https://doi.org/10.17221/46/2019-JFS

Forest management decision-making using goal programming and fuzzy analytic hierarchy process approaches (case study: Hyrcanian forests of Iran)

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Citation: Etemad S.S., Mohammadi Limaei S., Olsson L., Yousefpour R. (2019): Forest management decision-making using goal programming and fuzzy analytic hierarchy process approaches (case study: Hyrcanian forests of Iran). J. For. Sci. 65: 368–379.

Abstract: The aim of this study is to determine the optimum stock level in the forest. In this research, a goal programming method was used to estimate the optimal stock level of different tree species considering environmental, economic and social issues. We consider multiple objectives in the process of decision-making to maximize carbon sequestration, net present value and labour. We used regression analysis to make a forest growth model and allometric functions for the quantification of carbon budget. Expected mean price is estimated using wood price and variable harvesting costs to determine the net present value of forest harvesting. The fuzzy analytic hierarchy process is applied to determine the weights of goals using questionnaires filled in by experts in order to generate the optimal stock level. According to the results of integrated goal programming approach and fuzzy analytic hierarchy processes, optimal volume for each species was calculated. The findings indicate that environmental, economic and social outcomes can be achieved in a multi-objective forestry program for the future forest management plans.

Keywords: multipurpose forest management; fuzzy AHP; harvest scheduling; carbon sequestration

Forest management is a complex issue concerning several products and services provided by forest. Hence, in forest management decision-making, diverse criteria should be included for example economics, environmental and social topics. Most decision-makers involved in any kind of forest planning problem have a preferential construction to several decision-making criteria. Briefly, forest management is a problem where numerous criteria as well as several decision-makers are involved. The optimization problem underlying most real forest planning needs to be formulated within a multi-criteria framework (Diaz-Balteiro, Romero 2008). There is a number of techniques to integrate multiple objectives into forest management planning developments. Within a multi-criteria context Goal Programming (GP) is a generally used method for addressing forest management problems of constant nature. Although optimization methods like goal programming (GP) can convert rigid constraints into flexible ones by resorting to the goal implication, allowing also penalising contraventions of the right-hand side figures (Diaz-Balteiro et al. 2013). The use of GP models in forestry

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was started in 1973 and it has been widely used for addressing multiple forest management problems (Diaz-Balteiro et al. 2008).

Using GP, decision-makers try to attain the desirable goal levels as closely as possible by minimizing the deviations from the objectives while, at the same time, the influences of stakeholder precedence on the attainment of several aims can be explicitly examined. The analytic hierarchy process (AHP) (Saaty 1980) is a useful method that provides the capability to synthesize both qualitative and quantitative factors in decision-making and also that has been widely used as an effective tool or a weight estimation method in different cases (Vaidya, Kumar 2006). The AHP resolves complex decisions by organizing the alternatives into a hierarchical framework and it is also used to determine the weight or priority of the objectives in a multi-objective optimization problem (Ho 2007). Researchers modified Saaty's AHP to formulate and control uncertainty. On the other hand, the AHP method is mostly used in nearly crisp (non-fuzzy) decisions. Therefore, the AHP method does not take into account the uncertainty associated with the mapping (Cheng et al. 1999). Avoiding these risks to performance, the fuzzy AHP, a fuzzy extension of AHP, was expanded to solve the hierarchical fuzzy problems.To deal with problems involving the vagueness of human thinking, Dr Lotfi Zadeh proposed a new theory in 1965 called "Fuzzy Sets" (Chen 2005). The fuzzy set theory permits a gradual assessment of the membership of elements in a set; this is described with the aid of a membership function (Moradi, Mohammadi Limaei 2018). Fuzzy AHP is a multi-criteria decision-making method to specify the weights of the different goals in multipurpose forest management. There are many fuzzy AHP approaches suggested in the literature. These approaches are organized methods to the alternative selection and explanation of problems using the implication of fuzzy set model and hierarchical structure analysis (Haghighi et al. 2010). In this research, Chang's extent analysis method (Chang 1996) was selected because of its comparatively easier approach in comparison with the other fuzzy AHP methods. In cases with both quantitative and qualitative criteria, combining fuzzy AHP and GP approaches can be useful for solving optimization problems. In addition, the use of fuzzy AHP in forest and its different methods and applications have been well defined (Vahidnia et al. 2008). Chang and Boungiorno (1981) used GP to develop a multiple use forest management model for Nicolet National Forest in Wisconsin. They applied a preemptive GP (where goals are ranked by their importance and the higher ranked goals are achieved first followed by the lower ranked goals) without considering stakeholder preferences. Stirn (2006) integrated the fuzzy AHP with a dynamic programming approach for determining the optimal forest management decisions so that he could maximize economic, ecological and social benefits. Results indicated that this method can be successful in problems where different criteria are involved in decision-making. There are some studies that dealt with AHP or fuzzy sets to model forest fire risk such as: Chuvieco, Congalton 1989; Vadrevu et al. 2009; Sowmya, Somashekar 2010; Mahdavi et al. 2012; Zarekar et al. 2013; Atesoglu 2014; Eskandari et al. 2015. A GP model was used in land use planning and land allocation at a tactical level in Ramsar watershed, Iran. Results showed that it is feasible to extend the most valuable objectives such as maximizing of carbon sequestration, Net Present Value (NPV), stock, labours and minimizing of soil blowing (Samghabadi 2004). It was concluded in a study in Iranian Hyrcanian forests, based on the economic, social and environmental goals, that GP is an appropriate technique for multi-criteria programming in forest management (Mohammadi Limaei et al. 2014). Following Diaz Balteiro and Romero (2008), GP has been widely used for addressing several forest resource management problems. Furthermore, GP was used for sustainable forest management in Spain. The goals of the model were maximization of NPV, yield volume and the stock (Diaz-Balteiro et al. 2013). One more example is the GP model in Cuba that was used for timber harvest scheduling to achieve a stable age class dispensation of reforestation (Gomez et al. 2006). Considering the importance of Hyrcanian forests and their correct management, it is necessary to consider all aspects of management plans. Therefore, planning should be done according to multiple goals to increase quality and quantity. Conducted research in Iran has focused on one aspect so there is a lack of research considering several criteria. Hence the aim of this paper is to propose the optimum standing timber based on multi-criteria decision-making combined with the use of fuzzy AHP and GP approaches to help decision-makers towards tackling forest management problems.

