Ecological Modelling 484 (2023) 110471

Contents lists available at ScienceDirect

Ecological Modelling

journal homepage: www.elsevier.com/locate/ecolmodel

A new interval meta-goal programming for sustainable planning of agricultural water-land use nexus

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ARTICLE INFO

Keywords:
Sustainable cropping pattern
Uncertainty
Agroecosystem planning
Iran
Decision-Support System

ABSTRACT

Meta-Goal Programming (MGP) is a simultaneous cognitive evaluation of the degree of achievements for original decision goals considered in a GP model. However, in most real-world situations, environmental coefficients and related parameters are not easily available. In such a situation, the decision-maker must consider various conflicting targets in a framework of uncertain aspiration levels at the same time. On the other side, Interval Programming (IP) is a method used to increase the range of available decision-maker preference structures in GP. In the perspective of solving the conflicts between agriculture and water use towards sustainability, this paper proposes an Interval Meta-Goal Programming Model (IMGPM) dealing with imprecision in data that covers interval coefficients, target intervals, and interval bounds of meta-goals. This novel methodology has been tested in a study area in Iran to validate its added value in solving conflicting uses of natural resources by economic sectors. This integration together with its application for sustainable optimal cropping patterns (agroecosystem planning) represents a novelty in the field of ecological modeling. The management solutions of our method in terms of land allocation are different from those in Sen and Pal (2013) model. In the case of Iran, many socio-ecological-economic strategies and policies should be necessary for improving the agricultural sector. More specifically, on the basis of rainfall amounts and spatial patterns, this approach can represent a decision-support system able to define strategies for additional water storage useful to support crop production. Furthermore, the availability of water together with the sustainable use of fertilizers can mitigate the risk of land degradation, guaranteeing people employment, food security, and economic profits. Although the present methodology seems to solve the problem of multi-goals decision-making, the inclusion of spatial relationships is able to introduce dependencies between the management of land use in adjacent areas, making the present approach nearer to real-world functioning.

1. Introduction

Global food security faces numerous challenges that seriously threaten it, such as climate change, population growth, increasing urbanization, intensive consumption of non-renewable resources, etc. (Chopra et al., 2022; Abd-Elmabod et al., 2020; FAO, 2017; Popp et al., 2014; Tomlinson, 2013). In addition, uncontrolled exploitation of resources due to changing food patterns, which require the production of

Abbreviations: UN, United Nations; GP, Goal Programming; MGP, Meta-Goal Programming; IGP, Interval Goal Programming; SDGs, Sustainable Development Goals; FAO, Food and Agriculture Organization; IP, Interval Programming; IMGPM, Interval Meta-Goal Programming Model; GIS, Geographic Information System; DM, Decision-Makers; POS-LOW, The lower bound of possible regret in IGP; POS-UP, The upper bound of possible regret in IGP; NES-LOW, The lower bound of necessary regret in IGP; NES-UP, The upper bound of necessary regret in IGP; META_POS-LOW, The lower bound of possible regret in IMGPM; META_POS-UP, The upper bound of possible regret in IMGPM; META_NES-LOW, The lower bound of necessary regret in IMGPM; META_NES-UP, The upper bound of necessary regret in IMGPM.

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https://doi.org/10.1016/j.ecolmodel.2023.110471
Received 8 June 2023; Received in revised form 17 July 2023; Accepted 19 July 2023
Available online 27 July 2023

more products, can cause degradation and loss of soil productivity (Tóth et al., 2018). Therefore, effective global food security insurance must necessarily seek to achieve the second goal of the 17 United Nations (UN) Sustainable Development Goals (SDGs), namely Zero Hunger (SDG-2) (Ruben et al., 2019) without impacting natural resources such as biodiversity (SDG-15), water (SDG-6), and climate change (SDG-13). Food security is, thus, strongly linked with the sustainable development of agriculture that can no longer be separated from the formulation of land and water management policies based on an integrated approach that considers economic, environmental, and social objectives (Cao et al., 2022; Siebrecht, 2020). However, water and land are considered increasingly limited resources, making difficult the achievement of sustainability in the agriculture field (Laurett et al., 2021). In addition, the intensification of competition among different economic sectors for water resources and land along with climate change has led to imbalances in water resources capacity (Abdelkader and Elshorbagy, 2021; Mirzaei and Zibaei, 2021; Pastor et al., 2019; Brinegar and Ward, 2009).

Access to water resources is a global challenge today (Ma et al., 2023), in fact, it is estimated that at least 30 percent of the world's population lacks access to clean water (WWAP, 2019). Moreover, water scarcity has led to catastrophic ecological-environmental consequences over the past 100 years, such as forest degradation, loss of nearly half of the world's wetlands, drying up of lakes, etc. In such a worrying context, the sector that is the most affected by the increasing global water scarcity is undoubtedly agriculture, which is also the main cause of water consumption (Li et al., 2020; Mekonnen and Hoekstra, 2016). In this sense, it is the greatest user of water, since it causes almost 69 percent of global water consumption (UNESCO and UN-Water, 2020). In the last centuries, the agriculture sector, however, has been considered one of the most vulnerable sectors to scarcity of water resources (Mardani Najafabadi and Ashktorab, 2022; Li et al., 2018; Davidson, 2014), and without suitable accessible freshwater, humans do not have possibilities for agricultural production (e.g., irrigating crops) and then for guaranteeing food security (Zhai et al., 2022).

Given this strong nexus between agriculture and water, in recent years it has been possible to notice a convergence between scientific research and land policies, by identifying as a key element the "land use" that can have different impacts not only on water resources (Tekleab et al., 2014; Maes et al., 2012), but also on soil erosion, land contamination, and pollution (Jiang et al., 2019; Shangguan et al., 2012).

In this perspective, land use planning by converting and managing land for socio-economic benefits (Xie and Wang, 2015), could put into practice aims at best meeting the present needs of people while safeguarding resources for the future. For a good planning, there must be the need for change, better management, or the need for another pattern of land use arising from changing situations. Agricultural ecosystems vary in many environmental and socioeconomic aspects that are interrelated in space and time (Scown et al., 2019). In fact, they represent a dynamic and complex socio-ecological system that needs to be analyzed for reaching sustainability (Müller et al., 2020). Therefore, an interdisciplinary approach at different temporal and spatial scales must be used to assess the sustainability of alternative agricultural systems (Yu et al., 2020; Ingram et al., 2020).

Nowadays, methods to resolve water-agriculture conflicts are based on land-use planning adopted to achieve different goals in the agricultural sector (Hirji and Davis, 2009). Managing the water resource optimally and sustainably implies direct consequences for crop development and food production (Jacobs et al., 2016). In this perspective, mathematical programming models are a valuable tool for land-use planning by determining appropriate agricultural patterns. The application of mathematical models for land-use planning has taken a considerable interest over time in scientific literature, with a significant growth in more recent years (Khorsandi et al., 2023; Ghaffari et al., 2022; Mardani Najafabadi et al., 2022; Mellaku and Sebsibe, 2022; Zeng et al., 2017; Accorsi et al., 2016; Woodruff and BenDor, 2016; Pilehforooshha et al., 2014; Cao et al., 2012; Darradi et al., 2012). However, most of the agroecosystem planning issues show a multi-objective, risky, and uncertain nature. In this sense, economic models of agriculture, land-use models, systemic theories, GIS techniques, and geospatial data are key methodologies to address several challenges related to the achievement of SDGs (Avtar et al., 2020; Weiss et al., 2020).

In the perspective of solving the conflicts between agriculture and water use, this paper proposes an Interval Meta-Goal Programming Model (IMGPM) dealing with imprecision in data that covers interval coefficients, target intervals, and interval bounds of meta-goals. In particular, the interval and MGP method is based on the combination of the methods proposed by Sen and Pal (2013) and by Rodriguez Uria et al. (2002) to overcome uncertainty in MGP. This new methodology has been tested in a study area in Iran to validate its added value in solving conflicting uses of natural resources by economic sectors. This integration together with its application for sustainable optimal cropping patterns (agroecosystem planning) represents a novelty in the field of ecological modeling.

The remainder of this paper proceeds as follows: Section 2 discusses the conceptual framework. Section 3 presents the materials and methods. Section 4 shows the results, while the following Section 5 gives a discussion of the empirical results. Finally, Section 6 concludes.

2. Conceptual framework

The environmental and ecological processes have been strongly affected by anthropogenic activities such as land use changes that can remarkably alter the provision of ecosystem services (Wu et al., 2018; Fan and Shibata, 2015; Hansen and DeFries, 2007). In fact, land use is a major driver of changes in the landscape spatial pattern with consequences on the provision of ecosystem services (Lawler et al., 2014), and on ecological processes, with a remarkable influence on water resources and food production (Divinsky et al., 2017; Tian et al., 2016; Cavender-Bares et al., 2015).

On the other hand, agriculture is an extremely risky sector (Adnan et al., 2021; Hardaker et al., 2015), and producers are continuously facing production, financial and marketing, and environmental risks (Velandia et al., 2009; Musser and Patrick, 2002). Therefore, farmers' decision-making process based on the adoption of appropriate strategies is affected by their knowledge of these risks (Kalbali et al., 2021). Gordon et al. (2010), for example, highlighted trade-offs between food production and ecosystem services resulting from agriculture-induced changes to manage water for agricultural uses. Cropland planning is essential for water management in agriculture (Karrou and Oweis, 2012), as it can optimize agricultural production and irrigation water productivity concomitantly. In the context of land use change, crop area planning is a complex decision-making issue for many goals, constraints, or coefficients. It cannot be defined precisely because of the many stakeholders involved, which show several and very often conflicting objectives (Puustinen et al., 2022; Sarker and Quaddus, 2002). Therefore, optimized results should provide decision support for efficient agricultural production and effective use of irrigation water (Zhang et al., 2023).

