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What trees are more suitable for agroforestry implementation? A case study in Northwestern Iran

Mohammad Kheiri · Jafar Kambouzia · Saeid Soufizadeh · Abdolmajid Mahdavi Damghani · Romina Sayahnia · Hossein Azadi

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Abstract Agroforestry is an integrative farm management approach in which trees are deliberately integrated with other crops. Agroforestry systems can be effective if appropriate trees are chosen based on particular environmental and economic factors. However, it is crucial to identify suitable trees for agroforestry implementation (AI). The objective of the current study was to recognize the most suitable trees for AI in the agricultural lands of Nazar Kahrizi (NK) rural district of Hashtroud city, located in the northwest of Iran using a multi-dimensional approach. The study area was environmentally evaluated using ArcGIS, which led to the creation of 16 classes with different features. Then, based on the preference of 126 local farmers (from 26 villages of NK), 19 native trees were selected for AI assessment. These trees were evaluated and compared considering seven criteria (i.e., frostbite resistance, salinity resistance, sensitivity to drainage, storm resistance, drought resistance, preventing soil erosion, and economic benefits). Finally, a flexible multi-criteria decision analysis (MCDA) tool (PROMETHEE II) was applied to provide a complete ranking of preferred trees from the best to the worst for each class. The findings showed that the agricultural lands should be allocated for planting elaeagnus (about 79.6%, 27,446 ha), almond (13.5%, 4619 ha), quince (4.6%, 1573 ha), apple (1.8%, 635 ha), and walnuts (0.5%, 176 ha). Measurements showed that AI with the recommended trees in the study area will lead to CO_2 sequestration of about 12.96 Mg yr^{-1}. The approach used in this study provides a valuable resource for decision-making in AI evaluations and, therefore, contributes to preserving the lands from degradation and ensures sustainable AI.

Keywords Native trees · PROMETHEE II · Fuzzy-AHP · CO_2 sequestration · Agroforestry · Climate change

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M. Kheiri · J. Kambouzia (✉) · S. Soufizadeh · A. Mahdavi Damghani · R. Sayahnia
Department of Agroecology, Environmental Sciences Research Institute, Shahid Beheshti University, Tehran, Iran
e-mail: J_Kambouzia@sbu.ac.ir

H. Azadi (✉)
Department of Economics and Rural Development, Gembloux Agro-Bio Tech University of Liège, Liège, Belgium
e-mail: hossein.azadi@uliege.be

Introduction

Nowadays, the negative impacts of climate change (CC) on the agricultural sector have intensified the concerns about the future of the world's food security. Extreme weather and climatic disasters have exposed millions of people to severe diseases caused by food. Moreover, unsustainable agricultural development, driven by CC, leads to competition for natural resources and enhances the vulnerability of food production systems around the globe. According to the findings of Iizumi et al. (2018), the global grain yield of corn, wheat, and soybean decreased by an average of 4.1%, 1.8%, and, 4.5% during 1981–2010, compared with the pre-industrial period. In addition, agricultural production is expected to decrease by 20–30% due to CC by the end of 2100 (IPCC 2023). Although the agricultural sector is overwhelmingly dominated by the adverse consequences of CC, it plays a considerable role in the exacerbation of global warming (Udeigwe et al. 2015). In this regard, about one-fourth of the global greenhouse gases (GHG) emissions are attributed to unsustainable agricultural activities (Zhang et al. 2018). Currently, conventional agricultural practices (i.e., the use of agrochemicals, pesticides and fossil fuels, and monoculture) have been welcomed by farmers due to the benefits of higher production and lower costs. However, their adverse effects on the environment have often not been considered (Alvarez et al. 2017). In addition, intense and frequent tillage operations, common in conventional agriculture, cause soil degradation and transfer of the sequestrated carbon (C) in the soil to the atmosphere (Dubey et al. 2020). The introduction of concepts such as "sustainable intensification" and "climate-smart agriculture" has resulted from the increasing challenges associated with CC, land-use change, and deforestation (Jayne et al. 2019). These two concepts aimed to increase land productivity; mitigate the loss of natural resources, biodiversity, and habitat; and improve ecosystem services via safe and sustainable methods (Sarkar et al. 2020).

Agroforestry is regarded as one of the appropriate techniques for "climate-smart agriculture" and "sustainable intensification" to improve ecosystem services and preserve natural resources (Amadu et al. 2020; Kheiri et al. 2023). Agroforestry is the most important integrative farm management strategy in which trees and shrubs are intentionally mixed with other crops. This approach is the most efficient agricultural land-use policy which simultaneously benefits all four groups of ecosystem services including supporting, regulation, provisioning, and cultural (Rosenstock et al. 2019). In fact, agroforestry reduces environmental, social, and economic problems in the agricultural sector and fills up the existing gap between agriculture and forestry. As Brown et al. (2018) argued, agroforestry systems enhance the resilience of agricultural lands and mitigate the negative impacts of CC. Agroforestry provides a wide range of benefits including timber, coal, fiber, food (fruits, honey, oil, etc.), and medicine; improves soil structure and biodiversity; increases soil organic matter; and accelerates nutrients' cycle (Benjamin and Sauer 2018). In addition, agroforestry is a nature-based solution for the world's livelihood asset development concerns, such as CC, degradation of land, and high poverty levels (Muthee et al. 2022).

Recently, many studies (e.g., Hübner et al. 2021; Dangai et al. 2021; Martinelli et al. 2019) have focused on providing ecosystem services by agroforestry systems, paying particular attention to C sequestration potential. In these studies, the amount of C sequestration of existing agroforestry systems has been measured. For instance, Hübner et al. (2021) assessed the soil C sequestration using agroforestry systems in China and reported that shelterbelt, agrisilvicultural, and silvopastoral systems could sequestrate C at about 0.92, 0.72, and 0.52 Mg ha^{-1} yr^{-1} in top soils (0–20 cm), respectively. Dangai et al. (2021) evaluated the role of *Daniellia oliveri* agroforestry parklands in CC reduction by predicting C stock in Cameroon's Sudanian-Sahelian zone. Their findings revealed that C sequestration potential of *Daniellia oliveri* agroforestry parklands varies from 312.71 ± 40.77 CO_2eq ha^{-1} for young parklands (1–10 years) to 865.77 ± 18.20 CO_2eq ha^{-1} for older ones (higher than 30 years). Martinelli et al. (2019) investigated the environmental performance of agroforestry systems in mitigating global warming and providing ecosystem services in the Cerrado biome of Brazil and found the significant capacity of agroforestry systems in C sequestration to be 263 to 496 t CO_2 ha^{-1} yr^{-1}. Some other studies (e.g., Kheiri et al. 2023; Nath et al. 2021; Chuma et al. 2021; Kay et al. 2019; Ahmad et al. 2019; de Mendonça et al. 2022) have investigated the land suitability of an area for agroforestry implementation (AI). For instance, Nath et al. (2021) used multi-criteria assessment modeling to assess the land suitability of arable lands in the Eastern Indian Himalayan area for agroforestry. To create an agroforestry suitability map, they considered many factors related to climate, soil, topography, and ecological and socioeconomic dimensions. Their findings revealed that ~77% (60,523 km^2) of arable land offers very good to good agroforestry suitability. Chuma et al. (2021) investigated the land suitability for AI in Congo applying the AHP method in GIS. They reported four zones including very high (~29.2%), high (~22.3%), moderate (~34%), and low (~14.5%) suitable zones for AI. Kay et al. (2019) assessed nine environmental pressures associated with agroforestry benefits to identify the suitability of agricultural land for AI in Europe. According to their investigation, 136,758 km^2, or around 8.9% of all the agricultural land in Europe, has the greatest potential for AI. Ahmad et al. (2019) assessed the land potentiality for agroforestry in India using FAO land suitability standards and a variety of land, soil, climatic, and topographic issues. According to their findings, 32.8% of the region is perfect for AI. Although the land suitability evaluation is the first and the most crucial step in AI (de Mendonça et al. 2022), the most important question is as follows: "Which woody elements should be planted in the suitable areas?" However, few studies have been conducted to identify suitable trees for AI.