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MATERIAL AND METHODS

Data collection

The data for a model were taken from district No. 9 at Shafaroud forests, Guilan province in northern Iran. The study area is situated between the eastern longitude of 48°51'–48°48' and the northern latitude of 37°30'–37°26' with the altitude ranging from 850 to 2,000 m a.s.l. and covers an area of 2,382 ha (Fig. 1).

The study area was inventoried using a systematic random method design within a 150 × 200 m grid including circular sample plots of 10 m^2 in size. In each plot, variables such as diameter at breast height (DBH) of all trees with diameters larger than 7.5 cm, total height (m), the azimuth and distance of neighbouring tree (m) were measured. Based on the collected data, species numbers per hectare were calculated in each diameter class. Using the local tariff of Choka (Iran Wood and Paper Industries) for healthy species (positive volume table of Choka and num-

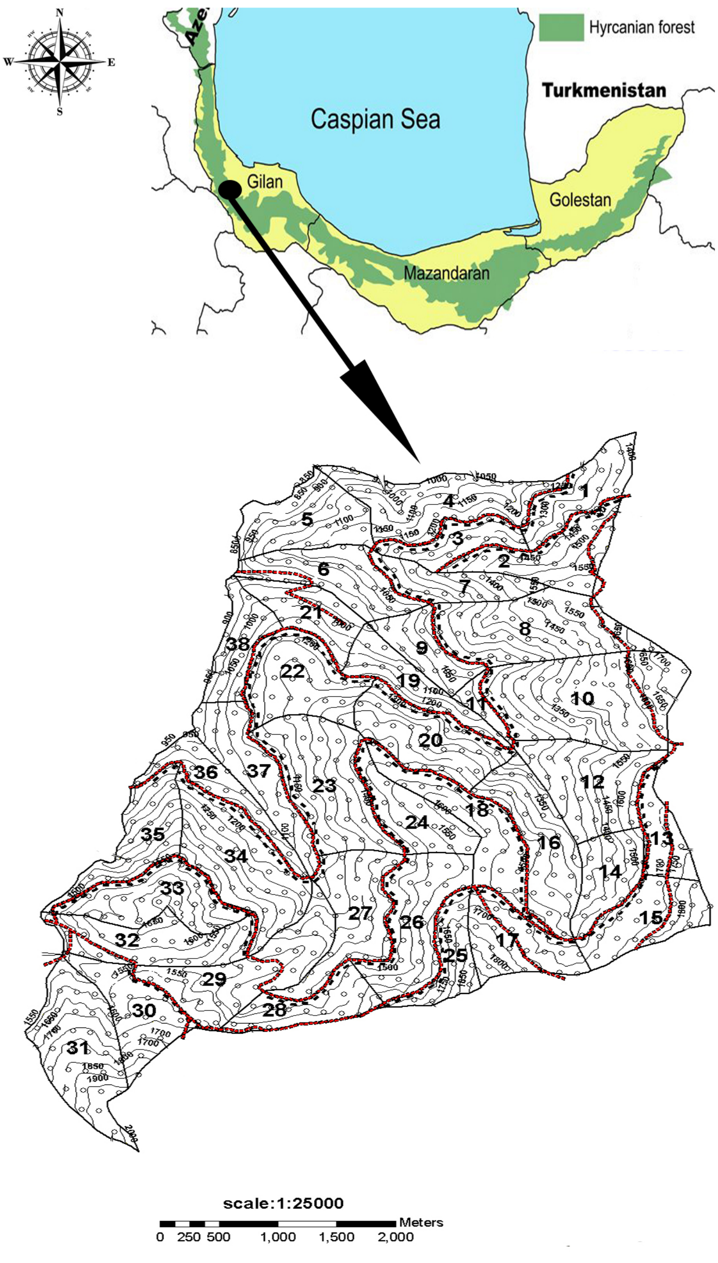

Fig. 1. Study area in the Shafaroud forest, Guilan province (district No. 9)

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ber per hectare in each diameter class), the volume per hectare for each diameter class was determined (Bayat et al. 2014). Collected data for making the GP model were annual growth and stock of each species, carbon sequestration, price and cost of wood transportation, logging, and required labour to manage forest. Annual growth data was collected from previous research in order to determine the growth function (Bonyad 2005; Mohammadi et al. 2018). In addition, we used allometric equations to determine the sequestered carbon data (Kabirin Koupaei 2009). In order to assign weights to the different goals to determine the limitations of the model, questionnaires were used. For this purpose, relative importance of criteria, optimal volume of each species and harvesting were suggested and compared by 24 experts. Finally these questionnaires were analyzed by Expert Choice software (Expert Choice Inc.).

