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Multi-objective cropping pattern optimization and comparative assessment with the food-energy-water nexus

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ABSTRACT

Agriculture is the largest consumer of water, accounting for nearly 70% of global freshwater consumption, and it also uses about 30% of the world's energy. This creates an increasing challenge for the efficient use of water and energy resources while adequately meeting food demand. Therefore, understanding the interrelations between food, energy, and water resources is crucial. In this study, a multi-objective linear programming model was employed to identify alternative scenarios for optimal cropping areas that minimize water use in agriculture and maximize agricultural income. Different weight coefficients were assigned to these objective functions to generate various cropping scenarios. Once the optimal cropping patterns for each scenario were determined, parameters such as water use, energy requirements, agricultural revenue, and carbon dioxide emissions were calculated based on the food-energy-water nexus. The results for each alternative crop pattern scenario were then analyzed. The results indicate that prioritizing the objective of minimizing water use leads to an average reduction of 3.35% in water use, 1.18% in energy demand, and 0.26% in carbon dioxide emissions, while agricultural income increases by an average of 1% compared to the base scenario. Conversely, when maximizing agricultural income is prioritized, there is an average increase of 2.05% in agricultural income.

Key words: agricultural production planning, crop pattern, food-energy-water nexus, multi-objective linear programming, optimization

HIGHLIGHTS

- Optimization of cropping patterns through multi-objective linear programming for different scenarios.
- Obtaining water usage, energy requirement, agricultural revenue, and carbon dioxide emission outcomes for all scenarios based on food-energy-water nexus.
- Comparative assessment of the results achieved for each scenario.
- Reduced water usage and energy requirements, coupled with increased agricultural revenue.

INTRODUCTION

Planning and scheduling for irrigation play crucial roles in effectively managing water in irrigated agriculture. For the effective management of water in agriculture, it is necessary to optimize the utilization of both land and water, ensuring the optimal cropping pattern within specified constraints (Vivekanandan & Viswanathan 2007). Regional development relies on water resources for essential aspects like daily life, industrial production, and agriculture. In each area, water sources should be chosen based on local conditions and geographical factors to ensure sustainable use and availability (Zhu 2023). In the mountainous regions where water resources are particularly scarce, it is essential to harness springs as potential irrigation sources and optimize both the available water and arable land for irrigation. Additionally, planning and implementing resilient management strategies to adapt to future changes is crucial for the sustainable development of agriculture in these areas (Kumar & Sen 2020). A systematic decision support methodology for optimizing land and water resource allocation can effectively ensure food security, mitigate water shortages, and align with macroeconomic policies by re-allocating spatial cropping patterns and optimizing the distribution of water resources to ensure more sustainable and efficient use of both land and water in agricultural production (Cheng *et al.* 2023). Water management in agriculture is a process that fosters the sustainable development and integrated resource management within ecosystems to optimize the balance between socio-economic welfare and ecosystem sustainability (Zhang *et al.* 2024). In the context of climate change pressures, the agricultural sector's primary goals should focus on water conservation and strategically allocating this scarce resource to crops with the highest potential economic returns. Crop allocation is closely tied to land use planning and management, influencing a range of socio-economic sectors (Economidou *et al.* 2021). To address limited water resources, efficient and practical solutions are essential for optimizing water allocation, which can be achieved by enhancing water economic productivity and creating an optimal cropping pattern (Mirzaei *et al.* 2022). Planning the crop area can determine the allocation of water to various cultivated areas and achieve specific objectives, such as maximizing returns from the cultivated land while adhering to limitations on land and water resources (Zeng *et al.* 2010). When dealing with multiple conflicting objectives, the optimal solution for one objective may not be optimal for others. In such cases, the concept of a best compromise solution can be introduced, seeking a balanced resolution that accommodates competing objectives. For instance, to maximize the net return from agricultural activities, there is a need for increased usage of water resources, whereas ensuring the sustainability involves reducing overall water consumption (Amini Fasakhodi *et al.* 2010). In such situations with conflicting objectives, it is necessary to define a compromise solution that strikes a balance between them (Stancu-Minasian & Pop 2003).

Nowadays, mathematical programming models are particularly valuable in determining suitable agricultural patterns and water allocation strategies. Optimizing crop patterns is crucial for achieving high-benefit agricultural management and conserving water resources (Mirzaei *et al.* 2022). Many researchers have opted for the multi-objective linear programming (MOLP) model as it is suitable for addressing the multiple conflicting objectives inherent in crop planning. Mainuddin *et al.* (1997) created a MOLP model with the aim of maximizing net return and irrigated area, then assessed each irrigation scenario under varying levels of water resource availability using an analytic hierarchy process (AHP). Ren *et al.* (2019) similarly integrated multi-objective optimization and the AHP to develop a series of optimal irrigation and planting schemes under multiple uncertainties, aiming to promote the sustainable development of Wuwei city. Raju & Kumar (1999) employed a MOLP model for the planning of cropping area and determined the optimal scenario through the application of cluster analysis and multi-criteria decision-making. Saker & Quaddus (2002) devised a model for crop planning utilizing goal programming (GP) and examined the significance of three distinct objectives in addressing the case problem. Xevi & Khan (2005) addressed the irrigation management by employing a GP technique, taking into account potential conflicts arising from net revenue, variable cost, and the quantity of groundwater pumped.

Amini Fasakhodi *et al.* (2010) presented two ratios, namely 'net return/water consumption' and 'labor employment/water consumption', as metrics to evaluate the sustainability of water resources and to ascertain the optimal crop pattern in a farming system. Their objective was to simultaneously optimize these ratios as sustainability indicators. For this purpose, the study applied a multi-objective fractional goal programming (MOFGP) method. The MOFGP approach yielded better results compared to those obtained from single-objective fractional programming. This was demonstrated by the improved sustainability indicator outcomes, which outperformed the results of single-objective fractional programming models. Keramatzadeh *et al.* (2011) proposed a MOLP model aimed at maximizing farmers' net income by optimizing both the cropping pattern and water allocation. Their findings indicated that aligning optimized cropping patterns with effective irrigation water allocation has considerable potential to enhance net agricultural returns. Ye *et al.* (2023) employed linear and multi-objective programming models to maximize five indicators, namely, cost-effectiveness (CE), irrigation effectiveness (IE), energy productivity (EP), energy effectiveness (EE), and food effectiveness (FE) when determining the crop pattern for small-scale farms. The findings indicated that utilizing multi-objective planning for determining cropping patterns enhanced both irrigation and energy efficiencies. Given the constraints of limited water resources in the region and alignment with national agricultural policies, cropping patterns which maximizes IE and CE were recommended. Bhatia & Rana (2020) conducted an analysis of the cropping practices adopted by growers in various districts of Rajasthan, considering the availability of resources. Given Rajasthan's arid topography and diverse weather conditions, coupled with limited water resources, the formulated model suggested alternative crop combinations. Employing a MOLP model, the study aimed to minimize input costs and maximize farm revenues. Niu *et al.* (2019) proposed a multi-objective linear fractional programming (MOLFP) approach to depict relations and tradeoffs within the water-ecosystem-agriculture nexus. Employing this approach, they evaluated the effects of changes in hydrological conditions, land use, and water management on the agricultural system in the Zhangye Basin.

