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Optimizing Forest Management: Balancing Environmental and Economic Goals Using Game Theory and Multi-Objective Approaches

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Abstract: Forests are complex ecosystems that require integrated management to balance economic, social, and environmental dimensions. Conflicting objectives among stakeholders make optimal decision-making particularly challenging. This study seeks to balance the economic gains of forest harvesting with the goals of environmental conservation, with a focus on the Shafarood forest in Northern Iran. We applied multi-objective optimization and game theory to maximize the net present value (NPV) of forest harvesting while enhancing carbon sequestration. The research utilized data on stumpage prices, harvesting costs, tree density, volume per ha, growth rates, interest rates, carbon sequestration, and labour costs. Applying the epsilon-constraint method, we derived Pareto optimal solutions for a bi-objective model, and game theory was applied to negotiate between economic and environmental stakeholders. In the fifth round of bargaining, a Nash equilibrium was achieved between the two players. At this equilibrium point, the economic player achieved NPV from forest harvesting of 9001.884 (IRR 10,000/ha) and amount of carbon sequestration of 159.9383 tons/ha. Meanwhile, the environmental player achieved NPV from forest harvesting of 7861.248 (IRR 10,000/ha), along with a carbon sequestration of 159.9731 tons/ha. Results indicate significant trade-offs but reveal potential gains for both economic and environmental goals. These findings provide a robust framework for sustainable forest management and offer practical tools to support informed decision-making for diverse stakeholders.

Keywords: sustainable forest management; economic benefits; environmental impact; decision-making; multi-objective optimization; game theory; Nash equilibrium; carbon sequestration; stakeholder alignment

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1. Introduction

Forest ecosystems deliver a variety of essential services that underpin human well-being, supported by intricate interconnections among forest ecosystem services (FESs) [1]. Developing sustainable forest management policies require insight into the trade-offs, conflicts, and synergies between key FESs, underscoring the need for robust decision-support tools that accommodate multiple objectives [2,3]. However, the complexity and diversity within forest ecosystems create challenges for effective planning and management.

The Hyrcanian (Caspian) forests of Iran are critically endangered due to ongoing deforestation, biodiversity loss, and conflicting management approaches. Despite their significance, these forests have declined from 3.5 million ha in 1964 to 1.9 million ha, with a continued reduction in both quality and diversity [4]. The main stakeholders, including local users relying on traditional livelihoods and industrial stakeholders focused on timber production, often have conflicting objectives, which have led to a decline in forest health, clashing with environmental conservation efforts [1,5]. Without balanced and sustainable management strategies, the future of these forests is at risk. Thus, the central question is: How can sustainable forest management strategies reconcile the need for economic development with environmental considerations in the Hyrcanian forests?

In response to emerging challenges, researchers have explored optimal management strategies utilizing multi-criteria decision analysis (MCDA) and modeling methods to provide both generalized and specific solutions. These solutions, represented through quantitative data, can be applied across both discrete and continuous temporal and spatial dimensions [6]. Notably, foundational research by Mendoza and Martins (2006) [7] reviewed methods for MCDA in natural resource management, emphasizing innovative modeling frameworks that facilitate integration across diverse management objectives [8].

Iran's Hyrcanian forests, remnants of the Northern Hemisphere's broad-leaved forests, are particularly critical to resource management. However, these forests are experiencing significant losses in quality and diversity [4]. Studies confirm ongoing degradation, characterized by substantial deforestation and a decline in biodiversity [8]. As Kangas and Kuusipalo (1993) [9] emphasized, incorporating biodiversity into forest management planning is essential for achieving conservation goals while accommodating resource use. This approach is vital for the sustainable management of Iran's Hyrcanian forests [10].

This research contributes to existing literature by offering a novel integration of multi-objective optimization methods with game theory to address the conflicting interests of diverse stakeholders in forest management. This combined approach provides a comprehensive framework for analyzing stakeholder dynamics and resource allocation, advancing the optimization of forest resource management as demonstrated in previous studies by García-Gonzalo et al. (2011) [11] and Strange et al. (2007) [12]. Focusing specifically on the Hyrcanian forests, this study fills a critical gap in the literature on sustainable forest management in this unique region by addressing its specific economic and environmental challenges [4,5]. Finally, the research offers practical implications for policymakers and forest managers, presenting a decision-making framework that balances economic and environmental goals to support informed management strategies. By synthesizing multiple objectives, as highlighted in recent literature [13,14], this study delivers actionable insights aligned with contemporary forest management needs.

The main stakeholders in the Hyrcanian forests, including local users relying on traditional livelihoods and industrial stakeholders focused on timber production, often have incompatible approaches. This divergence has led to a reduction in forest quantity and quality, clashing with conservation efforts [1,5]. These conflicts are not unique; Hoen and Solberg (1994) [15] argue that policy analyses require a range of techniques to balance forest policy outcomes with ecological sustainability, highlighting the need for effective resource allocation to address stakeholder conflicts in forest management [16].

Differences in stakeholder perspectives often lead to conflicts in forest management. Effective natural resource management necessitates the involvement of diverse stakeholders, especially when objectives differ. This inclusiveness fosters more rational goal-setting and facilitates efficient outcomes at lower costs. However, engaging a wide range of stakeholders also increases complexity and the costs associated with participatory processes, which poses challenges in achieving balance. Despite these challenges, the coalition and cooperation of all stakeholders are essential for successful participation [17,18].

Optimal forest management seeks to establish a "win–win" balance that integrates human welfare with ecosystem conservation. A primary challenge lies in bridging the gaps between various stakeholder priorities [19]. Optimal reserve selection, as noted by Strange et al. (2007) [12], is a dynamic process that takes evolving environmental conditions into account, making it relevant to both the conservation and sustainable use of the Hyrcanian forests [20].

Balancing the economic goals of forest users (local stakeholders, forest dwellers, etc.) with environmental objectives set by policymakers often requires trade-offs [21]. Conventional optimization techniques offer insights into these trade-offs. For instance, studies by García–Gonzalo et al. (2011) [11] demonstrated how integrating risks, like fire hazards, in management scheduling could help reconcile environmental preservation with economic objectives in forest planning [22]. Multi-objective and game theory models, for example, prioritize system-wide goals over individual stakeholder interests, providing a framework for handling complex forest management scenarios [23].

Since the 1960s, multi-objective planning methods have been applied to forestry, with models increasingly favoring approaches such as Linear Programming (LP) and Goal Programming (GP) to manage multiple objectives effectively [14,15]. Numerous studies, such as [24–31], underscore the utility of these methods, although deterministic models with more than two objectives remain limited [32–37]. Additionally, many forest management studies assume deterministic parameters. However, parameters like timber prices, interest rates, timber growth, and mortality are often uncertain, especially under long-term climate change influences [3,38–44].

Game theory has increasingly been utilized to analyze strategic interactions among forestry stakeholders, including governments, forest owners, and environmental groups, by modeling decision-making processes in conservation and forest policy. Originally introduced by Neumann and Morgenstern in 1944, it was further developed with Nash's concept of "Nash equilibrium" in 1950. Game theory serves as a valuable tool for predicting rational behaviors and supporting decision-making in complex management contexts [45–47]. Its applications have expanded across various fields, including economics [48], social sciences [49], land use [50], fire control [51,52], water resource management [53–56], and timber and paper markets [38,57,58], as well as forest and watershed management [26,59–61].

This study aims to address the central challenge of balancing economic benefits for forest-dependent communities and industrial stakeholders with environmental conservation objectives in the Hyrcanian forests. Specifically, it seeks to identify optimal stock (standing volume) levels by applying multi-objective optimization methods and game theory to propose a sustainable forest management strategy.

To address the conflicting interests of environmental and economic stakeholders in Iran's Hyrcanian forests, this study combines both economic and environmental perspectives to propose a balanced, innovative approach. Specifically, it aims to identify the optimal stock for these forests using multi-objective decision-making methods and game theory, including determining the Nash equilibrium and Pareto-optimal solutions for forest management strategies.

Following this introduction, the methodology section outlines the multi-objective optimization methods and game theory frameworks employed to analyze the Hyrcanian forests. It describes the data-collection process, including the variables considered, such as stumpage prices, tree density, and carbon sequestration rates. The results section presents the findings of the analysis, showcasing the Pareto optimal solutions and Nash equilibrium outcomes derived from the models. This section includes quantitative data to illustrate the effectiveness of the proposed management strategies in balancing economic and environmental goals.

In the discussion section, the implications of the findings are explored, highlighting the potential for integrating stakeholder perspectives in forest management. The challenges of reconciling economic and environmental objectives are addressed, along with recommendations for policy implications. Finally, the conclusion summarizes the key contributions of the study to the literature on sustainable forest management, emphasizing the innovative approaches used and suggesting avenues for future research.

2. Materials and Methods

2.1. Study Area

The study was District 7 (Bargah Zamin) in the Shafarood watershed, Guilan Province, Iran. Maps of the study area were acquired from the Guilan Department of Natural Resources and Watershed Management. These maps were processed and organized using ArcMap (Version 10.8.2, Esri, Redlands, CA, USA), with a focus on delineating provincial boundaries, the watershed, and the specific study site. These forests span altitudes ranging from 1000 to 2050 m and cover an area of 1064 ha (Figure 1). The region experiences an average annual rainfall of 899 mm, with an average temperature of 10.8 °C. The forest is primarily dominated by Oriental beech (*Fagus orientalis* Lipsky) with trees ranging from middle-aged to old-growth. Geologically, District 7 belongs to the Mesozoic Era, specifically the Cretaceous period. This area has experienced significant degradation, highlighting the urgent need for sustainable management practices [62].

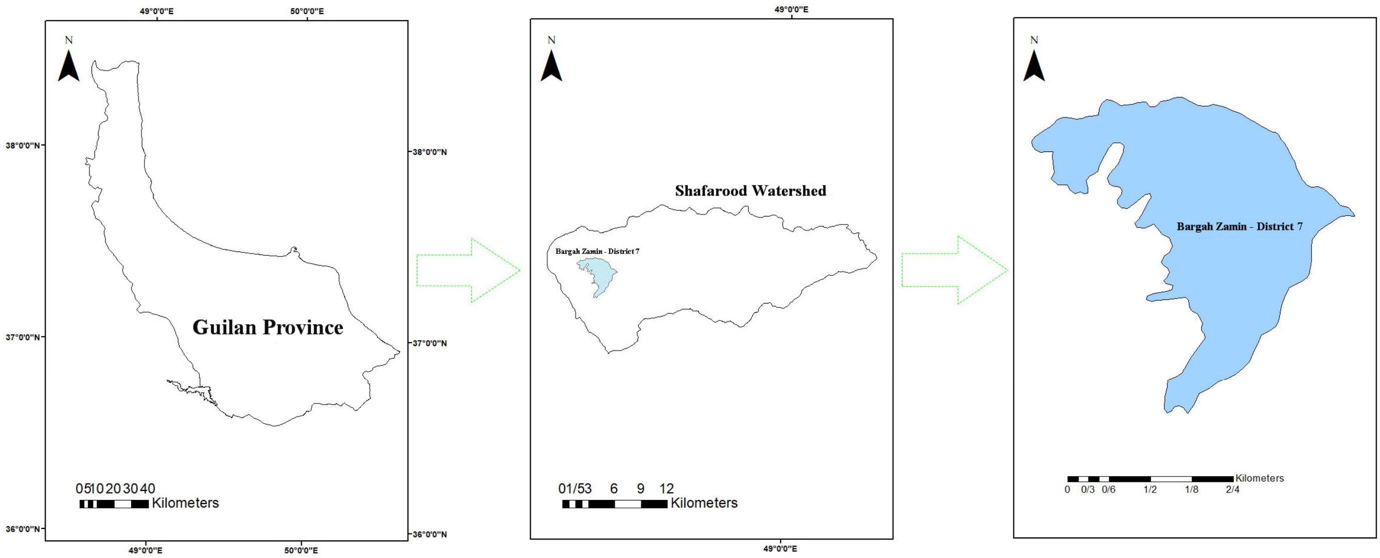

Figure 1. Study area, from left to right: Guilan province, Shafarood watershed, Bargah Zamin (District, 7).

