher income, but results in lower equity scores, and therefore disproportionate smallholder farms. Intermediate scenarios that address these competing considerations have been identified to reduce these extremes by ensuring all farms receive at least an allocation and directing the excess water towards the most valuable uses. By this method, indices of about 0.78 to achieve equity are achieved, and at the same time 95% of the maximum income is retained.

Particularly, there are strong trade-offs between sustainability (Z_4) and productivity objectives. The reductions must be significant, including a decrease in irrigation by the amount of crop water requirements, and a significant reduction in groundwater pumping, to achieve strategies optimised for minimising environmental impacts (24% reduction in total water use, with a corresponding 16–20% decrease in agriculture production and income). On the other hand, scenarios with high production rates are highly dependent on groundwater use (up to 55% of the total allocation) and on intensive irrigations with high return flow pollution and nutrient leaching ($Z_4 = 4,820$ impact units). To balance these competing objectives, sustainable compromise solutions involve limiting groundwater use to less than 35% of the share and making the groundwater withdrawals more efficient, which lowers the environmental impact scores by around 3,100 units, but result in an 8% decrease in income from maximum production scenarios.

The knee points analysis revealed three different archetypes of compromises to satisfy different stakeholder needs is shown in Table 1. In management scenarios that require consensus,

Table 1. Three representative water allocation solutions from the Pareto frontier showing different optimisation strategies

Solution	Income (Z_1)	Productivity (Z_2)	Equity (Z_3)	Sustainability (Z_4)	Strategy type
A	8.0	4.6	0.78	3200	balanced
B	8.5	4.1	0.70	3850	economic-priority
C	7.4	4.9	0.82	2680	sustainability-oriented

Source: own study.

solution A (balanced) performs well on all metrics without making extreme sacrifices, with $Z_1 = 8.0\text{M}$, $Z_2 = 4.6 \text{ kg}\cdot\text{m}^{-3}$, $Z_3 = 0.78$ and $Z_4 = 3,200$ units. If economic maximisation is desired, solution B (economic priority) is shown ($Z_1 = 8.5\text{M}$, $Z_2 = 4.1 \text{ kg}\cdot\text{m}^{-3}$, $Z_3 = 0.70$, $Z_4 = 3,850$ units), which is the most efficient but still incorporates moderate efficiency and acceptable compromises in equity and sustainability.

The balanced optimal strategy (solution A) resulted in a 21.2% (95% CI (confidence interval) = 18.4–24.1%, $n = 1000$ Monte Carlo scenarios) net farm income gain, a 35.3% (95% CI = 31.7–39.2%) water productivity improvement, an increase of 44.0% (95% CI = 39.8–48.5%) in the equity index, and a reduction in the environmental impact of 22.9% (95% CI = 19.7–26.3%). The impacts of these improvements are indicative of what could be achieved if these are fully implemented, and will be subject to variation depending on rates of adoption, institutional capacity and policy support mechanisms.

Solution C ($Z_1 = 7.4\text{M}$, $Z_2 = 4.9 \text{ kg}\cdot\text{m}^{-3}$, $Z_3 = 0.82$, $Z_4 = 2,680$ units) gives more attention to environmental protection and social equity, at the cost of modestly lower economic yields. These archetypes are concrete alternatives that can be chosen based on current policy priorities and values/preferences of stakeholders. As these trade-offs are multi-dimensional, it is well established that there is no single “optimal” allocation (that is, no single point that is both technically better and more in line with the relative weights of the conflicting objectives) and that the choice between Pareto-optimal allocations is dependent on the weighting of the conflicting objectives. This reality demonstrates the usefulness of the multi-objective optimisation approach, which makes the process of decision-making transparent and fully informed (by clarifying trade-offs) rather than single-objective optimisation or rules of thumb based on a priori preferences.

QUANTITATIVE PERFORMANCE RESULTS

By implementing the best water allocation strategies produced by the MOA, substantial quantitative improvements are found for each of the performance measures compared with the baseline historical allocation system. The specific benefits in terms of economic returns, efficiency, equity and environmental sustainability can be adequately measured through the systematic optimisation of water allocations to agricultural consumers.