Agriculture stands as the largest consumer of water, accounting for 70% of global freshwater consumption. Additionally, the food production and supply chain collectively utilize approximately 30% of the world's consumed energy (FAO 2011).

The Food and Agriculture Organization (FAO) projects an approximate 60% increase in food demand compared to the levels observed in 2005/2007, if the nutritional needs of a population expected to reach 9.1 billion by the year 2050 is to be met (FAO 2009). Hence, there is a growing challenge to meet the food demand of present and future human populations, all within the constraints of limited land availability and changing water resource availability. This task becomes more complex as there is a simultaneous need to minimize energy and water consumption while also prioritizing environmental conservation efforts (Nie *et al.* 2019). The food-energy-water (FEW) nexus represents the crucial interconnectedness of three fundamental resources vital for human societies. This extended concept has been introduced to address and navigate challenges related to scarcity in these resources. The objective of the nexus is to establish effective tradeoffs between food, energy, and water, taking into account inter-sectoral policies, as well as social and environmental impacts (Albrecht *et al.* 2018).

The nexus and conflicts among water, energy, and food sources were elucidated during the Water-Energy-Food Nexus Conference in Bonn (in 2011). It was during this conference that the term 'Nexus' was introduced to characterize the intricate relationships among these crucial resources (Hoff 2011). Since the Bonn conference, numerous research studies have focused on the FEW nexus. Bazilian *et al.* (2011) conducted a comprehensive analysis, taking into account factors such as climate change and land use. IRENA's (2015) report evaluated eight nexus assessment tools based on input, output, and analytical characteristics. Only two of the eight tools met the requirement for being considered a 'simple' nexus tool noting that comprehensive tools typically have substantial data requirements and demand significant resources in terms of time, capacities, and financing (IRENA 2015).

Daher & Mohtar (2015) developed WEF Nexus Tool 2.0 which is utilized for online calculations that assess the interconnections between food, energy, and water and their interactions with the external environment. Halbe *et al.* (2015) employed a causality diagram to examine the fundamental relationships within the FEW nexus. Li *et al.* (2019) created an optimized model for resource allocation in agriculture within the FEW nexus under uncertain conditions. This model aims to enhance sustainable resource management practices. Nie *et al.* (2019) introduced the basis of a systematic engineering framework to analyze tradeoffs and optimize stressed interrelated FEW nexus networks. A strategy of multi-objective optimization is employed for trade-off analysis to support decision-making and evaluate various processes and technological alternatives. Their findings indicated that the framework is effective in balancing multiple objectives and serving as a benchmark for systematic decision-making in competitive scenarios. Dargin *et al.* (2019) endeavored to offer a method for comparing the complexity of nexus tools available from international organizations. They introduced and discussed eight distinct criteria to evaluate the complexity index for each tool in order to ascertain the relative simplicity or complexity of a tool. Tools with higher complexity scores, although adept at capturing details in specific resource interactions, face limitations in simultaneously addressing numerous interactions compared to tools with lower complexity scores.

Wang *et al.* (2022) introduced a regional FEW interaction model that incorporates both supply and demand aspects, aiming to elucidate the nexus between FEW resources and their impact on the overall development of a region. A sustainability index indicator was utilized to quantitatively assess the relations between supplies and demands in the FEW nexus. The analysis results underscored the pivotal role of energy in the FEW nexus and its significant impact on regional development. Siah & Zabiri (2022) endeavored to create a systematic model for the planning of resource allocations optimally in Malaysia's agricultural sector. The framework, derived from a case study in Perak, plays a crucial role in implementing the FEW nexus system at the local level and models the tradeoffs among different subunits. Mirzaei *et al.* (2021) formulated a multi-objective programming model with the aim of maximizing the FEW nexus index and farmers' gross return. Simultaneously, the model seeks to minimize the usage of chemical fertilizer and chemical pesticides, taking into account the constraint on groundwater resources. The outcomes demonstrated that despite the economic objective within the proposed system, revenues of farmers could experience a significant decrease. Therefore, implementing policies to enhance the economic incentives for farmers was recommended. Namany *et al.* (2019) proposed an innovative methodology that applies FEW nexus to inform decision-making in the food sector. The approach assesses some alternative technologies for local food production in Qatar, focusing on economic performance measured by capital and operating costs, alongside considerations for environmental performance.

In this context, the objectives of the present study were to optimize the cropping pattern by considering multiple conflicting goals in agricultural production and perform a comparative assessment of the outcomes obtained as a result of the product pattern scenarios generated. In this study, minimizing water usage in agricultural production and maximizing agricultural revenue are considered to be conflicting objectives, and the MOLP method was employed to determine the optimal crop patterns. In the MOLP method, alternative crop pattern scenarios reflecting different perspectives were created by varying the weights assigned to each objective function. Subsequently, the cropping patterns obtained through MOLP for various scenarios were used to calculate water usage, energy consumption, agricultural income, and CO_2 emissions based on the FEW nexus. These scenarios were then evaluated in a comparative manner. The primary innovation of this study was the incorporation of a FEW nexus assessment into the optimization of crop patterns. The aim of this study was to investigate how these outcome parameters change based on the relative importance attributed to the two conflicting objectives and to contribute to a better understanding of the tradeoffs between them.

METHODS

Multi-objective linear programming

The origins of mathematical programming with multiple objectives trace back to economic theory. In 1906, Pareto introduced a fundamental concept for this field, known as the Pareto optimal solution (also referred to as nondominated or noninferior solution). A solution is considered nondominated when there is no other feasible solution that can enhance all the objective function values simultaneously, any improvement in one objective entails a deterioration, at least, in one of the other objective functions (Zeleny 1974). The initial algorithms specifically designed for MOLP emerged in the early 1970s (Antunes *et al.* 2016). These algorithms were first proposed by Evans & Steuer (1973) and later by Yu & Zeleny (1975).