2.2. Determination of the Volume per ha

Tree species in the area include beech, hornbeam (*Carpinus betulus* L.), oak (*Quercus castaneifolia* C.A.Mey), alder (*Alnus subcordata* C.A.Mey), and other industrial species, which account for 55.93%, 25.47%, 12.21%, 1.04%, and 5.35% of the volume per ha, respectively, with a combined volume of 303.96 (m^3/ha) [62]. The volume per ha for these species is distributed as follows: beech 170 (m^3/ha), hornbeam 77.42 (m^3/ha), oak 3.16 (m^3/ha), alder 37.11 (m^3/ha), and other industrial species 16.26 (m^3/ha).

To determine the optimal volume per ha and the target species distribution, a survey was conducted among local forestry experts. The analysis considered several key factors, including altitude, growth rates, regional potential, and climatic conditions. These considerations were essential to determine the optimal volume in forest management.

The volume per ha for each species was calculated using Equation (1), which incorporates the percentage of each species and the total volume (Table 1, Equation (1)).

2.3. Growth Model

To estimate the harvest amount for each period, the relationship between volumetric growth and standing inventory is needed. This requires having the growth rate and stock for different species in various diameter classes [63]. By employing regression relationships between volume and growth, the growth equation specific to the region was derived, as shown in Table 1 (Equation (2)).

2.4. Carbon Sequestration Rate

The carbon content in the stand is estimated by determining the dry weight of the above-ground biomass, which includes both tree canopies and trunks. The weight of tree trunks is calculated based on diameter classes, using species-specific volume and density data. Canopy weight (in kg) is determined using tree density per ha and allometric equations [64]. For forest trees, it is assumed that 50% of the dry biomass weight corresponds to stored carbon [65].

The carbon model for different species in the stand is developed by relating the carbon stored per ha to the volume of standing biomass per ha (Table 1, Equation (3)).

Finally, NPV of carbon sequestration, denoted as NPVc, is calculated using Equation (4) (Table 1).

Table 1. Calculation indexes and equations for growth, carbon sequestration, and stumpage price.

Equations	Calculation	Formula	Variables Explained
(1)	Volume per ha	$V_i = \left(\frac{P_i}{100}\right) \times V_{total}$	V_i: Volume per ha for species i; P_i: The percentage of total volume attributed to species i; V_{total}: Total volume per ha for the forest stand.
(2)	Growth rate	$G = a\ln(V) + b$	G: Growth rate; V: Volume of tree species per ha; a, b: Regression parameters
(3)	Carbon storage	$Cs = \mathrm{WD} \times 0.5 \times \mathrm{V}$	Cs: Carbon storage (t/ha); WD: Wood density (kg/m^3); V: Volume per ha (m^3/ha)
(4)	NPV of carbon sequestration	$NPV_c = \frac{C_a \times P_c}{i}$	C_a: Annual carbon storage; P_c: Carbon price per ton; i: Interest rate
(5)	Stumpage price model	$P_{t+1} = \alpha + \beta p_t + \varepsilon$	P_{t+1}: Expected stumpage price at time $t+1$; p_t: Stumpage price at time t. α, β: Parameters from regression analysis; ε: Error term
(6)	Expected mean stumpage price	$P_{eq} = \frac{\propto}{1-\beta}$	P_{eq}: Expected mean stumpage price. α, β: Parameters from regression analysis
(7)	NPV of harvestable volume	$NPV_\partial = \frac{\partial_b \times P_\partial}{i}$	∂_b: Harvestable volume (m^3/ha); P_∂: Expected mean stumpage price (IRR 10,000/m^3); i: Interest rate

2.5. Expected Mean Stumpage Price

To calculate the expected mean stumpage price for tree species, the timber price at the forest roadside was adjusted by subtracting variable harvesting costs during the study period from 1993 to 2019. The consumer price index was used to adjust for inflation. Subsequently, a first-order autoregressive model was employed to predict the stumpage price, as detailed in Table 1 (Equation (5)) [66].

We assumed that ε is a series of normally distributed errors with mean zero and autocorrelation zero. Then, the equilibrium price (the expected mean stumpage price) for various species was calculated (Table 1, Equation (6)).

Finally, the NPV of harvestable volume (NPV_∂) was calculated using Equation (7) (Table 1).

2.6. Determining Number of Labour

The required number of labour for forest harvesting was determined through a questionnaire. Coefficients representing the labour-to-volume ratio were uniformly derived across tree species by dividing the total labour count by the volume per ha of the respective trees.

2.7. Questionnaire Design

To establish model constraints such as optimal stock, percentage of tree species volume, annual harvest amount, and required labour per ha, a structured questionnaire was developed and implemented. This questionnaire included nine questions, each with four predefined options and an additional section for respondents to provide alternative answers based on their expertise. The survey was administered to academic members of the Faculty of Natural Resources at University of Guilan and forest experts from the Guilan Department of Natural Resources and Watershed Management, Iran.

Based on the accumulated responses, and averaging the preferred options, the outcomes were integrated into the relevant equations for analysis and implementation.

2.8. Multi-Objective Model

A classical multi-objective programming model can be outlined as follows:

$$\begin{gathered} Max\ Z(x) = \left[Z_1(x), Z_2(x), \ldots, Z_p(x)\right] \\ s.t.g_j(x) \leq 0, j = 1, 2, \ldots, m \\ x_k \geq 0,\ k = 1, 2, \ldots, n \end{gathered} \tag{8}$$

where Z(x) is an objective function and $\left[Z_1(x), Z_2(x), \ldots, Z_p(x)\right]$ is a set of all p objective functions. $g_j(x)$ is the j th constrain function and x_k is the kth decision variable.

In multi-objective problems, instead of having a single objective function, multiple objective functions are simultaneously optimized. This results in the existence of more than one optimal solution, known as Pareto optimal responses. The primary aim of multi-objective optimization is to identify a set of Pareto optimal responses. Forest management objectives typically encompass social, economic, and environmental aspects. In this study, the economic objective involves maximizing the NPV of wood harvesting, while the environmental objective focuses on maximizing the amount of carbon sequestration. Therefore, the objective functions of the bi-objective programming model are as follows:

$$Max\ D = Z_1(x) \tag{9}$$

$$Max\ \mathrm{C} = Z_2(x) \tag{10}$$

where $Z_1(x)$ is an economic player's objective function and $Z_2(x)$ is an environmental player's objective function.

After establishing the objective functions and defining the problem with appropriate constraints, the set of Pareto optimal responses was derived.

An effective approach for obtaining optimal Pareto solutions is through the utilization of the epsilon-constraint method.

2.9. Epsilon (ε)-Constraint Method

A procedure that overcomes some of the convexity problems of the weighted sum technique is the epsilon-constraint method. This involves minimizing a primary objective, f_p, and expressing the other objectives in the form of inequality constraints.

In this method, we always focus on optimizing one of the objectives while defining the highest acceptable bound for the other objectives within the constraints. For a two-objective problem, the following mathematical representation will be obtained:

$$\begin{gathered} Min\ f_1(x) \\ s.t.f_2(x) \leq \varepsilon_2,\ f_3(x) \leq \varepsilon_3, \ldots, f_v(x) \leq \varepsilon_v,\ x \in S \end{gathered} \tag{11}$$

By altering the values of the right-hand side of the new constraints ε_i, the Pareto frontier of the problem will be obtained. One of the major drawbacks of the epsilon-constraint method is the computational burden, as multiple values of ε_i need to be tested for each of the transformed objective functions ($p - 1$ times). One common approach to implement the epsilon-constraint method is to first compute the maximum and minimum of each individual objective function without considering the other objective functions, in the space $x \in S$. Then, using the values obtained from the previous step, the relevant interval for each objective function is calculated. If we denote the maximum and minimum values of the objective functions, respectively, as f_i^{max} and f_i^{min}, then the interval for each of them is calculated using Equation (12):

$$r_i = f_i^{max} - f_i^{mix} \tag{12}$$

The r_i interval is divided into q_i intervals. Then, for ε_i in the Equation (12), it is possible to obtain $q_i = 1$, as different values are calculated through Equation (13).

$$k = 0, 1, \ldots,\ q_i \varepsilon_i^k = f_i^{max} - \frac{r_i}{q_i} \times k \tag{13}$$

In Equation (11), k represents the number of new points related to ε_i. Using the epsilon-constraint method, the multi-objective optimization problem can be transformed into $\prod_{i=2}^{p}(q_i + 1)$ single-objective optimization subproblems. Each subproblem has a solution space S, constrained by the inequalities associated with the objective functions $f_2, \ldots, f_p$. Each subproblem leads to a candidate solution for the desired multi-objective optimization problem, effectively constructing the Pareto optimal front. Sometimes, some of the sub-problems create irrelevant solution spaces. Ultimately, after obtaining the Pareto optimal front, the decision-maker can select the most suitable solution according to their preferences [67].

2.10. Lexicographic Optimization Method

In this approach, the various objectives are prioritized according to their importance to the decision-maker. For instance, objective f_1 holds the highest importance, followed by f_2, and so forth. Lexicographic optimization assumes that the decision-maker values even a slight improvement in f_1 over a significant improvement in f_2, f_3, f_4, and so on. Similarly, even a minor enhancement in f_2 is preferred over a substantial increase in f_3, f_4, and so forth. Essentially, the decision-maker has lexicographic preferences, arranging potential solutions based on a lexicographic order of their objective function values. Lexicographic optimization is sometimes referred to as preemptive optimization since a slight improvement in one objective value preempts a much larger improvement in less significant objective values. In this research, decision-makers place the highest priority on maximizing the NPV. They aim to maximize the NPV of wood harvesting while also seeking to maximize the amount of carbon sequestration. Therefore, they employ lexicographic optimization, where f_1 represents the NPV and f_2 represents the amount of carbon sequestration. A lexicographic maximization problem is typically expressed as follows:

$$\begin{gathered} \text{Lex max } f_1(x), f_2(x), \ldots, f_n(x) \\ \text{Subject to } x \in X \end{gathered} \tag{14}$$

The functions $f_1, \ldots, f_n$ represent the objectives to be maximized, arranged in descending order of importance; x denotes the vector of decision variables, and X represents the feasible set, which encompasses the potential values of x. A lexicographic minimization problem can be similarly characterized.