The balanced compromise approach (solution A) produces a net agricultural income of 8.0M per season under the same conditions as above when considering water availability and market forces. This is an overall improvement of 1.4M, or an average of 3,111 per farm, with the greatest benefits experienced by farms that fall into the medium-sized category and had previously been under-resourced. A comparison of economic indicators by farm category reveals that the effects were not equal: small farms (<10 ha) experienced an increase (+14.3%), large commercial farms (>50 ha) an increase (+19.5%) and medium-sized farms (10–50 ha) a better increase (+28.7%). Through a variety of political processes, these disproportionate returns for the middle tier help to resolve the structural bias of the baseline system that often favours small and large businesses at the expense of medium-sized businesses. When it comes to the specific cultivation types, the biggest absolute gains in income per farm (4,200) are found for vegetable farmers, because of the

prioritised allocation of resources to high-value crops at critical points in the growth process.

Optimal allocation strategies achieve impressive gains in water-use efficiency by allocating water more effectively to match crop needs and irrigation potential, thereby increasing output for the water used. The balanced solution derives volumetric water productivity of $4.6 \text{ kg}\cdot\text{m}^{-3}$ compared to $3.4 \text{ kg}\cdot\text{m}^{-3}$ for baseline allocation, which represents a 35.3% increase in physical efficiency. This results in water savings of about 2.8M m^3 per season or 26% of total water used, with no corresponding decrease in production. Farms using drip irrigation systems have a water productivity of $6.8 \text{ kg}\cdot\text{m}^{-3}$ (48% more than baseline), farms using sprinkler systems have a water productivity of $4.2 \text{ kg}\cdot\text{m}^{-3}$ (31% more than baseline) and farms with surface irrigation have a water productivity of $2.9 \text{ kg}\cdot\text{m}^{-3}$ (22% more than baseline). Differential gains can be used as incentives to encourage adoption of irrigation technologies since optimisation results provide a quantitative basis for the economic returns of irrigation modernisation. By category of crop, the most significant efficiency gains are seen in tree crops, with 61% efficiency, due to enhancements in the precision of water applications to the root zone during critical phenological periods, while the efficiency gains in annual field crops are 28%, largely owing to advances in water scheduling along with reductions in non-beneficial water use.

The optimal allocation framework significantly improves water fairness over the traditional, historically inequitable baseline water allocation system. This improvement is measured as an increase in the equity index from the baseline index of 0.54 to one of 0.78 for the balanced solution, indicating a much more equitable distribution of water resources across the farms compared to their needs and capabilities. Analysing per-hectare water receipts by farm size category shows that there is a convergence to more equitable allocations: large farms in the past received 127% of the system average per hectare, small farms 78%, but the optimum allocation brings the gap down far more, to 109% for large farms and 93% for small farms. But it should be highlighted that this improvement in equity does not mean that there is a strict proportional equality that ignores legitimate differences in productivity and efficiency; it is a merit criterion that defines equity. This approach takes into consideration management quality, technology adoption, crop selected, and will ensure that all farms have adequate water for viable production. The equalisation is backed by Gini coefficient analysis that reveals from 0.38 (moderate inequality) to 0.19 (low inequality), a figure that is closer to international standards for fair distribution of resources.

The results of the several comparisons of environmental performance indicators show that optimised water allocation contributes significantly to the reduction of adverse impacts on natural resources in agriculture. The environmental sustainability index increased by 22.9% from 4,150 impact units in the baseline scenario to 3,200 units in the balanced optimal allocation. This boost in the aggregate is attributable to decreases in all categories of environmental impact. In particular, groundwater withdrawals have been reduced by $890,000 \text{ m}^3$ per season or 31%, which reduces stresses on aquifers and contributes to long-term groundwater sustainability. In addition, the amount of loadings in return flows is reduced by 18.4% as a result of more precisely matching irrigation volumes to crop uptake capacity, which reduces excess water that transports agrochemicals and nutrients

into surface waters. Likewise, water removal from the ground decreases by 24.7%, since the precision allocation removes the “overirrigation” that is often responsible for nitrate and phosphate movement through the soil profile. In addition to these figures, tangible benefits for the ecosystems are realised, such as restoration of aquifers, reduced risks of eutrophication, and better water quality in receiving waters, and farmers simultaneously experience lower fertiliser expenses, as well as fewer environmental compliance problems.