According to Atangana et al. (2014), in order to achieve successful agroforestry, the trees must be evaluated in terms of various factors including environmental, socio-cultural, and economic conditions of a particular area. In addition, the effective implementation of a sustainable strategy such as agroforestry should be aimed at solving the main problems of farmers (Sathyan et al. 2018). Despite the many benefits proposed for agroforestry, its implementation fails and is not welcomed due to neglecting the interests of farmers and/or the natural capacities of an area. Therefore, relying on the method applied in this research, users will be able to identify the most suitable woody elements for AI from the socio-economic and environmental points of view. This study is novel because it uses a simple and understandable method that offers a valuable resource for decision-making in AI evaluations. As a result, it preserves the land from degradation and ensures sustainable AI. In addition, this study, for the first time, has evaluated the tree selection for AI and consequently CO_2 sequestration resulting from AI in Iran. This study aimed to identify the most suitable trees for AI according to the environmental and socio-economic conditions of the agricultural lands of Nazar Kahrizi (NK) rural district located in the northwest of Iran. The importance of this study is due to three main reasons: (1) It classifies the study area based on different environmental limitations to assess land suitability for AI; (2) It identifies the best tree(s) for each class considering farmers' preferences, the trees' adaptability or sensitivity to environmental conditions, and their economic benefits; (3) It measures the CO_2 sequestration of the identified tree(s) via actual information. Accordingly, this study seeks to answer the following questions:

1. Which tree(s) is/are the best suited option(s) to be planted in the study area?
2. What is the amount of CO_2 sequestration resulting from the AI?

Materials and methods

Study area

Hashtroud city, located in the northwest of Iran, has an area of about 1990 km^2 with an altitude of 1159 to 3182 m above sea level and is located between 37.10° and 37.40° N latitude and 46.20° and 47.20° E longitude. This city is one of the largest cities in East Azerbaijan province, and according to the topographic and geographical characteristics, it is classified as an area with a cold and mountainous climate. The amount of rainfall in this city varies from 250 to 300 mm. With about 12.2% of the East Azerbaijan province's agricultural lands, Hashtroud is one of the most important cereal production poles of the province. The income of ~75% of rural households is, directly and indirectly, dependent on the agricultural products in this area. Furthermore, wheat, barley, chickpea, and alfalfa are the major crops cultivated in Hashtroud. The city consists of seven rural districts, of which Nazar Kahrizi (NK) is the widest rural district. This rural district consists of 79 villages, with 4092 farmers, and contains 34.2% of the total farmers of Hashtroud. As mentioned earlier, this study was conducted in the agricultural lands of NK. The selection of NK for the purposes of this study has certain advantages: (1) The climate of this region is semi-arid (Kheiri et al. 2021), similar to most regions of Iran (Tabari et al. 2014), and, therefore, it can represent the climate of Iran; (2) The majority of its population consists of farmers who are mostly smallholders; (3) It is the most strategic hub for the production of agricultural products in Hashtroud city; (4) This region has both irrigated and rainfed irrigation types and has a large variety of trees, which allows the evaluation of the research objectives for various scenarios and conditions. The land cover map of NK is illustrated in Fig. 1. To generate the map of the land cover of NK, the latest and highest quality data of the Sentinel-2B satellite were downloaded from the United States Geological Survey (USGS) website. Then, the processing of these images was carried out using eCognition Developer 9.01 software to determine the type of land cover. The validity of the current map was double-checked by comparing it with Google Earth Pro, and its quality and accuracy were confirmed by the experts and agronomists of the Agricultural Jahad Office of Hashtroud as well.

Identification of the trees for AI based on farmer preference

According to Kay et al. (2019), the most effective way to use AI is to use trees that farmers are interested in and are most likely to use. A tree that a farmer dislikes for whatever reason is always a non-starter in extension, therefore farmers' interest in AI has to align with the advantages associated with a tree (Tengnäs 1994). In addition, Jose (2009) claimed that because native trees are well-known and well-adapted to the environmental condition of a particular area, it is worth choosing them as permanent elements (trees) of agroforestry systems. The native trees retain agrobiodiversity and enhance agricultural systems' sustainability (Shelef et al. 2017). Therefore, it is necessary to first identify a set of native trees that local farmers prefer for AI. Since it was not possible to reach all the farmers in the study area, the sampling method was used. The