Data processing and analysis

Annual growth per hectare is supposed to be a function (f) of the stock (Mohammadi Limaei 2006) as Eq. 1 below:

$$G = f(V) \tag{1}$$

where:
G – growth ($m^3 \cdot ha^{-1}$),
V – stock level ($m^3 \cdot ha^{-1}$).

Based on these values, regression analysis was used to evaluate the growth function. After that, optimum growth was calculated for each species (beech, hornbeam, oak, alder and other species) using growth functions and optimum stock levels from the questionnaire. We first calculated the stand biomass in order to estimate the carbon function, then 0.5 of stand dry weight is considered as the amount of aboveground sequestered carbon (Snowdon et al. 2002). The useful model for biomass studies is in Eq. 2:

$$Y = a \times DBH^b \tag{2}$$

where:
Y – total tree dry biomass at above ground,
a, b – coefficients and they usually vary with species, stand age, location quality, climate and stand stock,
DBH – diameter at breast height as reported in Baskerville (1965).

Table 1. Allometric equations for species (Function $Y = a \times DBH^b$)

Species	a	b	Source
Beech	0.003	2.802	Kabiri Koupaei (2009)
Hornbeam	0.013	2.492	Kabiri Koupaei (2009)
Oak	0.0021	3.306	Yuste et al. (2005)
Alder	0.000003	2.8805	Yuste et al. (2005)
Other species	0.005	2.696	Kabiri Koupaei (2009)

Y – total tree dry biomass at above ground; a, b – coefficients and they usually vary with species, stand age, location quality, climate and stand stock, DBH – diameter at breast height as reported in Baskerville (1965)

In this study, carbon sequestration was estimated by allometric equations (Yuste et al. 2005; Kabiri Koupaei 2009) (Table 1). After using regression analysis to estimate the carbon sequestration function, optimum carbon sequestration was calculated for each species.

First of all, we derived the stumpage price data from the actual timber prices at forest roadside minus the harvesting costs in order to determine the expected mean price process. Then, the stumpage price was adjusted or deflated by the consumer price index (CPI) of Iran for the base year 2017 (Mohammadi Limaei et al. 2014). Then, after determining the regression relation to estimate the expected mean price, values of parameters (α and β) were obtained. Finally, the estimated parameters were used to determine the expected mean price by Eq. 3 (Mohammadi Limaei 2011):

$$P_{eq} = \alpha/(1 - \beta) \tag{3}$$

where:
P_{eq} – expected mean price,
α, β – calculated parameters.

The minimum employment for harvesting of different species was obtained from the questionnaires.

After collecting the data of the questionnaires, the fuzzy AHP was used to specify the weights of the goals. The outlines of Chang's extent analysis method on fuzzy AHP are explained as follows:

Let $X = \{x_1, x_2, ..., x_n\}$ be an object set and $G = \{g_1, g_2, ..., g_n\}$ be a goal set. According to Chang's extent analysis, each object is taken and extent analysis for each goal g_i is performed. Therefore, m extent analysis values for each object can be determined by the following steps: $M_{gi}^1, M_{gi}^2, ..., M_{gi}^m, i = 1, 2, ..., m$

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where all M_{gi}^{j} (j = 1, 2, 3, ..., m) in equations are triangular fuzzy numbers (Haghighi et al. 2010).

The steps of (Chang 1996) extent analysis can be given as follows:

Step 1: The value of fuzzy synthetic extent with respect to theobject is defined as Eq. 4

$$S_i = \sum_{j=1}^{m} M_{gi}^{j} \otimes \left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^{j} \right]^{-1} \quad (4)$$

where:

⊗ – fuzzy number multiplication.

To obtain $\sum_{j=1}^{m} M_{gi}^{j}$ (fuzzy summation of row), the fuzzy addition operation of m extent analysis values for a particular matrix is performed like in Eq. 5:

$$\sum_{j=1}^{m} M_{gi}^{j} = \left(\sum_{j=1}^{m} a_j, \sum_{j=1}^{m} b_j, \sum_{j=1}^{m} c_j \right), \qquad i = 1,2,\ldots,n \quad (5)$$

where:

a_j, b_j, c_j – triangular fuzzy numbers whose parameters are depicting least, most and largest possible values respectively, j = 1, 2, 3, ..., m.

and to obtain $\left[\sum_{j=1}^{n} \sum_{j=1}^{m} M_{gi}^{j} \right]^{-1}$, the fuzzy addition of M_{gi}^{j} (j = 1, 2, ..., m), i = 1, 2, 3, ..., n, values is performed like in Eq. 6:

$$\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^{j} = \left(\sum_{j=1}^{m} a_j, \sum_{j=1}^{m} b_j, \sum_{j=1}^{m} c_j \right) \quad (6)$$

(Summation of Column) and then the inverse of the vector above is computed like in Eq. 7:

$$[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^{j}]^{-1} = \left(1/\sum_{i=1}^{n} c_i, 1/\sum_{i=1}^{n} b_i, 1/\sum_{i=1}^{n} a_i \right) \quad (7)$$