The Goal Programming (GP) approach is recognized as one of the most important tools for multi-objective analysis of decisions in agroecosystem planning (Aksaraylı and Pala, 2018; Zhuang and Hocine, 2018; Hanks et al., 2017; Tu and Chang, 2016). Also, there are some methods that deal with uncertainty and imprecision in GP formulation such as Interval GP (IGP) (Sen and Pal, 2013; Chang and Lin, 2009; Chang, 2006; Vitoriano and Romero, 1999), Fuzzy GP (Wang and Liang, 2006; Nishizaki and Sakawa, 2000), and Stochastic GP (Aouni et al., 2012; Aouni and Torre, 2010). Conversely, Charnes and Collomb (1972) presented IGP to allow decision-makers (DM) to select an interval target value that is acceptable from the end of the interval target level.

In the context of sustainable cropping patterns, Fig. 1 shows the main ecological, social, and economic targets to avoid irreparable losses in the agricultural sector and the failure of cropping patterns in long-term

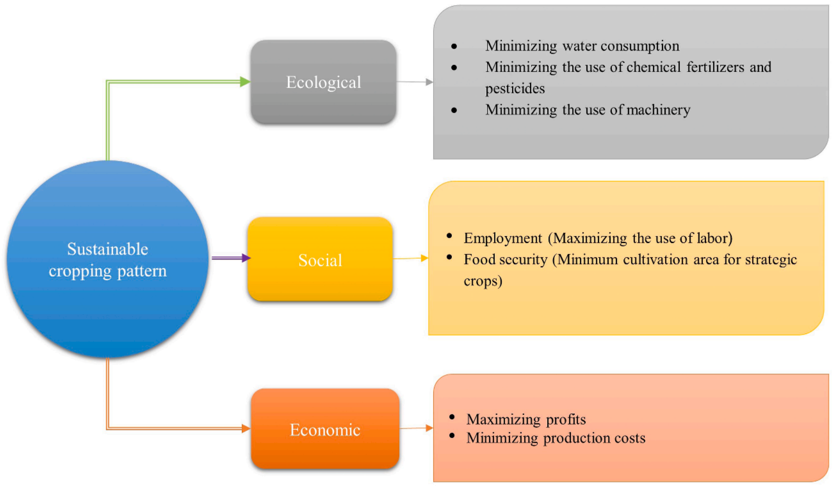

Fig. 1. Conceptual framework of sustainable cropping pattern based on ecological, social, and economic targets.

agricultural planning.

The framework used in this study and described by the conceptual diagram in Fig. 2 can be seen as a starting point for establishing a Decision Support System (DSS) that identifies the most suitable management practices while balancing agricultural production and the sustainable use of water. This methodology is finalized to illustrate the reliability and flexibility of the present model by proposing an IMGPM for agroecosystem planning to achieve different goals and manage the imprecision of included data flow coefficients, target ranges, and flow limits. Notably, this approach leads to four formulations of the meta-goal problem, including META-POS-LOW, META-POS-UPP, META-NES-LOW, and META-NES-UPP and is based on the combination of the methods proposed by Sen and Pal (2013) and Rodriguez Uria et al. (2002) to overcome uncertainty in meta-goals programming models.

Finally, the model has been tested in a study area that has highlighted the potentiality of the methodology to face uncertainty when not all data are available (Fig. 2). Selections for achievement functions have been carried out by introducing the concept of meta-goal that is based on a mix of functions (Zhuang and Hocine, 2018; Rodriguez Uria et al., 2002). Thus, this approach is more flexible in terms of expressing the preferences of a DM to derive a meta-achievement function for a decision-making problem (Caballero et al., 2006; Rodriguez Uria et al., 2002). In other words, Meta-Goal Programming (MGP) is a simultaneous cognitive assessment of original decision goals considered in a GP model (Lin et al., 2009).

3. Materials and Methods

3.1. Study area

Some attractive aspects of the framework developed in this study are presented through the application to an agroecosystem planning problem related to the production of the principal crops grown on the right side of the Nekooabad agricultural irrigation network, which covers 15,000 ha in Isfahan province, Iran (Fig. 3). Although Iran is a water-scarce country its water consumption in agriculture is almost half the

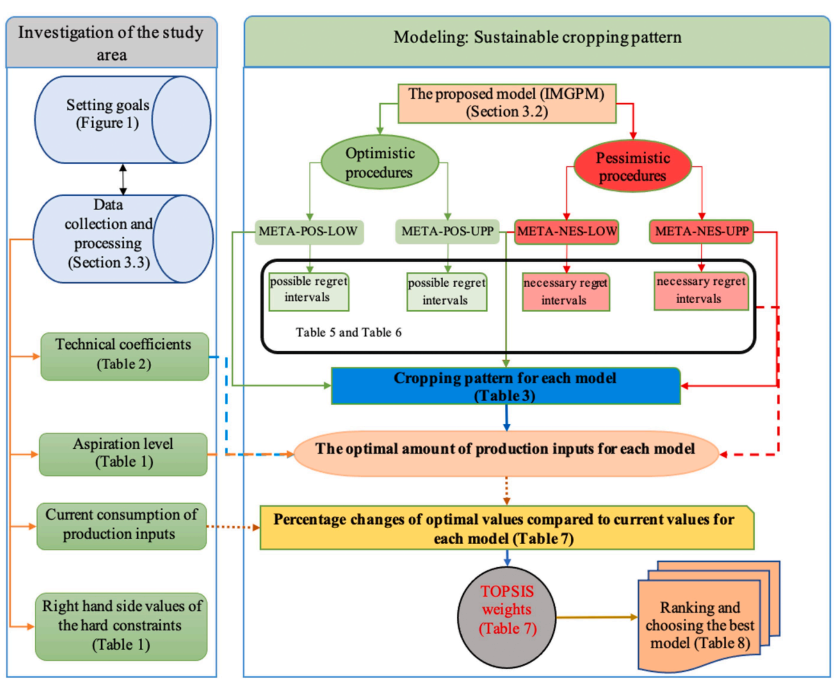

Fig. 2. Conceptual diagram of the model.

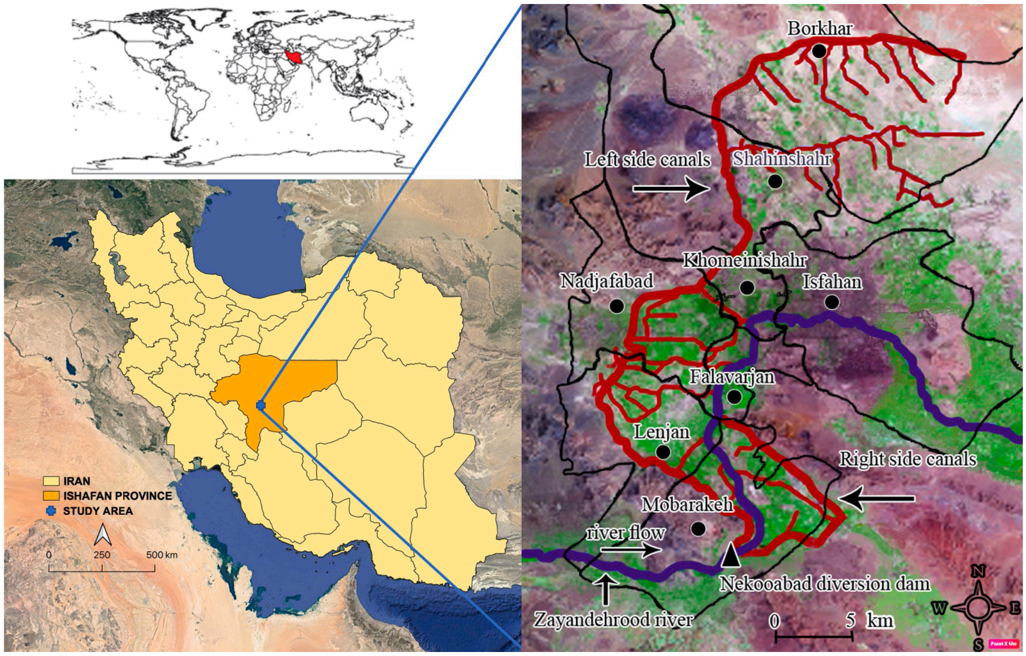

Fig. 3. The study area.

world average (Nazari et al., 2018). In addition, the pressure on water availability in Iran has increased (Saemian et al., 2022), despite the decrease in water availability, irrigated agricultural land has been maintained or expanded in recent decades (Maghrebi et al., 2020).

So, such unsustainable development of agricultural land in this arid country has resulted in the drought of streams (Madani, 2014) and large groundwater drawdown, since half of Iran's fresh water is delivered by groundwater reserves (Loghmani Khouzani, et al., 2022). The economic and population growth amplified groundwater withdrawal from 16,517 Mm^3 in 1972 to about 61,093 Mm^3 in 2014 (Emadodin et al., 2019). Also, studies show that the amount of irrigation water consumption is much higher than the average of similar regions in terms of climate and soil texture due to the lack of proper management of the cultivation program in the region (Mardani Najafabadi et al., 2019; Sabouni and Mardani, 2013). Due to the indiscriminate use of this scarce input, the excess irrigation water in this network returns to the rivers through the drains and causes water contamination because of excess of fertilizers and pesticides. In addition, surveys show that this region is facing many problems in terms of the employment of agricultural labor and the livelihood of rural households (Nikouei et al., 2022; Nikouei et al., 2012). According to the official statistics of government organizations, the consumption of fertilizers and pesticides in the lands of the study area is 5.3 times the average in Iran. Therefore, choosing this region to determine the sustainable planning of agricultural crops, which leads to the optimal use of inputs, increasing employment, and gross profit of farmers in the region, seems appropriate.

