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Managing environmental impacts of water and energy use by a multipurpose cropping pattern optimization

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ABSTRACT

The present study proposes a multipurpose cropping pattern optimization to minimize the environmental impacts of water and energy use on agriculture through the income–energy–river ecosystem nexus approach in different hydrological conditions. The following three main purposes are considered in the optimization model: (1) mitigating greenhouse gas emissions due to farming by considering minimization of agricultural energy consumption; (2) mitigating environmental impacts on the river ecosystem by considering it as the main source for supplying irrigation demand in the case study and (3) maximizing farmers' income. Field studies are carried out in the case study for recording energy inputs to assess average energy use, irrigation demand, production yield and other required parameters for the selected crops. The fuzzy physical habitat simulation is utilized to develop an environmental impact function in the river ecosystem. Based on the results of the case study, the optimization model is able to balance energy use, impacts on the river ecosystem and farmers' income. However, its performance is not best in terms of all the defined purposes. The results indicate that more than 50% of the initial income is provided, while energy use is mitigated by more than 70% on average. Furthermore, the river ecosystem is protected properly.

Key words: Energy use, Farmers' income, Multipurpose optimization model, Particle swarm optimization, River ecosystem

HIGHLIGHTS

- A multipurpose cropping pattern optimization model is developed.
- The environmental impacts of water and energy on agriculture are minimized simultaneously.
- River habitat simulation is used for minimizing the impact of water use.
- Greenhouse gas emissions are minimized.
- An optimal cropping pattern is proposed.

1. INTRODUCTION

The role of energy use in agriculture has been highlighted in the literature (e.g. Kumar *et al.*, 2020). Many previous studies have focused on the assessment of energy use in agriculture that highlights direct and indirect energy use for different crops (e.g. Khoshroo *et al.*, 2018). All previous studies corroborate the importance of energy consumption optimization in agriculture (e.g. Elhami *et al.*, 2016; Kaab *et al.*, 2019; Mostashari-Rad *et al.*, 2019). Two aspects should be considered as the advantages of energy-use optimization: reducing the costs of cultivation and mitigating greenhouse gas (GHG) emissions. It should be noted that agricultural activities are responsible for 10–12% of the total GHG emissions in the world (Hosseinzadeh-Bandbafha *et al.*, 2018).

According to the literature, crops might have different energy consumption patterns in the production process, which highlights the fact that selecting appropriate crops or cropping patterns might prove effective in terms of energy consumption or GHG emission. Water and energy use, which are the principal inputs of agricultural systems, are simultaneously effective in terms of production yield, a fact which should be highlighted in any economic analysis of agriculture (Barbosa *et al.*, 2015). Rivers are one of the main freshwater resources to supply irrigation demand, which might play a significant role in maximizing the yield of agricultural production (Thoms & Cullen, 1998). However, excessive water use might pose a challenge to the river ecosystem. In fact, increasing population and water demand have reduced the instream flow of rivers, which might be exacerbated in the future (Postel, 1998). Hence, the concept of environmental flow has been defined to protect the river ecosystem (more details by Mwelwa-Mutekenya, 2021). In other words, a proper environmental flow regime might guarantee the preservation of the sustainable ecological status of the river ecosystem. Different methods have been proposed to assess environmental flow, such as hydrologic desktop methods, hydraulic rating methods, habitat simulation methods and holistic methods (Williams *et al.*, 2019). However, some methods such as hydrological desktop methods do not focus on regional ecological values, which might reduce the reliability of these methods to assess the environmental flow regime (Sedighkia *et al.*, 2017). Conversely, holistic methods such as building block methodology (BBM) might entail considerable costs for their implementation in river basins (more details regarding BBM are proposed by de Villiers *et al.*, 2008). So, with limited choices available, it appears that habitat simulation methods are reliable and acceptable to assess the environmental flow regime in rivers. On the one hand, these methods do not need extensive field studies, which means they are not expensive. On the other hand, they focus on the target species in rivers, which means regional ecological values are considered in the assessment of the environmental flow regime. The instream flow incremental methodology (IFIM) proposes the univariate physical habitat simulation method to assess the environmental flow regime, in which the suitability of physical parameters can be assessed independently (more details by Nalamothu (2021) and Nestler *et al.* (2018)). Then, a mathematical model can be utilized to simulate combined physical habitat suitability. However, this method has been criticized due to its incapability to simulate the interactions between physical parameters (Noack *et al.*, 2013; Railsback, 2016). Hence, the fuzzy logic multivariate method has been proposed to simulate physical habitat suitability as well (Jorde *et al.*, 2020). The previous studies corroborate this method for habitat simulation because it considers the interactions between parameters by developing verbal fuzzy rules. Utilizing expert opinion for generating verbal fuzzy rules is the main advantage of this method, which has been applied to assess the environmental flow regime in recent years (e.g. Sedighkia *et al.*, 2021).

Due to interactions between water and energy in agriculture, an integrated optimization system is seen as a requirement for minimizing the environmental impacts of energy use or GHG emission and the environmental impacts on water resources such as rivers. In fact, the environmental impacts of water and energy use should be mitigated in an integrated framework, while economic benefits or farmers' income are maximized. Hence, utilizing the income–energy–river ecosystem nexus approach in optimizing energy use for agricultural lands in which rivers are responsible for supplying irrigation demand might be necessary. Due to the use of the optimization methods in the present study, it is required that these methods be reviewed. Optimization is a critical task for engineers in their efforts to solve many of their problems. The simplest method with regard to optimization is linear programming (LP), in which linear objective functions can be handled for finding the best solution (Zhou & Ang, 2008). However, LP methods might not be suitable for nonlinear objective functions. Thus, nonlinear programming (NLP) and dynamic programming (DP) have been proposed to handle nonlinear optimization problems (more details by Soleimani *et al.*, 2016). Some functions might be very complex for optimizing, which means the efficiency of the methods should be considered as well. Evolutionary algorithms are artificial intelligence (AI) methods that have been applied for the optimization of complex problems. These methods might be categorized into two groups: classic and new-generation algorithms (Dokeroglu *et al.*, 2019). Classic algorithms such as the genetic algorithm (GA) or particle swarm optimization (PSO) have been extensively applied for energy optimization in the literature (e.g. Elsheikh & Abd Elaziz, 2019; Lü *et al.*, 2020). Some previous studies have used new-generation algorithms such as the bat algorithm for finding the optimal solutions (Yang & He, 2013; Sangaiah *et al.*, 2019). However, these new-generation algorithms might not be advantageous in all cases because the previous studies have highlighted that classic algorithms are robust enough for optimizing energy (e.g. Lü *et al.*, 2020).

Cropping pattern is a key point for studying agriculture on a larger scale such as a river basin (Rosegrant *et al.*, 2000). Hence, it is highlighted in many previous studies into improving the efficiency of agriculture in different regions. For example, using a mathematical model for optimizing the cropping pattern indicated that 53% savings in water use could be achieved by an optimal cropping pattern (Alabdulkader *et al.*, 2012). A multiobjective structural planning of cropping pattern is able to reduce irrigation water consumption by 17% and increase profits by 58%, which demonstrates the advantages of using optimal cropping models for better management of agriculture (Najafabadi *et al.*, 2019). Recent studies have applied the cropping pattern models beyond the optimization of water use or benefit. For example, an efficient optimization model has been developed for land-use planning and sustaining biofuel production with minimal food security impacts, which is an urgent need in the modern conditions of managing complexities in agriculture (Femeena *et al.*, 2018). It seems that one of the important research fields for the future is to focus on cropping pattern models to improve agriculture in the river basin scale. As reviewed, previous studies on using cropping pattern models have not focused on the environmental impacts of agriculture, in which optimal cropping patterns might be an effective strategy to mitigate the environmental impacts of GHG emission on water resources. In other words, it is essential to integrate the environmental impacts with the economic aspects of agriculture in cropping pattern modelling. Due to this research need, the present study proposes the income–energy–river ecosystem nexus approach for mitigating the conflicts of environmental and economic impacts associated with energy and water use in agriculture by proposing an optimal cropping pattern. This study might open new windows on the optimization of energy use in agriculture. As reviewed, the previous studies on energy optimization in agriculture did not consider the cropping pattern in the river basin scale as an effective parameter for minimizing GHG emissions. However, our study also paves the way for using the cropping pattern model for future optimizations that could be done for other forms of agriculture, such as managing the environmental impacts of orchards by effecting necessary changes in the structure of the model.