Step 2: As $M_1 = (a_1, b_1, c_1)$ and $M_2 = (a_2, b_2, c_2)$ are two triangular fuzzy numbers, the degree of $M_2 = (a_2, b_2, c_2) \geq M_1 = (a_1, b_1, c_1)$ is defined as in Ertugrul, Karakasoglu (2007 and Wu et al. (2004) by Eq. 8:

$$V(M_2 \geq M_1) = \sup_{y \geq x} \left[\min\left(\mu_{M_1}(x), \mu_{M_2}(y) \right) \right] \quad (8)$$

and can be expressed as follows by Eq. 9:

$$V(M_2 \geq M_1) = \text{hgt}(M_1 \cap M_2) = \mu_{M_1(d)} = \quad (9)$$

$$= \begin{Bmatrix} 1 & if\ b_2 \geq b_1 \\ 0 & if\ a_1 \geq a_2 \\ \dfrac{a_1 - c_2}{(b_2 - c_2) - (b_1 - a_1)}, & otherwise \end{Bmatrix}$$

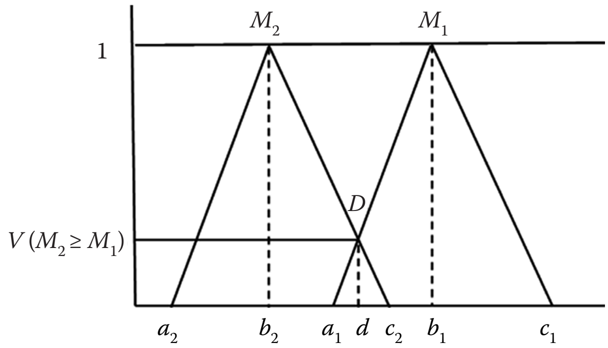

Fig. 2. The intersection between M_1 and M_2 (Zhu et al. 1999)

where:

$V(M_2 \geq M_1)$ – bigness degree,

M_2 – first S,

M_1 – secondary S,

hgt – height of a fuzzy set.

Fig. 2 illustrates Eq. (9) where d is the ordinate of the highest intersection point D between μ_{M_1} and μ_{M_2} to compare M_1 and M_2, we need both the values of $V(M_1 \geq M_2)$ and $V(M_2 \geq M_1)$.

Step 3: The degree of a possibility for a convex fuzzy number to be greater than k convex fuzzy M_i (i = 1, 2, k) numbers can be defined by

$V(M \geq M_1, M_2, ..., M_k) = V((M \geq M_1)$ and $V(M \geq M_2)$ and ... and $V(M \geq M_k)) = \min V(M \geq M_i)$, i = (1, 2, 3, ..., k).

Then the weight vector is given by Eq. 10:

$$d'(A_i) = \min V(S_i \geq S_K),\ k = 1, 2, ..., n;\ k \neq i. \quad (10)$$

where: S – successor function (fuzzy synthetic extent).

Then the weight vector is given by Eq. (11):

$$W' = (d'(A_1), d'(A_2), ..., d'(A_n))^T \quad (11)$$

where:

d' – calculated from equation 10, (unnormalized value),

A_1 = (i = 1, 2, ..., n) are n elements,

T – total objects.

Step 4: Via normalization, the normalized weight vectors are in Eq. 12:

$$W = (d(A_1), d(A_2), ..., d(A_n))^T \quad (12)$$

where:

W – nonfuzzy number,

d – normalized value.

Step 5: Determination of alternative final weight by Eq. 13:

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A_1 = (A_1 to C_1 × C_1 to GOAL)+(A_1 to C_2 × C_2 to GOAL) + (A_1 to C_3 × C_3 to GOAL) ….. + (A_1 to C_n × C_n to GOAL) (13)

where:
n – number of criteria,
A_1 = (i = 1, 2, ..., n) are n elements,
C_1 = (i = 1, 2, ..., n) are n elements,
$GOAL$ – optimal value.

A decision-maker compares the criteria or alternatives via linguistic terms shown in Table 2.

The goal programming model is an extension of the LP model to be able to take care of various goals and each of them has a value. Undesirable deviations should be minimized in an achievement function. All of the included goals in the GP are handled in a similar way: indicated by the goal limitation (Mohammadi limaei et al. 2014).The included objective constraint contains objective variables that estimate the quantity by which the augmentation of all actions to the target in question has a shortage and a surplus with respect to the goal level. The sum of the weighted deviations in the objective function of goal programming model should be minimized from all target levels. When goal variables are involved in a constraint, we avoid the problem of unfeasibility related to the constraint (Kangas et al. 2008). The GP objective Eq. 14 is as follows (Mohammadi limaei et al. 2014):

$$MinZ = \sum_{i=1}^{G} (\mathrm{W}_i d_i^- + \mathrm{W}_i d_i^+) \tag{14}$$

where:
d_i^- – underachieved deviation,
d_i^+ – overachieved deviation,
W_i – weight of each deviation from the target value.