3.2. Methodology

Let us consider the following generic GP problem (Romero, 2004):

$$
\begin{aligned}
&Min\,a = \mathrm{A}(\mathrm{n},\mathrm{p})\\
&subjectto\\
&\mathrm{f}_i(\mathbf{x}) + n_i - p_i = g_i \forall i\\
&\mathbf{x} \in \mathbf{F}\\
&n_i, p_i \geq 0 \forall i
\end{aligned}
\tag{1}
$$

where g_i (i=$1,\ldots,I$) is the aspiration level of the ith goal; n_i and p_i are the respective negative and positive deviations from target values of the ith goal; **F** is a feasible set of points in the decision space; $A(\boldsymbol{n},\boldsymbol{p})$ is the generic achievement function that includes vector of i negative deviational variables (**n**) and the vector of i positive deviational variables (**p**) that need to be minimized.

MGP is an extension of GP. The three types of meta-goal are proposed by Rodriguez Uria et al. (2002); these are as follows:

Type 1: a meta-goal involving the percentage sum of unwanted deviation variables on the set $S_k^1 = \{(H_k^1)|H_k^1 \subset \{1,\cdots,I\}, k = \{1,\cdots,r_1\}\}$.

Type 2: a meta-goal involving the maximum percentage deviation on the set $S_l^2 = \{(H_l^2)|H_l^2 \subset \{1,\cdots,I\}, l = \{1,\cdots,r_2\}\}$.

Type 3: a meta-goal involving the percentage of unachieved goals on the set$S_r^3 = \{(H_r^3)|H_r^3 \subset \{1,\cdots,I\}, r = \{1,\cdots,r_3\}\}$.

H is the subset of goals that are considered in each type of meta-goal.

In this way, the following MGP is presented in model (2):

$$
\begin{aligned}
&\min z = \left\{\beta_1^1,\ldots,\beta_{r_1}^1,\beta_1^2,\ldots,\beta_{r_2}^2,\beta_1^3,\ldots,\beta_{r_3}^3\right\}\\
&S.t.\\
&f_i(X) + n_i - p_i = g_i, && \forall i,\\
&X \in F,\\
&\sum_{i\in S_k^1}(\delta_i n_i + \lambda_i p_i) + \alpha_k^1 - \beta_k^1 = q_k^1 && \forall k,\\
&\delta_i n_i + \lambda_i p_i - W_l^d \leq 0, && \forall i \in S_l^2, \forall l\\
&W_l^d + \alpha_l^2 - \beta_l^2 \leq q_l^2, && \forall l\\
&-M_i < \delta_i n_i + \lambda_i p_i - M_i y_i \leq 0,\ y_i = \{1,0\}, && \forall i \in S_r^3,\\
&\frac{\sum_{i\in S_r^3} y_i}{card\left(S_r^3\right)} + \alpha_r^3 - \beta_r^3 \leq q_r^3, && \forall r,\\
&n_i, p_i \geq 0, && \forall i,\\
&\alpha_k^1,\beta_k^1,\alpha_l^2,\beta_l^2,\alpha_r^3,\beta_r^3 \geq 0.
\end{aligned}
\tag{2}
$$

In Eq. 2, the objective function is to minimize unwanted deviation variables. q_k^1 is a certain bound that the percentage sum of the unwanted deviation variables should be at least equal or smaller than it (first type of meta-goal). q_l^2 is a certain bound that the maximum percentage of the sum of unwanted deviation variables should be at least equal or smaller than it (second type of meta-goal). W_l^d is the maximum percentage of weighted deviation. The third type of meta-goal demonstrates the percentage of unachieved goals that should be at least equal or smaller than a certain bound q_r^3. This meta-goal is slightly modified with the introduction of a lower bound parameter $-M_i$ (Lin et al., 2009) compared to the model suggested by Rodriguez Uria et al. (2002). This lower bound parameter is necessary to guarantee y_i to have a value of 0 when unwanted deviation variables for a goal are 0.

$\delta_i = \omega_i / k_i$ is applied if negative deviational variables are unwanted, otherwise $\delta_i = 0$, $\tau_i = \omega_i / k_i$ if positive deviational variables are unwanted, otherwise $\tau_i = 0$. The parameters k_i and ω_i are the normalization constants associated with the ith goal and preference weights, respectively. α_k^1 and β_k^1 are negative and positive deviation variables of the kth Type 1 meta-goal, α_l^2 and β_l^2 are negative and positive deviation variables of the lth Type 2 meta-goal, and α_r^3 and β_r^3 are negative and positive deviation variables of the rth Type 3 meta-goal.

To formulate a GP problem with interval coefficients and target intervals, Sen and Pal (2013) method requires four formulations based on combinations of two kinds of deviation (a possible one and a necessary one) and two kinds of decision procedure (optimistic and pessimistic). Optimistic and pessimistic decision procedures are related to minimizing the lower bound and minimizing the upper bound of the regret interval functions, respectively.

The formulation of the generic GP problem with interval coefficients and target intervals proposed by the model presented by Sen and Pal (2013) is as follows:

$$
\begin{aligned}
&\mathit{Goals}\\
&\overset{J}{\underset{j=1}{(+)}}\, C_{ij}x_j = T_i \forall i\\
&\mathit{subjectto}\\
&X \in F
\end{aligned}
\tag{3}
$$

where $(+)$ is “a possibly extended operator addition” between intervals. C_{ij} ($i=1,\ldots,I$, $j=1,\ldots,J$) is the convention for denoting intervals for a possible region of coefficient c_{ij} closed by the left ($\underline{C}_{ij}$) and right ($\overline{C}_{ij}$) endpoints ($C_{ij} = \left[\underline{C}_{ij}, \overline{C}_{ij}\right]$). T_i ($i=1,\ldots,I$) is the convention of denoting intervals for a possible region of the target value t_i closed by the left ($\underline{T}_i$) and right ($\overline{T}_i$) endpoints ($T_i = [\underline{T}_i, \overline{T}_i]$).

Sen and Pal (2013) obtained two formulations of problem 3 that consider possible deviations. A possibly extended operator subtraction (–), the possible deviation ($D_i = [\underline{D}_i, \overline{D}_i]$) between $(+)_{j=1}^J C_{ij}x_j = \left[\sum_{j=1}^J \underline{C}_{ij}x_j, \sum_{j=1}^J \overline{C}_{ij}x_j\right]$ and the target interval of goals (T_i) was defined. The other two formulations of the problem consider the case of necessary deviations ($E_i = [\underline{E}_i, \overline{E}_i]$of $(+)_{j=1}^J C_{ij}x_j$ from T$_i$) by defining “a necessary extended operator subtraction”)-(. For more details see Appendix A.

In general, to solve the IGP problem 3 based on this method, four linear problems must be solved; two problems with an optimistic procedure based on possible deviations minimize the lower and upper bounds of the possible regret interval (POS-LOW and POS-UP problems) and two problems with a pessimistic procedure based on the necessary deviations minimize the lower and upper bounds of the necessary regret interval (NES-LOW and NES-UP problems). Again, for more details see Appendix A.

Based on this method, for each type of meta goal, a set of possible and necessary deviations was made and based on them, four problems were presented to solve IMGPM (for more details see Appendix B). If the DM considers minimizing the lower bound of this possible regret interval, then an optimistic procedure in the case of possible deviation is determined as follows (META-POS-LOW):

$$
\begin{aligned}
&\min \lambda \left(\sum_{k=1}^{r_1} w_k \left(\underline{\alpha}_k^{\prime 1} + \overline{\beta}_k^{\prime 1}\right) + \sum_{l=1}^{r_2} w_l \left(\underline{\alpha}_l^{\prime 2} + \overline{\beta}_l^{\prime 2}\right) + \sum_{r=1}^{r_3} w_r \left(\underline{\alpha}_r^{\prime 3} + \overline{\beta}_r^{\prime 3}\right) \right) + (1-\lambda)\underline{V}'\\
&S.t.\\
&\sum_{j=1}^{J} \overline{C}_{ij}x_j + \underline{D}_i^n - \underline{D}_i^p = \underline{T}_i, \quad \forall i,\\
&\sum_{j=1}^{J} \underline{C}_{ij}x_j + \overline{D}_i^n - \overline{D}_i^p = \overline{T}_i \quad \forall i,\\
&\sum_{i \in S_k^1} \left(\left(\overline{\varpi}_i / \underline{K}_i\right) \left(\underline{D}_i^n + \overline{D}_i^p\right) \right) + \underline{\alpha}_k^{\prime 1} - \overline{\beta}_k^{\prime 1} = \underline{Q}_k^1, \ \forall k,\\
&\sum_{i \in S_k^1} \left(\left(\underline{\varpi}_i / \overline{K}_i\right) \left(\underline{D}_i^n + \overline{D}_i^p\right) \right) + \underline{\alpha}_k^{\prime 1} - \overline{\beta}_k^{\prime 1} = \overline{Q}_k^1, \ \forall k,\\
&\left(\left(\overline{\varpi}_i / \underline{K}_i\right) \left(\underline{D}_i^n + \overline{D}_i^p\right) \right) - \underline{W}_l^{\prime d} \le 0, \quad \forall i \in S_l^2, \forall l,\\
&\left(\left(\underline{\varpi}_i / \overline{K}_i\right) \left(\underline{D}_i^n + \overline{D}_i^p\right) \right) - \overline{W}_l^{\prime d} \le 0, \quad \forall i \in S_l^2, \forall l,\\
&\underline{W}_l^{\prime d} \le \overline{W}_l^{\prime d}, \qquad \forall i \in S_l^2\\
&\overline{W}_l^{\prime d} + \underline{\alpha}_l^{\prime 2} - \overline{\beta}_l^{\prime 2} = \underline{Q}_l^2, \quad \forall l,\\
&\underline{W}_l^{\prime d} + \overline{\alpha}_l^{\prime 2} - \overline{\beta}_l^{\prime 2} = \overline{Q}_l^2, \quad \forall l,\\
&-M_i \le \left(\underline{D}_i^n + \overline{D}_i^p\right) - M_i \underline{Y}_i \le 0, \quad \forall i \in S_r^3,\\
&-M_i \le \left(\underline{D}_i^n + \overline{D}_i^p\right) - M_i \overline{Y}_i \le 0, \quad \forall i \in S_r^3,\\
&\underline{Y}_i \le \overline{Y}_i, \qquad \forall i \in S_r^3,\\
&\sum_{i \in S_r^3} \frac{\overline{Y}_i}{card\left(S_r^3\right)} + \underline{\alpha}_r^{\prime 3} - \underline{\beta}_r^{\prime 3} = \underline{Q}_r^3, \quad \forall r,\\
&\sum_{i \in S_r^3} \frac{\underline{Y}_i}{card\left(S_r^3\right)} + \overline{\alpha}_r^{\prime 3} - \overline{\beta}_r^{\prime 3} = \overline{Q}_r^3, \quad \forall r,\\
&\underline{\alpha}_k^{\prime 1} + \overline{\beta}_k^{\prime 1} \le \underline{V}', \qquad \forall k,\\
&\underline{\alpha}_l^{\prime 2} + \overline{\beta}_l^{\prime 2} \le \underline{V}', \qquad \forall l,\\
&\underline{\alpha}_r^{\prime 3} + \overline{\beta}_r^{\prime 3} \le \underline{V}', \qquad \forall r,
\end{aligned}
\tag{4}
$$