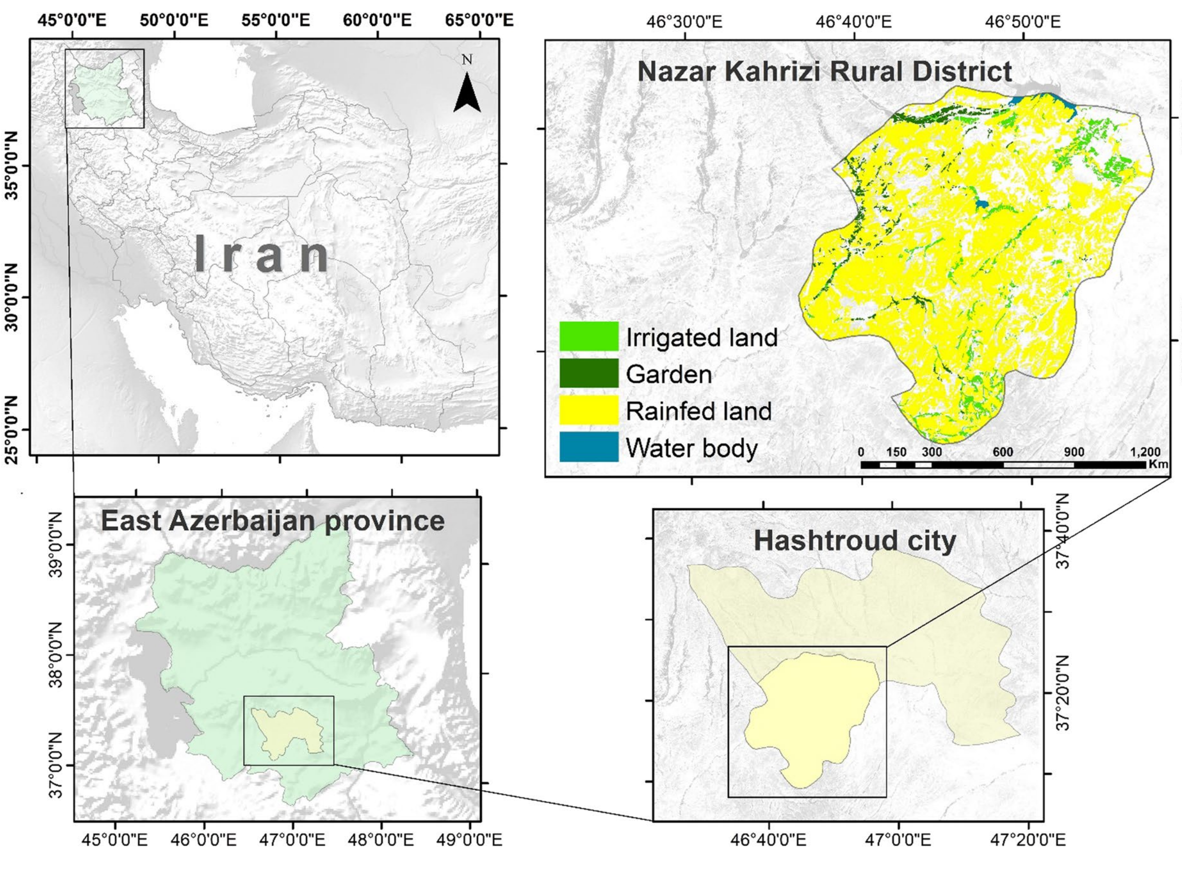


Fig. 1 Land cover map of the study area

study area has 4092 farmers, of which 126 (from 26 villages namely Asayesh, Alaqayeh, Borj-Sofla, Ganj-Abad-Sofla, Tilimkhan, Tarkhnlar, Tikma-Dash, Jiqil-Sofla, Jiqil-Olya, Chitiqlou, Sariqayeh, Shakar-Boolaqi, Umran-Kandi, Qoort-Qayasi, Qaraja-Qaya, Qooshelar, Goshayesh, Katala-Kamar, Bash-Khalaj, Khorshid, Mallajiq, Shordaraq, Nazar-Kahrizi, Yaniq, Yela-Qarshou, and Yaharchi) were selected as the sample group by cluster random sampling method. Then, a face-to-face interview was conducted with the sample group. At first, the concept of agroforestry and its benefits were explained to the farmers, and then they were asked to answer the following question: "What kind of native trees do you prefer to plant in your agricultural lands?" After collecting the preferred trees by farmers (PTF) for AI, they were reviewed and checked. The final list of PTFs is presented in Table 1. As illustrated, all trees are fruit-bearing, of which seven are rainfed and 12 are irrigated. Table 1 also shows other information including the range of planting altitude (m) of the PTF. This information was obtained from the Cold Trees Working Group (CTWG) of the horticulture department of the Ministry of Agriculture-Jahad (MAJ).

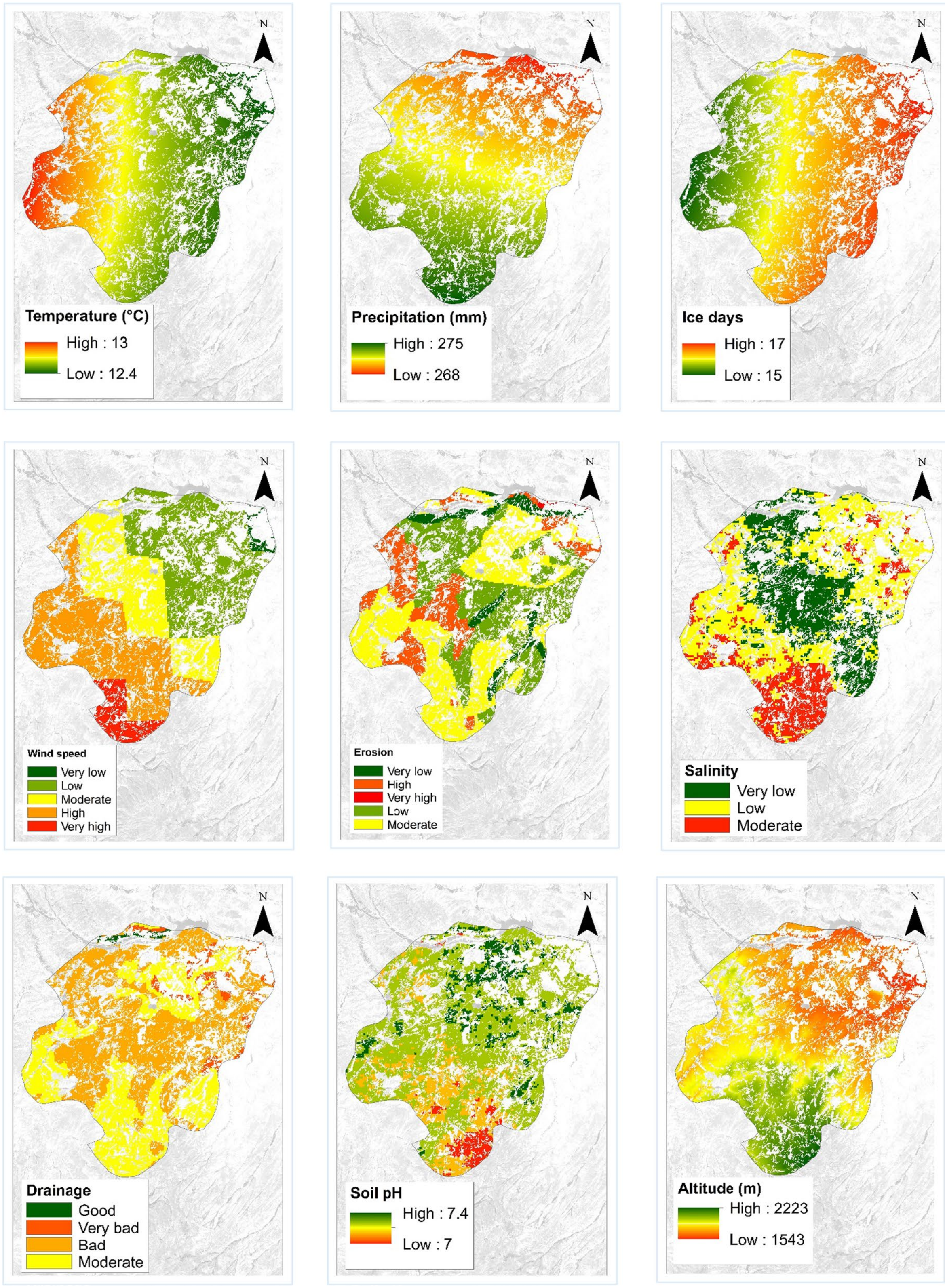
Environmental characteristics of the study area

Assessment of characteristics such as climatic conditions, land-use type, landscape, and other variables is critical to predicting ecosystem processes, understanding ecosystem function, and evaluating the effects of land-use change (Denton et al. 2017). According to Singh et al. (2022), AI will be effective if the climatic, soil, and topographic factors that define the study area are taken into account. Therefore, in this study, the environmental conditions of NK were assessed considering nine environmental variables including annual mean temperature (°C), precipitation (mm), ice days, wind speed, soil erosion, drainage, soil pH, soil salinity, and altitude (m). In this study, the term "ice days" refers to the number of days of each year when the lowest temperature is below 0 °C (Jamshidi et al. 2019). The selected variables are the most important factors affecting the growth and development of plants and were widely suggested in land suitability analysis for AI (Ahmad et al. 2019; Kay et al. 2019; Everest et al. 2021; Singh et al. 2022). Figure 2 shows the geographical distribution of the variables selected.