The problem of optimizing conflicting multiple linear objective functions at the same time within specified linear constraints is termed the MOLP problem (Sakawa *et al.* 2013). This problem can be generally expressed as follows:

$$\left.\begin{array}{c} \text{minimize } z_1(x) = c_1 x \\ \text{minimize } z_2(x) = c_2 x \\ \vdots \\ \text{minimize } z_k(x) = c_k x \\ \text{subject to } Ax \leq b \\ x \geq 0 \end{array}\right\} \tag{1}$$

where all the objective functions and constraints are linear.

$$c_i = (c_{i1}, \ \ldots, c_{in}), \ \ i = 1, 2, 3, \ \ldots, k \tag{2}$$

$$x = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix}, \ A = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{bmatrix}, \ b = \begin{pmatrix} b_1 \\ b_2 \\ \vdots \\ b_m \end{pmatrix} \tag{3}$$

where vector c corresponds to the coefficients of the objective function and A is the matrix of technological coefficients.

In cases where the objective functions conflict with each other, a complete optimal solution that simultaneously minimizes all multiple objective functions may not always exist. Therefore, instead of seeking a complete optimal solution, MOLP introduces a new solution concept known as Pareto optimality. Various computational methods have been suggested to characterize Pareto optimal solutions, contingent upon diverse scalarizations employed in addressing MOLP problems (Sakawa *et al.* 2013).

The weighting method for achieving a Pareto optimal solution involves solving a weighting problem, which is formulated by taking the weighted summation of all the objective functions in the original MOLP problem. Hence, the weighting problem is formulated by the following equation (Sakawa *et al.* 2013):

$$\text{minimize } wz(x) = \sum_{i=1}^{k} w_i z_i(x) \tag{4}$$

where $w = (w_1, \ldots, w_k)$ represents a vector of weighting coefficients assigned to the objective functions, and the weight values are assumed to be positive.

The weighting coefficients in the problem provide information on tradeoffs between the objective functions. They indicate the number of units of value from one objective function that must be sacrificed to gain one additional unit of value in another (Sakawa *et al.* 2013).

The weighted minimax method is another scalarization method utilized in addressing MOLP problems to characterize Pareto optimal solutions (Bowman 1976).

$$\left.\begin{array}{c}\text{minimize } v\\ \text{subject to } w_i z_i(x) \leq v,\ \ i = 1, 2, 3,\ \ldots, k\\ x \in X\end{array}\right\} \tag{5}$$

where v is an auxiliary variable.

In this study, minimizing water use and maximizing agricultural income are considered as conflicting objectives in agricultural production and the MOLP method is used to determine the optimum cropping patterns. The proposed model seeks to minimize the maximum weighted deviation among the objectives from a reference point, often an ideal point or a target value. The target value, or ideal point, refers to the value achieved when each objective in a multi-objective optimization problem is solved independently. The objective function of the MOLP model used in this study can be formulated by the following equation:

$$\underset{i=1,\ldots,k}{\text{Min}}\ w_i \left| \frac{z_i(x) - z_i^*}{z_i^*} \right| \tag{6}$$

where z_i* is a reference point or target value for the ith objective.

The main constraints were set such that the income obtained through the model was equal to or higher than the current situation, water use was equal to or lower than the current situation. These constraints can be formulated by the following equations:

$$R = \sum_{i=1}^{n} Y_i L_i U_i \geq\ R_e \tag{7}$$

where n is the number of crops, L_i, Y_i, and U_i represent the cultivation area, yield, and unit price of each crop, respectively. R_e is the existing revenue.

$$W_c = \sum_{i=1}^{n} W_{c_i} L_i \leq W_{c_e} \tag{8}$$

where W_c is the total water usage for all crops, and $W_{c,i}$ is the water requirement for each crop.

Another constraint is the addition of limits that allow for a maximum of 5% change to avoid too large changes in the acreage allocated for each crop to adequately meet food demand.

$$L_{\text{min}_i} \leq L_i \leq L_{\text{max}_i} \tag{9}$$

where $L_{\text{min},i}$ and $L_{\text{max},i}$ denote the lower and upper bounds for the cultivation areas of each crop.

FEW nexus

A nexus is described as 'one or more linkages connecting two or more things' (Leck *et al.* 2015). This definition, along with the concept of the FEW nexus, was first developed in the early 2010s (Hoff 2011). The FEW nexus emerged as a valuable concept for describing, addressing, and analyzing complicated and interconnected natural resource systems, along with user goals and interests (Yuan & Lo 2022). One of the primary strengths of the FEW nexus is its ability to emphasize potential synergies and tradeoffs within the nexus that might be missed with a single-disciplinary approach. These tradeoffs are often initially understood through the connections between the physical resource systems themselves. Over the past decade, the nexus has been strongly emphasized in research environments as a tool to transition societies toward a green economy and generally enhance resource security (Proctor *et al.* 2021). Recently, many researchers have recognized the importance of the complex relationships between water, energy, and food (Geressu *et al.* 2020; Yue & Guo 2021; Siderius *et al.* 2022).

The nexus is widely regarded as a promising approach for achieving sustainable management of ecosystem and natural resources, while addressing the developmental needs such as increasing demands for food, energy, and water. This approach enables more integrated and efficient policy development, planning, and evaluation across different branches of the nexus (El-Gafy 2017). It can also affect food production and consumption by influencing water usage, as well as the demand for and cultivation of water-intensive crops (Caputo *et al.* 2021). Food production necessitates adequate use of water and land resources, electricity, fertilizers, pesticides, and agricultural machinery. These farming activities release significant amounts of greenhouse gases, which contribute to the trend of global warming (Yue *et al.* 2021). Therefore, it is essential to maintain a balance among these resources to ensure their security (Mohtar & Daher 2012). To comprehend their interdependencies, it is necessary to quantify their connections using data-driven and quantitative modeling approaches (Degirmencioglu *et al.* 2019).

Modeling based on the WEF nexus can enhance the coherence of decision-making processes aimed at sustainable resource allocation policies. Daher & Mohtar (2015) developed the WEF Nexus Tool 2.0 as a common platform to evaluate different scenarios for determining sustainable resource allocation strategies. This tool facilitates the creation of various scenarios based on varying conditions of water, energy, and food resources. Resource analyses typically yield outputs such as national-level resource requirements, consumption patterns, and carbon emissions. However, to capture detailed interactions among resources within a specific region, it is crucial to develop scenarios at a regional or watershed level (Mohtar & Daher 2014). Basin-specific studies enable the creation of optimal crop pattern scenarios that prioritize water security for crops cultivated within the basin. Outputs for each scenario can then be quantified, including metrics such as water usage, energy consumption, carbon dioxide emissions, and agricultural revenue. Clear indicators play a crucial role in assessing the impacts of proposed solutions. In the nexus approach, the development of nexus-specific indicators can significantly enhance the evaluation process. However, each assessment typically requires some level of adaptation to ensure a comprehensive analysis (UNECE 2018). For this purpose, each scenario is defined by considering potential changes in agricultural crop patterns based on water requirements and spreadsheets are generated to outline these scenarios.