While a pessimistic procedure in the case of possible deviation is as follows (META-POS-UP):

$$
\begin{aligned}
&\min \lambda\left(\sum_{k=1}^{r_1} w_k v_k+\sum_{l=1}^{r_2} w_l v_l+\sum_{r=1}^{r_3} w_r v_r\right)+(1-\lambda)\overline{V}'\\
&S.t\\
&\sum_{j=1}^{J}\overline{C}_{ij}x_j+\underline{D}_i^n-\underline{D}_i^p=\underline{T}_i,\ \forall i,\\
&\sum_{j=1}^{J}\underline{C}_{ij}x_j+\overline{D}_i^n-\overline{D}_i^p=\overline{T}_i,\ \forall i,\\
&\sum_{i\in S_k^1}\left((\overline{\varpi}_i/\underline{K}_i)\left(\underline{D}_i^n+\overline{D}_i^p\right)\right)+\underline{\alpha}_k^{\prime 1}-\underline{\beta}_k^{\prime 1}=\underline{Q}_k^1,\forall k,\\
&\sum_{i\in S_k^1}\left((\underline{\varpi}_i/\overline{K}_i)\left(\underline{D}_i^n+\overline{D}_i^p\right)\right)+\overline{\alpha}_k^{\prime 1}-\overline{\beta}_k^{\prime 1}=\overline{Q}_k^1,\forall k,\\
&\left((\overline{\varpi}_i/\underline{K}_i)\left(\underline{D}_i^n+\overline{D}_i^p\right)\right)-\underline{W}_l^{\prime d}\le 0,\ \forall i\in S_l^2,\forall l,\\
&\left((\underline{\varpi}_i/\overline{K}_i)\left(\underline{D}_i^n+\overline{D}_i^p\right)\right)-\overline{W}_l^{\prime d}\le 0,\ \forall i\in S_l^2,\forall l,\\
&\underline{W}_l^{\prime d}\le\overline{W}_l^{\prime d}\qquad \forall i\in S_l^2,\\
&\underline{W}_l^{\prime d}+\underline{\alpha}_l^{\prime 2}-\underline{\beta}_l^{\prime 2}=\overline{Q}_l^2,\ \forall l,\\
&\overline{W}_l^{\prime d}+\overline{\alpha}_l^{\prime 2}-\overline{\beta}_l^{\prime 2}=\underline{Q}_l^2,\ \forall l,\\
&-M_i\le\left(\underline{D}_i^n+\overline{D}_i^p\right)-M_i\underline{Y}_i\le 0,\quad \forall i\in S_r^3,\\
&-M_i\le\left(\underline{D}_i^n+\overline{D}_i^p\right)-M_i\overline{Y}_i\le 0,\quad \forall i\in S_r^3,\\
&\underline{Y}_i\le\overline{Y}_i,\qquad \forall i\in S_r^3,\\
&\sum_{i\in S_r^3}\frac{\underline{Y}_i}{card\left(S_r^3\right)}+\underline{\alpha}_r^{\prime 3}-\underline{\beta}_r^{\prime 3}=\overline{Q}_r^3,\ \forall r,\\
&\sum_{i\in S_r^3}\frac{\overline{Y}_i}{card\left(S_r^3\right)}+\overline{\alpha}_r^{\prime 3}-\overline{\beta}_r^{\prime 3}=\underline{Q}_r^3,\ \forall r,\\
&\underline{\beta}_k^{\prime 1}\le v_k,\overline{\alpha}_k^{\prime 1}\le v_k,v_k\le\overline{V}',\qquad \forall k,\\
&\underline{\beta}_l^{\prime 2}\le v_l,\overline{\alpha}_l^{\prime 2}\le v_l,v_l\le\overline{V}',\qquad \forall l,\\
&\underline{\beta}_r^{\prime 3}\le v_r,\overline{\alpha}_r^{\prime 3}\le v_r,v_r\le\overline{V}',\qquad \forall r.
\end{aligned}
\tag{5}
$$

In order to obtain the two other formulations (necessary formulation) of the MGP problem 2, consideration is given to minimizing the lower and upper bounds of these necessary regret intervals. An optimistic procedure in the case of necessary deviation is as follows (META-NES-LOW):

$$
\begin{aligned}
&\min \lambda\Bigg(\sum_{k=1}^{r_1} w_k\left(z_k\left(\underline{\alpha}_k^{\prime\prime 1}+\overline{\beta}_k^{\prime 1}\right)+(1-z_k)\left(\underline{\beta}_k^{\prime\prime 1}+\overline{\alpha}_k^{\prime\prime 1}\right)\right)+\\
&\quad\sum_{l=1}^{r_2} w_l\left(z_l\left(\underline{\alpha}_l^{\prime\prime 2}+\overline{\beta}_l^{\prime 2}\right)+(1-z_l)\left(\underline{\beta}_l^{\prime\prime 2}+\overline{\alpha}_l^{\prime\prime 2}\right)\right)+\\
&\quad\sum_{r=1}^{r_3} w_r\left(z_r\left(\underline{\alpha}_r^{\prime\prime 3}+\overline{\beta}_r^{\prime 3}\right)+(1-z_r)\left(\underline{\beta}_r^{\prime\prime 3}+\overline{\alpha}_{\backslash r}^{\prime\prime 3}\right)\right)\Bigg)+(1-\lambda)\underline{U}'\\
&S.t.\\
&\sum_{j=1}^{J}\underline{C}_{ij}x_j+\underline{E}_i^n-\underline{E}_i^p=\underline{T}_i,\qquad \forall i,\\
&\sum_{j=1}^{J}\overline{C}_{ij}x_j+\overline{E}_i^n-\overline{E}_i^p=\overline{T}_i,\qquad \forall i,\\
&\sum_{i\in S_k^1}\left((\underline{\varpi}_i/\overline{K}_i)\left(\underline{E}_i^n+\overline{E}_i^p\right)\right)+\underline{\alpha}_k^{\prime\prime 1}-\underline{\beta}_k^{\prime\prime 1}=\underline{Q}_k^1,\forall k,\\
&\sum_{i\in S_k^1}\left((\overline{\varpi}_i/\underline{K}_i)\left(\underline{E}_i^n+\overline{E}_i^p\right)\right)+\overline{\alpha}_k^{\prime\prime 1}-\overline{\beta}_k^{\prime\prime 1}=\overline{Q}_k^1,\ \forall k,\\
&\left((\underline{\varpi}_i/\overline{K}_i)\left(\underline{E}_i^n+\overline{E}_i^p\right)\right)-\underline{W}_l^{\prime d}\le 0,\quad \forall i\in S_l^2,\forall l,\\
&\left((\overline{\varpi}_i/\underline{K}_i)\left(\underline{E}_i^n+\overline{E}_i^p\right)\right)-\overline{W}_l^{\prime d}\le 0,\quad \forall i\in S_l^2,\forall l,\\
&\underline{W}_l^{\prime d}\le\overline{W}_l^{\prime d},\qquad \forall i\in S_l^2\\
&\underline{W}_l^{\prime d}+\underline{\alpha}_l^{\prime 2}-\underline{\beta}_l^{\prime 2}=\underline{Q}_l^2,\qquad \forall l,\\
&\overline{W}_l^{\prime d}+\overline{\alpha}_l^{\prime 2}-\overline{\beta}_l^{\prime 2}=\overline{Q}_l^2,\qquad \forall l,\\
&-M_i\le\left(\underline{E}_i^n+\overline{E}_i^p\right)-M_i\underline{Y}_i\le 0,\qquad \forall i\in S_r^3,\\
&-M_i\le\left(\underline{E}_i^n+\overline{E}_i^p\right)-M_i\overline{Y}_i\le 0,\qquad \forall i\in S_r^3,\\
&\underline{Y}_i\le\overline{Y}_i,\qquad \forall i\in S_r^3\\
&\sum_{i\in S_r^3}\frac{\underline{Y}_i}{card\left(S_r^3\right)}+\underline{\alpha}_r^{\prime\prime 3}-\underline{\beta}_r^{\prime\prime 3}=\underline{Q}_r^3,\qquad \forall r,\\
&\sum_{i\in S_r^3}\frac{\overline{Y}_i}{card\left(S_r^3\right)}+\overline{\alpha}_r^{\prime\prime 3}-\overline{\beta}_r^{\prime\prime 3}=\overline{Q}_r^3,\qquad \forall r,\\
&z_k\left(\underline{\alpha}_k^{\prime\prime 1}+\overline{\beta}_k^{\prime\prime 1}\right)+(1-z_k)\left(\underline{\beta}_k^{\prime\prime 1}+\overline{\alpha}_k^{\prime\prime 1}\right)\le\underline{U}',\forall k,\\
&z_l\left(\underline{\alpha}_l^{\prime\prime 2}+\overline{\beta}_l^{\prime\prime 2}\right)+(1-z_l)\left(\underline{\beta}_l^{\prime\prime 2}+\overline{\alpha}_l^{\prime\prime 2}\right)\le\underline{U}',\forall l,\\
&z_r\left(\underline{\alpha}_r^{\prime\prime 3}+\overline{\beta}_r^{\prime\prime 3}\right)+(1-z_r)\left(\underline{\beta}_r^{\prime\prime 3}+\overline{\alpha}_r^{\prime\prime 3}\right)\le\underline{U}',\ \forall r,
\end{aligned}
\tag{6}
$$