2. APPLICATION AND METHODOLOGY

2.1. Overview of the methodology

Due to the complexities of the proposed method, it might be useful to review the main components of the developed method. A drought analysis was used to assess the mean monthly flow in dry years, normal years and wet years. Field studies in farms were carried out to assess energy inputs and the required irrigation demand for different crops. Then, the parameters of average energy consumption and water use for selected crops were applied to the structure of the optimization model. The fuzzy physical habitat simulation was utilized to develop the ecological impact function of the river ecosystem. Furthermore, a standalone optimization model was applied to optimize the cropping pattern by considering the conventional method, in which maximizing farmers' income was considered as the main purpose of optimization. Then, the outputs of this optimization model were utilized in the structure of the main optimization by considering the economy–energy–river ecosystem nexus. In the next step, optimal cropping patterns were simulated for dry years, normal years and wet years in the case study.

Finally, the outputs of the optimization model were analysed to ascertain the reliability and robustness of the novel optimization system. Figure 1 displays the workflow of the proposed method. More details regarding each component of the proposed method are presented in the following sections.

2.2. Ecological impact function of the river ecosystem

Fuzzy physical habitat simulation was utilized to develop the ecological impact function for the river ecosystem that was applied in the optimization directly. The methodology of the fuzzy physical habitat simulation has been described in the literature as cited in the previous section. However, it is briefly explained in this section as well. A representative river reach was selected downstream of the diversion dam in the case study, which is responsible for irrigation supply. Field studies including observing fish, measuring hydraulic characteristics and surveying cross sections were carried out in the representative reach. Electrofishing as one of the known methods was utilized in the fish observations (more details by Harby *et al.*, 2004). Then, verbal fuzzy rules were developed on the basis of the fish observations and expert opinion. Finally, the verbal fuzzy rules were combined with the one-dimensional hydraulic simulation in the representative reach to develop a normalized weighted useable area (WUA) function that was applied as the ecological impact function in the optimization model. Figure 2 displays the workflow of the fuzzy physical habitat simulation.

2.3. Drought analysis

The stream drought index (SDI) was utilized as a known index to analyse dry and wet years in the river ecosystem. At the first step, it is required to provide a time series of monthly flow. Then, cumulative stream flow volume should be calculated, as displayed in the following equation:

$$V_{i,k} = \sum_{j=1}^{3k} Q_{i,j} \quad i = 1, 2, \ldots, 12 \quad k = 1, 2, 3, 4 \tag{1}$$

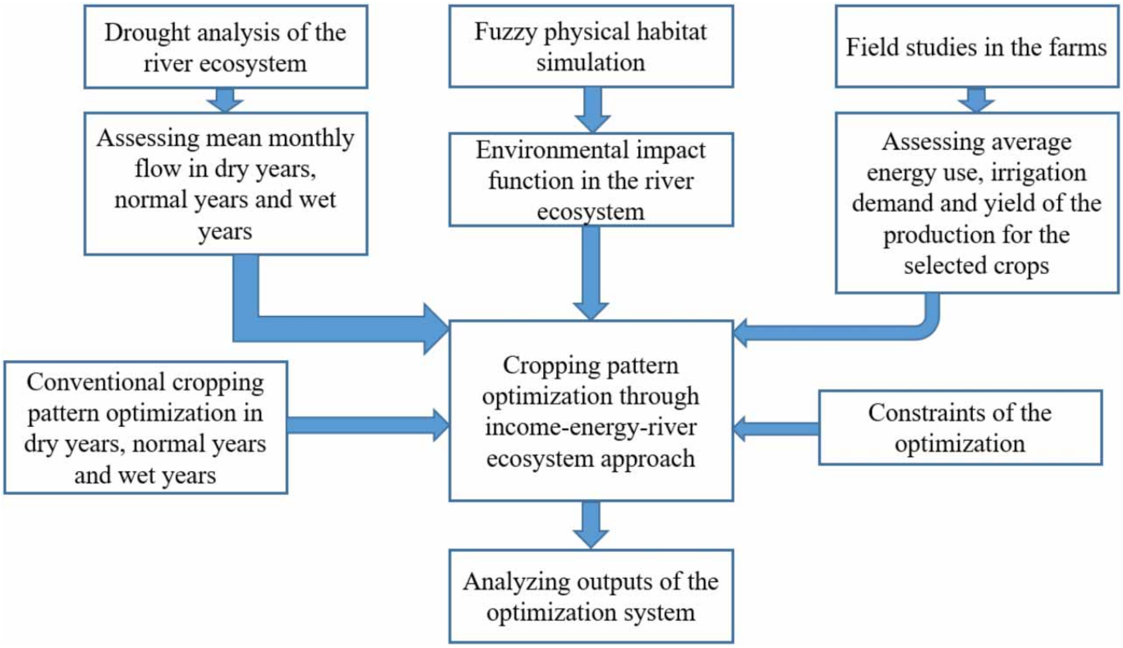

Fig. 1 | Workflow of the proposed method.

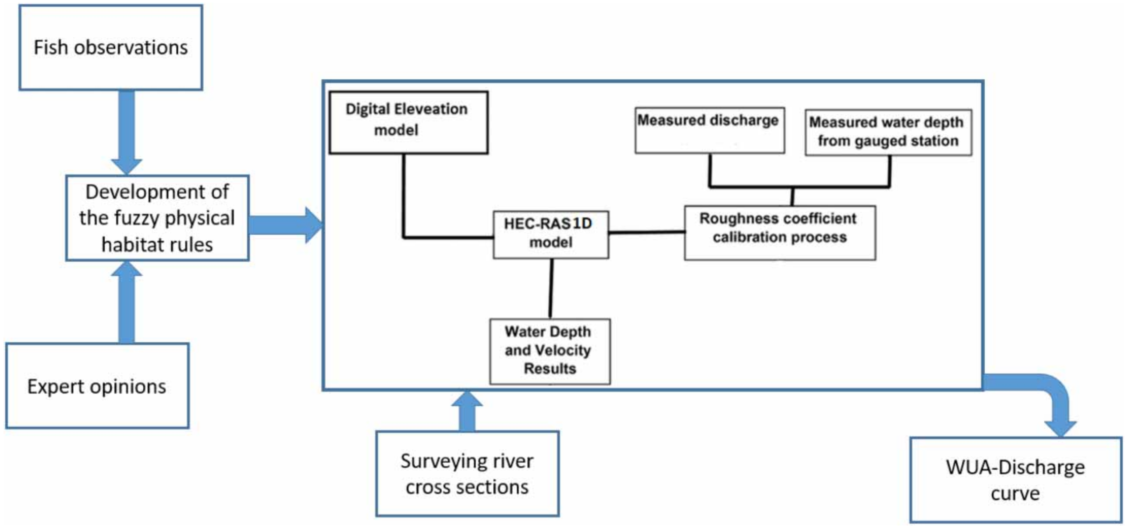

Fig. 2 | Flowchart of the physical habitat simulation in the proposed framework.

where K means the period of drought analysis (3–12 months). In the next step, it is required to use the following equation to compute the SDI:

$$SDI_{i,k} = \frac{v_{i,k} - V_k}{S_K} \quad i = 1, 2, \ldots, 12 \quad k = 1, 2, 3, 4 \tag{2}$$

where V and S are the mean and standard deviation of cumulative stream flow volume, respectively. More details on the SDI are provided in the literature (Akbari *et al.*, 2015). We used the SDI on the basis of the recommendation given in the literature, as displayed in Table 1 (Akbari *et al.*, 2015).