Water demand is intrinsic to agricultural crop production, where each crop type requires a distinct amount of irrigation water. To meet the total water demand for cultivating agricultural crops in the watershed, various sources such as surface water and groundwater can be utilized. For a more comprehensive calculation of the total water demand for the agricultural sector, the amount of water consumed by livestock is added to the crop water requirement (Kulat *et al.* 2019). This calculation considers the average daily water requirement per animal for both small and large livestock, accounting for their specific water consumption patterns. The total agricultural water consumption is determined by adding together the water requirements for both crops and livestock (Kulat *et al.* 2019).

$$W_c = \sum_i W_{c_i} L_i \tag{10}$$

$$W_l = \sum_i W_{l_i} N_i \cdot 365 \tag{11}$$

$$W_T = W_c + W_l \tag{12}$$

where L_i is the land allocated for the specific crop, W_c represents the total water requirement for all crops for irrigation, N_i indicates the number of large and small livestock, W_l denotes the total annual water requirement for livestock, and W_T stands for the total agricultural water requirement, which encompasses both crop irrigation and livestock water needs.

Energy within the watershed is essential for supporting various farming operations during the production process in the fields and for sourcing water from different available sources. The energy requirements for utilizing surface or groundwater for irrigation are assessed according to the respective energy footprint values associated with each type of water source. Energy requirements for farming activities include tasks such as soil preparation, planting, cultivation, harvesting, fertilization, and other agricultural operations. This assessment is carried out independently for each type of agricultural crop. The total energy needed for agricultural activities is determined by summing up the energy needs for all agricultural crops. This calculation considers fuel consumption across all stages, from tillage to harvesting, for each individual crop. The energy requirements for each agricultural crop type are determined by multiplying the fuel consumption necessary for these stages with the cultivated area dedicated to that crop. The total energy need is calculated by adding together the energy requirements for water transmission and all farming operations such as tillage, planting, cultivation, and harvesting (Kulat *et al.* 2019).

$$E_T = E_{sw} + E_{gw} + E_{fo} \quad (13)$$

$$E_{sw} = \alpha_{sw} \times V_{sw} \quad (14)$$

$$E_{gw} = \alpha_{gw} \times V_{gw} \quad (15)$$

where E_T represents the total energy requirement, E_{sw} denotes the energy required for conveying surface water, E_{gw} represents the energy needed for pumping groundwater, and E_{fo} indicates the energy required for farming operations. Additionally, α stands for the energy needed per unit volume of water, and V signifies the volume of water used for irrigation, which varies based on the type of water utilized. The energy footprint of water resources varies depending on the type of water source utilized. Conventional water resources considered in the study included groundwater and surface water. Non-conventional sources such as brackish water, seawater, and wastewater require additional treatment and desalination processes, resulting in a higher energy footprint for these sources (Kulat *et al.* 2019). The energy requirements per unit volume of water are 0.4068 kWh/m^3 for groundwater and 0.209 kWh/m^3 for surface water (Degirmencioglu *et al.* 2019).

CO_2 emissions serve as an essential metric for assessing the sustainability of a scenario. These emissions predominantly stem from energy consumption. Each energy type utilized within a scenario carries specific coefficients that denote CO_2 emissions in tons per unit of energy consumed. The emissions from each energy type are assessed individually and subsequently aggregated to evaluate the overall emissions impact of the scenario (Degirmencioglu *et al.* 2019).

$$CO_2 = \sum_i E_i \Delta_i \quad (16)$$

where E denotes the different types of energy consumption, while Δ represents the amount of CO_2 emissions in tons per unit of energy consumed.

Agricultural revenue is an important metric for the financial assessment of each scenario. The total agricultural revenue can be determined by multiplying the total production values of each agricultural product by their respective unit market prices (Degirmencioglu *et al.* 2019).

$$R = \sum_i P_i U_i \quad (17)$$

where R represents the total agricultural revenue, P denotes the agricultural production, and U stands for the unit market price of each agricultural product.

The methodology used in this study is summarized in Figure 1.

Study area

The Gediz Basin is situated in the Aegean Region in western Turkey. It encompasses the area where water drains into the Aegean Sea via the Gediz River and its tributaries. The basin spans across areas between the Northern Aegean, Susurluk, and Küçük Menderes Basins. The geographical location of Gediz Basin is shown in Figure 2.

The Gediz Basin spans an area of approximately 17,140 km^2, which makes up about 2.2% of Turkey's total land area. The Gediz River stretches approximately 275 km and is the primary water source within the basin (SYGM 2019). When analyzing the water budget of the Gediz Basin, the average annual precipitation is found to be 585 mm. Of this, an annual average of 343 mm is lost through evaporation and transpiration (SYGM 2018). On an annual basis, 79 mm leaves the basin through surface runoff. The groundwater recharge across the basin averages 163 mm/year (SYGM 2018).

The basin features a typical Mediterranean climate, characterized by hot, dry summers and cool, rainy winters. The average annual precipitation in the basin is higher around Kemalpaşa and Demirci stations. In general, the highest average monthly

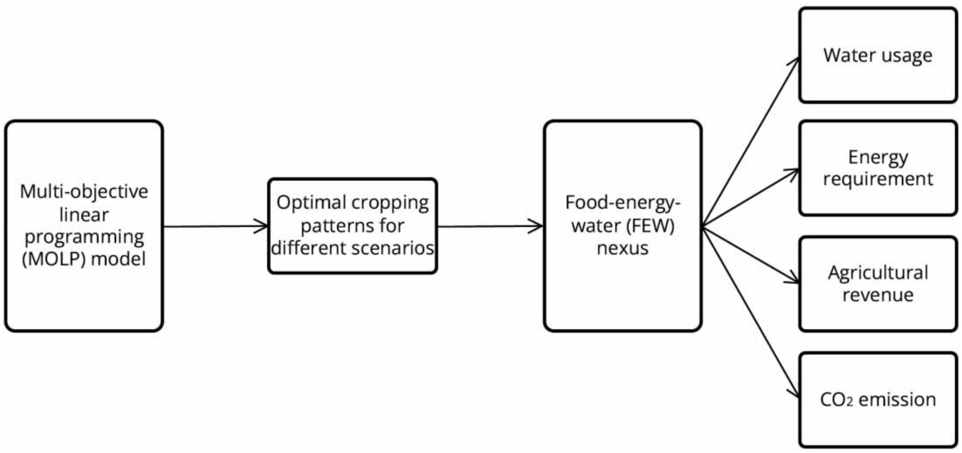

Figure 1 | Flowchart of the methodology.