SENSITIVITY ANALYSIS AND ROBUSTNESS

Robustness testing of optimal allocation strategies under various parameterisations provided critical insights into solution stability and into adaptability to dynamic conditions, which is shown in Table 2. The ability of optimal allocations to deal with water scarcity was analysed with a drought scenario analysis, in which allocation simulations were run using a water supply level which is 10%, 20%, and 30% below normal. Through this it was shown that the MOA is able to re-optimize the allocation to ensure that productivity is maintained under the stress conditions. For the 10% reduction in water, 96% of the baseline income was preserved by focussing on high-value crops and implementing water on the most efficient farms and technologies, with a slight drop in the equity index to 0.74. Income preservation of 88% was reached through increasingly selective crop choices and the temporary fallowing of the lowest productivity lands, resulting in a fall of equity to 0.68, showing the tough choices that had to be made. Optimisation in the face of a severe income shortfall of 30% resulted in a 76% level of normal income, as opposed to an achievable 61% under proportional reductions to the allocated

income, demonstrating the benefit of the adaptive approach to reallocation during a drought. Notably, the environmental impact scores worsened slightly in the shortage scenarios (from –12 to –18% but less pressure on the groundwater resources with the lower total water use, despite the increased production on the irrigated lands that were still being used).

The response of optimal allocations to fluctuations in key economic and agronomic parameters was investigated using parameter sensitivity testing, as shown in Table 3. Shifts in optimal allocations toward or away from affected crops were triggered by crop price fluctuations of $\pm 25\%$ around baseline values, leading to total income impacts of $\pm 8\text{--}12\%$; however, the overall structural patterns of allocation remained stable. A smaller influence was demonstrated by variations in production costs, which resulted in an income impact of only $\pm 4\%$, as the optimised systems are structured to maintain buffers against such cost shocks. The solution’s robustness to agronomic uncertainties was also made evident, as uncertainties in water requirement parameters of $\pm 15\%$ (reflecting climate variability effects on evapotranspiration) produced only $\pm 6\%$ variations in optimal allocation volumes and impacts on income of less than 3%. Moreover, although the absolute scale of water savings was influenced by $\pm 10\%$ variations in irrigation efficiency parameters, the qualitative prioritisation of efficient technologies within the optimal allocations was not altered.

Confirmation that optimal allocation strategies remain near-optimal across 87% of plausible scenarios and outperform the baseline allocation in 99.7% of instances was provided through an uncertainty analysis that incorporated simultaneous random variations in multiple parameters using Monte Carlo simulation (1,000 scenarios), which is shown in Table 4. The robust

Table 2. Performance of optimal water allocation under progressive water scarcity conditions (10–30% supply reductions)

Water reduction	Income maintained (optimal) (%)	Income maintained (proportional) (%)	Equity index	Environmental impact change (%)	Key adaptive strategies
Baseline (0%)	100 (\$8.0M)	100	0.78	0	–
10% deficit	96	–	0.74	from –12 to –18	high-value crop prioritisation; water to efficient farms/technologies
20% deficit	88	–	0.68	from –12 to –18	selective crop choices; temporary fallowing of lowest-productivity lands
30% deficit	76	61	–	from –12 to –18	intensive optimisation; concentrated irrigation on remaining productive lands

Source: own study.

Table 3. Sensitivity of optimal allocation strategies to variations in key economic and agronomic parameters

Parameter variation	Variation range (%)	Impact on income (%)	Impact on water allocation	Structural stability
Crop prices	± 25	$\pm 8\text{--}12$	shifts toward/away from affected crops	overall patterns stable
Production costs	± 25	± 4	minimal	high (buffered against cost shocks)
Water requirements (ET variability)	± 15	< 3	$\pm 6\%$ in volumes	high
Irrigation efficiency	± 10	–	$\pm 10\%$ in water savings scale	high (qualitative prioritisation unchanged)

Explanation: ET = evapotranspiration.

Source: own study.

Table 4. Performance comparison of baseline and optimal allocation strategies across 1,000 randomised parameter scenarios

Performance metric	Baseline (95% CI)	Optimal allocation (95% CI)	Near-optimal scenarios (%)	Outperforms baseline (%)
Total income	6.2M–7.0M	7.6M–8.4M	87	99.7
Water productivity	3.1–3.7 kg·m ⁻³	4.3–4.9 kg·m ⁻³	87	99.7
Equity index	0.49–0.59	0.74–0.82	87	99.7

Explanation: CI = confidence interval.