2.11. Multi-Objective Game Theory Model (MOGM)

To apply a MGOM to bi-objective problems concerning economic–environmental equilibrium, two distinct groups of environmental stakeholders were identified as players. The economic player (Player 1) comprises the users of Shafarood forests, such as operating companies, among others. On the other hand, the environmental player (Player 2) consists of advocates dedicated to preserving the environment and forests, including Natural Resources and Watershed Management Organization of Iran, Environmental Organization of Iran, and environmental NGOs.

To establish the negotiation framework within the game, and to determine the payoff in the game theory analysis, each player aims to ascertain their maximum (D_{max} or C_{max}) or minimum values (D_{min} or C_{min}) through the optimization of each individual objective analysis. Consequently, the range of maximum and minimum values (D, C) for each player was delineated as follows:

$$\text{For Player 1 } \mathrm{EcoD_{min}} \leq \mathrm{EcoD} = Z_1(x) \leq \mathrm{EcoD_{max}} \tag{15}$$

$$\text{For Player 2 EnvC}_{\min} \le \text{EnvC} = Z_2(x) \le \text{EnvC}_{\max} \tag{16}$$

Once the range is established, signifying a pair of simulated values, namely $Z_1(x)$ and $Z_2(x)$, derived from the initial MGOM outcomes, the first round of negotiations commences. Subsequently, each player defines their respective objective values of $\text{EcoD}_{\max}$ or $\text{EnvC}_{\max}$ as EcoDgoal and EnvCgoal, respectively. The ensuing equations indicate that each player's objective value will be treated as a constraint for the opposing party [54].

The approach adopted by Player 1 is as follows:

The strategy of Player 1 is:

$$\begin{gathered} Max\ \text{EcoD} = Z_1(x) \\ s.t. g_j(x) \le 0,\ j = 1, 2, \ldots, m \\ Z_2(x) \le \text{EnvCgoal} \\ x_k \ge 0,\ k = 1, 2, \ldots, n \end{gathered} \tag{17}$$

The strategy of Player 2 is:

$$\begin{gathered} Max\ \text{EnvC} = Z_2(x) \\ s.t. g_j(x) \le 0,\ j = 1, 2, \ldots, m \\ Z_1(x) \le \text{EcoDgoal} \\ x_k \ge 0,\ k = 1, 2, \ldots, n \end{gathered} \tag{18}$$

If both players find the outcomes satisfactory, a Nash equilibrium will be achieved. Nash (1950, 1951) [47,68] introduced the pivotal concept of "Nash equilibrium", where no player has an incentive to change their strategy because no alternative strategy provides a better outcome due to the choices of others. He demonstrated that in non-cooperative games, equilibrium solutions converge to the Nash bargaining solution as uncertainty diminishes over the bargaining set. The Nash bargaining solution maximizes the product of players' gains relative to their disagreement payoff [69]. Nash (1950) [68] established this solution as unique, adhering to principles such as scale invariance, symmetry, efficiency, and independence of irrelevant alternatives. Initially, in the first round of bargaining, players selected strategies aligned closely with their respective goals ($\text{C}_{\min}$ and $\text{D}_{\max}$).

However, unsatisfied with the outcomes, the second round of negotiations commenced. Player 1 adjusted their economic income expectations downwards, while Player 2 relaxed their environmental concerns. To ascertain each player's concession value, the max and min values of D and C were subdivided into small, equal segments. Concessions were incrementally raised with each round, with coefficient determining the most appropriate concession value that would not significantly diminish the satisfaction of both players [70]. Throughout the bargaining process, the disparity between the revised objective values and the MOGM results gradually diminished. This process continued until the final solutions of D_{final} and C_{final} were reached.

$$\text{For Player 1}: \ \text{EcoD}_{\text{final}} \le \text{EcoDgoal} \tag{19}$$

$$\text{For Player 2}: \ \text{EnvC}_{\text{final}} \le \text{EnvCgoal} \tag{20}$$

The Nash bargaining solution refers to the resolved value (D_{final}, C_{final}).

2.12. Sensitivity Analysis

Initially, the multi-objective model and game theory were employed to optimize forest inventory management among stakeholders with diverse objectives. Subsequently, a sensitivity analysis was conducted to assess the risk and accuracy of the model results. The original model computed the optimal solution using validated computations, followed by sensitivity analysis to evaluate the robustness of the outcomes.

In this study, a real interest rate of 6% was utilized, and sensitivity analysis involved varying interest rates to gauge their impact. Changes in the objective functions of both models were evaluated against an optimal stock of 457 m^3 per ha, as determined from the questionnaire results across different interest rates. The simulated values of the objective functions at various interest rates were then compared to a reference present value to ascertain their sensitivity and reliability.

2.13. Objective Functions and Input Parameters

The input parameters for both models (multi-objective and game theory models) are presented in Table 2. The index b represents the species type (beech, hornbeam, oak, alder, and other industrial species).

Table 2. Input parameters of the bi-objective game theory model.

Parameters	Explanations
∂_b	The NPV of forest harvesting of species b
h_b	Amount of harvesting coefficient for species b
Th_b	Growth rate of species b
NH_b	Number of species b per ha
VH_b	Volume of species b per ha
$\widetilde{P}$	Maximum number of labour
π_b	Coefficient used for each labour
$\widetilde{IP}$	Income of each labour
d_b	Income coefficient from each labour for harvesting species b
G_b	Allowed growth capacity for species b
Q_b	Growth coefficient for species b
Inv_b	Optimal inventory for species b
vhv_b	Value of harvestable volume for species b
f_b	Coefficient of harvestable volume for species b
$\widetilde{income}$	Total NPV
m_b	NPV coefficient
$\widetilde{cs}$	Amount of carbon sequestration
l_b	Carbon sequestration coefficient

Table 3 shows the objective functions and input constraints of the model. In this context, (x_b) denotes the harvest amount of species b.

Figure 2 illustrates a step-by-step approach to achieving optimal forest management, starting with defining objectives and input parameters, followed by game theory design, multi-objective modeling, sensitivity analysis, and ending with a determination of Nash equilibrium and Pareto optimality.

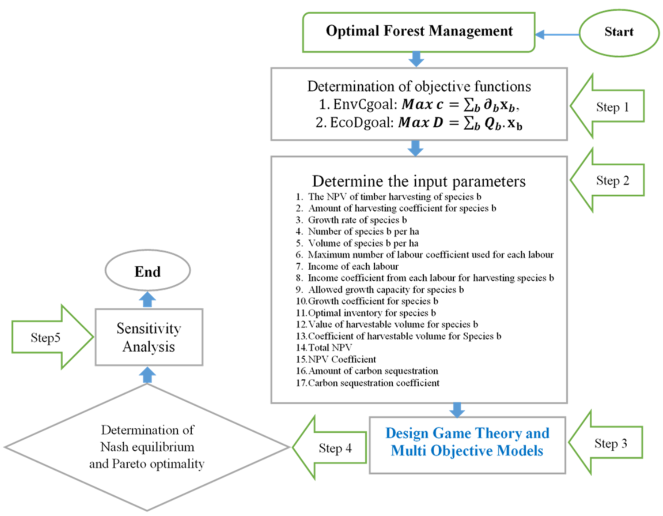

Figure 2. Game theory and multi-objective modeling for optimal forest management.

Table 3. Objective functions and input constraints for both models.

		Equation	Condition
Objective functions	(1)	$Max\ c = \sum_b \partial_b x_b$	
	(2)	$Max\ D = \sum_b Q_b \cdot x_b$	
Constraints	(1)	$h_b \cdot x_b \leq Th_b$	$\forall b \in B$
	(2)	$x_b \leq NH_b$	$\forall b \in B$
	(3)	$x_b \leq VH_b$	$\forall b \in B$
	(4)	$Q_b \cdot x_b \leq G_b$	$\forall b \in B$
	(5)	$x_b \leq Inv_b$	$\forall b \in B$
	(6)	$f_b \cdot x_b \leq vhv_b$	$\forall b \in B$
	(7)	$\sum_b x_b \cdot \pi_b \leq \widetilde{P}$	
	(8)	$\sum_b x_b \cdot d_b \leq \widetilde{IP}$	
	(9)	$\sum_b x_b \leq 457$	
	(10)	$m_b \cdot x_b \geq \widetilde{income}$	$\forall b \in B$
	(11)	$l_b \cdot x_b \widetilde{cs}$	$\forall b \in B$
	(12)	$x_b \geq 0$	

3. Results

3.1. Determining Volume per ha for Different Tree Species

According to the questionnaire results, the optimal target volume for the region is 457 ($m^{3)}$ per ha. The distribution of tree species is as follows: 55% beech, 13% hornbeam, 16% oak, 9% alder, and 7% other industrial species (Table 4).

Table 4. Volume and type of studied species.

Species Name	Variable	Acceptable Volume (%)	Acceptable Volume (m^3/ha)
Beech	X_1	55	251.4
Hornbeam	X_2	13	59.4
Oak	X_3	16	73.1
Alder	X_4	9	41.1
Other Industrial Species	X_5	7	32
Total	X	100	457

Due to the percentage of each species, the volume per ha for each species was determined and used in the volume Equation (21):

$$X_1 + X_2 + X_3 + X_4 + X_5 \geq 457\ (\mathrm{m}^3/\mathrm{ha}) \tag{21}$$

3.2. Carbon Storage in Optimal Biomass

The optimal carbon storage amounts per tree species were determined as follows: beech 84.22 (tons/ha), hornbeam 20.8 (tons/ha), oak 11.92 (tons/ha), alder 23.39 (tons/ha), and other industrial species 19.88 (tons/ha). Furthermore, the carbon stored in the forest floor amounts to 160.21 tons per ha.

Each coefficient in Table 5 acts as a weighting factor that reflects how much each species contributes to the overall carbon storage in the forest.

Table 5. Numerical values of various variables used in estimating the predicted carbon model in the study area.

Species Name	Carbon Model	Predicted Volume (m^3/ha)	Predicted Carbon (Tons/ha)	Coefficients
Beech	$Y = 0.335\ X + 0.0000004$	251.4	84.22	0.335
Hornbeam	$Y = 0.3501\ X + 0.000008$	59.4	20.8	0.3501
Oak	$Y = 0.32\ X + 0.0003$	73.1	23.39	0.32
Alder	$Y = 0.29\ X + 0.000004$	41.1	11.92	0.29
Other Industrial Species	$Y = 0.3107\ X + 0.0002$	32	19.88	0.3107
Total	-	457	160.21	-

The equation for stored carbon in the standing biomass under study incorporates five variables: beech, hornbeam, oak, alder, and other industrial species. These variables are calculated as coefficients by dividing the predicted carbon by the predicted volume of each respective tree species. They are utilized in the equation to determine the stored carbon in the forest tree biomass.

$$0.335X_1 + 0.3501X_2 + 0.32X_3 + 0.29X_4 + 0.3107X_5 \geq 160.21\ (\text{tons/ha}) \tag{22}$$

- The NPV of carbon sequestration

The average global carbon price was USD 27.2 per ton [71], which converted to IRR 6,923,064.4 [72] in the free-market exchange rate. Therefore, the value of carbon sequestration for 160.21 (m^3/ha) amounts to 685.1780327 (IRR 10,000/ha).