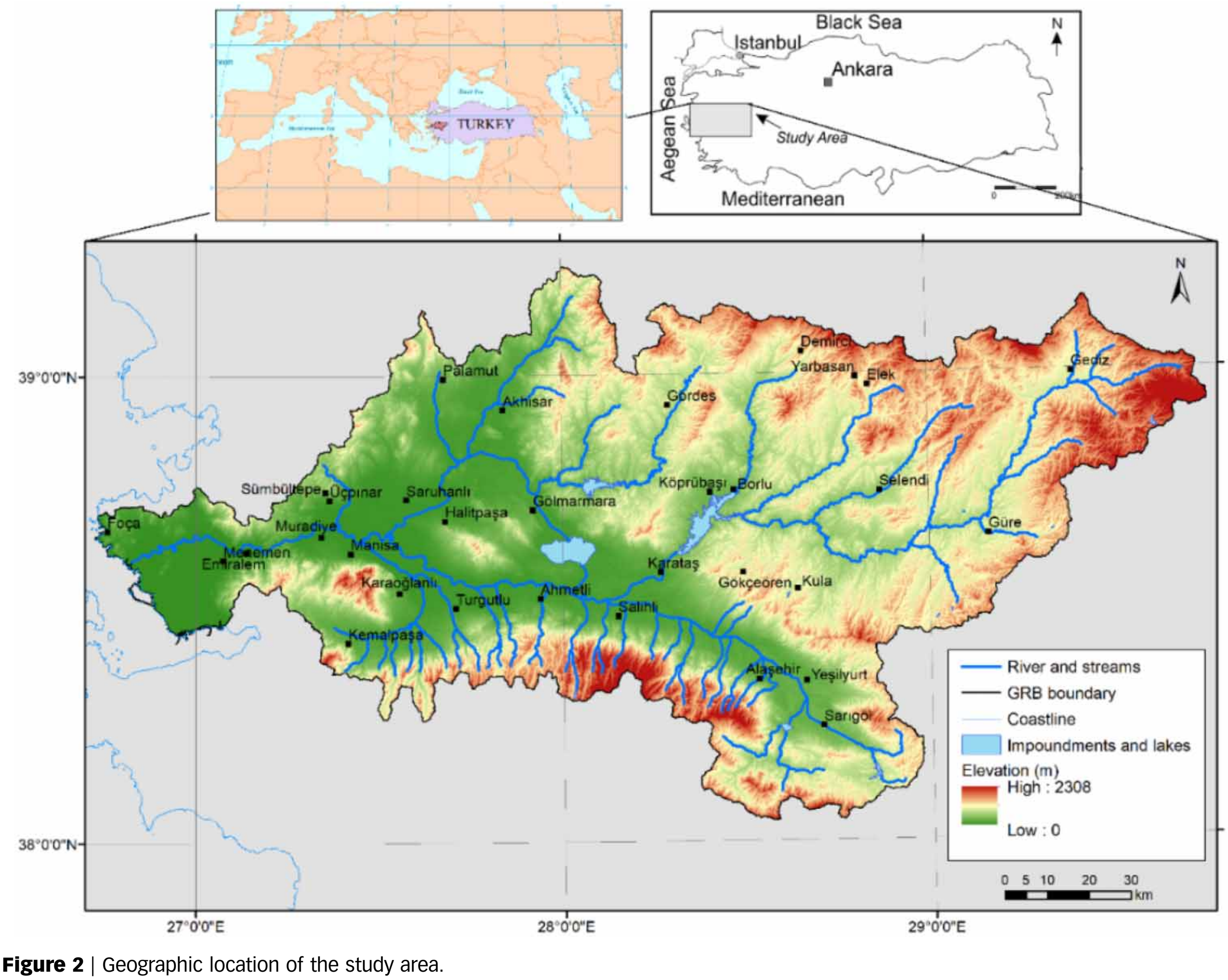

Figure 2 | Geographic location of the study area.

precipitation is observed in December and January, while the lowest precipitation is recorded in July and August (SYGM 2019).

According to the observations of the meteorological stations located in the basin, annual average temperature values vary between 12 and 18 °C (SYGM 2018). In terms of temperature across the basin, the highest average monthly temperatures are observed in July and August, while the lowest average temperatures are recorded in January (SYGM 2019).

The basin-wide monthly reference evapotranspiration (ET_0) values for the growing season from May to September, calculated using the Penman-Monteith method, were determined as follows: 132.5 mm for May, 167.35 mm for June, 194.5 mm for July, 178.7 mm for August, and 126.4 mm for September (Yıldırım *et al.* 2019). These data indicate that, depending on the climatic conditions in the region, crop water requirements are highest in July and August during the growing period.

The land use status of the Gediz Basin region, determined using the CORINE 2012 database, was obtained from a comprehensive report previously prepared for the basin (SYGM 2018). The land use distribution of the basin is presented in Figure 3 according to CORINE's first-level classification, and a more detailed breakdown is shown in Figure 4 using CORINE's second-level classification (SYGM 2018).

Agricultural, urban, and industrial zones together constitute approximately 54% of the total land area in the Gediz Basin, and the spatial distribution of these zones plays a critical role in influencing the basin's overall environmental and resource management (SYGM 2018). Forests cover 17.7% of the basin, while shrubland or herbaceous vegetation account for 24.6%, and regions with sparse or no vegetation make up 2.2%. These zones are predominantly found in the northern and northeastern mountainous areas of the basin (SYGM 2018). In the western part of the basin, land degradation risk is elevated due to improper land use, urbanization, industrialization, tourism, and intensive farming. Conversely, the eastern parts tend to have higher land productivity levels (SYGM 2018). Dengiz (2018) examined land degradation impacts by assessing land

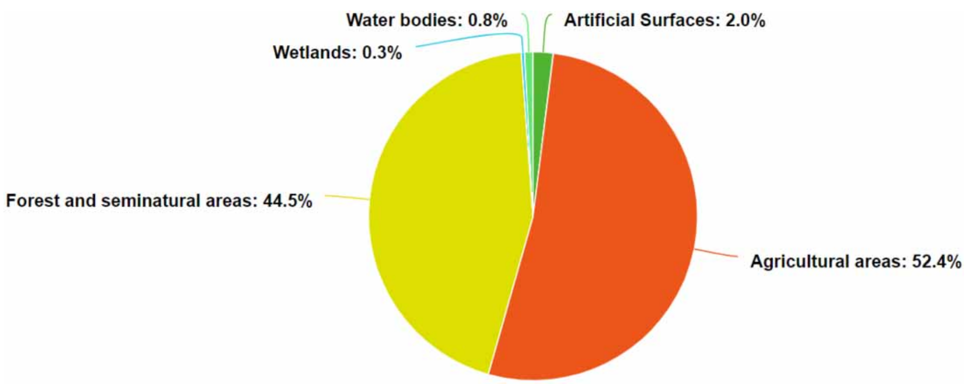

Figure 3 | Gediz Basin first-level land use.