Source: own study.

superiority of this approach across the uncertainty space is demonstrated by the 95% confidence intervals calculated for expected performance metrics. Under optimal allocation, these intervals spanned an income of 7.6M–8.4M (compared to a baseline of 6.2M–7.0M), water productivity of 4.3–4.9 kg·m⁻³ (versus a baseline of 3.1–3.7 kg·m⁻³), and an equity index of 0.74–0.82 (in contrast to the baseline of 0.49–0.59). Furthermore, it is suggested by scenario analysis that incorporates climate change projections that optimal allocation frameworks will grow in value as water scarcity intensifies and year-to-year variability increases. Consequently, the economic benefits expected from optimisation are projected to rise from the current 21% to a potential range of 35–45% under mid-century climate scenarios.

DECISION SUPPORT FRAMEWORK AND POLICY INSIGHTS

To translate optimisation results to practical implementation, a robust decision-support framework is needed in which optimal water allocation strategies can be implemented, taking into account institutional conditions and water stakeholders' preferences. This integrated framework has five interconnected modules as shown in Figure 2, which is the architecture of the

integrated framework. The data management module integrates information from various sources such as meteorological services, farm registries, market information systems and groundwater monitoring networks; automated procedures are built into the data management module for data quality control and update. Second, Pareto-optimal allocation strategies are generated by the optimisation engine, the MOA is applied by configuring the objective priorities and constraint specifications that users can do. Third, optimal solutions are presented by the visualisation and trade-off interface, which allows the decision-maker to explore the trade-offs and select preferred allocations based on policy priorities through multi-dimensional plots, parallel coordinate diagrams and scenario comparison tools. Fourth, the best allocations are translated by the implementation module to action plans for water delivery, farmer notification and monitoring plans. Finally, the adaptive management system can track the actual implementation outcomes, update the models based on that performance, and re-optimize if there are significant differences or conditions change significantly.

Irrigation districts have irrigation procedures that are outlined at different stages throughout the implementation guidelines in the practice. In a first phase, it is recommended