Finally, a pessimistic procedure in the case of necessary deviation of the MGP problem 2 leads to the following linear programming problem (META-NES-UPP problem):

$$
\begin{aligned}
&\min \lambda\left(\sum_{k=1}^{r_1} w_k u_k+\sum_{l=1}^{r_2} w_l u_l+\sum_{r=1}^{r_3} w_r u_r\right)+(1-\lambda)\overline{U'}\\
&S.t.\\
&\sum_{j=1}^{J}\overline{C}_{ij}x_j\underline{C}_{ij}x_j+\underline{E}_i^n-\underline{E}_i^p=\underline{T}_i,\forall i,\\
&\sum_{j=1}^{J}\overline{C}_{ij}x_j+\overline{E}_i^n-\overline{E}_i^p=\overline{T}_i,\quad \forall i,\\
&\sum_{i\in S_k^1}\left(\left(\overline{\varpi}_i/\underline{K}_i\right)\left(\underline{E}_i^n+\overline{E}_i^p\right)\right)+\underline{\alpha}''^{1}_{k}-\underline{\beta}''^{1}_{k}=\underline{Q}_k^1,\forall k,\\
&\sum_{i\in S_k^1}\left(\left(\underline{\varpi}_i/\overline{K}_i\right)\left(\underline{E}_i^n+\overline{E}_i^p\right)\right)+\overline{\alpha''}^{1}_{k}-\overline{\beta''}^{1}_{k}=\overline{Q}_k^1,\ \forall k,\\
&\left(\left(\overline{\varpi}_i/\underline{K}_i\right)\left(\underline{E}_i^n+\overline{E}_i^p\right)\right)-\underline{W}'^{d}_{l}\le 0,\quad \forall i\in S_l^2,\forall l,\\
&\left(\left(\underline{\varpi}_i/\overline{K}_i\right)\left(\underline{E}_i^n+\overline{E}_i^p\right)\right)-\overline{W'}^{d}_{l}\le 0,\quad \forall i\in S_l^2,\forall l,\\
&\underline{W}'^{d}_{l}\le\overline{W'}^{d}_{l},\qquad \forall i\in S_l^2\\
&\underline{W}'^{d}_{l}+\underline{\alpha}''^{2}_{l}-\underline{\beta}''^{2}_{l}=\overline{Q}_l^2,\qquad \forall l,\\
&\overline{W'}^{d}_{l}+\overline{\alpha''}^{2}_{l}-\overline{\beta''}^{2}_{l}=\underline{Q}_l^2,\qquad \forall l,\\
&-M_i\le\left(\underline{E}_i^n+\overline{E}_i^p\right)-M_i\underline{Y}_i\le 0,\qquad \forall i\in S_r^3,\\
&-M_i\le\left(\underline{E}_i^n+\overline{E}_i^p\right)-M_i\overline{Y}_i\le 0,\qquad \forall i\in S_r^3,\\
&\underline{Y}_i\le\overline{Y}_i,\qquad \forall i\\
&\sum_{i\in S_r^3}\frac{\underline{Y}_i}{card\left(S_r^3\right)}+\underline{\alpha}''^{3}_{r}-\underline{\beta}''^{3}_{r}=\underline{Q}_r^3,\quad \forall r,\\
&\sum_{i\in S_r^3}\frac{\overline{Y}_i}{card\left(S_r^3\right)}+\overline{\alpha''}^{3}_{r}-\overline{\beta''}^{3}_{r}=\overline{Q}_r^3,\quad \forall r,\\
&\underline{\beta}''^{1}_{k}+\underline{\alpha}''^{1}_{k}\le u_k,\overline{\alpha''}^{1}_{k}-\overline{\beta''}^{1}_{k}\le u_k,u_k\le\overline{U'},\quad \forall k,\\
&\underline{\alpha}''^{2}_{l}-\underline{\beta}''^{2}_{l}\le u_l,\overline{\alpha''}^{2}_{l}-\overline{\beta''}^{2}_{l}\le u_l,u_l\le\overline{U'},\quad \forall l,\\
&\underline{\alpha}''^{3}_{r}-\underline{\beta}''^{3}_{r}\le u_r,\overline{\alpha''}^{3}_{r}-\overline{\beta''}^{3}_{r}\le \mathrm{u_r},\mathrm{u_r}\le\overline{\mathrm{U}'}\quad \forall r.
\end{aligned}
\tag{7}
$$

Hence, the four formulated problems (META-POS-LOW, META-POS-UPP, META-NES-LOW, and META-NES-UPP) may achieve four types of solutions depending on decisions determined by DM.

The proposed model is presented and solved in GAMS software package. To familiarize the readers with how to code these models, the example of the equations written in this software for the META-POS-LOW model is given in Appendix C. Other models can also be coded with small changes[1].

3.3. Data collection and model characteristics

Data were collected from different agricultural planning units in Nekooabad agricultural irrigation network. The sources of data are the following: District Statistical Yearbook, Statistical Report of Irrigation Systems, and Statistical Report of Long-Term Development Strategies for Iran's Water Resources.

This study presents a problem with 12 goals, interval coefficients and target intervals, and 6 hard constraints (i.e., ones that must be satisfied). The interval data for aspiration levels (targets) of the goals and the Right-Hand Side (RHS) of the hard constraint are presented in Table 1.

[1] The complete GAMS files developed for this paper is available upon reasonable request by the Corresponding Author.

The goal numbers from 1 to 4 are for the economic dimension of sustainable cropping pattern, which leads to an increase in gross profit or a decrease in the production costs of agricultural products. Ecological dimensions are handled in goal numbers from 5 to 11, in which the consumption of inputs that pollute the environment (fertilizers and pesticides) and scarce resources (irrigation water) is reduced to the lowest possible amount. The important issue of labor employment and the self-consumption needs of rural communities, which are part of the social dimensions of the sustainable cultivation model, have been considered in goal number 12 and constraint numbers 7 and 8, respectively. In order to calculate the intervals related to the target levels, the study of Bertsimas and Sim (2004) was used. In their method, a certain data error limit and a symmetric probability distribution are used. Technical restrictions related to the cultivation of agricultural products, including soil quality and climatic conditions, are included in constraints 8 to 10 and, for this purpose, the maximum amount of cultivated area for each product has been determined.

The interval data descriptions for productive resource utilization are given in Table 2. In other words, the values of technical coefficients of constraints and objective function coefficients are included in this table. It is observed that there is a significant difference between agricultural products in the use of agricultural production resources and the amount of gross profit per unit area. This feature provides a suitable advantage for replanning crop cultivation based on the goals defined in the study. For example, the gross profit per hectare for the navy bean is 9.2 times that of the barley, while the amount of fertilizer and pesticide consumption in this crop is much higher than barley. Establishing a compromise between environmental, economic, and social goals in this situation requires specifying a suitable mathematical programming model.

Table 1
Crops, goals, and constraints discretion.

Goals Goal numbers	Discretion	Aspiration level (target)
1	Profit (in US $)	[9.28×10^5, 4.64×10^6]
2	Machine-hour (in hours)	[3.63×10^6, 8.63×10^6]
3	Cash expenditure (in US $))	[14.22×10^6, 16.10×10^6]
4	Seed requirement (in metric ton):	[5.45×10^3, 6.91×10^3]
5-7	Fertilizer requirement (in metric ton):	[1.10×10^3, 3.81×10^3]
	a Phosphate	
	a Nitrogen	[1.63×10^4, 5.70×10^4]
	a Potash	[4.84×10^2, 6.84×10^2]
8-10	Pesticides requirement (in kg):	
	a Insecticide	[9.01×10^4, 1.53×10^5]
	a Herbicide	[1.21×10^5, 2.67×10^5]
	a Fungicide	[3.78×10^4, 6.93×10^4]
11	Water consumption (in m^3)	[1.46×10^9, 1.75×10^9]
12	Man-days (in days)	[1.37×10^5, 3.92×10^6]

Constraints Hard constraint numbers	Discretion	RHS
1	Maximum available land (in ha)	1.5×10^4
2-6	Maximum available land for each crop (in ha):	
	Wheat (X_1)	8.18×10^3
	Barley (X_2)	5.58×10^3
	Potato (X_3)	1.57×10^3
	Corn (X_4)	8.20×10^3
	Navy Bean (X_5)	3.21×10^3
7-8	Minimum available land for each crop (in ha):	
	Wheat (X_1)	2.21×10^3
	Barley (X_2)	7.66×10^3

Source: authors' calculations in GAMS.

Table 2
The lower and upper bound of utilization resources for main crops in the study area.