According to Fig. 2, the annual mean temperature in NK varies between 12.4 and 13 °C. Furthermore,

Table 1 The final list of PTF for AI in the agricultural lands of NK rural district

Tree name	Scientific name	Irrigation	Planting altitude (m)
Apple	*Malus domestica*	Irrigated	1300–2200
Quince	*Cydonia oblonga Miller*	Irrigated	1300–2200
Pear	*Pyrus communis*	Irrigated	1300–2200
Peach	*Prunus persica*	Irrigated	1300–2200
Nectarine	*Prunus persica nucipersica*	Irrigated	1300–2200
Apricot	*Prunus armeniaca*	Irrigated	100–3000
Plum	*Prunus domestica*	Irrigated	100–3000
Greengage	*Reine Claude Verte*	Irrigated	100–3000
Cherry	*Prunus avium*	Irrigated	100–3000
Sour cherry	*Prunus cerasus*	Irrigated	200–2500
Walnuts	*Juglans regia*	Irrigated	1100–2200
Filbert	*Corylusavellana*	Irrigated	100–2200
Pomegranate	*Punica granatum*	Rainfed	100–1500
Grapes	*Vitis amresis*	Rainfed	1500–2200
White Mulberry	*Morus alba*	Rainfed	100–3000
Barberries	*Berberis*	Rainfed	100–1900
Hawthorns	*Crataegus*	Rainfed	100–3000
Almond	*Prunus amygdalus*	Rainfed	100–3000
Elaeagnus	*Elaeagnus angustifolia*	Rainfed	100–3000


Temperature (°C)
High : 13
Low : 12.4
Precipitation (mm)
High : 275
Low : 268
Ice days
High : 17
Low : 15
Wind speed
Very low
Low
Moderate
High
Very high
Erosion
Very low
High
Very high
Low
Moderate
Salinity
Very low
Low
Moderate
Drainage
Good
Very bad
Bad
Moderate
Soil pH
High : 7.4
Low : 7
Altitude (m)
High : 2223
Low : 1543

◂**Fig. 2** Spatial distribution of the environmental variables selected in the study area

the amount of precipitation in the study area varies from 268 mm in the south to 276 mm in the north. In addition, the ice days in the study area vary in the range of 15–17 days. Wind speed has decreased with increasing latitude, in a way that wind speed is very high in the south of the area and very low in the northern part. The spatial distribution of soil erosion indicates a heterogeneous distribution of the soil erosion level in the study area. In terms of drainage, a large part of the study area is located in the "weak" class. In addition, the soil salinity is at a "very low to medium" level. Finally, the study area is in the range of 7 to 7.4 in terms of soil pH and is located at altitudes of 1543 to 2223 (m).

Classification of the study area based on environmental characteristics

As shown in Fig. 2, the study area has slight fluctuations in terms of annual mean temperature, precipitation, and ice days. In terms of soil salinity, the study area has no limits and is in the "very low to medium" class. The pH of 7 to 7.4 for the study area does not physiologically limit the plantation of PTF, because the growth of a wide range of plants in the pH range of 6 to 7.5 is usually good (Wingeyer et al. 2015). Moreover, according to Table 1, the PTF can grow in the altitude range of the study area without restrictions. However, there are some limitations to tree plantation in the study area including "drainage," "wind speed," and "soil erosion". In this regard, the maps of these variables were reclassified using ArcGIS10.8 software to separate the areas that potentially create restrictions for planting trees. Accordingly, the study area is divided into two classes including "moderate to good" and "very weak to weak" in terms of drainage. Moreover, in terms of wind speed, it is classified into two classes: "high to very high" and "very low to medium". In terms of soil erosion, the study area is divided into "high to very high" and "very low to medium" classes. Apart from these three variables, "irrigation type" which expresses the limitation of access to water, was also chosen as the fourth variable in this study. Therefore, the study area is separated into two classes including "rainfed" and "irrigated" in terms of irrigation type. After reclassification of the maps of the selected variables, these maps were combined using the intersection technique of ArcGIS10.8. The combination of these maps led to the creation of 16 classes, as indicated in Table 2.

Data collection

Information on PTF

In this study, the required information for comparing and separating PTFs based on their capabilities and limitations was gathered through the survey method. To do this, a closed questionnaire was designed based on a nine-point scale, and the respondents were asked to evaluate the PTF in terms of seven criteria including "frostbite resistance", "salinity resistance", "drainage sensitivity", "storm resistance", "drought resistance", "preventing soil erosion", and "economic benefits". The sample group for this questionnaire included 31 members from university faculty members, experts of CTWG, and experts of Hashtroud Agricultural Jahad Office. The selection of the sample group was done through the snowball sampling technique. The validity of the questionnaire was checked with the experts' judgment of the Agroecology Department of Environmental Sciences and Research Institute (ESRI). Furthermore, the reliability of the questionnaire was proved using Cronbach's alpha coefficient of 0.84. This survey was conducted from April 2021 to June 2021, and data processing was carried out using SPSS software version 26 and Microsoft Excel.

Information on the environmental variables

The study area does not have a meteorological station. Thus, to calculate the maps of annual mean temperature, precipitation, and ice days, the climatic information of six meteorological stations distributed around Hashtroud city was gained from the Iranian Meteorological Organization (IMO) for the period 1990–2019 (See the supplementary material for detailed information on the average of annual weather variables as well as latitude, longitude, and altitude for the selected meteorological stations (Appendix 1)). The maps of these three variables were generated using ArcGIS10.8 and through the Inverse Distance Weighting (IDW) interpolation method. The Iranian

Table 2 The classes in the study area based on wind speed, drainage, soil erosion, and irrigation type

Class	Wind speed	Drainage	Soil erosion	Irrigation	Extent (ha)
1	Very low to medium	Moderate to good	High to very high	Rainfed	207
2	Very low to medium	Moderate to good	Very low to medium	Rainfed	4412
3	Very low to medium	Moderate to good	High to very high	Irrigated	151
4	Very low to medium	Moderate to good	Very low to medium	Irrigated	271
5	Very low to medium	Very weak to weak	High to very high	Rainfed	1786
6	Very low to medium	Very weak to weak	Very low to medium	Rainfed	11,275
7	Very low to medium	Very weak to weak	High to very high	Irrigated	258
8	Very low to medium	Very weak to weak	Very low to medium	Irrigated	819
9	High to very high	Moderate to good	High to very high	Rainfed	891
10	High to very high	Moderate to good	Very low to medium	Rainfed	7159
11	High to very high	Moderate to good	High to very high	Irrigated	25
12	High to very high	Moderate to good	Very low to medium	Irrigated	635
13	High to very high	Very weak to weak	High to very high	Rainfed	2878
14	High to very high	Very weak to weak	Very low to medium	Rainfed	3457
15	High to very high	Very weak to weak	High to very high	Irrigated	54
16	High to very high	Very weak to weak	Very low to medium	Irrigated	171

Soil and Water Research Institute (SWRI) provided maps of soil erosion, drainage, wind speed, and salinity of soil at a scale of 1:100,000. The SoilGrids open worldwide database, which distributes soil attributes data at a 250 m resolution, was also used to get the soil pH map. Finally, data from the Shuttle Radar Topography Mission (SRTM) with a resolution of 30 m was retrieved from the NASA website to generate an altitude map.