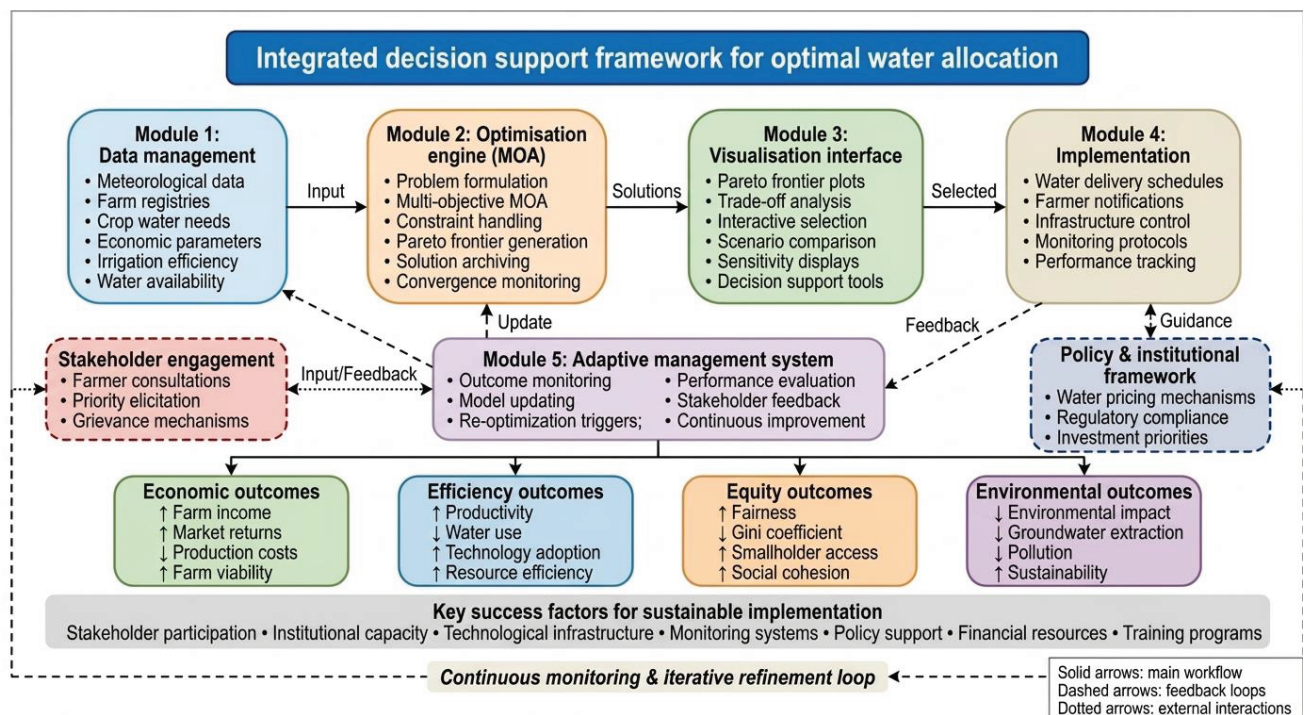


Fig. 2. Comprehensive decision support framework integrating five core modules (data management, optimisation engine, visualisation, implementation, and adaptive management) for agricultural water reallocation; MOA = masterpiece optimisation algorithm; source: own elaboration

to apply the framework in a pilot way during one cropping season whereby comparative monitoring takes place between the optimised and the traditional allocation zones to foster institutional capacity development and convince of benefits. Successful pilot applications are followed with a scaled implementation, with particular focus on the processes of engagement with stakeholders. These processes involve consultation with farmers to inform them about the rationale behind the allocations, a grievance process for handling concerns, and participatory target setting for objective priorities which reflect community values. Technical implementation requires improved water delivery infrastructure to allow flexibility in delivery schedules and installation of measurement devices at critical control points, but also capacity building of water authority staff with the operation of the decision-support system. Finally, monitoring tools should be designed to measure implementation fidelity (are the allocations delivered as anticipated) and outcome performance (are the anticipated outcomes achieved), with quarterly review of the monitoring ad hoc adjustments as needed.

This research has resulted in a set of policy recommendations, which tackle several institutional and economic aspects. First, it is recommended that water pricing systems be shifted away from flat-rate and from volumetric pricing toward performance-based pricing that will create incentives for efficiency improvements. This could involve tiered pricing systems where farmers are paid for higher water productivity; or subsidies for irrigation system modernisation investments that are connected to the system-level water productivity targets. Second, infrastructure investment priorities should be oriented to removing constraints to implementing optimal allocations. Special consideration should be given to irrigation technology adoption programmes for medium-sized farms in regions that have not considered such technologies, and to upgrades to conveyance systems that will allow for flexible delivery schedules, and on-farm storage facilities that will facilitate temporal load management, as these systems are found to offer the greatest potential for optimisation benefits. Third, in terms of institutional arrangements, it is necessary to establish protocols for the allocation decision so as to reconcile technical optimisation outcomes with the views of stakeholders. This balance can be realised, for example, by establishing advisory committees of members that represent different types of farms, and also through participatory processes of objective weight elicitation, which give a suitable weight to the equity objectives, in addition to the efficiency objectives.

Water authority staff must also be able to use the advanced decision-support tools, and this should be achieved through a range of capacity building initiatives, including training on optimisation principles, software operation and on how to interpret the results of a trade-off analysis. Equally important, the rationale of the optimisation-based allocation needs to be explained to the farmers in the education programmes and the advantages of the allocation at the individual farm level also needs to be explained, as well as advice on how to adjust production planning to the allocation pattern. Regarding scalability and transferability, it is indicated that the framework can be adapted to different agricultural regions as long as the parameters, formulations of the objective function and formulation of constraints are suitably adjusted to address local

conditions, and that compensatory mechanisms are put in place for farmers facing falls in allocation to ensure allocation is delivered on time, and that performance bonds are implemented to maintain producer confidence in allocation delivery. The basic architecture of optimisation is shared across regions, the main adaptations that are necessary include the development of data collection systems tailored to the local situation and the inclusion of adequate stakeholder engagement processes which take account of regional institutional arrangements and cultural norms. Lastly, the implementation platform could be deployed across multiple irrigation districts, using cloud-based platforms with centralised algorithm updates and distributed data management, which could help to lower the costs of implementation and speed up the uptake of water management optimisation practices worldwide.