Data	Lower bound Wheat	Barley	Potato	Corn	Navy Bean
Profit (US $/ha)	1.12×10^{3}	0.23×10^{3}	0.88×10^{3}	1.79×10^{3}	2.12×110^{3}
Machine hour (hrs/ha)	1.27×10^{1}	5.88×10^{0}	1.84×10^{1}	6.55×10^{1}	4.95×10^{0}
Cash expenditure (US $ /ha)	6.62×10^{2}	0.47×10^{2}	3.12×10^{2}	0.72×10^{2}	0.55×10^{2}
Seed requirement (kg/ha)	1.01×10^{2}	2.67×10^{0}	1.88×10^{2}	8.38×10^{1}	2.34×10^{3}
Fertilizer_Phosphate (kg/ha)	3.63×10^{0}	3.20×10^{0}	7.41×10^{0}	9.34×10^{0}	6.40×10^{1}
Fertilizer_Nitrogen (kg/ha)	7.71×10^{1}	2.55×10^{1}	1.79×10^{2}	1.11×10^{1}	4.81×10^{1}
Fertilizer_Potash (kg/ha)	8.90×10^{-1}	1.22×10^{-4}	4.86×10^{-1}	1.24×10^{0}	1.57×10^{0}
Pesticides_Insecticide (kg/ha)	4.48×10^{-1}	1.00×10^{-1}	3.34×10^{-1}	1.25×10^{-1}	6.53×10^{-1}
Pesticides_Herbicide (kg/ha)	3.57×10^{-1}	2.66×10^{-1}	2.18×10^{-1}	5.82×10^{-1}	9.24×10^{-1}
Pesticides_Fungicide (kg/ha)	6.24×10^{-3}	2.88×10^{-3}	5.71×10^{-3}	2.66×10^{-1}	1.64×10^{0}
Water consumption (m^3/ha)	3.78×10^{3}	1.20×10^{4}	6.23×10^{3}	1.81×10^{3}	6.45×10^{3}
Man-days (days/ha)	8.29×10^{0}	3.10×10^{0}	1.51×10^{1}	2.51×10^{1}	2.12×10^{1}
Data	**Upper bound Wheat**	**Barley**	**Potato**	**Corn**	**Navy Bean**
Profit (US $/ha)	1.6×10^{3}	1.90×10^{3}	3.44×10^{3}	4.44×10^{3}	3.36×10^{3}
Machine hour (hrs/ha)	3.30×10^{1}	1.24×10^{1}	2.96×10^{1}	9.57×10^{1}	1.69×10^{1}
Cash expenditure (US $ /ha)	14.08×10^{2}	4.44×10^{2}	21.00×10^{2}	1.89×10^{2}	4.9×10^{2}
Seed requirement (kg/ha)	3.78×10^{2}	2.52×10^{1}	2.73×10^{2}	1.67×10^{2}	5.23×10^{3}
Fertilizer_Phosphate (kg/ha)	6.44×10^{0}	6.53×10^{0}	1.88×10^{1}	2.43×10^{1}	1.93×10^{2}
Fertilizer_Nitrogen (kg/ha)	1.31×10^{2}	9.05×10^{1}	2.46×10^{2}	4.01×10^{1}	3.71×10^{2}
Fertilizer_Potash (kg/ha)	2.41×10^{0}	2.45×10^{-3}	1.66×10^{0}	4.16×10^{0}	2.76×10^{0}
Pesticides_Insecticide (kg/ha)	1.17×10^{0}	2.2010^{-1}	5.40×10^{-1}	6.50×10^{-1}	1.53×10^{-1}
Pesticides_Herbicide (kg/ha)	1.28×10^{0}	6.9010^{-1}	6.30×10^{-1}	1.97×10^{0}	1.92×10^{-1}
Pesticides_Fungicide (kg/ha)	2.60×10^{-1}	3.12×10^{-3}	2.40×10^{-3}	3.30×10^{-1}	2.70×10^{0}
Water consumption (m3/ha)	1.14×10^{4}	2.19×10^{4}	1.18×10^{3}	4.30×10^{4}	2.26×10^{4}
Man-days (days/ha)	1.20×10^{1}	8.65×10^{0}	2.77×10^{1}	3.93×10^{1}	3.75×10^{1}

Source: authors' calculations in GAMS.

Table 3
Comparison of land allocation plan for the proposed (IMGP) and Sen and Pal's model under different problems (Unit: ha).

Typology of procedures	Applied methods	Management Problems	Variables Wheat	Barley	Potato	Corn	Navy Bean	Total
Optimistic procedures	Proposed method	META-POS-LOW	7,635	2,585	1,567	0	3,212	15,000
		META-POS-UPP	7,635	2,585	1,567	0	3,212	15,000
	Sen and Pal (2013)	POS-LOW	8,181	2,038	1,567	0	3,212	15,000
		POS-UPP	8,181	2,585	0.00	1,020	3,212	15,000
Pessimistic procedures	Proposed method	META-NES-LOW	8,181	2,102	460	2,888	0	13,633
		META-NES-UPP	8,181	2,095	397	3,008	0	13,684
	Sen and Pal (2013)	NES-LOW	8,181	2,585	0	2,827	0	13,594
		NES-UPP	8,181	2,585	1,567	2,665	0	15,000

Source: authors' calculations in GAMS.

Table 4
Comparison of irrigation water allocation plan for the proposed (IMGP) and Sen and Pal's model under different problems (Unit: million m^3).

Typology of procedure	Applied method	Management Problems	Variables Wheat	Barley	Potato	Corn	Navy bean	Total
Optimistic procedures	Proposed method	META-POS-LOW	57.95	43.82	5.81	0.00	46.66	154.24
		META-POS-UPP	57.95	43.82	5.81	0.00	46.66	154.24
	Sen and Pal (2013)	POS-LOW	62.10	34.56	5.81	0.00	46.66	149.13
		POS-UPP	62.10	43.82	0.00	22.87	46.66	175.45
Pessimistic procedures	Proposed method	META-NES-LOW	62.10	35.64	1.71	64.71	0.00	164.16
		META-NES-UPP	62.10	35.52	1.47	67.41	0.00	166.50
	Sen and Pal (2013)	NES-LOW	62.10	43.82	0.00	63.34	0.00	169.26
		NES-UPP	62.10	43.82	5.81	59.73	0.00	171.46

Source: authors' calculations in GAMS.

4. Results

The land allocation values of crops for different problems are displayed in Table 3 where, except for the POS-LOW and META-POS-LOW problems, the management solutions of our method are different from those in Sen and Pal (2013). In addition, there is a significant variation among solutions determined by the four formulations presented in Sen and Pal (2013), while in our approach this variation is lower. As highlighted in Table 3, the proposed method does not show variation in land allocation values for each crop, while the results of Sen and Pal's method show solutions for each crop with a great variance. This variation determined by the comparison of these solutions leads to confusion and doubt in the decision-makers, even though the most optimistic (POS-LOW) or the most pessimistic (POS-UPP) procedure is chosen. However, the least variation in all problems is for wheat and barley production. This slight variation could be due to the lower bound of

Table 5
Possible deviations and possible regret intervals of goals and meta-goals for sustainable cropping pattern problem.

Variables	Optimistic procedures META-POS-LOW	META-POS-UPP	Pessimistic procedures META-NES-LOW	META-NES-UPP
D'^1_k	[0.30, 4.08]	[1.85, 49.51]	[0.90, 6.33]	[0.90, 6.33]
D'^2_l	[0.07, 0.81]	[0.07, 0.81]	[0.00, 0.97]	[0.00, 0.98]
D'^3_r	[0.00, 1.00]	[0.00, 0.58]	[0.00, 0.92]	[0.00, 1.00]
$D'(X)$	[0.21, 3.02]	[1.24, 33.24]	[0.60, 4.54]	[0.60, 4.55]
Variables	**POS-LOW**	**POS-UPP**	**NES-LOW**	**NES-UPP**
D_1	$[0.00\times10^0,1.42\times10^{10}]$	$[0.00\times10^0,1.35\times10^{10}]$	$[0.00\times10^0,8.11\times10^{10}]$	$[0.00\times10^0,1.06\times10^{10}]$
D_2	$[4.69\times10^5,8.27\times10^6]$	$[4.66\times10^5,8.26\times10^6]$	$[7.52\times10^5,8.46\times10^6]$	$[7.27\times10^5,8.46\times10^6]$
D_3	$[0.00\times10^0,7.73\times10^{11}]$	$[0.00\times10^0,7.73\times10^{11}]$	$[0.00\times10^0,7.73\times10^{11}]$	$[0.00\times10^0,7.73\times10^{11}]$
D_4	$[0.00\times10^0,1.21\times10^7]$	$[0.00\times10^0,1.15\times10^7]$	$[0.00\times10^0,1.18\times10^7]$	$[0.00\times10^0,1.18\times10^7]$
D_5	$[2.39\times10^5,1.72\times10^6]$	$[5.24\times10^5,1.82\times10^6]$	$[5.90\times10^5,1.84\times10^6]$	$[2.89\times10^5,1.74\times10^6]$
D_6	$[0.00\times10^0,3.94\times10^6]$	$[0.00\times10^0,3.89\times10^6]$	$[0.00\times10^0,3.88\times10^6]$	$[0.00\times10^0,3.81\times10^6]$
D_7	$[5.16\times10^4,6.69\times10^5]$	$[5.50\times10^5,6.72\times10^5]$	$[6.84\times10^4,6.76\times10^5]$	$[6.41\times10^4,6.73\times10^5]$
D_8	$[6.57\times10^4,1.47\times10^5]$	$[6.76\times10^4,1.48\times10^5]$	$[6.93\times10^4,1.48\times10^5]$	$[6.69\times10^4,1.47\times10^5]$
D_9	$[4.48\times10^4,2.61\times10^5]$	$[4.68\times10^4,2.62\times10^5]$	$[5.18\times10^4,2.63\times10^5]$	$[4.89\times10^4,2.62\times10^5]$
D_{10}	$[2.39\times10^4,6.58\times10^4]$	$[2.80\times10^4,6.84\times10^4]$	$[2.91\times10^4,6.92\times10^4]$	$[2.48\times10^4,6.67\times10^4]$
D_{11}	$[0.00\times10^0,3.66\times10^8]$	$[0.00\times10^0,3.60\times10^8]$	$[0.00\times10^0,3.44\times10^8]$	$[0.00\times10^0,3.36\times10^8]$
D_{12}	$[3.92\times10^5,3.71\times10^6]$	$[4.27\times10^5,3.74\times10^6]$	$[5.38\times10^5,3.81\times10^6]$	$[4.80\times10^5,3.78\times10^6]$
$D(X)$	$[2.88\times10^5,4.19\times10^{11}]$	$[3.29\times10^5,4.19\times10^{11}]$	$[4.63\times10^5,4.19\times10^{11}]$	$[4.34\times10^5,4.19\times10^{11}]$

Source: authors' calculations in GAMS.