A 12-month SDI was applied to determine the hydrological status including dry years, normal years and wet years. Then, we considered the years with the status of moderate to extreme drought as dry years, with mild drought as normal years and with other values as wet years.

2.4. Optimization system

The following three main objectives were considered for the optimization system: (1) minimizing the energy use of agriculture in the study area; (2) maximizing physical habitat suitability in the river ecosystem and (3)

Table 1 | Criteria for defining the SDI.

State	Description	Criterion of the SDI
0	Non-drought	$>= 0$
1	Mild drought	$-1.0 \geq$ and < 0.0
2	Moderate drought	$-1.5 \geq$ and < -1.0
3	Severe drought	$-2.0 \geq$ and < -1.5
4	Extreme drought	< -2.0

maximizing the net revenue or farmers' income in the study area. In fact, the defined objectives might be the drivers for ensuring sustainability in the study area, in which GHG emissions might be mitigated by minimizing energy use, with ecological impacts on the river ecosystem possibly being mitigated as well. The main component of each optimization system is the objective function, as displayed in Equation (3). It should be noted that the purposes of the optimization system are defined in the form of loss function. In fact, the objective function contains three loss functions, namely, ecosystem loss function, energy loss function and income loss function.

$$Minimize(OF) = (Loss_{physical\ habitat} - Loss_{energy} - Loss_{income})^2 \tag{3}$$

Equations (4)–(6) display the defined loss functions where OR is the optimal net revenue. IR is the ideal net revenue proposed by conventional cropping pattern optimization, ME is the maximum energy use by all crops proposed by conventional cropping pattern optimization and OE is the optimal energy use by all crops. $owua_t$ is the optimal normalized weighted useable area in the time step t. T is the time horizon, which is 12 months in the present study. According to the defined loss functions, the optimization model tries to maximize net revenue. In contrast, it tries to minimize energy use to 10% of the current energy use as an ideal value for minimizing GHG emissions. It should be noted that this value was determined on the basis of recommendations by local energy experts. Other values might be used in other cases. Furthermore, the optimization model minimizes the difference between the maximum normalized WUA (WUA = 1) and the optimal WUA in each monthly time step.

$$Loss_{income} = 1 - \frac{OR}{IR} \tag{4}$$

$$Loss_{energy} = 1 - \frac{0.1ME}{OE} \tag{5}$$

$$Loss_{physical\ habitat} = \frac{\sum_{t=1}^{T} (1 - owua_t)}{T} \tag{6}$$

Each optimization system might need some constraints that might be determined on the basis of the requirement and purposes of the optimization process. The following constraints were considered for the developed optimization in the present study:

- Environmental flow (utilized in the structure of the physical habitat loss function) should not be more than stream flow.
- Minimum physical habitat suitability in each monthly time step should not be less than 0.5. It should be noted that WUA = 0.5 is defined as the minimum requirement for protecting the river ecosystem on the basis of expert opinion given by an experienced ecologist. In physical habitat simulation, a direct relationship between biomass (population of the species) and habitat suitability is considered. In other words, WUA = 0.5 means that the model is able to protect at least 50% of the inhabited population of the target species in the study area. Based on the initial habitat survey, protecting 50% of the population can help sustain biological activities such as reproduction.
- Due to social concerns in the case study, cultivated area loss should not be more than 60% compared with the maximum cultivated area proposed by conventional cropping pattern optimization.
- Due to GHG emission concerns in the case study, energy loss should not be more than 50%.
- Due to economic concerns in the case study, the loss of net revenue should not be more than 50%.

Introducing constraints in the structure of the evolutionary algorithm might require the use of an appropriate computational method. One of the appropriate methods that has been utilized in many previous studies is the penalty function method. In fact, the penalty functions increase the penalty of the system when constraints are violated. Hence, five penalty functions were added to the optimization model as follows:

$$\begin{cases} \text{if} \quad ENV_t > ST_t \rightarrow P1 = c1\left(\dfrac{ENV_t - ST_t}{ST_t}\right)^2 \\ \text{if} \quad owua_t < 0.5 \rightarrow P2 = c2\left(\dfrac{owua_t - 0.5}{0.5}\right)^2 \\ \text{if} \quad Loss_{area} > 0.6 \rightarrow P3 = c3\left(\dfrac{Loss_{area} - 0.6}{0.6}\right)^2 \\ \text{if} \quad Loss_{energy} > 0.5 \rightarrow P4 = c4\left(\dfrac{Loss_{energy} - 0.6}{0.6}\right)^2 \\ \text{if} \quad Loss_{income} > 0.5 \rightarrow P5 = c5\left(\dfrac{Loss_{income} - 0.5}{0.5}\right)^2 \end{cases} \tag{7}$$

where *ENV* is the environmental flow and *ST* is the stream flow. The other parameters have been defined previously. The minimum and maximum cultivated area for each crop was added as the penalty function to the system. More details with regard to the constraints on the cultivated area for each crop are presented in the next section. The conventional method for optimizing the cropping pattern has been documented very well in the previous studies (e.g. Daghighi *et al.*, 2017; Osama *et al.*, 2017). Hence, more details are not presented here in this regard. It should be noted that maximizing the net revenue was considered as the objective of optimization in the conventional cropping model. The total available agricultural area, available water without considering environmental flow and minimum and maximum cultivated area for each crop were considered as the constraints in the conventional cropping pattern optimization.

We selected PSO for finding the optimal solution in the cropping pattern model, in which the position of each particle (solution) is updated in each iteration to find the best position of particles using a mathematical formula of computing velocity and position of the particle. More details on the theory of the method are given in the literature (Marini & Walczak, 2015). More discussions on the advantages of this method compared with other models follow in the next section (Results and Discussion).

2.5. Case study and data collection

The present study was carried out in Iran. Agriculture is one of the important economic activities in many regions of Iran. For example, it is highlighted as the most important economic activity of the people in the Kurdistan province. We focused on one of the constructed diversion dams (the Golbalagh diversion dam) that is responsible for irrigation supply of downstream agricultural lands. On the one hand, farmers prefer maximizing their revenue by applying the optimal cropping pattern without considering other limitations. On the other hand, there are serious concerns regarding environmental sustainability in the river basin in terms of two aspects. First, the downstream river of the dam is a valuable habitat for the native fish species, which means reducing instream flow might pose a serious threat to the river habitat. Increasing GHG emissions due to agriculture is another general environmental concern in the province. Due to conflicts between stakeholders (farmers) and environmental managers, it might be necessary to develop an integrated cropping optimization system to minimize agriculture energy use and ecological impacts on the river ecosystem in the study area. Figure 3 displays the location of the study area and a part of the agricultural lands at downstream of the diversion dam. It should be noted that storage in the diversion dam