Table 2. Linguistic terms and the corresponding triangular fuzzy numbers

Saaty scale	Definition	Fuzzy triangular scale
1	equally important	(1, 1, 1)
3	weakly important	(2, 3, 4)
5	fairly important	(4, 5, 6)
7	strongly important	(6, 7, 8)
9	absolutely important	(9, 9, 9)
2	the intermittent values between two adjacent scales	(1, 2, 3)
4		(3, 4, 5)
6		(5, 6, 7)
8		(7, 8, 9)

A goal programming model has some limitations that include goal variables that measure the variation between goal levels and real results. The model (Eq. 15) below is the function of goal constraints (Buongiorno, Gilless 2003):

$$\sum_{j=1}^{n} a_{ij} x_i \leq \; = or \geq b_i \;\; for\, i = 1, 2, \dots, \; G \tag{15}$$

where:
x_j – j^{th} decision variable,
a_{ij} – contribution to target i per unit of action j,
b_i – level of achieve to target i,
G – measured numerical value to target i.

Variables of the objective fill the gap between the goal levels. Other limitations may exist of the typical linear program variety (Buongiorno, Gilless 2003); see Eq. 16:

$$\sum_{j=1}^{n} a_{ij} x_i + d_i^- - d_i^+ = g_i \quad for\, i = 1, 2, \dots, G \tag{16}$$

where:
x_i – i^{th} decision variable,
a_{ij} – contribution to target i per unit of action j,
g_i – calculating the aim of goal i, of which there are G and x_j d_i^-, d_i^+ >= 0.

When the primary constraint or inequality is higher than a quantity, the negative deviation is inserted in the equation. Then it is written on the left side of the function and the inequality is changed to equality. In contrast, when the original constraint is lower than a quantity, the positive deviation is reduced from the left side of the function (Mohammadi limaei et al. 2014). The optimum volume was specified using prior functions (12 to 14). First of all, we determined limitations and the positive or negative deviation from the goals. In this study, there is not any positive deviation from the goal. For the next step, we minimized the negative deviations from the goal to determine the objective function (Mohammadi limaei et al. 2014).

Therefore, objective and constraint functions of the goal programming model are determined below by Eq. 17:

$$MinZ = \sum_{j=1}^{m} \mathrm{W}_j (d_j^-) s \times t \tag{17}$$

$$\sum_{i=1}^{G} X_i + d_T^- = g_T$$

$$X_i + d_{Vi}^- = g_{Vi}$$

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$$\sum_{i=1}^{G} a_i X_i + d_C^- = g_C$$

$$\sum_{i=1}^{G} b_i X_i + d_G^- = g_G$$

$$\sum_{i=1}^{G} m_i X_i + d_L^- = g_L$$

$$\sum_{i=1}^{G} n_i X_i + d_{\mathrm{NPV}}^- = g_{\mathrm{NPV}}$$

$$d_{\mathrm{T}}^-, d_{\mathrm{Vi}}^-, d_{\mathrm{C}}^-, d_{\mathrm{G}}^-, d_{\mathrm{L}}^-, d_{\mathrm{NPV}}^-, d_j^-, \mathrm{w}_j \geq 0$$

Definitions

All the definitions which are needed to understand the model in Eq. 17 are presented below:

d^- – negative deviation from goal value, w – weight given to each unit of deviation, j – 1 to 10: total stock, beech stock, hornbeam stock, oak stock, alder stock, other species stock, sequestered carbon, growth, labour and NPV]; i – 1 to 5: indicates decision variables such as beech, hornbeam, oak, alder and other species]; g_{T}, g_{Vi}, g_{C}, g_{G}, g_{L}, g_{NPV} – minimum total feasible stock (m^3·ha^{-1}), minimum feasible stock of each species, carbon sequestration (t·ha^{-1}), growth per hectare, labour and NPV (EUR·ha^{-1}); *a, b, m, n* – coefficients of sequestered carbon, growth, labour and NPV; d_{T}, d_{Vi}, d_{C}, d_{G}, d_{L}, d_{NPV} – negative deviation of total stock, n.d. of each species species stock; n.d. of carbon sequestration, n.d. of growth, negative deviation of labor, negative deviation of NPV.

Finally we solved the GP model consisting of objective function and constraints using the LINGO software (Version 12.0, Lindo system).

RESULTS AND DISCUSSION

Results from regression analysis show that the logarithmic and polynomial equations are the best