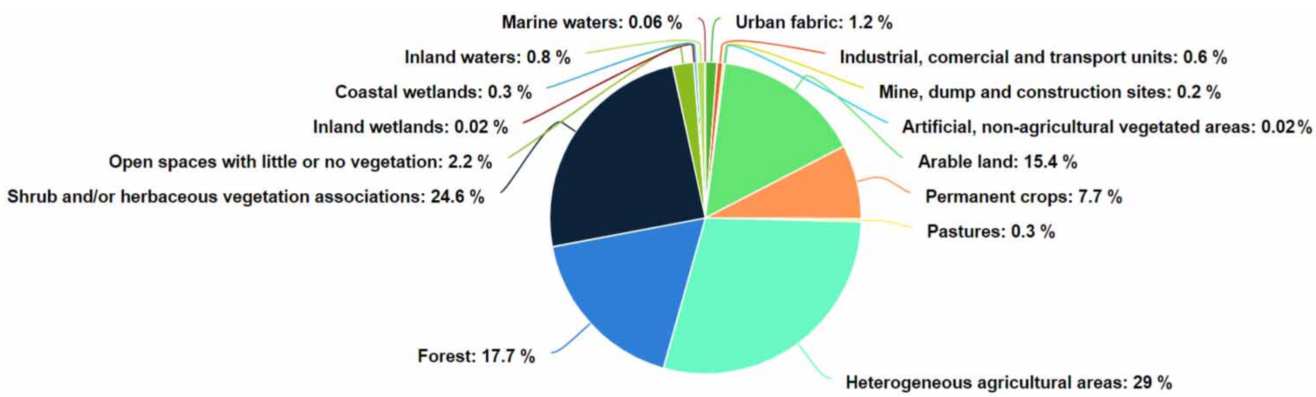

Figure 4 | Gediz Basin second-level land use.

productivity and soil organic carbon density within two neighboring microcatchments in the Gediz River Basin. The study utilized Landsat satellite imagery to analyze shifts in land use, land cover, and vegetation density over the period from 2001 to 2015. The findings indicate that over 23% of the catchment area experiences a noticeable decline in land productivity, while approximately 24% shows early signs of degradation (Dengiz 2018). Soil analysis across surface and subsurface layers revealed that areas with dense forest cover had the highest soil organic carbon levels. This high carbon content is attributed to the accumulation and slow decay of organic material on the surface. In contrast, cropland exhibited the lowest carbon levels due to intensive agricultural practices, especially soil tillage, which accelerates the decomposition and mineralization of organic matter. Therefore, it is essential to retain plant residues on the soil. Additionally, sustainable land management practices such as crop rotation, the use of green manure, and reduced tillage should be implemented to prevent issues like soil compaction, crusting, and structural degradation (Dengiz 2018). Diversifying plant species is a primary strategy for ecologically intensifying agroecosystems to enhance sustainability and resilience. Crop rotations help control pest and weed populations, reduce disease prevalence, and contribute to improved soil fertility and crop yields (Ripoche *et al.* 2021). Increased crop diversity is associated with enhanced soil biological communities, which contribute to higher levels of soil organic matter, total nitrogen, microbial activity, and overall soil fertility (Tiemann *et al.* 2015). Soil salinity and waterlogging, often caused by improper irrigation practices and insufficient drainage, are other significant forms of land degradation that lower agricultural productivity and reduce farm income, posing a threat to sustainable agriculture. Atis (2006) examined the economic effects of land degradation on cotton production in the Gediz Delta, finding that cotton yields dropped by 34.4%, and gross margins declined by \$860.2 ha^{-1} due to these degradation factors.

The agricultural production data for 2017, extracted from the Gediz Basin Drought Management Plan Final Report by the General Directorate of Water Management, along with projected annual production for future periods, are detailed in Table 1 (SYGM 2019).

In the basin's drought report, the projection period spans from 2015 to 2100 and in order to evaluate future water availability, precipitation projection data were derived from the HadGEM2-ES, MPI-ESM-MR, and CNRM-CM5.1 models, using RCP4.5 and RCP8.5 scenarios (SYGM 2019). The precipitation anomalies forecasted by these models are presented in Table 2.

Table 1 | The agricultural production data for 2017 and projected annual production for future periods

Planted crop	Production (tonnes) (2017)	Production (tonnes) (2025–2050)	Production (tonnes) (2050–2075)	Production (tonnes) (2075–2100)
Tomato	916,950	1,377,834	2,059,207	2,733,990
Wheat	257,807	291,761	305,572	350,489
Corn	251,641	325,543	457,944	621,618
Grape	1,098,109	1,368,957	1,836,569	2,307,080
Cherry	108,028	143,965	206,602	269,594
Olive	206,932	260,526	341,855	427,850

Table 2 | HADGEM, MPI, and CNRM models precipitation anomalies

Period	HadGEM RCP4.5 (%)	HadGEM RCP8.5 (%)	MPI RCP4.5 (%)	MPI RCP8.5 (%)	CNRM RCP4.5 (%)	CNRM RCP8.5 (%)
2015–2020	+4.66	−11.23	−8.46	−14.62	+10.76	−10.04
2021–2030	+8.06	+5.36	−10.82	−4.14	−0.25	−11.21
2031–2040	+0.19	+2.04	−8.75	−4.72	−4.46	−6.11
2041–2050	+8.19	−3.49	−7.09	+1.52	+4.76	−5.26
2051–2060	−7.92	−17.34	−3.2	−7.36	+0.11	−9.03
2061–2070	−16.57	−13.71	−10.66	−19.98	−3.24	−8.89
2071–2080	+0.37	−15.08	−7.81	−19.78	−3.05	−11.46
2081–2090	−1.66	−7.01	−3.17	−22.2	−4.48	−5.18
2091–2100	−7.53	−17.86	−8.36	−27.1	−1.38	−6.06

Table 3 displays the fertilizer requirements, seasonal water needs including irrigation requirements, and fuel consumption associated with tractor use for each crop in farming operations (TurkStat 2014).

Fuel consumption is the critical energy input in agricultural production processes, reflecting the reliance on diesel as the primary energy source for agriculture in Turkey. The energy requirement varies based on the type of water source utilized. Specifically, the energy requirements per unit volume of water are 0.4068 kWh/m^3 for groundwater and 0.209 kWh/m^3 for surface water (Degirmencioglu *et al.* 2019). Furthermore, the emission of carbon dioxide is 0.00268 tons/L from diesel use and 0.0026 tons/kg from nitrogen, phosphorus, and potassium fertilizer use in agricultural production processes (Wood & Cowie 2004).