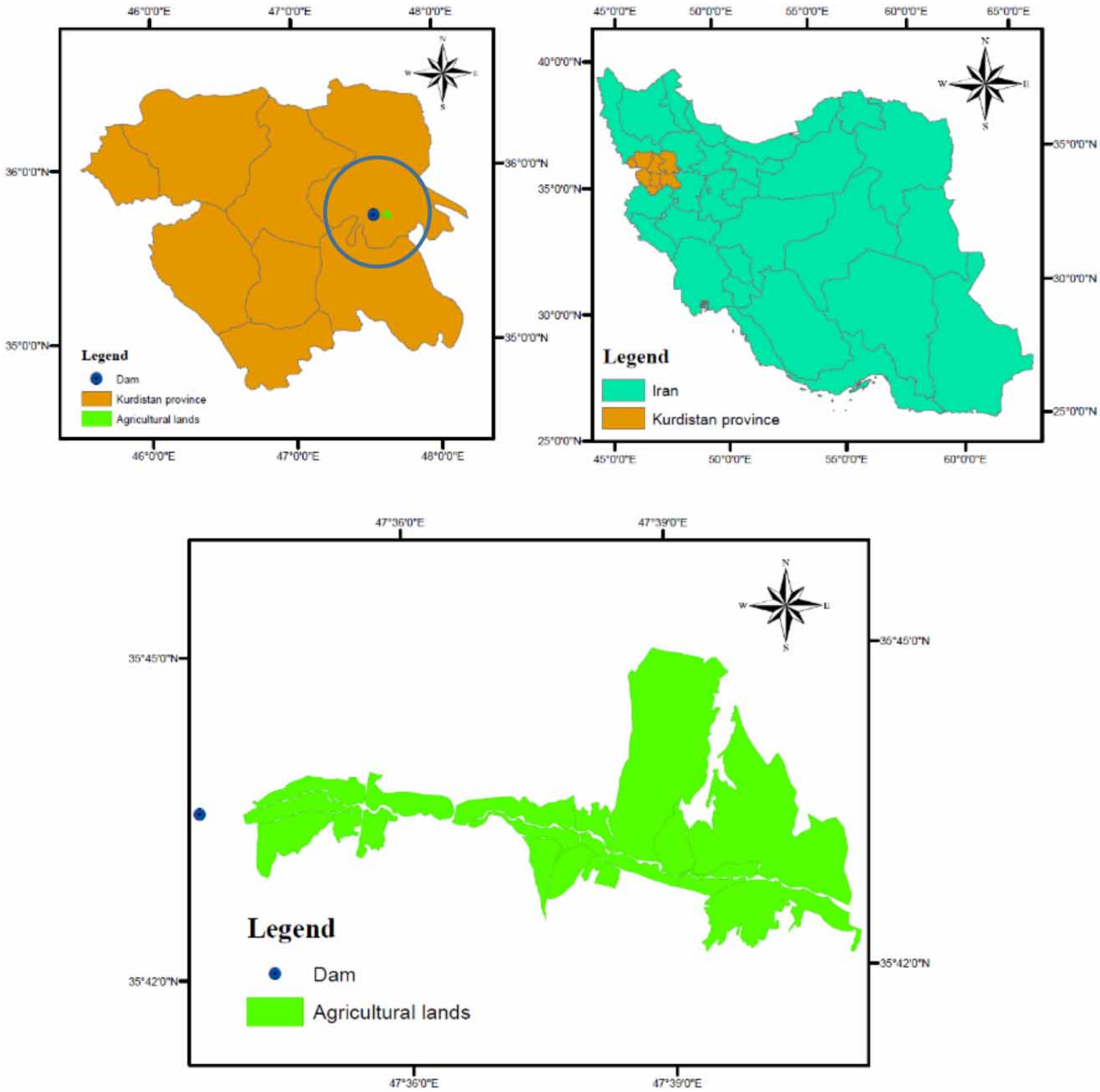

Fig. 3 | Location of the study area and diversion dam at upstream of lands.

was very limited to the extent that it was considered as zero storage in the optimization model. According to the recommendation by the department of agriculture, the minimum and maximum areas for the selected crops were considered on the basis of Table 2.

More details on the study area might be helpful for the readers. Hence, we present more details on the regional and climatic characteristics of the study area. This region is located in a temperate region in which the average daily temperature in summer is 18 °C, and in the winter, it is 9 °C. The average precipitation is 600 mm annually. However, the distribution of this precipitation is not appropriate, which means the precipitation is limited in the spring and summer seasons and in the cultivation period. Parts of the total irrigation demand could be supplied by precipitation. However, irrigation is essential due to the lack of enough precipitation in the cultivation period.

Table 2 | Constraints on the cultivated area for the selected crops.

Selected crop in the case study	Constraints
Wheat	Minimum area: 5% of the cultivated area Maximum area: 30% of the cultivated area
Peanut	Minimum area: 2% of the cultivated area Maximum area: 20% of the cultivated area
Corn	Minimum area: 5% of the cultivated area Maximum area: 30% of the cultivated area
Sugar beet	Minimum area: 5% of the cultivated area Maximum area: 25% of the cultivated area
Potato	Minimum area: 1% of the cultivated area Maximum area: 10% of the cultivated area
Tomato	Minimum area: 2% of the cultivated area Maximum area: 15% of the cultivated area
Other vegetables	Minimum area: 2% of the cultivated area Maximum area: 12% of the cultivated area

Surface water is the main water resource for meeting irrigation demand. It should be noted that the effect of precipitation is eliminated in the calculation of the net irrigation demand in the present study. In other words, we considered the average net irrigation in different months of the cultivation period, which should be supplied by the diversion dam.

A list of the common crops was provided in the study area, and a total of 100 farms were selected for collecting regional data. Two agricultural experts were involved in the data collection in the study area. More details on the number of collected points for each crop will be provided in the results and discussion section. It was essential to collect the required data for developing the optimization model. Two types of inputs were recorded in the selected farms: energy inputs (Table 3) and the required irrigation demand for each crop. Production yield was a question in the form as well. Finally, Equation (8) was used to assess total energy use (*TE*) for each crop, where F_i is the effective input of the energy use, C_i is the energy equivalent coefficient (EEC) and I is the total number of the

Table 3 | Energy inputs considered in the questionnaire.

Inputs	Unit
Human labour	h
Machinery	h
Farmyard manure	kg
Nitrogen	kg
Phosphate	kg
Potassium	kg
Diesel fuel	L
Electricity	kWh
Biocides	kg

inputs. *TE* is the total energy use in MJ/ha. In other words, Equation (8) computes the total energy consumption in the area unit of the farm. The EECs were selected on the basis of the previous studies, which pertained to energy-use analysis in the farming of the selected crops. Mean energy and water use were applied in the structure of the optimization model. Previous studies on different countries were used to select the EECs in the present study (e.g. Canakci *et al*., 2005; Esengun *et al*., 2007; Mohammadi *et al*., 2008; Asgharipour *et al*., 2012; Houshyar *et al*., 2012; Taghavifar, & Mardani, 2015; Hosseinzadeh-Bandbafha *et al*., 2018)

$$TE = \sum_{i=1}^{I} F_i \cdot C_i \tag{8}$$

3. RESULTS AND DISCUSSION

Table 4 displays the mean irrigation demand and mean energy use on the basis of the field studies in the case study. The mean yield of production is displayed in Table 4 as well. It seems that energy and water use is considerably different for the selected crops as well as the yield of production. Due to the requirements for cropping pattern optimization, the mean cost of the unit area and the price of the crops in the case study are given in Table 4, which were assessed on the basis of the available data and by collecting field information.