CONCLUSION

A multi-objective optimisation framework for agricultural water reallocation problem in semi-arid region is proposed in this study. The model is based on the masterpiece optimisation algorithm (MOA) with four critical objectives including maximise revenue, maximise water efficiency, fairness and minimise ecological consequences. This study on these complex trade-offs resulted in 187 Pareto-optimal strategies to be used in regional agricultural planning. The main results of the study are:

- The best strategies always resulted in higher net income (+21.2%), higher water productivity (+35.3%), higher equity (+44%) and lower environmental damage (−22.9%) than baseline practices.
- This framework was very resilient to water scarcity. Model achieved 88% of the optimised income under a 20% reduction in water supply, which is much better than traditional proportional allocation methods.
- The MOA was shown to be statistically superior to other popular methods such as NSGA-II and MOPSO. Namely, it achieved better convergence, 12.3% improvement in hypervolume and sound outcomes in 87% of the tested uncertainty scenarios.

This study theoretically presents a full four-objective framework and a reproducible solution process for water resource problems that are complex. The framework is, broadly speaking, a decision support tool which can directly support policy makers in assessing investments in infrastructure and in crafting more efficient water pricing policies. There are still some drawbacks of the existing method. The research is based on deterministic production functions, emphasises a single-season time period and utilises spatial aggregation. These limitations can be addressed in future studies through use of a stochastic programming approach to better represent the climate variability and the use of multi-period models to assess long-term sustainability. The framework will benefit from the addition of detailed Crop Growth and Water Quality simulations to enhance the relevance and accuracy of the framework.

CONFLICT OF INTERESTS

All authors declare that they have no conflict of interest.