The annual growth volume is 3.37 (m^3/ha), which corresponds to an annual carbon storage of 1.8 tons/ha. The NPV of carbon sequestration per unit growth is calculated to be 20,002.433 (IRR 10,000/ha/year). Notably, the NPV of carbon sequestration constraint was found to be infeasible in the initial models and was therefore excluded from further calculations.

3.3. Growth Prediction

The relationship between growth and volume per ha for various species was analyzed to assess the strength and direction of their association. Regression analysis was applied to model the effect of stock (m^3/ha) on growth (m^3/ha) for each species. A logarithmic model was selected to capture the growth pattern, with the R^2 value indicating the model's goodness of fit. By substituting the predicted stock (m^3/ha) for each species into this logarithmic model, the corresponding growth values were calculated. These logarithmic functions provided growth estimates based on stock for different species (Table 6). For stock level of 457 (m^3/ha), the minimum predicted growth value is 3.37 (m^3/ha).

Table 6. Logarithmic functions and coefficients for each species.

Species Name	Variable	Logarithmic Functions	Predicted Volume (m^3/ha)	Predicted Growth (m^3/ha)	Coefficients
Beech	X_1	$Y = 0.3094\ln(x) - 0.3711$	251.4	1.34	0.0053
Hornbeam	X_2	$Y = 0.1393\ln(x) - 0.1284$	59.4	0.44	0.0074
Oak	X_3	$Y = 0.0962\ln(x) - 0.0135$	73.1	0.4	0.0055
Alder	X_4	$Y = 0.1042\ln(x) + 0.2933$	41.1	0.68	0.0165
Other Industrial Species	X_5	$Y = 0.1144\ln(x) + 0.1143$	32	0.51	0.0159
Total	X	-	457	3.37	-

The growth equation derived from the results in Table 6 is used in the multi-objective and game theory programming models. This equation includes five variables (tree species) such as beech (X_1), hornbeam (X_2), oak (X_3), alder (X_4), and other species (X_5) (Equation (23)).

$$0.0053X_1 + 0.0074X_2 + 0.0055X_3 + 0.0165X_4 + 0.0159X_5 \geq 3.37\ (\mathrm{m}^3/\mathrm{ha}) \quad (23)$$

3.4. Determining the Relationship for Labor Requirements

The labor requirements for the forest management plan were examined to determine the minimum level of job creation and were incorporated into the model. Data on the number of workers were collected through a questionnaire, resulting in a total of 24 workers. Since the labor requirements do not depend on tree species, the labor coefficients were calculated uniformly. These coefficients were derived by dividing the total number of workers (24) by the optimal volume per ha (457 m^3/ha), yielding a coefficient of 0.0525, as shown in Equation (24).

$$0.0525X_1 + 0.0525X_2 + 0.0525X_3 + 0.0525X_4 + 0.0525X_5 \geq 24 \quad (24)$$

- Labour income

The income from labour during the forest management implementation period, after accounting for inflation, amounts to 10,269,990.29 (IRR 10 million).

3.5. Stumpage Price for Various Tree Species

The stumpage price per cubic meter of wood was assessed for different tree species during the period from 1993 to 2019, as explained in Section 2.4.

- NPV of harvestable volume

Based on the questionnaire results, the harvestable volume is estimated to be 50% of the growth. The NPV of this harvestable volume was calculated for each species (Table 7) using a real interest rate of 6.23%, as determined by Equation (7).

Table 7. NPV of harvestable volume.

Species Name	Variable	Mean Expected Stumpage Price (IRR 10,000/m^3)	Harvestable Volume (m^3/ha)	NPV of Harvestable Volume (IRR 10,000)
Beech	X_1	667.22	0.67	7175.56
Hornbeam	X_2	377.59	0.22	1333.38
Oak	X_3	405.46	0.2	1301.62
Alder	X_4	571.86	0.34	3120.91
Other Industrial Species	X_5	540.08	0.255	2210.58
Total	X	-	1.685	15,142.05

Equation (25) represents a constraint in the model, ensuring that the total NPV of harvestable volumes for all species exceeds a minimum threshold of 15,142,050 (IRR 10,000/m^3)

$$667.22X_1 + 377.59X_2 + 405.455X_3 + 571.86X_4 + 540.075X_5\ \geq 15142.05\ (\mathrm{IRR}10,000/\mathrm{ha}) \quad (25)$$

3.6. Multi-Objective Model Output

Based on the questionnaire results and the model output, the optimal stock per ha in the study area is estimated to be 457 (m^3/ha). The goal is to gradually increase the stock from 303.96 to 457 (m^3/ha) in the long term. Table 8 shows the optimal stock for each species at various levels.

Table 8. Optimal stock values for each species at different levels.

Objective Functions	Solution					
	Beech (X_1) (m^3/ha)	**Hornbeam (X_2) (m^3/ha)**	**Alder (X_3) (m^3/ha)**	**Oak (X_4) (m^3/ha)**	**Other (X_5) (m^3/ha)**	**Total (X) (m^3/ha)**
$MaxZ_1(x)$	170	77.42	3.16	37.11	16.26	303.96
	190.35	72.92	20.65	38.11	20.2	342.21
	210.7	68.41	38.13	39.11	24.13	380.475
$MaxZ_2(x)$	231.05	63.91	55.62	40.1	28.07	418.74
	251.4	59.4	73.1	41.1	32	475

The optimal stock levels for each management level are as follows: 303.96 (m^3/ha) at level 1, 342.21 (m^3/ha) at level 2, 380.475 (m^3/ha) at level 3, 418.74 (m^3/ha) at level 4, and 457 (m^3/ha) at level 5. The range of changes in the objective function values (NPVs) for an inventory of 303.96 (m^3/ha) is shown in Table A1 and Figure A1 in Appendix A.

The Pareto optimal frontier for the first stock level (303.96 m^3/ha) is shown in Figure A1 in Appendix A. As we move closer to the center of the graph, the objective function values become more balanced.

The Pareto optimal frontier for the first stock level (303.96 m^3/ha) is shown in Figure A1 in Appendix A. This graph illustrates the trade-off between the NPV of forest harvesting and the amount of carbon sequestration (tons/ha). Each point on the curve (Sol1 to Sol20) represents a solution where both objectives are balanced.

As we move closer to the center of the graph, the objective function values become more balanced, indicating an optimal trade-off between economic returns (NPV of forest harvesting) and environmental benefits (amount of carbon sequestration). The Pareto optimal points are defined as those situations where it is impossible to improve one objective without deteriorating another.

The range of objective function values for the second stock level of 342.21 (m^3/ha) is presented in Table A2 in Appendix A. The Pareto frontier of non-dominated solutions for this stock level is illustrated in Figure A2 in Appendix A, demonstrating how different stock levels influence the trade-offs between economic and environmental objectives.

For the third stock level of 380.475 (m^3/ha), the range of objective function values is shown in Table A3 in Appendix A, along with the Pareto optimal solutions depicted in Figure A3 and Table A4 in Appendix A displays the range of objective function values for the fourth stock level of 418.74 (m^3/ha), along with its corresponding Pareto optimal solutions in Figure A4.

Finally, the range of objective function values for the fifth stock level of 457 (m^3/ha) is detailed in Table A5 in Appendix A, accompanied by the Pareto optimal solutions presented in Figure A5.

3.7. Game Theory Model Output

Table 9 and Figure 3 display the objective function values for both the economic and environmental players for stock level of 1, which is 303.96 (m^3/ha). In the fifth round of bargaining, a Nash equilibrium was reached between the two players. At this equilibrium point, the NPV of forest harvesting and amount of carbon sequestration for the economic player are 6363.748 (IRR 10,000/ha) and 106.3633 (tons/ha), respectively. For the environmental player, the NPV of forest harvesting and amount of carbon sequestration are 5496.699 (IRR 10,000/ha) and 106.3897 (tons/ha), respectively. This equilibrium demonstrates a balanced outcome where neither player can improve their position without negatively impacting the other.

Table 9. Objective function results for each player at stock level 1.

Grid	Game Round	Players	NPV of Forest Harvesting (Z_1) (IRR 10,000/ha)	Amount of Carbon Sequestration (Z_2) (Ton/ha)
Grid 1 (303.96 m^3/ha)	1-1	Player 1	1275.408	106.517
	1-2	Player 2	9894.058	106.2324
	2-1	Player 1	2550.815	106.4786
	2-2	Player 2	8794.718	106.286
	3-1	Player 1	3826.223	106.4402
	3-2	Player 2	7695.378	106.3228
	4-1	Player 1	5101.001	106.4017
	4-2	Player 2	6596.038	106.3562
	5-1	Player 1	6363.748	106.3633
	5-2	Player 2	5496.699	106.3897

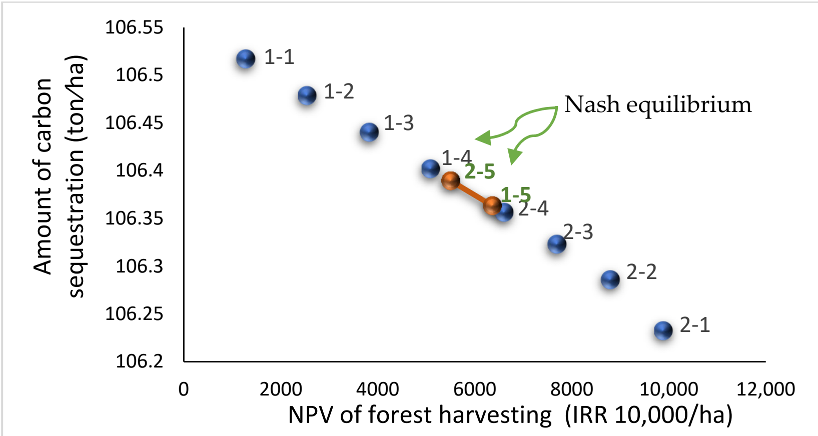

Figure 3. Range of objective function variations for each player at stock level 1.

Figure 3 illustrates the trade-off between NPV and amount of carbon sequestration for the economic and environmental players over several bargaining rounds.

- In the fifth round of bargaining, a Nash equilibrium was reached, indicated by the intersection marked "1–5" and "2–5." At this equilibrium point:
  - The economic player achieved an NPV of 6363.748 (IRR 10,000/ha) and carbon sequestration of 106.3633 (tons/ha).
  - The environmental player achieved an NPV of 5496.699 (IRR 10,000/ha) and carbon sequestration of 106.3897 (tons/ha).

This equilibrium demonstrates a balanced outcome where neither player can improve their position without negatively impacting the other. The positions of the points in Figure 3 reflect the trade-offs each player had to make to reach this balanced state.

Table 10 and Figure 4 show the objective function values for the economic and environmental players for stock level of 2, corresponding to 342.21 (m^3/ha). In the fifth round of negotiations, a Nash equilibrium between the two players is reached. The NPV and amount of carbon sequestration at this point for the economic player are 70,232.82 (IRR 10,000/ha) and 119.7571 (tons/ha), and for the environmental player are 60,878.36 (IRR 10,000/ha) and 119.7855 (tons/ha).