In the next step, it is necessary to present the results of developing the ecological impact function for the river ecosystem in the case study. As presented, the fuzzy physical habitat simulation was applied to develop the ecological impact function. Twenty-five fuzzy rules were developed in the physical habitat simulation. For example, two rules are presented as follows. The other rules were developed similarly.

Rule 1: If depth is medium, velocity is low, and if substrate is medium, then physical habitat suitability is low.

Rule 2: If depth is low, velocity is medium, and if substrate is high, then physical habitat suitability is high.

It seems that the impact of flow velocity on physical habitat suitability is more considerable than that of other physical parameters such as depth or substrate. Figure 4 displays the developed ecological impact function for the river ecosystem. Figure 5 displays the SDI for a long-term period in the case study. According to the presented methodology, the mean monthly flow in dry years, normal years and wet years are displayed in Figure 5 as well. In this figure, the SDI is computed on the basis of 12 months or annually. The down figure is only displayed for showing the changes in the SDI in the observed hydrological period. The inflow of the diversion dam (up) was used in the optimization model. Changing the hydrological condition in the river basins will have a remarkable

Table 4 | Collected agricultural data.

Selected crop in the case study	Number of collected points	Energy use (MJ/ha)	Irrigation demand (m^3/ha)	Cultivation cost (Rls/ha)	Price (Rls/kg)	Yield of production (ton/ha)
Wheat	20	30,626.4	2,760	39,720,000	13,000	3,638.12
Peanut	10	19,248.04	8,870	98,512,000	55,000	3,693.34
Corn	13	38,228.4103	7,090	53,134,000	10,500	7,357.18
Sugar beet	15	32,898.2	8,290	73,413,000	4,000	33,550.30
Potato	18	70,256.4	9,420	110,859,000	8,150	28,453.61
Tomato	14	42,302	7,780	121,944,900	9,400	29,800
other Vegetables	10	61,211	3,890	73,084,800	25,000	1,475

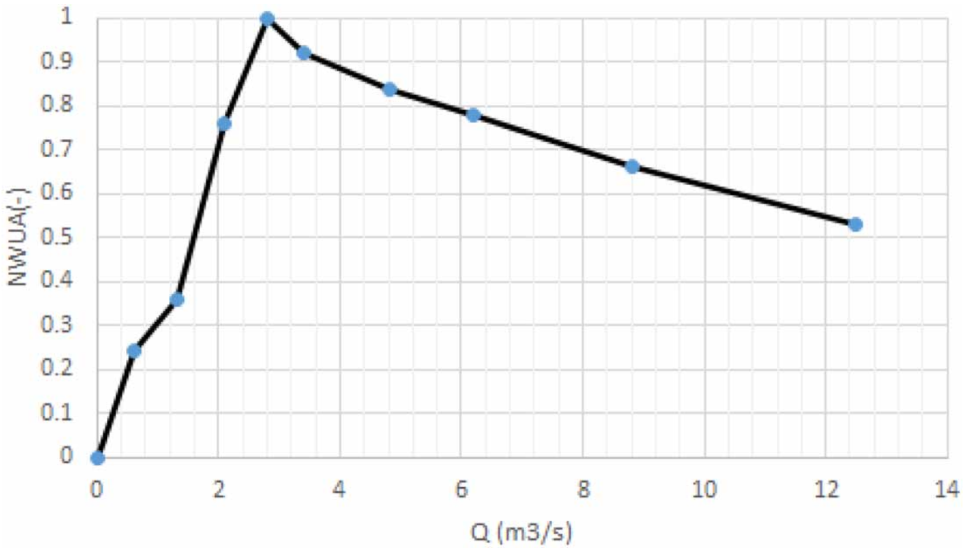

Fig. 4 | Normalized weighted useable area function in the case study.

effect on the availability of water for irrigation, which means that this effect will be felt on energy use and production yield as well.

Figures 6–8 display the outputs of the optimization model in three hydrological conditions: dry years, normal years and wet years. A non-environmental approach means using the conventional cropping pattern optimization. In contrast, an environmental approach means applying the income–energy–river ecosystem nexus approach to design an optimal cropping pattern in which energy consumption and ecological impacts on the river ecosystem are mitigated, while net revenue is maximized. The novel approach altered the total cultivated area (TCA) as well as the cropping pattern compared with the conventional cropping pattern optimization. *TE* is changed considerably. Three aspects were considered in the optimization framework: energy use, economic benefits and ecological impacts on the river ecosystem. Some criteria were defined in the optimization model that has been presented. These criteria might provide appropriate loss for each section in the optimization model. It should be noted that the optimization model might not be able to minimize losses on the basis of the initial defined criteria for the losses. In other words, the performance of the penalty functions might not be the best, and this aspect should be considered in the evaluation of the system performance of the optimization model.

Minimizing energy consumption is one of the main purposes of the present study, which might mitigate GHG emissions in the river basin scale. According to the initial purpose of the optimization model, reducing 90% of energy use was defined as the ideal value. However, the results of the optimization model in the case study indicate that the environmental optimization model reduced energy consumption by 78% compared with the non-environmental optimization model in the dry years. It decreased the energy consumption by 70% in the normal years and the wet years approximately. At first glance, it seems that the optimization model should reduce energy use in the normal and wet conditions more than in the dry years. However, the outputs of the optimization system do not demonstrate this. In fact, the optimization model would provide a balance between energy use, economic benefit and ecological impacts on the river ecosystem. Generally, the performance of the optimization model in terms of minimizing energy use is acceptable. In fact, the penalty function of energy loss showed a robust performance.

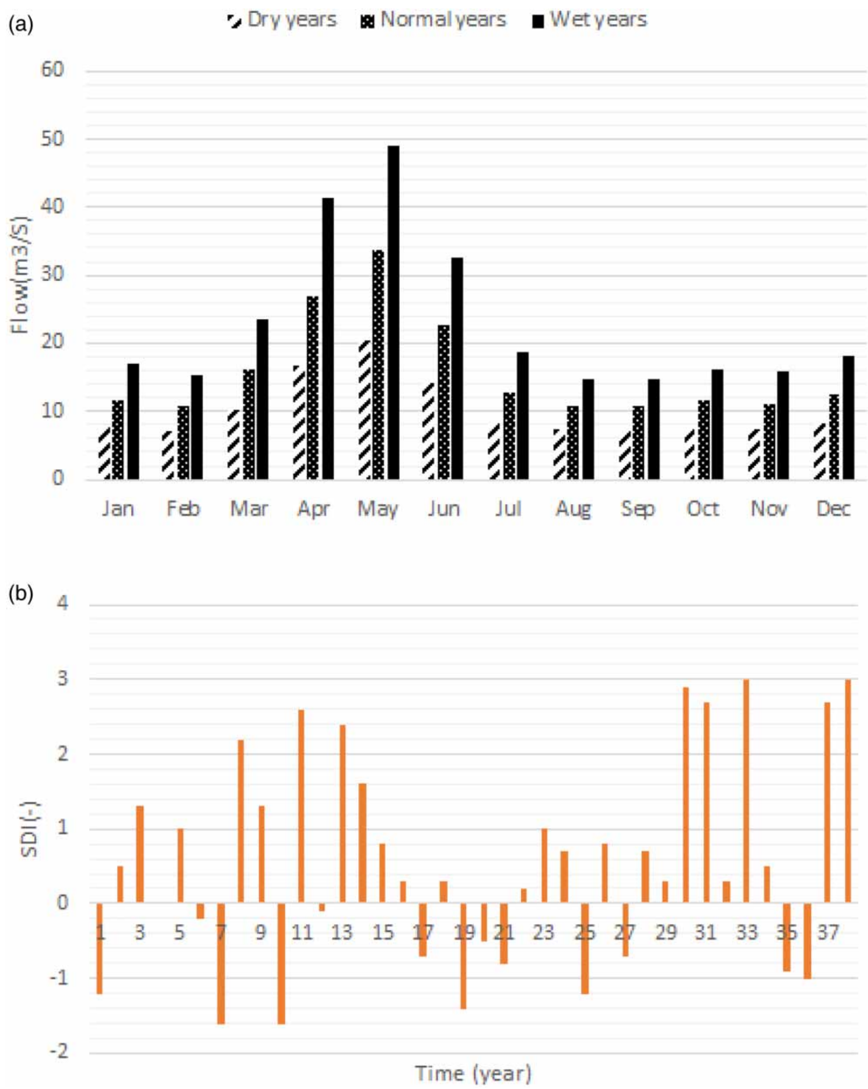

Fig. 5 | Drought analysis results in the case study (up: monthly flow in three hydrological condition and down: computed SDI to calculate the monthly flow in each hydrological condition).