RESULTS AND DISCUSSION

In this study, the MOLP method was used to examine the changes in cultivation areas based on different and conflicting perspectives in agricultural production and to obtain optimal cropping patterns. For the periods 2017, 2025–2050, 2050–2075, and 2075–2100, the existing production and projection data for the basin served as the base or reference scenario. Based on this available data, calculations were made for water usage, energy requirements, agricultural income, and carbon dioxide emissions for each of these time periods. In addition to the base scenario, alternative scenarios for changing crop patterns were generated. In the derivation of these scenarios, minimizing water use and increasing agricultural revenue were taken as objective functions in the MOLP method. The constraints were set so that income is equal to or higher than that in the base scenario, water use is equal to or lower than that in the base scenario, and the allowed variation range for crop planting areas is 5%.

In the optimization process with the MOLP method, firstly, the results obtained separately for each objective function are taken as target values. Then, both objectives are considered together, and Pareto optimal solutions are derived by minimizing the weighted deviations from these target values. To investigate how the results shifted according to the level of importance attributed to the objectives, five different scenarios were examined using varying weight coefficient ratios of 1:1, 1:2, 1:3, 2:1, and 3:1 for the objectives. This approach provides a comprehensive understanding of how different weighting schemes impact the balance between conflicting objectives, helping to identify solutions based on varying priorities.

In the naming of the examined scenarios, the base scenario relying on the available data is taken as a reference for comparisons and referred to as scenario 1. The case where both objective functions are equally weighted is designated as scenario 2. Scenarios that focus more on maximizing agricultural income with weight ratios of 1:2 and 1:3 are referred to as scenarios 3 and 4, respectively. Conversely, scenarios that emphasize minimizing water usage with weight ratios of 2:1 and 3:1 are labeled as scenarios 5 and 6.

Then, the parameters of water usage, energy requirements, revenue from agricultural products, and carbon dioxide emissions were calculated within the scope of the FEW nexus for all scenarios. For each time period, the scenarios are analyzed by comparing these parameters.

The results obtained with the scenarios examined for the year 2017 and comparisons of the scenario results are shown in Figure 5.

Comparing the results of the scenarios for the year 2017, in water use, the largest reduction of 19.7 million m^3 and 3.39% compared to the base scenario is observed in scenario 6, where the emphasis is on minimizing water use, and the smallest reduction of 8.74 million m^3 and 1.5% compared to the base scenario is observed in scenario 4, where the emphasis is on

Table 3 | Requirements and fuel consumption data for agricultural products

Planted crops	Nitrogen requirement (kg/ha)	Phosphorus requirement (kg/ha)	Potassium requirement (kg/ha)	Seasonal water requirement (m^3/ha)	Irrigation requirement (m^3/ha)	Gasoline consumption (L/ha)
Tomato	136.1	73.1	37.7	4,028.5	2,849.5	180.46
Wheat	120	40	0	4,836.1	1,182.9	65.6
Corn	272.7	166.6	0	2,530	1,794.9	159.1
Grape	55.8	51.5	41.6	6,584.5	5,396	225.55
Cherry	187.5	180.2	166.1	2,094.4	1,084.5	267.93
Olive	90	72	55.4	8,928.4	0	50.93

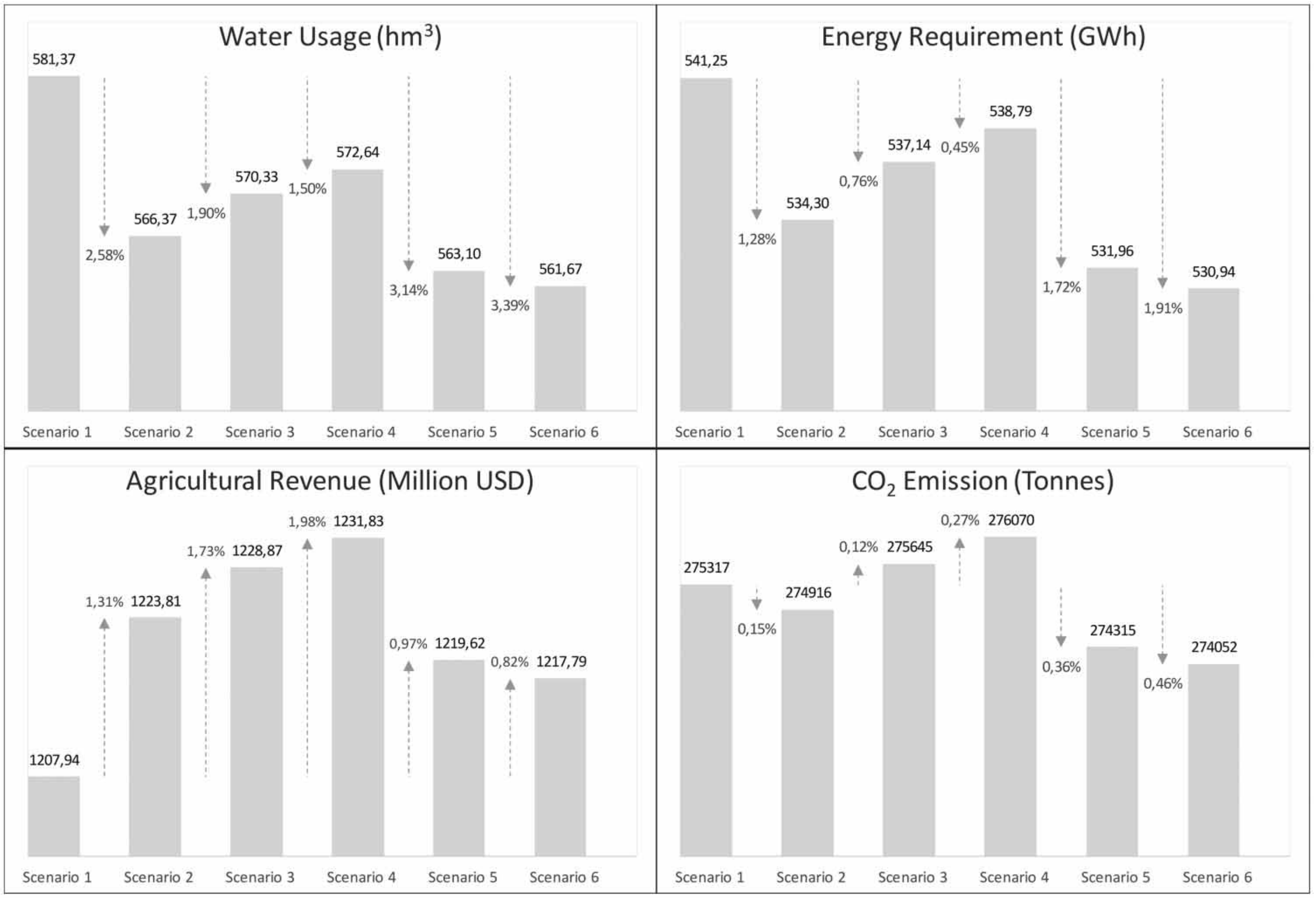

Figure 5 | Comparisons of the results for the year 2017.

maximizing agricultural income. Energy requirements decreased the most in scenario 6 by 1.91% compared to the base scenario, while the smallest decrease was observed in scenario 4 by 0.45%. In agricultural revenue, the largest increase was in scenario 4 with 1.98% compared to the base scenario, and the smallest increase was in scenario 6 with 0.82%. Carbon dioxide emissions decreased the most in scenario 6 by 0.46% compared to the base scenario, while in scenario 4, there was an increase of 0.27%. In scenario 2, where both objective functions were equally weighted, more balanced results were obtained between the objectives of reducing water use and increasing agricultural income.