Table 11 and Figure 5 show the objective function values for the economic and environmental players for the stock level of 3, which is 380.48 (m^3/ha). In the fifth round of negotiations, a Nash equilibrium was established between the two players. At this equilibrium point, the NPV and carbon sequestration for the economic player are 7682.816 (IRR 10,000/ha) and 133.1508 (tons/ha), respectively. For the environmental player, the NPV and carbon sequestration are 6678.973 (IRR 10,000/ha) and 133.1814 (tons/ha), respectively.

Table 10. Objective function results for each player at stock level 2.

Grid	Game Round	Players	NPV of Forest Harvesting (Z_1) (IRR 10,000/ha)	Amount of Carbon Sequestration (Z_2) (Ton/ha)
Grid 2 (342.21 m^3/ha)	1-1	Player 1	1407.427	119.9267
	1-2	Player 2	10,958.1	119.6128
	2-1	Player 1	2814.855	119.8843
	2-2	Player 2	9740.538	119.6699
	3-1	Player 1	4222.282	119.8419
	3-2	Player 2	8522.97	119.7114
	4-1	Player 1	5629.71	119.7995
	4-2	Player 2	7305.403	119.7485
	5-1	Player 1	7023.282	119.7571
	5-2	Player 2	6087.836	119.7855

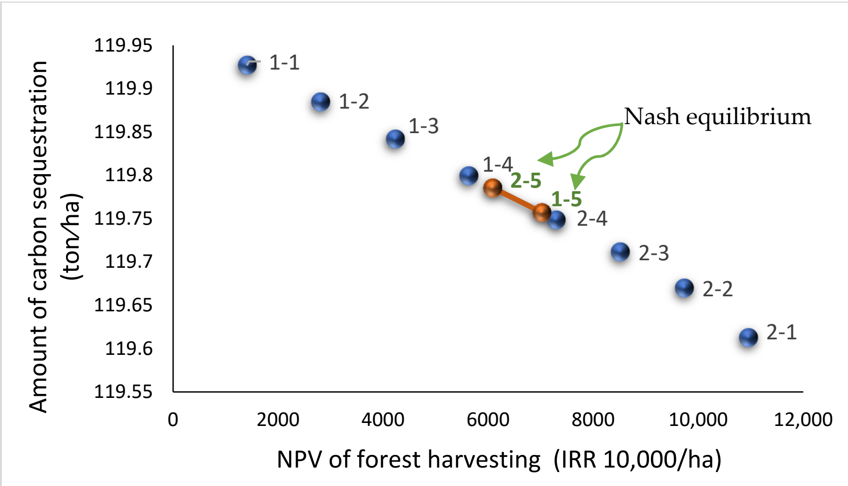

Figure 4. Range of objective function variations for each player at stock level 2.

Table 11. Objective function results for each player at stock level 3.

Grid	Game Round	Players	NPV of Forest Harvesting (Z_1) (IRR 10,000/ha)	Amount of Carbon Sequestration (Z_2) (Ton/ha)
Grid 3 (380.48 m^3/ha)	1-1	Player 1	1539.447	133.3363
	1-2	Player 2	12,022.15	132.9933
	2-1	Player 1	3078.895	133.29
	2-2	Player 2	10,686.36	133.0539
	3-1	Player 1	4618.342	133.2436
	3-2	Player 2	9350.562	133.1
	4-1	Player 1	6157.79	133.1972
	4-2	Player 2	8014.768	133.1407
	5-1	Player 1	7682.816	133.1508
	5-2	Player 2	6678.973	133.1814

Table 12 and Figure 6 display the objective function values for the two players, economic and environmental at a stock level of 4, corresponding to 418.74 (m^3/ha). In the fifth round of bargaining, a Nash equilibrium has been reached between them. At this equilibrium point, the economic player achieves an NPV of 8342.35 (IRR 10,000/ha) and carbon sequestration of 146.5446 (tons/ha), while the environmental player achieves an NPV of 7270.11 (IRR 10,000/ha) and carbon sequestration of 146.5772 (tons/ha).

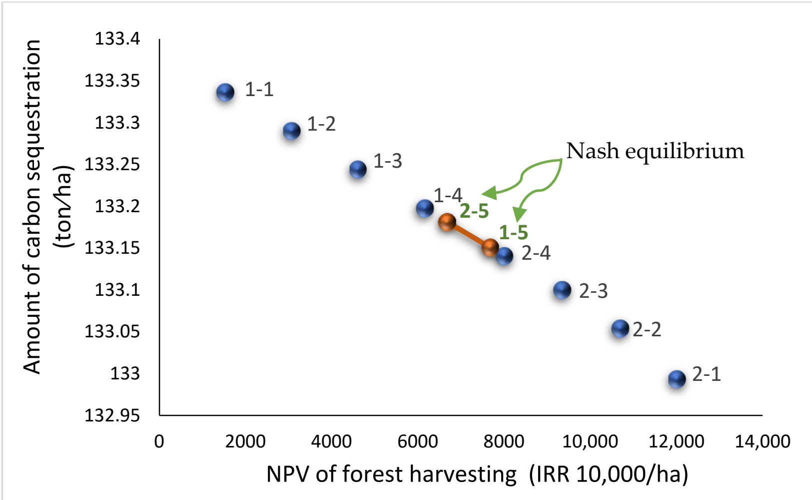

Figure 5. Range of objective function variations for each player at stock level 3.

Table 12. Objective function results for each player at stock level 4.

Grid	Game Round	Players	NPV of Forest Harvesting (Z_1) (IRR 10,000/ha)	Amount of Carbon Sequestration (Z_2) (Ton/ha)
Grid 4 ($418.74\ m^3/ha$)	1-1	Player 1	1671.476	146.746
	1-2	Player 2	13086.2	146.3737
	2-1	Player 1	3342.935	146.6975
	2-2	Player 2	11,632.18	146.4379
	3-1	Player 1	5014.402	146.6453
	3-2	Player 2	10,178.15	146.488
	4-1	Player 1	6685.87	146.5949
	4-2	Player 2	8724.133	146.533
	5-1	Player 1	8342.35	146.5446
	5-2	Player 2	7270.11	146.5772

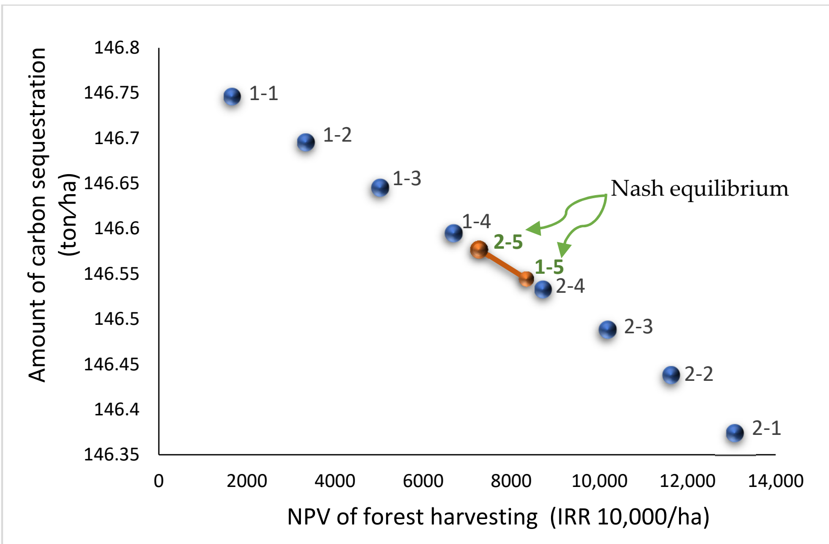

Figure 6. Range of objective function variations for each player at stock level 4.

Table 13 and Figure 7 present the objective function values for the economic and environmental players at a stock level of 457 m^3/ha, corresponding to stock level 5. In the fifth round of bargaining, a Nash equilibrium has been achieved between the two players.

At this equilibrium point, the NPV and carbon sequestration for each player are as follows: for the economic player, NPV of 9001.884 (IRR 10,000/ha) and carbon sequestration of 159.9383 (tons/ha); for the environmental player, NPV of 7861.248 (IRR 10,000/ha) and carbon sequestration of 159.9731 (tons/ha).

Table 13. Objective function results for each player at stock level 5.

Grid	Game Round	Players	NPV of Forest Harvesting (Z_1) (IRR 10,000/ha)	Amount of Carbon Sequestration (Z_2) (Ton/ha)
Grid 5 (457 m^3/ha)	1-1	Player 1	1803.487	160.1557
	1-2	Player 2	14,150.25	159.7526
	2-1	Player 1	3606.975	160.1013
	2-2	Player 2	12578	159.8218
	3-1	Player 1	5410.462	160.047
	3-2	Player 2	11,005.75	159.8761
	4-1	Player 1	7213.949	159.9927
	4-2	Player 2	9433.497	159.9252
	5-1	Player 1	9001.884	159.9383
	5-2	Player 2	7861.248	159.9731

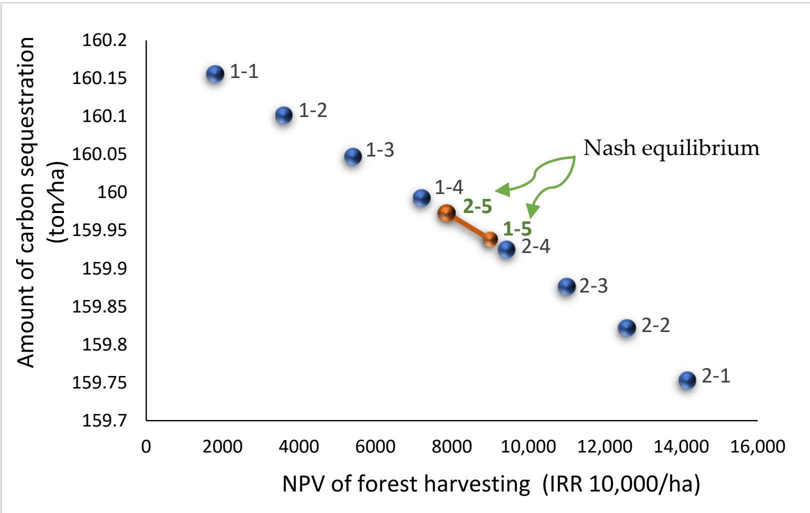

Figure 7. Range of objective function variations for each player at stock level 5.

Table 14 shows the growth and equilibrium harvest rates at each stock level, as well as the stock levels for each tree species.

Table 14. Objective function values, total growth, harvest amount, and stock by species at different levels of stock.