Assigning appropriate trees to the classes

The PROMETHEE II method was used for assigning the most appropriate tree among the PTFs to each class. The PROMETHEE II is a flexible multi-criteria decision analysis (MCDA) tool for examining the suitability of agricultural systems and providing valuable insights. The PROMETHEE II is used to produce a full rating of a finite collection of possible choices, from best to worst. The method's fundamental idea is based on a pairwise evaluation of alternatives along each criterion (Behzadian et al. 2010). This model was created to tackle multi-criteria issues, and its main advantage is that the information it requires is simple for analysts and decision-makers to grasp (Burak et al. 2022). Furthermore, running the PROMETHEE II needs the use of two extra types of data: the weighting technique and the preference function.

Weighting method

The PROMETHEE does not provide specific guidelines for determining the weight of criteria; however, it is assumed that the decision-maker is able to weigh the criteria appropriately (Macharis et al. 2004). In this research, the Fuzzy Analytic Hierarchy Process (Fuzzy-AHP) method, which relies specifically on expert judgment, was applied to determine the weight of the criteria. Detailed information on how the Fuzzy-AHP model works is provided in supplementary material (Appendix 2). Here, the criteria include "frostbite resistance", "salinity resistance", "drainage sensitivity", "storm resistance", "drought resistance", "preventing soil erosion", and "economic benefits". Therefore, 31 respondents, introduced earlier, were asked to judge the importance of these criteria for obtaining the final weight of each criterion.

Preference function

For certain criteria, a preference function transforms the difference between two options (i.e., PTF) into a preferred degree between 0 and 1. Brans et al. (1986) offered six fundamental categories of criteria to make it easier to choose a specific preference function: (1) usual criterion, (2) U-shape criterion, (3) V-shape criterion, (4) level criterion, (5) linear criterion, and (6) Gaussian criterion. There should only be one preference function used for each criterion. The selected criteria in this study are qualitative and based on a nine-point scale. Therefore, the level function was selected for these criteria in accordance with Brans et al.'s (1986) suggestion. However, in each preference function, the following three parameters should be set (Nasiri et al. 2013):

(i) Indifference threshold (*q*): It is referred to as the maximum deviation that may be overlooked by the decision-maker.
(ii) Preference threshold (*p*): It is referred to as the small deviation regarded to be adequate to produce a complete preference.
(iii) Gaussian threshold (*s*): It is referred to as the point at which the Gaussian preference function inverts.

PROMETHEE II is implemented in five steps: (1) Measuring deviations using pairwise comparisons, (2) Using a suitable preferred function for each criterion, (3) Determining the global preference index, (4) Determining positive and negative superiority flows for each option and partial ranking, and (5) Determining net outranking flow for each option and overall ranking. Detailed instructions for the PROMETHEE II can be found in the PROMETHEE 1.4 manual.

Scenarios

As indicated in Table 2, the study area was divided into 16 classes based on wind speed, drainage, soil erosion, and irrigation type. Therefore, according to the characteristics of each class, 16 different scenarios were defined. In the weighting step, the weights of the criteria associated with the limitations of each scenario were doubled to select the trees with more sensitivity and higher accuracy. For example, in *Class 9* the wind speed and soil erosion have "high to very high" levels. Therefore, the weights of "storm resistance" and "preventing soil erosion" criteria were doubled in the corresponding scenario. It should be noted that, in each scenario, the alternatives (i.e., PTFs) were selected based on the irrigation type of the corresponding class. In other words, for the classes with the "rainfed" irrigation type (i.e., 1, 2, 5, 6, 9, 10, 13, and 14 classes), only the rainfed trees were incorporated in the corresponding scenarios.

Estimation of CO_2 sequestration of the recommended trees

After determining an appropriate tree for each class, the CO_2 sequestration of that tree (called the recommended tree) was calculated. According to Ali et al. (2022), the required variables to calculate the CO_2 sequestration of a tree include height, age, and trunk diameter at the breast height of that tree. To collect the required information, a field sampling was conducted. In order to have the most similarity to the environmental condition of the agricultural lands of NK, the samples are collected from the nearest pastures and orchards around the study area. As illustrated in Fig. 3, there are five main steps to calculate the CO_2 sequestration of a tree (Toochi 2018):

Equation 1 was applied to determine the above-ground weight of each tree:

$$W_{above-ground} = \alpha \times D^2 \times H \begin{Bmatrix} \text{for trees with D} > 11,\ \alpha = 0.15 \\ \text{for trees with D} < 11,\ \alpha = 0.25 \end{Bmatrix} \tag{1}$$

where *W* is a tree's weight above ground in pounds (lbs), *D* is the trunk's diameter in inches, *H* is the tree's height in feet, and is *α* coefficient. A tree's underground structure weighs around 20% of what it does above-ground. Therefore, the total green weight of a tree is calculated by multiplying the increase in above-ground weight by 120% (Eq. 2).

$$W_{total\,(green)} = W_{above-ground} \times 120\% \tag{2}$$

A tree's entire weight is about equal parts dry matter (72.5%) and moisture (27.5%). Thus, the dry weight of a tree is determined by multiplying its overall green weight by 72.5% (Eq. 3).

$$W_{dry} = W_{total\,(green)} \times 72.5\% \tag{3}$$

In general, the average C content of a tree is 50% of the overall tree weight. As a result, the C weight of a tree is calculated through the multiplication of the dry weight by 50% (Eq. 4).

$$W_{carbon} = W_{dry} \times 50\% \tag{4}$$

To determine the CO_2 sequestered in a tree, the C weight must be multiplied by 3.67, which is the weight of CO_2 (43.999915) divided by the atomic weight of C (12.001115) (Eq. 5).