REFERENCES

- Abdulhameed, I.M. *et al.* (2022) "Optimising water resources management by using Water Evaluation and Planning (WEAP) in the West of Iraq," *Journal of Water and Land Development*, 53, pp. 176–186. Available at: <https://doi.org/10.24425/jwld.2022.140795>.
- Amoura, M., Douani, M. and Tahri, T. (2022) "Study of a smart irrigation system for water managing for potatoes in Chlef region, Algeria," *Journal of Water and Land Development*, 54, pp. 101–108. Available at: <https://doi.org/10.24425/jwld.2022.141560>.
- Babamiri, O. and Marofi, S. (2021) "A multi-objective simulation-optimisation approach for water resource planning of reservoir-river systems based on a coupled quantity-quality model," *Environmental Earth Sciences*, 80(11), 389. Available at: <https://doi.org/10.1007/s12665-021-09681-9>.
- Boubguira, S. *et al.* (2021) "Suitability of surface water for irrigation in the Maffragh basin, North-East of Algeria," *Journal of Water and Land Development*, 48, pp. 94–98. Available at: <https://doi.org/10.24425/jwld.2021.136151>.
- Cui, S. *et al.* (2024) "Optimal resource reallocation can achieve water conservation, emissions reduction, and improve irrigated agricultural systems," *Agricultural Systems*, 221, 104106. Available at: <https://doi.org/10.1016/j.agsy.2024.104106>.
- FAO (2021) *The state of the world's land and water resources for food and agriculture – systems at breaking point. Synthesis report 2021*. Roma: Food and Agriculture Organization. Available at: <https://doi.org/10.4060/cb7654en>.
- Ghasemi, M.R., Haji Aghajanzpour, N., and Ghohani Arab, H. (2025) "Masterpiece optimisation algorithm: A new method for solving engineering problems," *Journal of Soft Computing in Civil Engineering*, 9(1), pp. 1–21. Available at: <https://doi.org/10.22115/SCCE.2024.404534.1677>.
- Grafton, R.Q. *et al.* (2018) "The paradox of irrigation efficiency," *Science*, 361(6404), pp. 748–750. Available at: <https://doi.org/10.1126/science.aat9314>.
- Intergovernmental Panel on Climate Change (IPCC) (2023) *Climate change 2022 – Impacts, adaptation and vulnerability: Working group II contribution to the sixth assessment report of the intergovernmental panel on climate change*. Cambridge: Cambridge University Press. Available at: <https://doi.org/10.1017/9781009325844>.
- Janga Reddy, M. and Nagesh Kumar, D. (2020) "Evolutionary algorithms, swarm intelligence methods, and their applications in water resources engineering: A state-of-the-art review," *H2Open Journal*, 3(1), pp. 135–188. Available at: <https://doi.org/10.2166/h2oj.2020.128>.
- Kahil, M.T., Dinar, A. and Albiac, J. (2015) "Modeling water scarcity and droughts for policy adaptation to climate change in arid and semiarid regions," *Journal of Hydrology*, 522, pp. 95–109. Available at: <https://doi.org/10.1016/j.jhydrol.2014.12.042>.
- Kahil, T. *et al.* (2019) "A nexus modeling framework for assessing water scarcity solutions," *Current Opinion in Environmental Sustainability*, 40, pp. 72–80. Available at: <https://doi.org/10.1016/j.cosust.2019.09.009>.
- Kayhomayoon, Z. *et al.* (2022) "A simulation-optimisation modeling approach for conjunctive water use management in a semi-arid region of Iran," *Sustainability*, 14(5), 2691. Available at: <https://doi.org/10.3390/su14052691>.
- Latinopoulos, D. (2009) "Multicriteria decision-making for efficient water and land resources allocation in irrigated agriculture," *Environment, Development and Sustainability*, 11(2), pp. 329–343. Available at: <https://doi.org/10.1007/s10668-007-9115-2>.
- Maier, H.R. *et al.* (2014) "Evolutionary algorithms and other metaheuristics in water resources: Current status, research challenges and future directions," *Environmental Modelling and Software*, 62, pp. 271–299. Available at: <https://doi.org/10.1016/j.envsoft.2014.09.013>.
- Mancosu, N. *et al.* (2015) "Water scarcity and future challenges for food production," *Water*, 7(3), pp. 975–992. Available at: <https://doi.org/10.3390/w7030975>.
- Molden, D. *et al.* (2010) "Improving agricultural water productivity: Between optimism and caution," *Agricultural Water Management*, 97(4), pp. 528–535. Available at: <https://doi.org/10.1016/j.agwat.2009.03.023>.
- Mukhitdinov, O. *et al.* (2025) "An Industry 4.0 framework for the smart production management of renewable energy and water systems: an application of AI, IoT, and digital twin technologies," *International Journal of Industrial Engineering and Management*, 16(4), pp. 428–443. Available at: <https://doi.org/10.24867/IJIEM-397>.
- Rosa, L. *et al.* (2020) "Global agricultural economic water scarcity," *Science Advances*, 6(18). Available at: <https://doi.org/10.1126/sciadv.aaz6031>.
- Safari, A., Abbaspour, M. and Javid, A.H. (2021) "The application of multi-criteria (AHP-PROMETHEE) decision-making methods in selecting and prioritizing the green area irrigation resources," *International Journal of Environmental Science and Technology*, 18(5), pp. 1135–1146. Available at: <https://doi.org/10.1007/s13762-020-02875-x>.
- Sánchez-Daniel, Á. *et al.* (2024) "Sensitivity of water reallocation performance assessments to water use data," *Water Resources and Economics*, 48, 100252. Available at: <https://doi.org/10.1016/j.wre.2024.100252>.
- Sobieraj, J. (2025) "Analysis of the "Adaptation strategy for sectors and areas vulnerable to climate change to 2020 with an outlook to 2030 (SPA 2020)," *Archives of Civil Engineering*, 71(2), pp. 257–277. Available at: <https://doi.org/10.24425/ace.2025.154120>.
- Tilman, D. *et al.* (2017) "Future threats to biodiversity and pathways to their prevention," *Nature*, 546(7656), pp. 73–81. Available at: <https://doi.org/10.1038/nature22900>.
- Wang, J., Ju, K. and Wei, X. (2024) "Water–energy–land reallocation and multiobjective optimisation in the agricultural system," *Water Resources Management*, 38(14), pp. 5783–5806. Available at: <https://doi.org/10.1007/s11269-024-03934-5>.
- Wheeler, S.A. *et al.* (2020) "The rebound effect on water extraction from subsidising irrigation infrastructure in Australia," *Resources, Conservation and Recycling*, 159, 104755. Available at: <https://doi.org/10.1016/j.resconrec.2020.104755>.
- Yu, Y. *et al.* (2021) "Multi-objective game theory optimisation for balancing economic, social and ecological benefits in the Three Gorges Reservoir operation," *Environmental Research Letters*, 16(8), 085007. Available at: <https://doi.org/10.1088/1748-9326/ac0b69>.
- Zhang, K. *et al.* (2022) "Multi-objective optimisation of energy-water nexus from spatial resource reallocation perspective in China," *Applied Energy*, 314, 118919. Available at: <https://doi.org/10.1016/j.apenergy.2022.118919>.
- Zokirov, K. *et al.* (2025) "The impact of water resources management and resource optimisation during drought periods," *Journal of Water and Land Development*, 66, pp. 106–120. Available at: <https://doi.org/10.24425/jwld.2025.155307>.