Stock (m^3/ha)	Game Round	Objective		Solution						
		Amount of Carbon Sequestration (Z_2) (Ton/ha)	NPV of Harvesting (Z_1) (IRR 10,000/ha)	Growth	Harvest	X_1 (Beech)	X_2 (Hornbeam)	X_3 (Alder)	X_4 (Oak)	X_5 (Other)
303.96	5-1	106.36	6363.75	1.78	0.59	170	77.42	3.16	37.11	16.26
303.96	5-2	106.39	5496.7	1.87	0.5					
342.21	5-1	119.76	7023.28	1.97	0.65	190.35	72.92	20.65	38.11	20.2
342.21	5-2	119.82	6087.84	2.06	0.56					
380.48	5-1	133.15	7682.82	2.16	0.71	210.7	68.41	38.13	39.11	24.13
380.48	5-2	133.18	6678.97	2.26	0.61					
418.74	5-1	146.54	8342.35	2.35	0.77	231.05	63.91	55.62	40.1	28.07
418.74	5-2	146.58	7270.11	2.46	0.66					
457	5-1	159.94	9001.88	2.54	0.83	251.4	59.4	73.1	41.1	32
457	5-2	159.97	7861.25	2.66	0.71					

Table 15 shows the growth and equilibrium harvest rates for each species at various stock levels for each player. By analyzing these rates, stakeholders can make informed decisions regarding harvesting practices and stock management to optimize both economic returns and environmental health.

Table 15. Optimal growth and harvest volumes for each species at various stock levels for each player.

Stock (m^3/ha)	Harvest, Growth (m^3/ha)	Players	Beech	Hornbeam	Alder	Oak	Other
303.96	Growth	Player 1	0.45	0.57	0.017	0.47	0.3
		Player 2	0.45	0.57	0.017	0.57	0.3
	Harvest	Player 1	0.453	-	-	0.139	-
		Player 2	0.453	-	-	0.048	-
342.21	Growth	Player 1	0.51	0.54	0.113	0.49	0.322
		Player 2	0.51	0.54	0.113	0.58	0.322
	Harvest	Player 1	0.507	-	-	0.145	-
		Player 2	0.507	-	-	0.047	-
380.48	Growth	Player 1	0.56	0.51	0.21	0.5	0.38
		Player 2	0.56	0.51	0.21	0.6	0.38
	Harvest	Player 1	0.562	-	-	0.151	-
		Player 2	0.562	-	-	0.046	-
418.74	Growth	Player 1	0.62	0.47	0.3	0.51	0.45
		Player 2	0.62	0.47	0.3	0.62	0.45
	Harvest	Player 1	0.616	-	-	0.157	-
		Player 2	0.616	-	-	0.044	-
457	Growth	Player 1	0.67	0.44	0.4	0.52	0.51
		Player 2	0.67	0.44	0.4	0.64	0.51
	Harvest	Player 1	0.67	-	-	0.163	-
		Player 2	0.67	-	-	0.043	-

3.8. Results of Sensitivity Analysis

- Multi-objective model

The sensitivity of the objective function was analyzed for the multi-objective model at interest rates of 4%, 5%, 6%, 7%, 8%, 9%, 10%, 15%, and 20%, with an optimal stock of 457 m^3/ha. The results indicated that as the interest rate increases, the expected NPV decreases (Figure 8).

The analysis shows a clear trend where the increase in the interest rate results in a decrease in the NPV, reflecting the diminishing returns on future revenues when discounted at higher rates.

- Game theory model

The game theory model also examined the variation in the objective function at the same interest rates for the optimal stock of 457 (m^3/ha). Similarly, it was observed that as the interest rate rises, the expected NPV decreases (Figure 9).

For both models, the economic player's objective function was found to be sensitive to interest rate changes, where the NPV of forest harvesting was inversely related to the interest rate. However, changes in the interest rate did not affect the environmental player's objective function, as the carbon sequestration amount remained constant and unaffected by interest rate variations. While the NPV of carbon sequestration was initially included as a constraint, it was later excluded from both models due to the lack of feasible solutions.

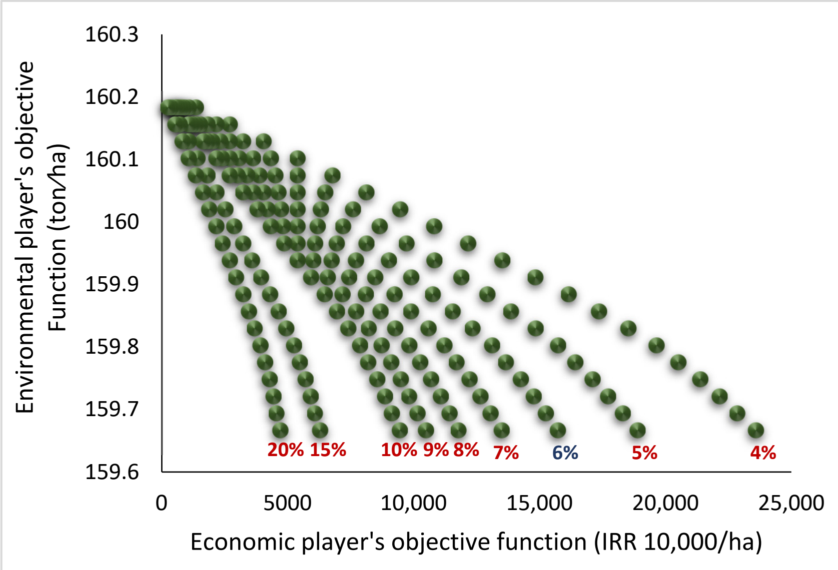

Figure 8. Sensitivity of NPV to interest rate changes for optimal stock of 457 (m^3/ha).

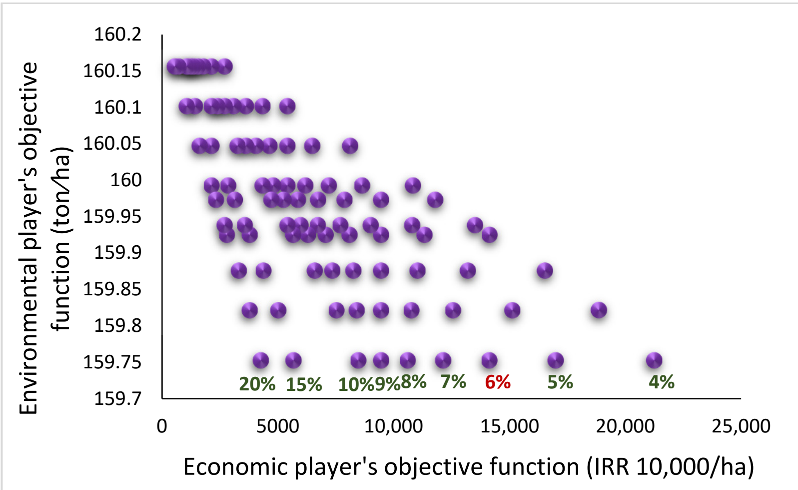

Figure 9. Sensitivity of NPV to interest rate changes for optimal standing inventory of 457 (m^3/ha).

4. Discussion

The Nash equilibrium identified in the game theory model of this study simplifies decision-making conditions for environmental and economic stakeholders, enabling informed choices based on available options. This approach becomes crucial when decision-making is complex due to the involvement of diverse stakeholders, allowing adaptation to environmental challenges while fostering economic growth within the constraints defined by the Nash equilibrium. The findings of this study align with those of Moradi and Mohammadi Limaei (2018) [73], highlighting the effectiveness of Nash equilibrium in addressing decision-making dilemmas in competitive situations. In a similar study, Koltarza (2024) [74] focuses on the use of Nash equilibrium as a tool for developing optimal harvesting strategies. The study demonstrates that employing Nash equilibrium can lead to the development of optimal harvesting strategies that consider both economic and environmental benefits. In another study, Siangulube (2024) [75] emphasizes the necessity of private-sector participation and the importance of prioritizing local needs and the demands of marginalized people while downplaying the usefulness of formal laws and regulations as the ultimate means to resolve landscape issues. In similar contexts, Ratner et al. (2022) [76] emphasized that in the absence of trust and other democratic elements, negotiating trade-offs is difficult, and the governance paradigm mostly shifts to relying on dominant formal systems of rules and regulations, which may escalate conflicts.

Comparison between Nash equilibrium values and Pareto optimal values reveals distinct methodologies in game theory and multi-objective optimization. This disparity has been previously discussed by Moradi and Mohammadi Limaei (2018) [73], Madani (2010) [77], and Lee (2012) [61]. The multi-objective optimization model offers a spectrum of Pareto optimal points, each representing a feasible compromise between environmental and economic considerations that decision-makers can select based on stakeholder preferences. In contrast, the game theory model, after iterative negotiation rounds, converges on a Nash equilibrium where players pursue self-interest, presenting decision-makers with a limited yet balanced range of choices encompassing economic and environmental objectives. Eyvindson et al. (2023) [19] emphasize stakeholder engagement through interactive tools that allow users to examine the impact of different scenarios in forest planning, aiding in better and more balanced decision-making. Their study uses multi-objective optimization techniques to determine Pareto optimal points in forest planning, helping decision-makers find a balance between various objectives.

In this study, direct interaction with stakeholders across different scenarios was not explored. Instead, the focus was on decision-making outcomes using game theory models and multi-objective optimization, specifically aiming for Nash equilibrium and Pareto optimal points in managing the Hyrcanian forests. While the multi-objective model and the Pareto frontier contribute to balancing economic and environmental objectives, Nash equilibrium plays a more prominent role in improving the decision-making process for optimal forest resource management.

Our findings align with the study by Moradi and Mohammadi Limaei (2018) [73], which highlights the advantages of the game theory model in decision-making by simplifying the selection process. In contrast, the multi-objective epsilon-constraint method employed in this research, while effective in ranking and narrowing the Pareto optimal range, offers a broader decision-making framework. As a result, the game theory model proves to be more efficient for decision-makers aiming to balance environmental protection with economic development goals [73].

Çalışkan and Özden (2022) [78] also emphasize the potential of game theory to enhance sustainability policies in international forestry. They underscore how game theory can illustrate the necessity of strategic cooperation among countries and stakeholders for more effective forest resource management. Their findings indicate that game theory can refine decision-making processes in international forestry policies. Specifically, bargaining games can aid in resource allocation, zero-sum games can assess competitive dynamics between countries, and the prisoner's dilemma can underscore the importance of strategic cooperation. Our study similarly addresses sustainability in the management of the Hyrcanian forests, aiming to balance economic and environmental objectives through game theory techniques. Both studies explore the impact of varying parameters—such as interest rates in our study and game conditions in Çalışkan and Özden's (2022) [78] study—on outcomes. The parallels between these studies highlight the efficacy of game theory in forest resource management and in enhancing decision-making processes. Both demonstrate that game theory can help achieve a better balance between economic and environmental objectives while fostering stronger cooperation among stakeholders. These shared insights offer a valuable foundation for advancing policies and management strategies in forestry and natural resource management.

Nabhani et al. (2024) [3] investigated the optimization of economic and environmental objectives in ecosystem services under conditions of uncertainty. Their study provides a comprehensive analysis of Pareto optimal points in ecosystem service optimization, demonstrating how these points can represent the balance between various objectives. However, their focus is predominantly on the application of game theory models and multi-objective optimization under deterministic conditions. While the study explores both Pareto optimal points and the distinction between Nash equilibrium and Pareto optimal points, it places greater emphasis on Nash equilibrium. A sensitivity analysis was conducted for both the multi-objective and game theory models at the optimal stock level of 457 (m^3/ha), considering interest rates ranging from 4% to 20%. The results consistently indicate that as interest rates increase, the NPV decreases while the harvest volume rises. This trend suggests that higher interest rates incentivize earlier harvesting, as the expected NPV declines with increasing interest rates. These findings are consistent with those of Mohammadi Limaei and Mohammadi (2023) [79].