Another technical aspect is how the optimization model can mitigate the ecological impact on the river ecosystem. The river is the main source for supplying irrigation demand in the case study. Thus, excess water diversion might negatively affect the ecological status in the river ecosystem. As presented, the minimum physical habitat suitability in each month was considered as 0.5 by applying the penalty function in the optimization model. In other words, if the physical habitat suitability is less than 0.5, it might be very detrimental to the river's ecosystem. It seems that the performance of the suitability penalty function is robust in all the hydrological conditions of dry years, normal years and wet years. Its performance is more robust in the dry years than in the wet years. In fact, the optimization model is able to protect 50% of the suitable area in all the hydrological conditions. However, it provides a higher suitable area in the dry years. It should be noted that the relationship

Fig. 6 | Output of the optimization systems in dry years (a: cropping pattern by the non-environmental approach, b: cropping pattern by the environmental approach, c: total cultivated area in each approach, d: total energy use in each approach, e: net revenue converted to M$, f: physical habitat suitability time series proposed by the environmental approach and g: proposed environmental flow (instream flow) and total and offstream flow by the optimization model).

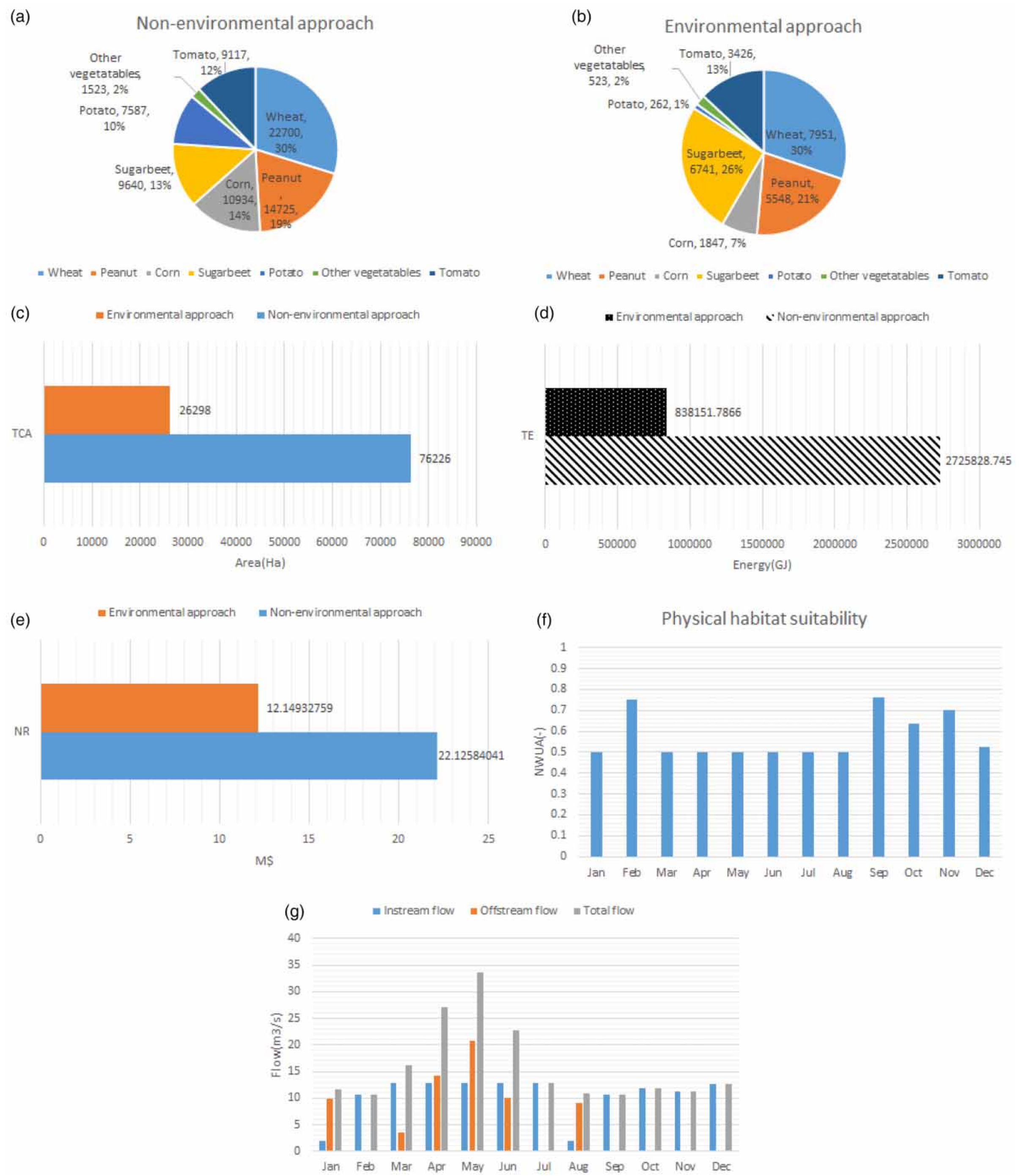

Fig. 7 | Output of the optimization systems in normal years (a: cropping pattern by the non-environmental approach, b: cropping pattern by the environmental approach, c: total cultivated area in each approach, d: total energy use in each approach, e: net revenue converted to M$, f: physical habitat suitability time series proposed by the environmental approach and g: proposed environmental flow (instream flow) and total and offstream flow by the optimization model).