Table 6
Necessary deviations and necessary regret intervals of goals and meta-goals for sustainable cropping pattern problem.

Variables	Optimistic procedures META-POS-LOW	META-POS-UPP	Pessimistic procedures META-NES-LOW	META-NES-UPP
E'^1_k	[1.30, 3.08]	[2.85, 48.51]	[1.90, 5.33]	[1.90, 5.33]
E'^2_l	[0.07, 0.82]	[0.07, 0.82]	[0.22, 0.50]	[0.23, 0.50]
E'^3_r	[0.00, 0.75]	[0.00, 0.58]	[0.00, 0.17]	[0.00, 0.00]
$E'(X)$	[0.87, 2.32]	[1.91, 32.57]	[1.30, 3.67]	[1.30, 3.64]
Variables	**Optimistic procedures POS-LOW**	**POS-UPP**	**Pessimistic procedures NES-LOW**	**NES-UPP**
E_1	$[4.38\times10^9,6.08\times10^9]$	$[3.07\times10^9,5.39\times1^9]$	$[0.00\times10^0,3.99\times10^8]$	$[2.05\times10^9,2.47\times10^9]$
E_2	$[7.73\times10^5,7.97\times10^6]$	$[7.65\times10^5,7.96\times10^6]$	$[9.65\times10^5,8.25\times10^6]$	$[9.58\times10^5,8.22\times10^6]$
E_3	$[0.00\times10^0,7.19\times10^{11}]$	$[0.00\times10^0,7.15\times10^{11}]$	$[0.00\times10^0,7.14\times10^{11}]$	$[0.00\times10^0,7.11\times10^{11}]$
E_4	$[0.00\times10^0,4.86\times10^6]$	$[0.00\times10^0,8.72\times10^6]$	$[0.00\times10^0,9.22\times10^6]$	$[0.00\times10^0,4.70\times10^6]$
E_5	$[5.35\times10^5,1.43\times10^6]$	$[6.28\times10^5,1.71\times10^6]$	$[6.52\times10^5,1.78\times10^6]$	$[5.52\times10^5,1.48\times10^6]$
E_6	$[0.00\times10^0,2.77\times10^6]$	$[0.00\times10^0,3.12\times10^6]$	$[0.00\times10^0,3.09\times10^6]$	$[0.00\times10^0,2.52\times10^6]$
E_7	$[7.77\times10^4,6.43\times10^5]$	$[7.99\times10^4,6.47\times10^5]$	$[8.39\times10^4,6.60\times10^5]$	$[8.14\times10^4,6.56\times10^5]$
E_8	$[7.51\times10^4,1.38\times10^5]$	$[7.59\times10^4,1.39\times10^5]$	$[7.61\times10^4,1.41\times10^5]$	$[7.51\times10^4,1.39\times10^5]$
E_9	$[5.92\times10^4,2.46\times10^5]$	$[6.03\times10^4,2.48\times10^5]$	$[6.17\times10^4,2.53\times10^5]$	$[6.02\times10^4,2.51\times10^5]$
E_{10}	$[2.83\times10^4,6.14\times10^4]$	$[3.09\times10^4,6.55\times10^4]$	$[3.17\times10^4,6.66\times10^4]$	$[2.92\times10^4,6.23\times10^4]$
E_{11}	$[2.32\times10^7,1.35\times10^8]$	$[1.76\times10^7,1.41\times10^8]$	$[1.70\times10^6,2.40\times10^8]$	$[0.00\times10^0,2.08\times10^8]$
E_{12}	$[5.19\times10^5,3.59\times10^6]$	$[5.41\times10^5,3.62\times10^6]$	$[6.16\times10^5,3.73\times10^6]$	$[5.83\times10^5,3.67\times10^6]$
$E(X)$	$[2.37\times10^9,3.90\times10^{11}]$	$[1.66\times10^9,3.88\times10^{11}]$	$[6.57\times10^5,3.87\times10^{11}]$	$[1.11\times10^9,3.85\times10^{11}]$

Source: authors' calculations in GAMS.

Table 7
Percentage changes of optimal values compared to current values and weighted values of TOPSIS method for different models.

Targets	Criteria	Optimistic procedures Proposed method META-POS-LOW	META-POS-UPP	Sen and Pal (2013) POS-LOW	POS-UPP	Pessimistic procedures Proposed method META-NES-LOW	META-NES-UPP	Sen and Pal (2013) NES-LOW	NES-UPP
Economic	Total Profit	-31	32	-29	32	-40	23	-41	12
	Total Cash expenditure	-15	-25	-6	-12	-8	-3	-10	18
Ecological	Total Fertilizer	-9	-6	-11	5	-5	-47	-20	-36
	Total Pesticides	-15	61	9	73	-10	-12	-8	59
	Total Water consumption	-11	34	-4	24	-23	7	-3	24
Social	Total Man-days	-28	23	-27	24	-32	8	-35	19
	TOPSIS weights	0.54	0.54	0.46	0.49	0.51	0.66	0.49	0.43

Source: authors' calculations in GAMS.

constraints for food security in these two strategic crops (hard constraint numbers from 7 and 8 in Table 1).

It should be noted that in the pessimistic procedures, the navy bean is removed from all optimization models, while in the three optimistic modes, META-POS-LOW, META-POS-UPP, and POS-LOW, corn is removed from the cultivation plan. In general, in all optimistic models, the total amount of available cultivated area has been used, while in most pessimistic cases (except NES-UPP), the cultivated area has decreased by about 9%.

Table 4 shows the amount of optimal allocation of available water resources between products for different models. It can be seen that in optimistic procedures, the amount of irrigation water consumption in the proposed cropping pattern was lower than in the model of Sen and Pal (2013). This case is also observed in the pessimistic procedures but with a smaller difference. For example, the difference in the amount of irrigation water consumed between optimistic models META_POS_UPP and POS_UPP was 21.21 million m^3, while between pessimistic models META_NES_UPP and NES_UP was 4.96 million m^3.

In the pessimistic procedures, corn consumes a lot of irrigation water. Although in this case, the area under wheat cultivation is 2 to 3 times (in different models) of this product, even due to the higher water requirement of corn, the irrigation water consumption of these products is not much different. For example, in the META_NES_UPP model, the amount of irrigation water for wheat and corn is 62.10 and 67.41 million m^3, but their cultivated area is 8181 and 3008 hectares, respectively (Table 1). It can be seen that in this case, a difference of 5173 hectares of the cultivated area has only led to a difference of 5.31 million m^3 in irrigation water consumption. On the other hand, by referring to Table 2, it is clear that corn's water requirement at the upper bound of resource utilization is 31,600 m^3 per hectare more than wheat.

A product like potatoes does not make much difference in the allocation of irrigation water between models. Of course, it should be noted that due to the technical issues of planting in the study area, such as the lack of access to harvesting machines, the type of soil, and the quality of water, this product has a limit on the maximum area under cultivation (Table 1), which has led to this lack of difference.

The results for possible deviations and possible regret intervals for each problem are summarized in Table 5. The necessary deviations and the necessary regret intervals are displayed in Table 6. Results are presented from Eqs. 4-7 (D_i,$E_i$$E(X)$, and $D(X)$) for Sen and Pal (2013)'s method (D'^{1}_{k}, D'^{2}_{l}, D'^{3}_{r}, E'^{1}_{k}, E'^{2}_{l}, E'^{3}_{r}, $E'(X)$, and $D'(X)$) for the proposed method. As shown in Table 4, the lower bound value of the POS-LOW problem is equal to 2.88×10^5 ($D(x)=$ [2.88×10^5,4.19×10^{11}]). In other words, the objective value in this problem gives a value of 2.88×10^5. There are no alternatives for this problem in terms of possible and necessary regret intervals. Thus, under an optimistic perspective, the decision-maker should select the solution of the POS-LOW problem. On the other hand, under a pessimistic perspective, the decision-maker should select the solution of the POS-UPP problem.

Furthermore, the solution of the META-POS-LOW problem is the best one, because the objective value in this problem (the lower bound value) is equal to 0.21 and there are no alternatives for this problem between the META-NES-LOW and META-NES-UPP. Finally, if the decision-maker wishes to follow a pessimistic procedure, the solution determined by the META-POS-UPP problem should be selected.

It should be noted that all the ranges introduced in Tables 5 and 6 are needed to calculate the optimal values of the used resources. The amount of these deviations is deducted from the target values and finally shows the optimal values of ideals. In other words, one of the most basic things needed to calculate the difference between what is (current conditions) and what should be (optimal conditions) is the deviation values calculated in these tables.

Table 7 shows the amount of this difference in terms of percentage and also reports the results of the TOPSIS method for each model. It should be noted that for summarization, the percentage of change for chemical fertilizers and pesticides has not been done separately for their types, and a general amount has been calculated. For example, in the case of using the META-POS-LOW agricultural program, the amount of use of three types of chemical fertilizers will be reduced by 9%.