Çalışkan and Özden (2022) [78] used sensitivity analysis to explore the effects of various game scenarios on decision-making, illustrating how alterations in game conditions can lead to different outcomes. In our study, the sensitivity analysis of interest rates reveals their impact on harvest volume and net present value, demonstrating how fluctuations in interest rates can influence managerial decision-making. This study demonstrates the feasibility of achieving simultaneous economic and environmental objectives through both multi-objective and game theory models in optimizing Hyrcanian forest management. Nabhani et al. (2024) [3] underscore the importance of considering multiple objectives in forest management and policy under uncertain wood prices, preventing undesired effects from a singular or deterministic approach. This study provides insights into trade-offs and synergies, contributing to strategic planning and policy design. Owing to the current logging moratorium on Iran's Hyrcanian forests, proactive planning is essential for the post-moratorium period. Determining optimal growth and harvest volumes that balance economic benefits with environmental sustainability will be crucial.

5. Conclusions

The modeling framework employed in this research offers valuable insights into planning sustainable forest harvesting levels, aiming to maximize forest growth potential while maintaining optimal standing volumes. Additionally, the model's flexibility facilitates the integration of various uses, such as social benefits and ecotourism, which can be prioritized based on evolving societal needs.

To enhance the resilience and sustainability of forest management practices in the region, integrating climate change considerations into game theory modeling is recommended to prepare for future environmental challenges. Additionally, addressing social concerns alongside economic and environmental goals.

These strategies aim to refine forest management approaches, ensuring alignment with economic, environmental, and social objectives amidst evolving conditions. By adopting these measures, stakeholders can effectively navigate the complexities of forest management and foster sustainable development in the Hyrcanian forests and beyond.

Limitations and future directions:

This study acknowledges several limitations that may affect the robustness of the findings. Key constraints include data limitations, model simplifications, and uncertainties in market and environmental conditions that influence long-term forest planning. These limitations highlight the need for improved data-collection methods and the integration of more comprehensive datasets to better capture the complexities of forest ecosystems.

To address these limitations, future research should focus on incorporating adaptive management frameworks that can accommodate ecological and economic uncertainties. This approach can enhance the flexibility and responsiveness of sustainable management strategies.

Additionally, improving multi-objective models by integrating diverse stakeholder perspectives and objectives is essential for developing effective forest management policies. Future studies could consider a broader range of objectives and employ various techniques to refine sustainable management strategies for the Hyrcanian forests and similar ecosystems.

Policy Implications:

The findings of this study suggest that policymakers must prioritize collaborative approaches that incorporate the needs and perspectives of all stakeholders, including local communities and industrial interests. By fostering dialogue and cooperation among diverse groups, policies can be developed that balance economic benefits with environmental sustainability. Implementing adaptive management strategies will also be essential in responding to changing ecological and economic conditions, ensuring the long-term viability of forest resources.

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Data Availability Statement: The data are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Optimal values of the Pareto for objective functions at stock level 1.

Grid	Solutions	NPV of Forest Harvesting (Z_1) (IRR 10,000/ha)	Amount of Carbon Sequestration (Z_2 (Ton/ha)	Growth (G) (m^3/ha)	Amount of Harvest (m^3/ha)
Grid 1 (303.96 m^3/ha)	Solution 1	10,993.4	106.17	1.185	1.128
	Solution 2	10,648.08	106.19	1.24	1.073
	Solution 3	10,302.76	106.21	1.295	1.018
	Solution 4	9957.43	106.23	1.35	0.963
	Solution 5	9612.11	106.25	1.4	0.913
	Solution 6	9266.79	106.27	1.459	0.854
	Solution 7	8779.62	106.29	1.519	0.794
	Solution 8	8223.06	106.31	1.581	0.732
	Solution 9	7626.5	106.32	1.645	0.668
	Solution 10	6995.12	106.34	1.712	0.601
	Solution 11	6363.75	106.36	1.778	0.535
	Solution 12	5732.37	106.38	1.844	0.469
	Solution 13	5101	106.4	1.91	0.403
	Solution 14	4463.93	106.42	1.969	0.344
	Solution 15	3826.22	106.44	2.026	0.287
	Solution 16	3188.52	106.46	2.083	0.23
	Solution 17	2550.82	106.48	2.141	0.172
	Solution 18	1913.11	106.5	2.198	0.115
	Solution 19	1275.41	106.52	2.255	0.058
	Solution 20	637.7	106.54	2.313	0

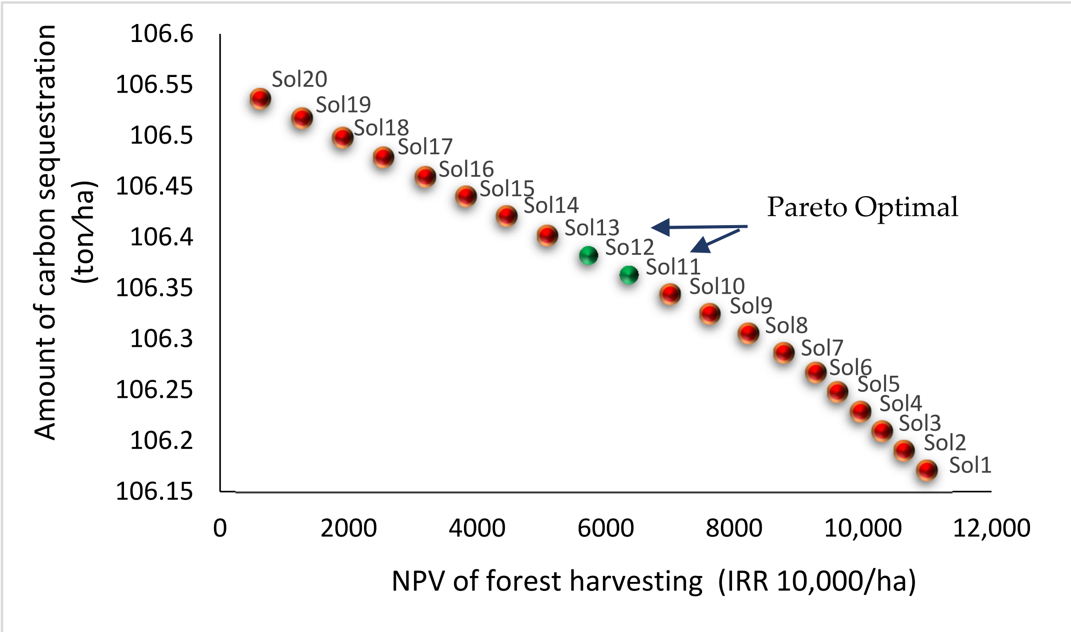

Figure A1. Pareto optimal frontier at stock level 1.

Table A2. Pareto optimal values for objective functions at stock level 2.

Grid	Solutions	NPV of Forest Harvesting (Z_1) (IRR 10,000/ha)	Amount of Carbon Sequestration (Z_2 (Ton/ha)	Growth (G) (m^3/ha)	Amount of Harvest (m^3/ha)
Grid 2 (342.21 m^3/ha)	Solution 1	12,175.67	119.55	1.31	1.25
	Solution 2	11,794.61	119.57	1.37	1.19
	Solution 3	11,413.54	119.59	1.43	1.13
	Solution 4	11,032.47	119.61	1.49	1.07
	Solution 5	10,651.41	119.63	1.55	1.01
	Solution 6	10,234.36	119.65	1.62	0.94
	Solution 7	9672.23	119.67	1.68	0.88
	Solution 8	9058.06	119.69	1.75	0.81
	Solution 9	8416.74	119.71	1.82	0.74
	Solution 10	7720.01	119.74	1.89	0.67
	Solution 11	7023.28	119.76	1.97	0.59
	Solution 12	6326.55	119.78	2.04	0.52
	Solution 13	5629.71	119.8	2.11	0.45
	Solution 14	4926	119.82	2.18	0.38
	Solution 15	4222.28	119.84	2.24	0.32
	Solution 16	3518.57	119.86	2.3	0.26
	Solution 17	2814.86	119.88	2.37	0.19
	Solution 18	2111.14	119.91	2.43	0.13
	Solution 19	1407.43	119.93	2.49	0.07
	Solution 20	703.14	119.95	2.56	0

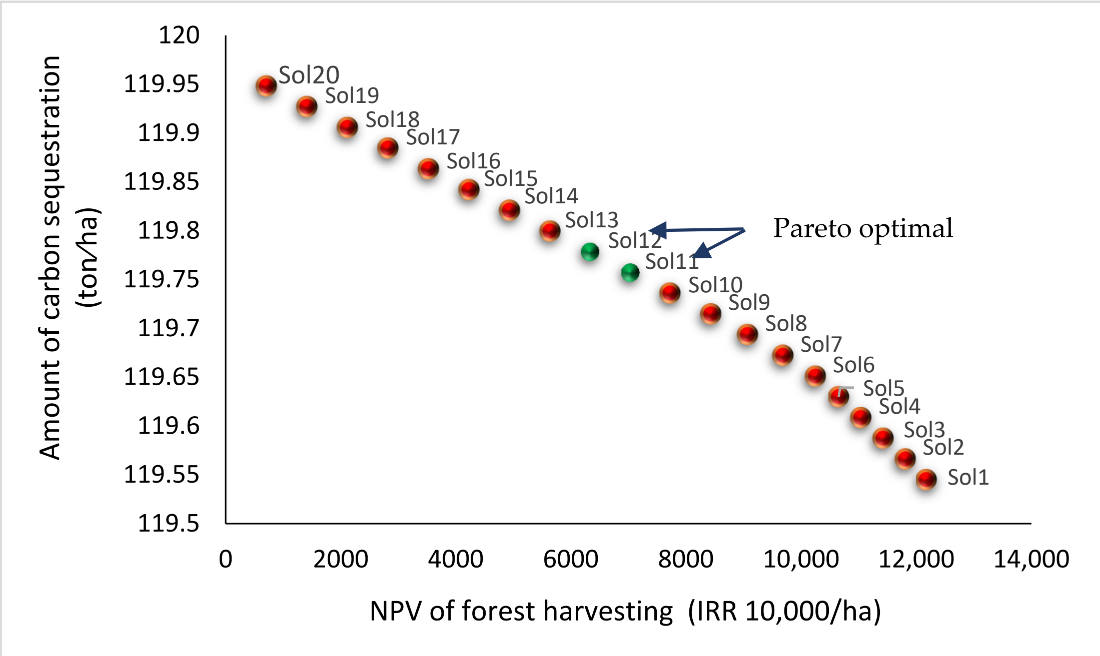

Figure A2. Pareto optimal frontier at stock level 2.

Table A3. Pareto optimal values for objective functions at stock level 3.