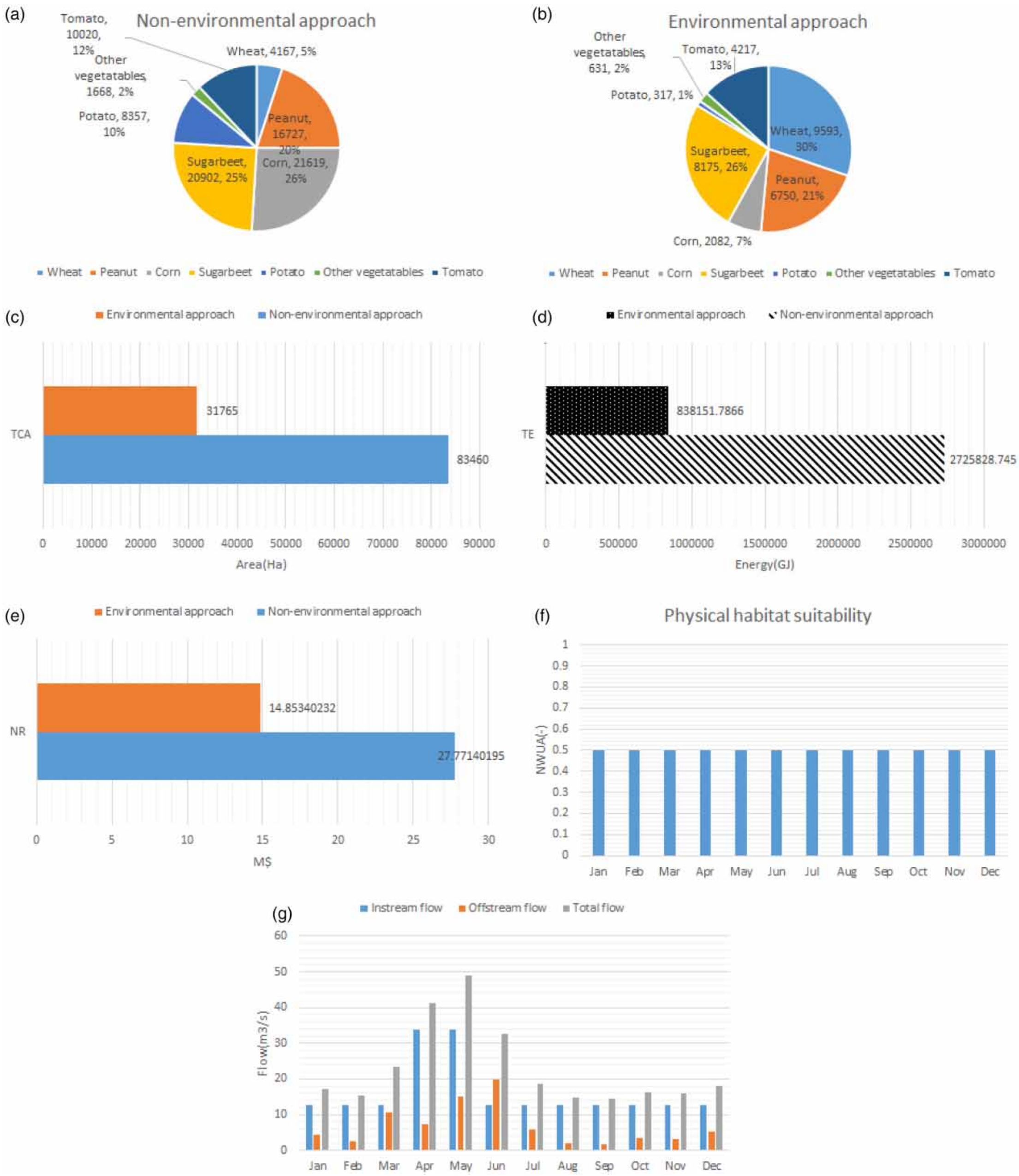

Fig. 8 | Output of the optimization systems in wet years (a: cropping pattern by the non-environmental approach, b: cropping pattern by the environmental approach, c: total cultivated area in each approach, d: total energy use in each approach, e: net revenue converted to M$, f: physical habitat suitability time series proposed by the environmental approach and g: proposed environmental flow (instream flow) and total and offstream flow by the optimization model).

between ecological impact and stream flow is not linear, which means using a robust optimization model is necessary to provide a balance between losses in the river basin. It is judgeable that the performance of the optimization model is reliable in terms of mitigating the ecological impact on the river ecosystem.

In the next step, it is necessary to investigate the performance of the optimization model in terms of the cultivated area. In fact, the cultivated area might be important in terms of the social aspect in river basins. In other words, a considerable reduction of the cultivated area is not favourable in the case study. However, it might be inevitable due to the other aims of the optimization model. Initially, the maximum loss of the cultivated area was defined as 0.6. However, the performance of the optimization in different hydrological conditions demonstrated that it is not possible to keep the cultivated area on the basis of the predefined loss of the cultivated area. According to the results of the optimization system, the cultivated area reduced by 73% in the dry years. However, the cultivated area decreased in the normal years and wet years by 66 and 62%, respectively. Interestingly, the optimization model considered more reduction of the cultivated area and energy use and higher physical habitat suitability in the dry years, which might be advantageous for the river ecosystem. In fact, the river ecosystem might experience more stresses in the dry years, which means that higher physical suitability might be more important compared with the normal and wet years. It should be noted that the performance of the optimization model in terms of cultivated area is not robust in the case study. However, it might not be a significant problem in terms of the robustness of the optimization system. In fact, protecting the initial cultivated area is not the main purpose of the optimization model.

In the next step, it is required to review the performance of the optimization model in terms of farmers' revenue in the case study. In fact, maximizing farmers' income is one of the main purposes of the optimization model. The maximum economic loss was defined as 0.5 through the penalty function, which means the optimal income should not be less than 50% of the available income through the non-environmental approach for optimizing the cropping pattern. It seems that the performance of the optimization system is robust and acceptable in this regard. According to the results of the case study, the economic loss is less than 50% in all the hydrological conditions, which demonstrates the applicability of the optimization model to achieve a fair balance between income, energy use and mitigating ecological impacts on the river ecosystem. The performance of the optimization model in different hydrological conditions is similar, which might be appropriate for farmers, who need to have sustainable income in different years without considering the changes in the hydrological condition of the river. In fact, the optimization model is able to balance energy use and water use to provide a sustainable income for the farmers.

Every optimization system will have advantages and disadvantages that should be considered in their application. It is essential to review the future research fields for upgrading the developed optimization system. First, it should be noted that the proposed method might open a new window on the application of cropping pattern optimization in terms of energy use. In fact, traditionally, cropping pattern optimization has been applied to either maximize revenue or minimize water use, and it has not been able to consider energy use in the structure of the cropping pattern. Thus, the first important novelty of the developed model is to include energy consumption in cropping pattern optimization. In fact, GHG emission is a serious environmental problem in modern times, which might exacerbate global warming. Thus, it is essential to minimize GHG emissions in all economic activities, including agriculture. The previous studies focused on minimizing GHG emissions in agriculture using the optimization of energy inputs including direct and indirect energy inputs. However, this strategy might not be adequate for river basins in which different crops should be managed on a large scale. The previous studies were not able to consider the ecological impacts of irrigation in an integrated framework. Therefore, the present study proposed a novel form of an optimization system in which energy and water use could be optimized in the structure of the cropping pattern model. The proposed method is helpful in minimizing protracted negotiations between farmers as stakeholders and environmental managers. On the one hand, farmers want to design the cropping pattern on the basis of economic benefits without considering environmental sustainability in river basins. On the other hand, environmental managers try to mitigate all environmental impacts in river basins, including ecological impacts on the river ecosystem and GHG emissions due to energy consumption. Hence, the income–energy–river ecosystem nexus is able to consider all the needs of stakeholders and managers in the environmental management of river basins. In other words, this method can help find optimal solutions for both stakeholders and environmental managers. Hence, it can be claimed that this optimization approach might reduce concerns with regard to environmental sustainability in river basins.

The present study focused on some specific crops in the case study. However, it is recommended to add other crops to the system that might be challenging to grow. For example, orchard crops such as apple might have some specific requirements in cropping pattern optimization that should be added to the optimization system. Soil and land suitability might be another technical consideration that should be added to the system. In our case study, soil and land suitability was not a serious concern, which means all the available agricultural lands were appropriate for cultivating the selected crops. However, it might not be possible to cultivate different crops in all lands for other cases. Thus, it is recommended to add the constraints of agriculture to the optimization system.

The computational aspects of the proposed method should be discussed as well. PSO was applied in the present study, which is a single objective optimization algorithm. First, it should be highlighted why this algorithm might be more advantageous than other optimization methods. Many previous studies in agriculture used LP in cropping pattern optimization. However, these methods are not useable in the present research due to the nonlinear nature of the optimization model. Furthermore, using NLP and DP is not efficient because the developed objective function is highly complex, which means these methods might not be able to find the best solutions with a reasonable computational cost. The main advantage of PSO compared with other single objective evolutionary algorithms is its speed for finding the best solution, which is a significant advantage in terms of computational cost. Thus, we selected this algorithm for the present study.