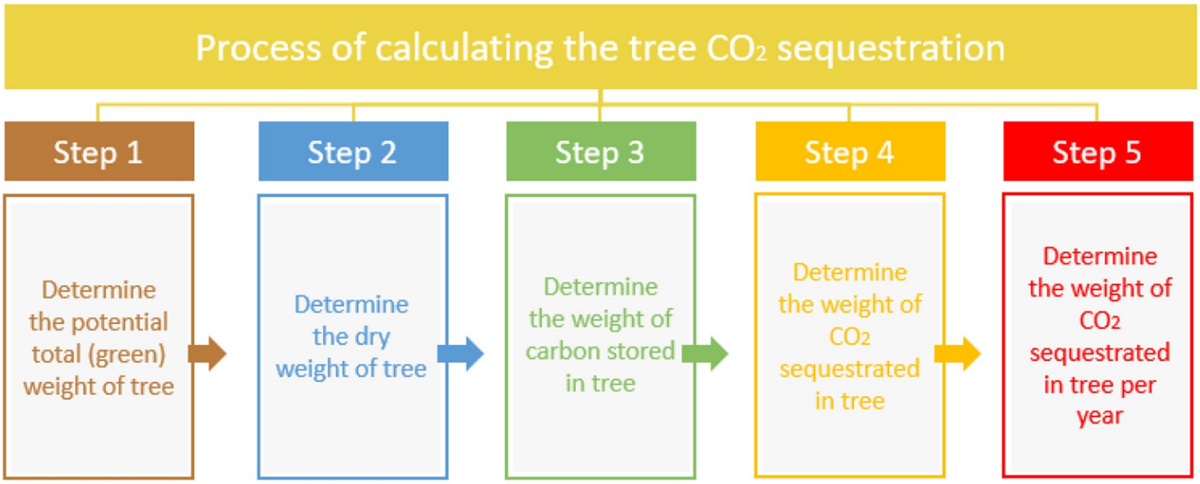


Fig. 3 The process of calculation of CO_2 sequestration of a tree (Toochy 2018)

$$W_{CO_2} = W_{carbon} \times 3.67 \tag{5}$$

Finally, the age of the tree is divided annually to calculate the weight of CO_2 sequestered in that tree. It should be noted that according to Zomer et al. (2009), the tree cover of greater than 10% of the agricultural land is defined as agroforestry. In this study, a similar definition for AI has been retained, and it is assumed that 10% of the extent of each class is allocated for tree plantations.

Results and discussion

Land classification for AI

In this study, nine environmental variables were selected for the evaluation of agricultural land in the NK district, among which five variables were not limited to tree planting in the agroforestry system. Nevertheless, the study area was affected by the three variables of "soil erosion", "drainage", and "wind speed". The combination of these three variables along with "irrigation type" led to the creation of 16 classes with unique characteristics (Table 2). Determining the variables for the evaluation of a natural system is always arbitrary because the importance of a particular variable varies in different systems, and it is a location-based concept (Heikkinen 2021). However, the importance of the selected variables in this study has been widely discussed. For instance, according to Panagos et al. (2015), soil erosion has a negative impact on agricultural ecosystems and food production, making it a severe environmental problem. Moreover, according to Zhu et al. (2019) and Muthee et al. (2022), the use of agroforestry can significantly improve soil quality and fertility, prevent soil erosion, and reduce greenhouse gas emissions (via carbon sequestration). Abd-Elmabod et al. (2017) explained that soil drainage is one of the most important variables that determine which type of trees grow appropriately in an area. Gardiner et al. (2016) described that wind has long been considered an important ecological factor because it carries water vapor and heat energy and affects evapotranspiration. Severe winds can erode the soil and cause severe damage to trees by uprooting, breaking branches, and damaging the canopy.

Figure 4 shows the spatial distribution of the 16 classes. In general, the agricultural lands of the study area included 34,449 ha, of which 93.1% was rainfed and 6.9% was irrigated (Table 2). The results showed that 19,179 ha of the study area had a "very low to medium" and 15,270 ha had a "high to very high" wind speed. In addition, 13,751 ha of the study area had a "moderate to good" while 20,698 ha had a "very weak to weak" drainage. Furthermore, 6250 ha of the study area had "high to very high" and 28,199 ha had "very low to moderate" soil erosion (Table 2). According to the results, most of the study area (11,275 ha) located in *Class 6*, which was "rainfed" and had "very low to medium" wind speed, "very

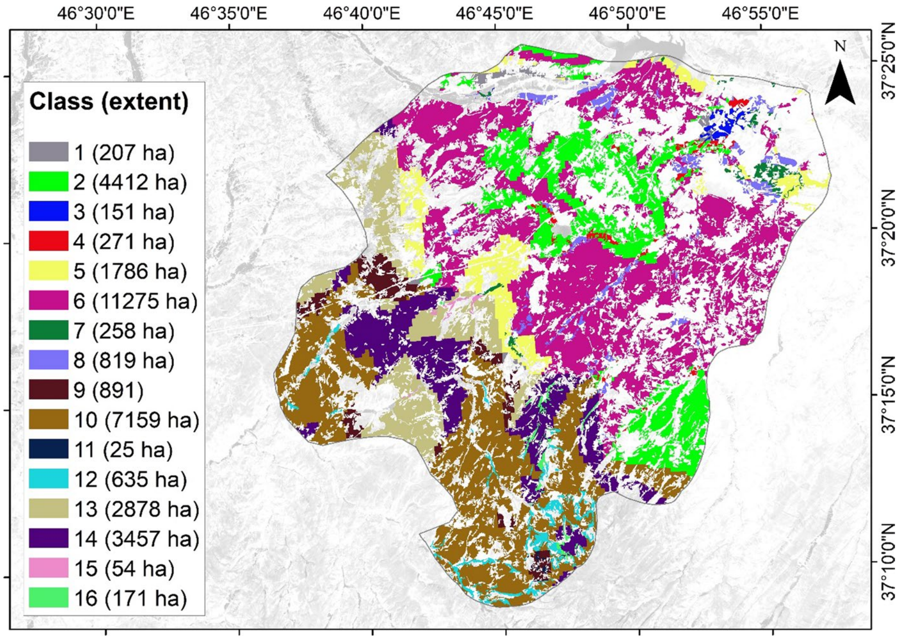


Fig. 4 Spatial distribution of defined classes in the study area

weak to weak" drainage, and "very low to moderate" soil erosion (Table 2). The smallest extent belonged to *Class 11*, with an area of only 25 ha (Fig. 4 and Table 2). The findings of this study also revealed that only 271 ha of the study area had no limitations (*Class 4*), while 2878 ha had limitations in terms of soil erosion, drainage, wind speed, and land use type (*Class 13*) (Table 2). In addition, 99.23% of the area had at least one limitation. In this study, "no limitations" refers to areas that have very low to medium erosion, moderate to good drainage, very low to medium wind speed, and irrigated irrigation type.