Grid	Solutions	NPV of Forest Harvesting (Z_1) (IRR 10,000/ha)	Amount of Carbon Sequestration (Z_2) (Ton/ha)	Growth (G) (m^3/ha)	Amount of Harvest (m^3/ha)
Grid 3 (380.475 m^3/ha)	Solution 1	13,357.95	132.92	1.44	1.36
	Solution 2	12,941.14	132.94	1.5	1.3
	Solution 3	12,524.32	132.97	1.57	1.23
	Solution 4	12,107.51	132.99	1.63	1.17
	Solution 5	11,677.99	133.01	1.7	1.1
	Solution 6	11,188.32	133.03	1.77	1.03
	Solution 7	10,564.83	133.06	1.85	0.95
	Solution 8	9893.06	133.08	1.92	0.88
	Solution 9	9206.98	133.1	2	0.8
	Solution 10	8444.9	133.13	2.08	0.72
	Solution 11	7682.82	133.15	2.16	0.64
	Solution 12	6920.73	133.17	2.24	0.56
	Solution 13	6157.79	13.2	2.32	0.48
	Solution 14	5388.07	133.22	2.39	0.41
	Solution 15	4618.34	133.24	2.45	0.35
	Solution 16	3848.62	133.27	2.52	0.28
	Solution 17	3078.9	133.29	2.59	0.21
	Solution 18	2309.17	133.31	2.66	0.14
	Solution 19	1539.45	133.34	2.73	0.07
	Solution 20	769.72	133.36	2.8	0

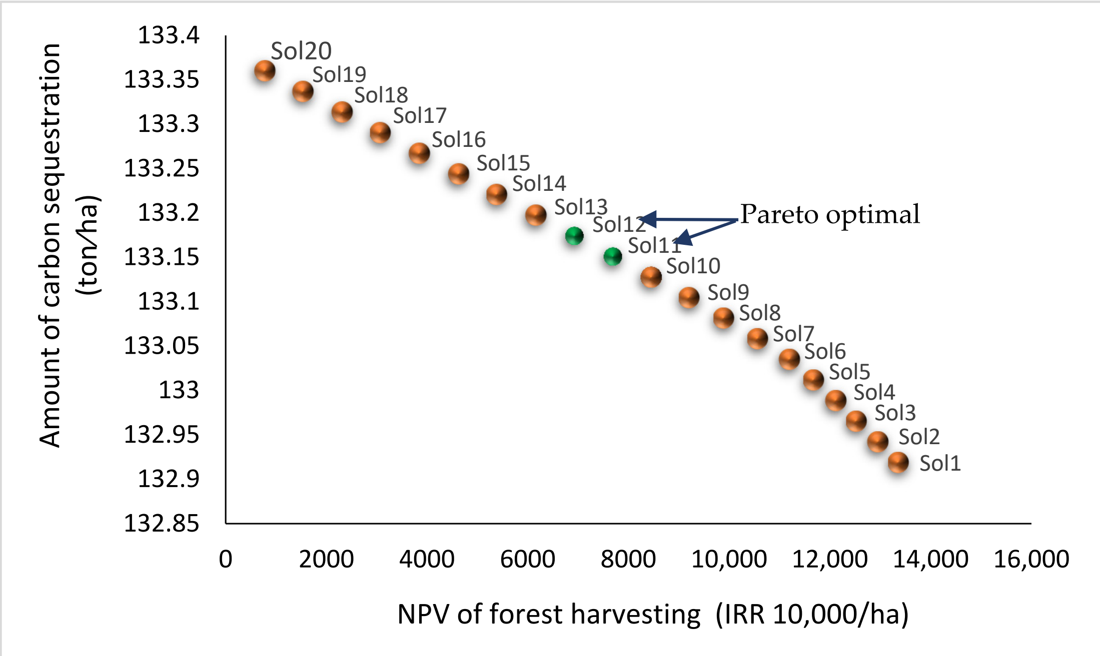

Figure A3. Pareto optimal frontier at stock level 3.

Table A4. Pareto optimal values for objective functions at stock level 4.

Grid	Solutions	NPV of Forest Harvesting (Z_1) (IRR 10,000/ha)	Amount of Carbon Sequestration (Z_2) (Ton/ha)	Growth (G) (m^3/ha)	Amount of Harvest (m^3/ha)
Grid 4 (418.74 m^3/ha)	Solution 1	14,540.22	146.29	1.56	1.48
	Solution 2	14,087.67	146.32	1.63	1.41
	Solution 3	13,635.11	146.34	1.7	1.34
	Solution 4	13,182.55	146.37	1.78	1.27
	Solution 5	12,673.94	146.39	1.85	1.19
	Solution 6	12,142.27	146.42	1.93	1.11
	Solution 7	11,457.44	146.44	2.01	1.03
	Solution 8	10,728.05	146.47	2.09	0.95
	Solution 9	9997.23	146.49	2.17	0.87
	Solution 10	9169.79	146.52	2.26	0.78
	Solution 11	8342.35	146.54	2.35	0.7
	Solution 12	7514.91	146.57	2.43	0.61
	Solution 13	6685.87	146.59	2.52	0.53
	Solution 14	5850.14	146.62	2.59	0.45
	Solution 15	5014.4	146.65	2.67	0.38
	Solution 16	4178.67	146.67	2.74	0.3
	Solution 17	3342.94	146.7	2.82	0.23
	Solution 18	2507.2	146.72	2.89	0.15
	Solution 19	1671.47	146.75	2.97	0.08
	Solution 20	835.73	146.77	3.04	0

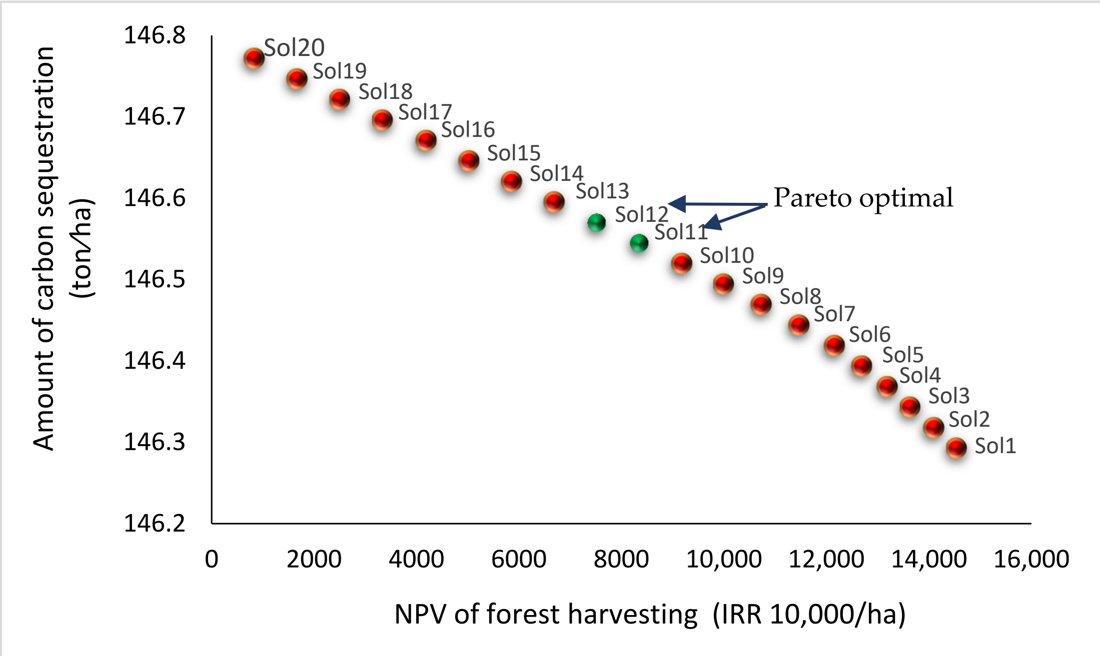

Figure A4. Pareto optimal frontier at stock level 4.

Table A5. Pareto optimal values for objective functions at stock level 5.

Grid	Solutions	NPV of Forest Harvesting (Z_1) (IRR 10,000/ha)	Amount of Carbon Sequestration (Z_2) (Ton/ha)	Growth (G) (m^3/ha)	Amount of Harvest (m^3/ha)
Grid 5 ($475\ m^3/ha$)	Solution 1	15,722.5	159.67	1.69	1.6
	Solution 2	15,234.19	159.69	1.76	1.53
	Solution 3	14,745.89	159.72	1.84	1.45
	Solution 4	14,243.54	159.75	1.92	1.37
	Solution 5	13,669.88	159.78	2	1.29
	Solution 6	13,096.23	159.8	2.09	1.2
	Solution 7	12,350.05	159.83	2.18	1.11
	Solution 8	11,536.05	159.86	2.26	1.03
	Solution 9	10,776.06	159.88	2.35	0.94
	Solution 10	9894.68	159.9	2.44	0.85
	Solution 11	9001.88	159.94	2.54	0.75
	Solution 12	8109.09	159.97	2.63	0.66
	Solution 13	7213.95	159.99	2.72	0.57
	Solution 14	6312.21	159.02	2.8	0.49
	Solution 15	5410.46	160.05	2.88	0.41
	Solution 16	4508.72	160.07	2.96	0.32
	Solution 17	3606.98	160.1	3.05	0.24
	Solution 18	2705.23	160.13	3.13	0.16
	Solution 19	1803.49	160.16	3.21	0.08
	Solution 20	901.74	160.18	3.29	0

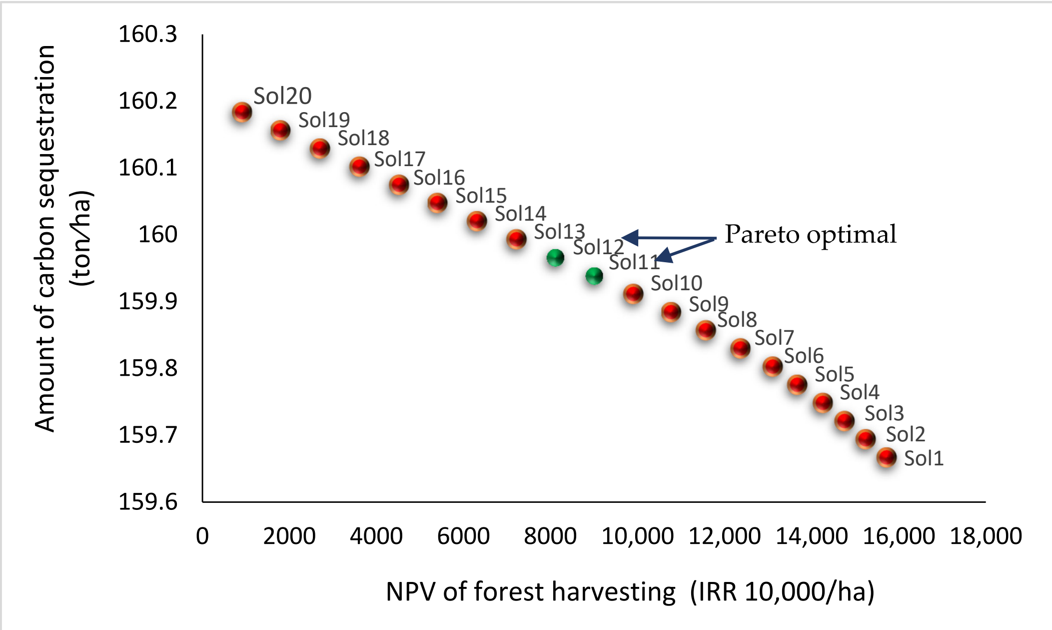

Figure A5. Pareto optimal frontier at forest stock level 5.

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