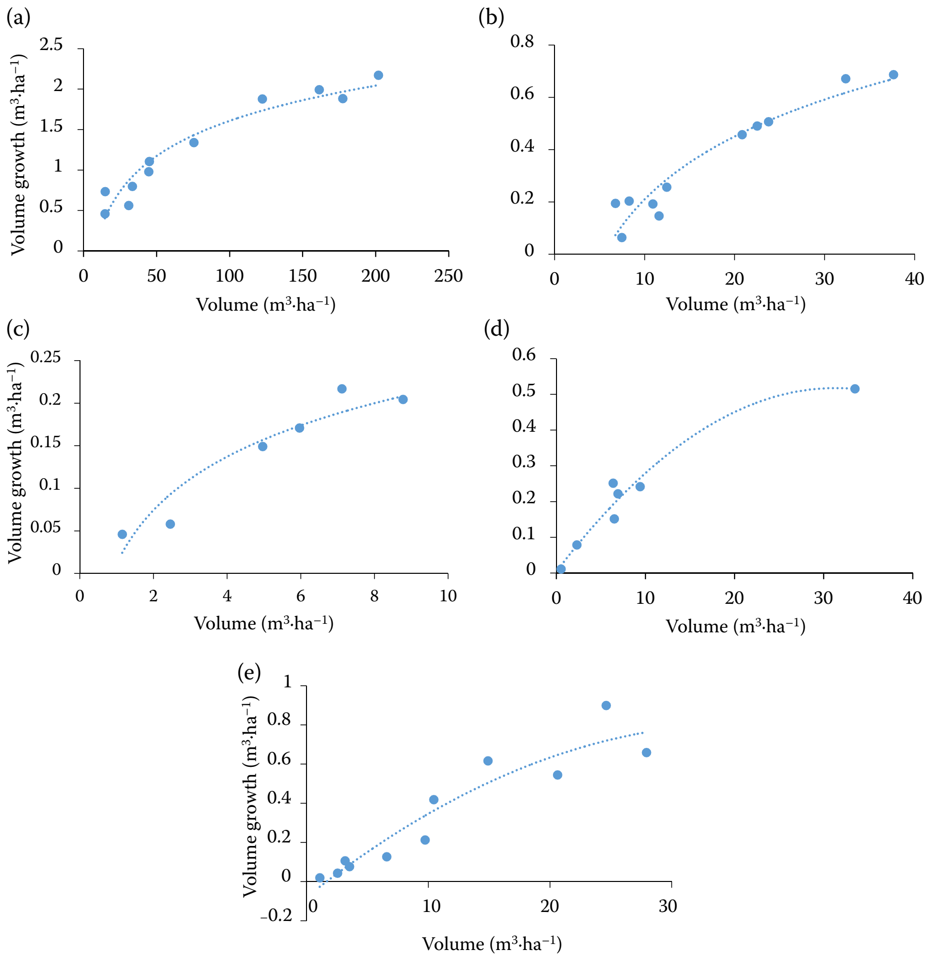

Fig. 3. Regression analysis between annual volume growth (m^3·ha^{-1}) and stock in beech (a), hornbeam (b), oak (c), alder (d), other species (e) (m^3·ha^{-1})

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Table 3. Growth equations

Species	Function	R^2
Beech	$Y = 0.6287 \ln(X) - 1.284$	0.92
Hornbeam	$Y = 0.3479 \ln(X) - 0.5916$	0.91
Oak	$Y = 0.096 \ln(X) - 0.0115$	0.90
Alder	$Y = -0.0005X^2 + 0.0328X + 0.0038$	0.95
Other species	$Y = 0.0007X^2 + 0.0494X + 0.0787$	0.89

Y = average growth (m^3·ha^{-1}·a^{-1}, X = stock (m^3·ha^{-1}).

by the allometric function for each species (Fig. 4 and Table 4). Results of regression analysis indicate that all of the functions are reliable to estimate carbon sequestration ($R^2 = 0.99$).

Table 5 shows the values of expected mean prices and parameters of the regression analysis which were calculated using Equation (2) at the significance level of 0.05.

The fuzzy comparison matrices are prepared with the help of questionnaire. The fuzzy compari-

Table 4. Estimated functions of carbon sequestration for different species

Name of species	Function	R^2
Beech	$Y = 0.2527X$	0.99
Hornbeam	$Y = 0.3134X$	0.99
Oak	$Y = 0.7356X$	0.92
Alder	$Y = 0.2509X$	0.92
Other species	$Y = 0.3655X$	0.99

Table 5. Expected mean price and estimated parameters of each species

Name of species	Estimated parameters			
	a	*b*	*P*-value	Expected mean price (EUR/m^3)
Beech	163.222	0.755	0.0152	66.6212
Hornbeam	51.633	0.894	0.0631	33.7025
Oak	166.926	0.623	0.0051	44.2775
Alder	161.074	0.719	0.0114	57.3217
Other species	131.654	0.719	0.0235	46.8520