Another computational aspect is the possibility of applying multiobjective algorithms. It is observable that the developed objective function contains different terms. In fact, the objective function was applied in an aggregated form. At first glance, it seems that utilizing the multiobjective evolutionary algorithms might be a better solution for the developed optimization model. However, some computational limitations make the single objective evolutionary algorithm worthy for the developed optimization system. The first limitation is computational complexities, which might be an important limitation for applying the optimization algorithms in practice. According to the literature, computational complexities have been defined as the given time and memory to the optimization algorithms for finding the best solutions for the designed optimization problems. The proposed optimization model has fewer computational complexities, which might be a significant advantage. However, it should be noted that it provides an upgradable and flexible environment that other models could be used in the structure of the optimization model as well. For example, data-driven models of energy use and river ecosystem analysis might be added to the model in future studies, which might increase computational complexities remarkably. One of the important drawbacks of the multiobjective optimization models is higher computational complexities compared with the single objective optimization algorithms. It should be noted that adding the data-driven models to the structure of the developed optimization model will increase the running time and required memory in the form of multiobjective optimization, which might reduce the applicability of the model in practice. In fact, engineers are not willing to utilize complex models in their projects due to the requirement for long periods of simulation or covering a long-term period. Hence, the proposed optimization model is valuable in terms of computational complexities. Only a limited number of multiobjective optimization algorithms such as multiobjective GAs have been developed in the literature, which might cause a problem for using multiobjective optimizations. In fact, the main disadvantage of the evolutionary algorithms is their inability to guarantee global optimization, which makes it necessary to apply different evolutionary algorithms in practical projects. In the present study, one algorithm was used to test the developed optimization model. However, it is recommended to apply other classic and new-generation algorithms to find the best solutions. Using a robust decision-making system to select the best solution among the used algorithms might be a good option to finalize the optimal solutions in projects. Using the multiobejctive optimization might confine the application of different evolutionary algorithms, which means the single objective optimization model is advantageous in this regard.

The fuzzy physical habitat simulation was applied in the present study. However, using other ecological impacts models might be applicable as well. For example, neural network models might be another option to consider the ecological impacts in the structure of the optimization model. The previous studies demonstrated the applicability and advantages of the data-driven models such as neuro fuzzy inference systems to simulate the ecological impacts on the river ecosystem. The present study highlighted physical habitat suitability in the river ecosystem. However, water quality might be a serious problem for some river ecosystems. Hence, it is recommended to add the water quality models to the optimization model in future studies. It should be noted that water quality was not a challenge in the case study. Furthermore, climate change might be effective for stream flow, which means that it would also be effective for irrigation, energy use and production yield in the agricultural area due to the strong relationship between water, energy, and economy. Thus, simulating the impact of climate change in the developed structure might be another future research field.

There might be a question as to how human labour was considered in the energy assessment of agriculture in the present study. Many previous studies added human labour in the energy assessment of agriculture, which means that it is frequently recommended in the literature to add human labour in the energy optimization of agriculture (e.g. Khoshroo *et al.*, 2018). According to the literature, human labour is a part of renewable energy in agriculture, which means the contribution of human labour would be considered in different agricultural operations, including used human labour in farmyard manure application, harvesting, land preparation and pruning operations. In other words, energy consumption by hired workers will be added to the total energy by multiplying the total hours of work and the related energy coefficients. More details are provided in the literature (Khoshroo *et al.*, 2018). It should be noted that we considered the total energy in the optimization process, which is an effective strategy in terms of computational aspects and flexibility of the framework. First, using numerous terms of the energy input in the optimization process would reduce the efficiency and accuracy of the optimization algorithms considerably. In other words, the optimization algorithm would not be able to optimize several variables properly, which is an inherent weakness of the optimization algorithms. Increasing the number of variables would reduce the applicability of the algorithms for global optimization. Second, the developed framework would enhance the flexibility of the model in practice. In other words, farmers will be able to adjust their energy inputs on the basis of technical and regional limitations.

Crop requirement is a key point in the development of cropping pattern optimization. The selected crops should be based on the growing season and other factors such as crop demand. In the present study, we initially selected crops on the basis of regional crop requirements. In other words, all the selected crops could be cultivated in the region. This means we considered the factor of generic land suitability in the selection of crops. There was no limitation for cultivating the selected crops in terms of effective factors such as soil suitability or water quality. Besides, no further investment is needed for cultivating the selected crops in the study area. However, these factors in the study area are not correct assumptions for other regions, which means applying the proposed method might have some limitations in other regions. Two options are available in this regard, which are recommended for the application of the proposed method. First, selecting crops on the basis of regional crop requirements, which means there should be no limitation or no further investment should be needed for cultivating the selected crops. However, this strategy might circumscribe the number of the selected crops in the model as implemented in the study area. Another strategy is to add other factors such as land suitability, water quality limitations and necessary investments in the structure of the optimization model. It might be advantageous in terms of adding the number of crops. However, it increases the complexity of the optimization model remarkably. Hence, the proposed optimization model could be highly applicable in its original form like the case study or the upgraded form.

Another important issue that merits discussion is the importance of dam storage and how storage could have positive effects on output. The availability of storage would be useful in increasing the weighted usable area (WUA) or physical habitat suitability in each time step of optimization. In other words, storage helps the system to release more water during periods of drought in which enough inflow is not available. In large dams, it is needed to modify the structure of the model for considering the storage in the model. The present structure is developed for diversion dams, which might not be applicable for reservoirs. Improving the proposed framework for reservoirs is recommendable in future studies. The availability of storage would be highly helpful for reducing the potential environmental impacts on the river ecosystem.

It should be noted that the relationship between river flow and physical habitat suitability is not linear, as displayed in Figure 4. As a result, the optimization model could provide higher suitability in dry years. In other words, increasing the river flow would not guarantee improvement in physical habitat suitability. Thus, it is entirely justifiable to have higher habitat suitability in dry years in some cases such as our case study. However, it might be changed in other cases on the basis of the characteristics of habitats. In this case study, the proposed cropping pattern is feasible because reducing the cultivated area is possible due to generic land suitability for the selected crops. In other words, farmers are able to maintain more than 50% of the net revenue, while the TCA is reduced. Each farmer is able to reduce the cultivated area on the basis of the total available area of his own farm. It should be noted that diminishing the net revenue is inevitable due to the need for protecting the environment.

4. CONCLUSIONS

The present study developed the income–energy–river ecosystem nexus approach to minimize agricultural energy use in the river basin scale in which an integrated cropping pattern optimization model was developed. Three aims were considered in the optimization system: mitigating GHG emissions due to farming by considering minimization of energy consumption, minimizing ecological impacts on the river ecosystem, which was the main source for supplying irrigation demand, and maximizing farmers' revenue in the study area. PSO was applied to simulate the case study using the developed approach in three hydrological conditions, namely, dry years, normal years and wet years. According to the results of the case study, the developed optimization system had defensible performance in terms of the defined purposes. However, its performance is not best in all aspects. In other words, the optimization system is able to balance energy and water use and revenue. It is recommended to apply the proposed approach in those river basins in which negotiations between farmers as stakeholders and environmental managers who are willing to mitigate GHG emissions and river ecological impacts are minimized.

CONCFLICT OF INTERESTS

None.

DATA AVAILABILITY STATEMENT

Data cannot be made publicly available; readers should contact the corresponding author for details.

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