The importance of the selected criteria

The weights of criteria applied to assign an appropriate tree to each class are shown in Fig. 5. The consistency ratio (CR), which was calculated to demonstrate reliable consistency, was lower than 0.10 for comparisons. According to the 31-member team of experts, the "drought resistance" with a weight of 0.28 was recognized as the most important criterion. In addition, the criteria of "economic benefits" and "frostbite resistance" were in the second and third places with weights of 0.18 and 0.17, respectively (Fig. 5). The lowest values with weights of 0.04 and 0.07 were attributed to "salinity resistance" and "drainage sensitivity" criteria, respectively. These findings are in line with other similar studies. For instance, according to Reisman-Berman et al. (2019), drought is a key abiotic stressor that inhibits tree development, and tree selection for afforestation, especially in rainfed conditions, is mostly based on drought resistance. Bhusal et al. (2021) revealed that the frequency and intensity of drought are expected to increase due to CC; therefore, the trees for plantation should be selected by considering drought resistance for maximum survival and conservation of natural habitats. Similar findings were also reported by Klein (2020) and Poschenrieder et al. (2022). In terms of economic benefits, most of the smallholder farmers, similar to the local farmers in the study area, seek to increase their income and improve their livelihood. Therefore, the economic benefits of trees are very important, and farmers are more interested in trees that have higher economic benefits (Turner-Skoff and Cavender 2019). The welfare of humankind is affected by the direct and indirect benefits of trees that are beyond estimation. According to Szalay et al. (2019), the damage produced by frost has an impact on how well fruit trees are planted and cared for, and consistently, the frost is a persistent abiotic enemy that must be overcome. Therefore, selecting trees that have high resistance and tolerance to frostbite reduces the risk of damage caused by this abiotic stressor.

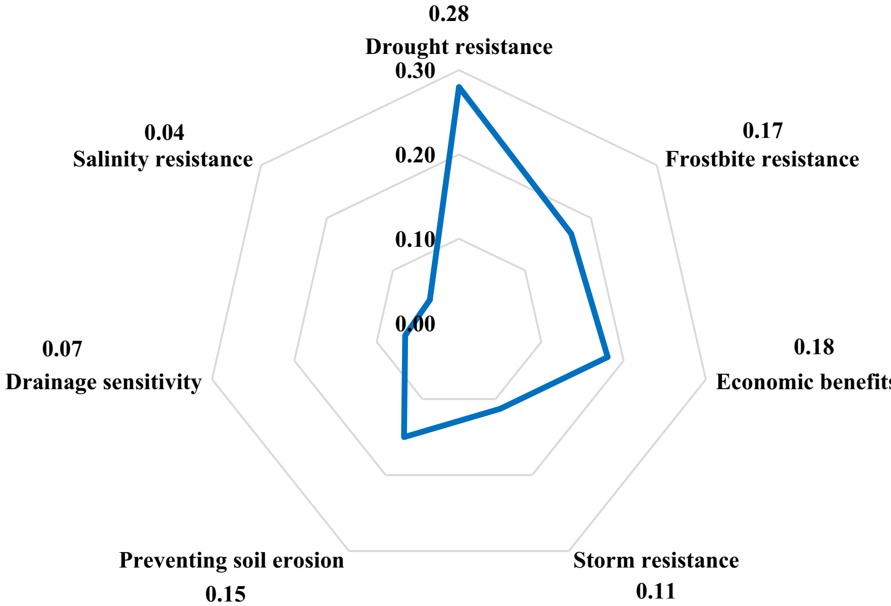


Fig. 5 The final weights of the selected criteria based on experts' judgments

Prioritization of the trees for land classes

The PTF was allocated for each of the classes based on the experts' judgments and through the PROMETHEE II method (Fig. 6). Accordingly, the elaeagnus tree was the best alternative for planting in *Class 5*, *Class 6*, *Class 9*, *Class 10*, *Class 13*, and *Class 14* (all of which are rainfed). The results also showed that in *Class 1* and *Class 2*, which are both rainfed with the extents of 207 and 4412 ha, respectively, the almond tree was the best alternative for AI (Fig. 6). Quince tree was considered the most suitable tree for *Class 4*, *Class 7*, *Class 8*, *Class 15*, and *Class 16* (Fig. 6). Furthermore, the experts determined that the walnut tree should be considered for *Class 3* and *Class 11*. Finally, apple was the best alternative to be planted in *Class 12* (Fig. 6). Generally, the findings revealed that the study area should be allocated for planting elaeagnus (about 79.6%, 27,446 ha), almond (13.5%, 4619 ha), quince (4.6%, 1573 ha), apple (1.8%, 635 ha), and walnuts (0.5%, 176 ha). Based on these findings, the majority of the agricultural lands (93.1%), which were all rainfed, were suggested to be allocated to planting elaeagnus and almond. Elaeagnus and almond are fruits with low water requirements and high capability for planting in rainfed areas, and the plantation of these two trees has been widely suggested for marginal and degraded croplands (Dubovyk et al. 2016; Paudel et al. 2020; Prgomet et al. 2020). Consistent with the findings of this study, Dong et al. (2021) assessed the establishment of an ecological forest system in a heavily saline and dry wasteland and suggested the elaeagnus tree as a tolerant tree for these areas. In another study, Tavakoli et al. (2021) evaluated the feasibility of growing almond trees with rainwater in arid environments of the East Azerbaijan province of Iran (where the NK rural district is located) and reported that this area is highly suitable for almond plantation. The spatial distribution of the recommended trees for AI is illustrated in Fig. 7. The characteristics of the classes in Fig. 7 are indicated in Table 2.

CO_2 sequestration of the recommended trees

The required variables to measure CO_2 sequestration of the recommended trees are illustrated in Table 3. Considering that the measurement of these variables was done from sample trees with different ages, the results include a wide range of values of these variables. The annual CO_2 sequestration of each recommended tree was measured and indicated in Fig. 8. On average, as the agroforestry systems in the study area, the recommended trees can sequestrate CO_2 between 3.13 and 51.18 t ha^{-1} yr $^{-1}$. Accordingly, the highest amount of CO_2 sequestration with 51.18 t ha^{-1} yr $^{-1}$ was observed in walnuts. Furthermore, the lowest amount of CO_2 sequestration with 3.13 t