The highest amount of increase in total profit has happened in the high-limit optimistic models (META-POS-UPP and POS-UPP) in the amount of 32%. While the biggest cost reduction has occurred only in the proposed META-POS-UPP model by 25%. It can be noted that each of the criteria in this study has achieved more success in one of the models. Therefore, multi-criteria methods such as TOPSIS can be used for prioritizing and helping to select models. The last column in Table 7 reports the results of the weights obtained by the TOPSIS method for each model. However, the META-NES-UPP model has the most weight and then the META-POS-LOW model has the most weight. Carefully in other weightings, it is determined that all the models proposed in this study are ranked 1-4 and the models of Sen and Pal (2013) are ranked 5-8.

5. Discussion

In this paper, many socio-economic-environmental indicators have been analyzed in order to assure the sustainability of land use management. The adoption of a wider goal programming only in part solves the problem. In the past, multi-objective problems have been solved through a single objective approach, defined by a weighted sum of the objectives (Stewart et al., 2004). As a consequence, most of the past procedures have been focused on the selection of optimal sites for a single land use type within an area. However, recent trends in the decision-making process have brought the development of different types of algorithms able to face the increased complexity derived from the existence of multiple objectives, which may not always be linear or additive. In this perspective, the GP model is a well-known combination procedure for solving multi-objective or attribute decision problems. One of the biggest difficulties in GP models is the choice between different types of achievement functions, a selection that has a significant effect on the final solutions. Thus, MGP is a flexible approach to combine different achievement functions simultaneously. Another related problem is that when any of the conventional models of GP is used, the target value of goals and other parameters are assumed as known. However, these data in real-world problems are often imprecise or vague.

In the agriculture field decision makers have to select crops requiring low levels of water, considering that an extensive part of water resources is utilized in the agriculture sector under the current uncertain climatic conditions that make water resources more vulnerable (Jain et al., 2023). A multi-objective model trying to link together crop productivity and water resource optimization could increase the crop net return by maintaining the water availability in arid and semi-arid lands characterized by water deficit. Water resource optimization in agriculture is a multi-goal, complex, and non-linear problem, where an efficient IMGPM could allow for obtaining optimal solutions when data are not available or vague. A quantification is crucial to control more effectively the use of water, soil, and nutrient input taking into account the need of different crops simultaneously (Gogoi et al., 2021).

In the case of Iran, many socio-ecological-economic strategies and policies should be necessary for improving the agricultural sector, which could be applicable to the broader Middle East region. More specifically, on the basis of rainfall amounts and spatial patterns, it could be possible to delineate strategies for additional water storage useful to support crop production. Furthermore, the availability of water together with the sustainable use of fertilizers can mitigate the risk of land degradation, guaranteeing people employment, food security, and economic profits (Petrosillo et al., 2023; Valente et al., 2023).

Examining the results of the case study, it emerges that the Navy bean was removed in all the pessimistic models. The reason for this is the high gross profit for this product, which leads to uncertainty at a higher level. More protection of mathematical models against uncertainty by removing products that have more gross profit and less certainty is normal and has been proven in many studies (Shirzadi Laskookalayeh et al., 2022; Kalbali et al., 2021; Mardani Najafabadi et al., 2019). Of course, it should be noted that in our study a product like corn has been removed from the cropping pattern in most optimistic cases. The existence of gross profit and the employment of more labor for the Navy bean has caused the optimal pattern to shift from corn to Navy bean

Table 8
Schematic report of the models' achievement of the three aspects of the sustainable cropping pattern and TOPSIS ranking.

		Optimistic procedures				Pessimistic procedures			
		Proposed method		Sen and Pal (2013)		Proposed method		Sen and Pal (2013)	
Targets	Criteria	META-POS-LOW	META-POS-UPP	POS-LOW	POS-UPP	META-NES-LOW	META-NES-UPP	NES-LOW	NES-UPP
economic	Total Profit	✗	✓	✗	✓	✗	✓	✗	✓
	Total Cash expenditure	✓	✓	✓	✓	✓	✓	✓	✗
ecological	Total Fertilizer	✓	✓	✓	✗	✓	✓	✓	✓
	Total Pesticides	✓	✗	✗	✗	✓	✓	✓	✗
	Total Water consumption	✓	✗	✓	✗	✓	✗	✓	✗
social	Total Man-days	✗	✓	✗	✓	✗	✓	✗	✓
	TOPSIS ranking	2	3	7	5	4	1	6	8

Notes: The signs ✓ and ✗ are to confirm or not the achievement of the desired model to the criteria, respectively.

Source: authors' calculations in GAMS.

cultivation in optimistic cases where there is a higher probability of access to resources. In general, it was found in the proposed model that the amount of total cultivated area decreases in pessimistic cases. In other words, it can be said that by increasing the protection of the model against uncertainty, the use of land resources will decrease. This trade-off between the use of the land resource and the protection of the model can be seen in Mardani Najafabadi and Ashktorab (2022), which led to a 3.63% reduction in this resource.

The amount of irrigation water allocation in the pessimistic cases was generally higher than in the optimistic cases in all models. The main reason for this was the choice of a product with high water requirements such as corn instead of Navy beans (in this case). Thus, if the only factor was the uncertainty of the amount of available water (unlike our model), opposite results might be obtained in the field of irrigation water use. For example, Shirzadi Laskookalayeh et al. (2022) showed that the amount of irrigation water consumption was reduced by increasing the amount of protection of the model against uncertainty.

To choose the most suitable model, it should be checked the success of each model to consider the three main aspects of the optimal sustainable cropping pattern (Fig. 1). For this purpose, Table 8 schematically shows the achievement of desired models of these three aspects based on predetermined criteria. The ranking of the mentioned models based on the TOPSIS method is also reported in the last column of the table. It is quite clear that the META-NES-UPP model is the most suitable sustainable cropping pattern for decision-makers. The reason for choosing this model is the number of attainable criteria (five) and its first rank in the TOPSIS method. This result seems completely logical, under two aspects. First, as mentioned before, the lands covered by the study area are facing many problems in terms of economic, social, and ecological problems. The chosen model has successfully achieved the highest number of examined criteria. Second, this model is classified in the category of pessimistic procedures, which seems to be closer to reality due to the existence of data with a high error percentage and several problems in the region. The only criterion that this model could not achieve was the minimization of irrigation water consumption (the failure rate of this criterion was insignificant). Therefore, in order to reduce the consumption of irrigation water to approach the target value of this goal, the irrigation efficiency of the region should be increased by using modern irrigation methods. It is worth noting that in many studies that have used various methods to optimize the consumption of agricultural inputs, all the criteria desired by the researchers have not been fully realized (i.e., Kavand et al., 2023; Mardani Najafabadi et al., 2019).

Another point that deserves attention in Table 8 is that the proposed models (META) were more suitable than the Sen and Pal (2013) model in terms of achieving the target values. Of course, these models have a lot of computational complexity and modeling for new applications. The existence of upper and lower limits in the data and results will lead to the difficulty of interpreting the results. Therefore, it is suggested to use other methods of dealing with uncertain data, such as the robust optimization method (Bertsimas and Sim, 2004). Some studies, such as Hanks et al. (2017) and Ghahtarani and Najafi (2013), which combined this method with GP, can make it easier to model Robust MGP.

6. Conclusions

Land-use planning and management is a complex process, since decisions must be taken both on what to do and on where to do it, adding a whole extra variability to the decision-making process. In this perspective, sustainability in agriculture is a prerequisite for global food security (Mc Carthy et al., 2018) as well as land-use planning is a crucial aspect in the perspective of policy implementation and evaluation.

Sustainable agricultural practices can be achieved both by increasing understanding of the spatial and temporal interactions between economic and environmental processes and, by understanding how these interactions are affected by changes in land use and/or management actions, by providing access to knowledge by individuals and groups involved in land use planning, including farmers, policymakers, and scientists. All that, in order to improve the knowledge of stakeholders on ecological issues and to make positive decisions and policies that favor an effective agricultural production system (Acero Triana et al., 2022).

By working together, farmers, scientists, and policymakers can enhance strategies to protect water and land, by fighting soil erosion towards the achievement of the UN Sustainable Development Goals (Liu et al., 2021).

The IMGPM will make it possible to create an efficient decision support system that allows people or authorities responsible for spatial planning to acquire adequate knowledge of the issues related to their management actions. The proposed model has been tested in a study area but can be applied to different areas with similar problems.

The future research perspective might be oriented to face multiple objectives within a spatial context that can add spatial coordinates to all attribute values, increasing the number of attributes to be handled and, thus, the complexity of the problem. Although the present methodology seems to solve the problem of multi-goals decision-making, the inclusion of spatial relationships is able to introduce dependencies between the management of land use in adjacent areas, making the present approach nearer to real-world functioning. This research is a novel way to solve policy questions at the frontiers of the future orientation in policy research.

CRediT authorship contribution statement

Mostafa Mardani Najafabadi: Conceptualization, Writing – original draft, Methodology, Writing – review & editing, Software, Validation. **Cosimo Magazzino:** Conceptualization, Writing – original draft, Writing – review & editing, Methodology, Software, Validation. **Donatella Valente:** Conceptualization, Writing – original draft, Writing – review & editing, Formal analysis. **Abbas Mirzaei:** Conceptualization, Writing – original draft, Methodology, Writing – review & editing, Software, Validation. **Irene Petrosillo:** Conceptualization, Writing – original draft, Writing – review & editing, Formal analysis, Supervision.

Declaration of Competing Interest

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

Data availability

Data will be made available on request.

Acknowledgments

This study is a part of research (Introducing a new interval MGP to sustainable agricultural water-land rescores managing (No. 1401.10)) with the support of the Research and Technology Deputy of Agricultural Sciences and Natural Resources University of Khuzestan.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ecolmodel.2023.110471.

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