When analyzing outcomes of the scenarios for the periods 2025–2050, 2050–2075, and 2075–2100, it becomes evident that, similar to the findings for 2017, scenario 6 and scenario 4 emerge as the prominent scenarios.

The percentage changes in water use, energy requirements, agricultural revenue, and CO_2 emissions for both scenario 6 and scenario 4, when compared to the base scenario, are collectively summarized in Table 4 for each time period. This comparative analysis highlights the impact of these scenarios on resource efficiency and agricultural performance, providing valuable insights for sustainable agricultural planning.

In this study, both water-centered and income-centered perspectives are examined, with constraints that include maintaining income at least at the level of the base scenario, ensuring that water use does not exceed that of the base scenario, and restricting changes in crop cultivation areas. The findings reveal that altering cropping patterns can lead to substantial reductions in water consumption and energy demands, while also boosting agricultural revenue. These findings are intended to provide valuable insights to policymakers for enhancing sustainability in agriculture through agricultural production planning in the Gediz Basin. Suggestions for further practical measures that can increase agricultural irrigation efficiency can be mentioned as rehabilitation of the irrigation system and promotion of crops suitable for the basin's climate and water resources. Studies focused on determining optimal cropping patterns face certain limitations, including the necessity to

Table 4 | Changes in water usage, energy demand, agriculture income, and CO_2 emissions in periods 2017, 2025–2050, 2050–2075, and 2075–2100

Change in	Scenario	2017	2025–2050	2050–2075	2075–2100
Water usage	Scenario 4	−1.5%	−1.53%	−1.54%	−1.55%
	Scenario 6	−3.39%	−3.36%	−3.33%	−3.32%
Energy	Scenario 4	−0.45%	−0.41%	−0.35%	−0.33%
	Scenario 6	−1.91%	−1.82%	−1.71%	−1.67%
Agricultural revenue	Scenario 6	+0.82%	+0.97%	+1.08%	+1.12%
	Scenario 4	+1.98%	+2.05%	+2.08%	+2.1%
CO_2 emissions	Scenario 6	−0.46%	−0.32%	−0.14%	−0.11%
	Scenario 4	+0.27%	+0.39%	+0.55%	+0.57%

adjust cultivation areas within specific boundaries to ensure adequate food supply, as well as the availability of suitable land for agriculture. Although the findings of this study are specific to a particular region, the methodology applied is adaptable and can be utilized effectively across diverse applications.

Most previous studies have primarily focused on increasing income and have sought to find the optimal allocation of land or water among different crops. A comprehensive review of the conducted studies reveals that despite differing objectives, many studies apply similar constraints, such as land availability, water availability, and limitations on the total cropping area. Osama *et al.* (2017) aimed to maximize total net benefit by determining the optimal cropping pattern, considering key constraints such as water availability, total land area, and planting area over a 5-year period from 2008 to 2012. After optimization, an average increase of 6.44% in gross net benefit was observed compared to previous cropping patterns over the time period considered. Daghighi *et al.* (2017) focused on maximizing agricultural profit as the target function, using 2015 as the reference year, and developed optimal cropping patterns for every 5-year interval from 2020 to 2040. The model incorporated constraints such as a maximum 20% variation in cropping areas, limitations on irrigation water availability, and water allocation based on crop types. As a result, the final net profit increased by 8% compared to the reference year.

From a modeling perspective, multi-objective programming methods are the most commonly applied techniques in crop planning problems (Yıldırım *et al.* 2023). This is due to the fact that such problems involve strategic decisions in agricultural production that must account for various aspects of farming, such as resource allocation, sustainability, and economic returns, all of which require balancing multiple objectives. Studies addressing crop maintenance frequently emphasizes environmental sustainability, with a focus on reducing the use of chemicals such as herbicides and pesticides and applying fertilizers in the correct amounts and at optimal times (Ahodo *et al.* 2019). Mardani Najafabadi & Ashktorab (2022) examined the ecological and social dimensions of sustainable agricultural production by optimizing the cropping pattern in the Gotvand region of southwest Iran. The results showed a 2.2% increase in employment, alongside notable reductions in the use of critical disruptive inputs to sustainable agriculture, such as fertilizers and chemical pesticides, which decreased by 5.9 and 8.19%, respectively. Mardani Najafabadi *et al.* (2019) proposed a multi-objective model for optimizing regional cropping pattern decisions in Isfahan province, Iran. The model addressed economic, social, and environmental objectives. The results demonstrated a 37% increase in net profit, a 20% reduction in irrigation water consumption, a 9% increase in employment, and reductions of 14 and 12% in the use of fertilizers and pesticides, respectively.

CONCLUSIONS

In this study, a MOLP method was used to optimize cropping patterns in six different scenarios, prioritizing different perspectives in agricultural production. Parameters such as water use, energy requirements, agricultural revenue, and carbon dioxide emissions were calculated within the FEW nexus. The main contribution of this study is the integration of a FEW nexus-based assessments into the process of optimizing planting patterns.

According to the results obtained, all crop pattern change scenarios showed a decrease in water use and energy requirements, and an increase in agricultural income. However, carbon dioxide emissions increased in scenarios where maximizing agricultural income was given more weight, whereas they decreased in scenarios where minimizing water use was given more weight.

It was determined that placing more emphasis on minimizing water usage was more effective in reducing water demand and energy requirements, but less effective in increasing agricultural income and reducing carbon dioxide emissions. Conversely, placing more emphasis on maximizing agricultural revenue was observed to be more effective in increasing income, but less effective on the reduction in water use and energy requirements and increases carbon dioxide emissions.

When the results obtained for all time periods are examined, scenario 6, which provides an average 3.35% reduction in water use, an average 1.18% reduction in energy demand, an average 0.26% reduction in carbon dioxide emissions, and an average 1% increase in agricultural income compared to the base scenario, is determined as the best scenario if the objective of minimizing water use is prioritized. However, when maximizing agricultural income was prioritized, scenario 4 was identified as the most suitable, providing an average increase of 2.05% in agricultural income across all time periods.

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AUTHOR CONTRIBUTIONS

V.H.: methodology, writing – original draft, visualization. M.Ö.: conceptualization, writing – review & editing, supervision.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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