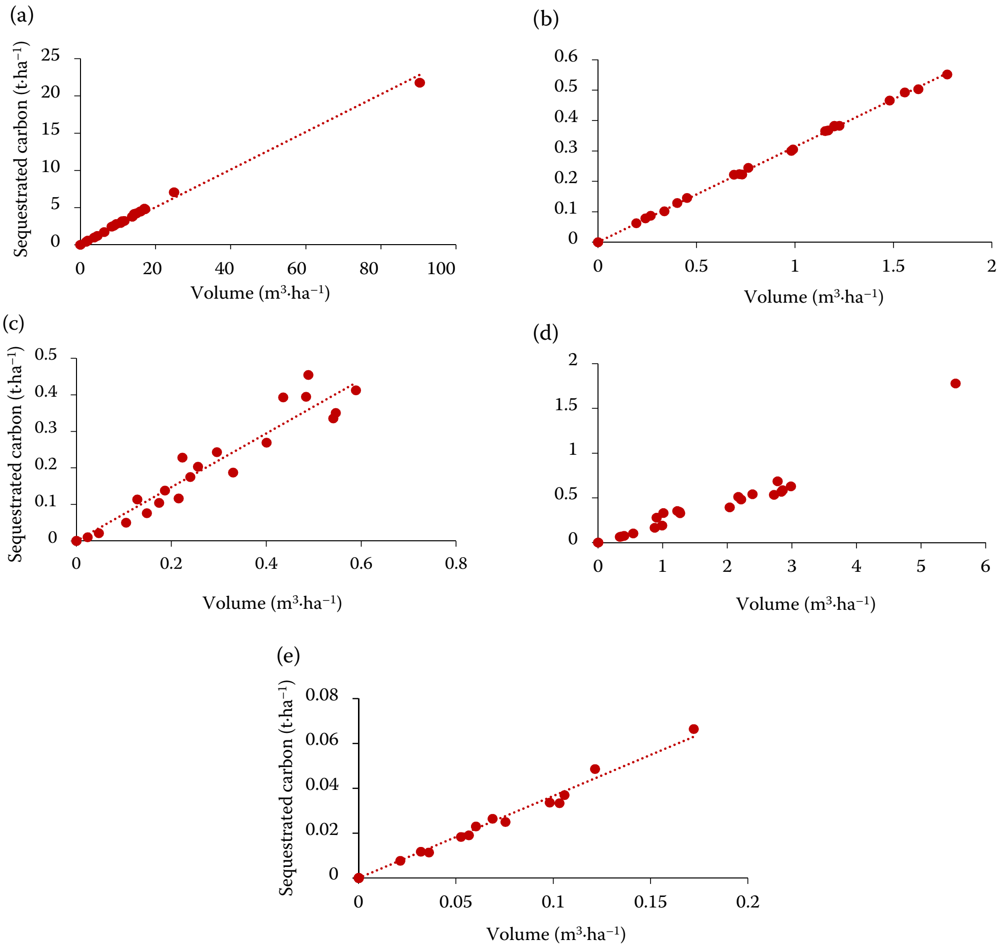

Fig. 4. Regression analysis between sequestered carbon and stock in beech (a), hornbeam (b), oak (c), alder (d), other species (e)

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Table 6. The fuzzy comparison matrix of management criteria (NPV – net present value)

	Growth ($m^3 \cdot ha^{-1}$)	NPV	Carbon sequestration ($t \cdot ha^{-1}$)	Labour
Growth	(1,1,1)	(1,2,3)	(1/3,1/2,1)	(1/3,1/2,1)
NPV	(1/3,1/2,1)	(1,1,1)	(1,2,3)	(1,2,3)
Carbon	(1,2,3)	(1/3,1/2,1)	(1,1,1)	(2,3,4)
Labour	(1,2,3)	(1/3,1/2,1)	(1/4,1/3,1/2)	(1,1,1)

Table 7. The fuzzy comparison matrix of species criteria

	Beech	Hornbeam	Oak	Alder	Other species
Beech	(1,1,1)	(3,4,5)	(3,4,5)	(2,3,4)	(1,2,3)
Hornbeam	(1/5,1/4.1/3)	(1,1,1)	(2,3,4)	(2,3,4)	(1,2,3)
Oak	(1/5,1/4.1/3)	(1/4,1/3.1/2)	(1,1,1)	(1,2,3)	(2,3,4)
Alder	(1/4,1/3.1/2)	(1/4,1/3.1/2)	(1/3,1/2.1)	(1,1,1)	(2,3,4)
Other species	(1/3,1/2.1)	(1/3,1/2.1)	(1/4,1/3.1/2)	(1/4,1/3.1/2)	(1,1,1)

Table 8. The values of coefficients in GP model

i	Species name	*a*	*b*	*m*	*n*
1	Beech	269.533	8.371	61	7931.098
2	Hornbeam	313.889	13.721	61	4012.206
3	Oak	729.607	8.517	61	5271.125
4	Alder	238.329	22.786	61	6824.013
5	Other species	360.011	31.262	61	5577.614

a – coefficient of sequestrated carbon, *b* – coefficient of growth, *m* – coefficient of labour, *n* – coefficient of NPV

son matrices of criteria with calculated weights are shown in Tables 6 and 7. These calculations can be performed easily using Excel Sheet.

Results of Table 6 show the ranking of economic, environmental and social goals based on expert knowledge in questionnaires.

The ranking of various species based on expert knowledge is shown in Table 7. The parameter values of constraints are shown in Table 8.
models for predicting the growth function (Fig. 3 and Table 3).

The relationship between carbon sequestration ($t \cdot ha^{-1}$) (*Y*) and the stock ($m^3 \cdot ha^{-1}$) (*X*) was shown The optimal values in respect of the questionnaire and fuzzy AHP are shown in Table 9. NPV and beech volume have the highest value for management and ranking of species criteria. In contrast, social criterion (labour) has the lowest ranking.

Table 10 shows the results of the solution to the GP model where D_{VT}, D_B, D_H, D_O, D_A and D_{OS} are negative deviations of total stock, beech, hornbeam, oak, alder and other species. D_C, D_G, D_L and D_{NPV} are negative deviations of carbon sequestration, growth, laboor and NPV. The results show that the optimal stock of beech, hornbeam, alder and other species is 256.2, 61.2, 20.4 and 20.4 $m^3 \cdot ha^{-1}$, respectively. Because their negative deviations are zero and it means that they have quite achieved the goal. Table 10 shows that the negative deviations of NPV, labour, growth, oak stock and total stock are 8189.396, 782.67, 923.74 per hectare, 1.99 and 10.99 $m^3 \cdot ha^{-1}$ respectively. These constraints meet the objectives with adding the deviations. Results also show that the carbon sequestration has not any deviation.

Accordingly, the total optimal yield stock from the achieved result is 397.005 $m^3 \cdot ha^{-1}$. There-

Table 9. The value of goals and weights based on questionnaire and fuzzy AHP method

j	*g* ($m^3 \cdot ha^{-1}$)	*w*	*j*	*g* ($m^3 \cdot ha^{-1}$)	*w*
Total volume	408	0.2446	Other species volume	20.4	0.1135
Beech volume	256.2	0.4130	Sequestered carbon ($t \cdot ha^{-1}$)	128783.16	0.2675
Hornbeam volume	61.2	0.2006	Growth ($m^3 \cdot ha^{-1}$)	4509.834	0.2446
Oak volume	40.8	0.1243	Labour	25000	0.1829
Alder volume	20.4	0.1485	NPV ($EUR \cdot ha^{-1}$)	281692.937	0.3050

j – criteria, *g* – minimum feasible stock, *w* – weight of each deviation, NPV – net present value

https://doi.org/10.17221/46/2019-JFS

Table 10. Results of GP model

Variable	Value	Reduced Cost
D_{VT}	10.99464	0.000000
D_B	0.000000	11.85468
D_H	0.000000	114.2278
D_O	1.994640	0.000000
D_A	0.000000	505.2847
D_{OS}	0.000000	464.4562
D_C	0.000000	0.5317411
D_G	923.7415	0.000000
D_L	782.6730	0.000000
D_{NPV}	8189.396	0.000000
$X1$	256.2000	0.000000
$X2$	61.20000	0.000000
$X3$	38.80536	0.000000
$X4$	20.40000	0.000000
$X5$	20.40000	0.000000

D_{VT} – negative deviation of total stock, D_B – negative deviation of beech, D_H – n.d. of hornbeam, D_O – n.d. of oak, D_A – n.d. of alder, D_{OS} – n.d. of other species, D_C – n.d. of carbon sequestration, D_G – n.d. of growth, D_L – n.d. of labor, D_{NPV} – n.d. of NPV, $X1$ – optimal stock of beech, $X2$ – optimal stock of hornbeam, $X3$ – optimal stock of oak, $X4$ – optimal stock of alder, $X5$ – optimal stock of other species, NPV – net present value

fore we fully achieve the goals related to the optimal harvest stock of beech, hornbeam, alder and other species. However, for the oak, the optimum goal programming method presents a deviation with consideration of the primary optimal values. Hence, the goal programming model estimates the optimal value of different criteria to reach sustainable forest harvesting.

This research is performed in order to compute the optimum volume by GP based on the fuzzy AHP method for attaining sustainable forest management in Iranian Hyrcanian forests. Mohammadi Limaei et al. (2014) used a goal programming technique to determine the optimal harvest volume for the Iranian Caspian forest. They calculated sequestered carbon, growth and mean price. Their results indicated that the optimum volumes of species were 250.25 $m^3 \cdot ha^{-1}$ for beech, 59 $m^3 \cdot ha^{-1}$ for hornbeam, 73 $m^3 \cdot ha^{-1}$ for oak, 41 $m^3 \cdot ha^{-1}$ for alder, and 32 $m^3 \cdot ha^{-1}$ for other species. The total optimum volume was 455.25 $m^3 \cdot ha^{-1}$. There is some similarity between the results of their research and this paper. However, the method to determine the constraints and the equation coefficients of the goal programming model was different in these two researches. They used a questionnaire only to determine the weights of goals whereas in this research the fuzzy AHP is applied in order to generate the optimal stock level. Diaz-Balteiro et al. (2013) used a GP model to define the optimum forest management regarding carbon sequestration in Spain. The goal of that model was to maximize NPV, harvested volume control, area control at different ages and final volume. Hence, there is some similarity between the results of their model and this research.

Ostadhashemi et al. (2014) developed an optimal sustainable forest plantation based on goal programming and AHP methods in the Iranian Caspian forest. Results showed that using mathematical modelling provided a more logical set of consequences compared to using ecological modelling. In addition, the ability to change the weighting of the variables in mathematical equations allowed decision-makers to choose the best solution. The results from this study are in line with the results of our research.

CONCLUSION

In this study we tried to determine the optimal combination for multi-purpose management using fuzzy AHP and goal programming approaches with considering economic, environmental and social goals.

A GP model is the most extensively used method for dealing with persistent issues to resolve multi-objective problems in management. It is also necessary to mention that the goal programming model allows fining out the contrast between the various criteria in the decision-making systems. Briefly, this approach is a tactic for decision aids in forest management concerning sustainability. These findings indicate that we can achieve economic, environmental and social outcomes in a multi-objective forestry program for the future forest management plans. Hence, given the significance of commercial species in the northern forests of Iran, the threat of species extinction is imminent. Making the necessary predictions is necessary in management plans to maintain these species. Nowadays, there are many risks like the levels of decline, pests and diseases, livestock in the forest and so on that threaten Hyrcanian forests in northern Iran. Besides these reasons, climatic changes may turn into a threat and be a threat to their exis-

https://doi.org/10.17221/46/2019-JFS

tence. An increase in global temperatures, long-term droughts, and reduced precipitation are among the climate change risks. It is recommended that the effect of climate changes be taken into account in climate change strategies and management plans should have enough flexibility while facing these threats in determining the long-term strategies and management plans. Among these measures is the possibility of decreasing or increasing levels and volume of harvesting, increasing levels of afforestation, genetic storage, and scion production capacity, and preparing for dealing with pests, diseases and so on.

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Received for publication April 14, 2019
Accepted after corrections September 9, 2019