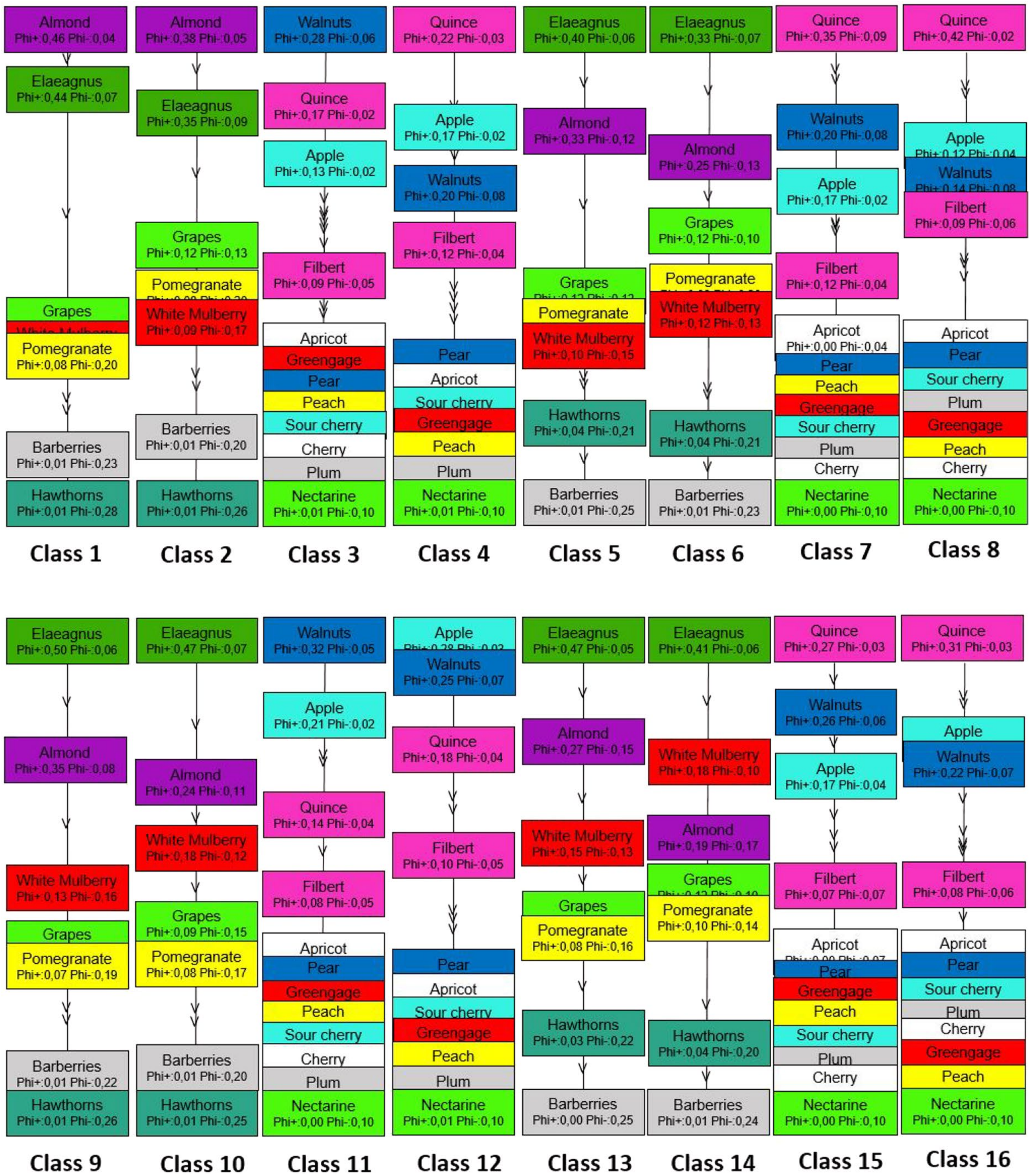


Fig. 6 Ranking the PTF for each class based on experts' judgments and through the PROMETHEE II method

ha^{-1} yr^{-1} was observed in elaeagnus. In this regard, walnut, apple, almond, quince, and elaeagnus trees, as the recommended trees for AI in the study area, ranked first to fifth in terms of the amount of CO_2 sequestration. Kay et al. (2019) investigated the annual C storage potential of the woody elements in each geographical region of Europe and indicated that the agroforestry systems in European farmlands and

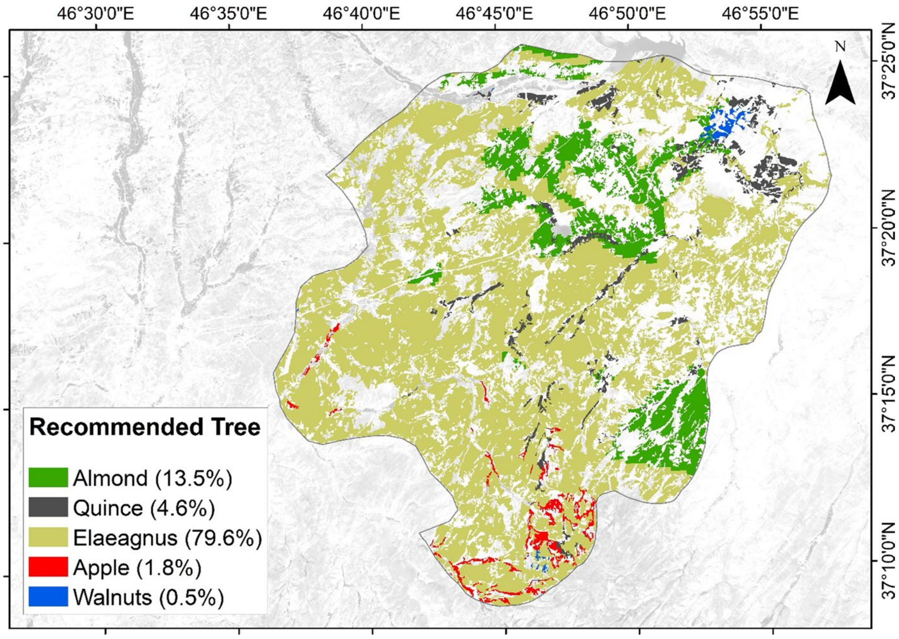


Fig. 7 Spatial distribution of the recommended trees for AI in the study area

Table 3 The measured variables of the recommended trees for AI in the study area

Tree	D (inches)		H (feet)		W_{total} (lbs)		Age		GR		Planting intervals	N
	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max		
Almond	8.3	10.1	19.1	21.3	404.3	581.6	10	12	33.7	48.5	7×7	31
Quince	2.1	2.7	9.9	13.1	13.6	45.8	1	2	13.6	22.9	5×5	38
Elaeagnus	6.3	8.2	19.7	23	234.1	431.6	9	13	18	33.2	7×7	63
Apple	8.8	13.7	19.8	29.4	453.8	967.1	25	30	16.2	34.5	5×5	53
Walnuts	23.8	29.8	59.2	78.3	6975.7	11,825.2	29	34	225	407.8	6×6	32

D, Trunk diameter at the breast height; H, Height of a tree; W, Total (green) weight of a tree; GR, Growth rate of a tree (lbs yr^{-1}); N, Sample size

pastures sequestrate C between 0.09 and 7.29 t ha^{-1} yr^{-1}. In a study conducted by Cardinael et al. (2017), C stock under agroforestry systems was investigated, and the results showed that walnut tree could sequestrate 4.68 t C ha^{-1} yr^{-1}, which is equivalent to 17.18 t CO_2 ha^{-1} yr^{-1}. In another study, Lopez-Bellido et al. (2016) assessed the C sequestration and C footprint of different trees in southern Spain and revealed that an almond tree could sequestrate 1.36 t C ha^{-1} yr^{-1}, which is equivalent to 4.99 t CO_2 ha^{-1} yr^{-1}. Johnson and Gerhold (2001) evaluated the C storage by utility-compatible trees in European hills and stated that an apple tree in the silvoarable system sequestrated about 0.93–1.43 t C ha^{-1} yr^{-1}, which is equivalent to 3.41–5.25 t CO_2 ha^{-1} yr^{-1}. There are some differences in the values reported in these studies and the findings of the current research. It should be noted that the values reported in this study are based on the standard planting intervals (see Table 3), while the values reported in the presented studies are related to agroforestry systems in which the planting intervals are different and subsequently the planting density is less than the standard condition. In addition, the environmental conditions for the growth of trees were different and not the same. According to Jandl et al. (2007), the kind, age, and density of trees; the qualities of the soil; the latitude; and associated climatic variables all affect the rate of carbon sequestration. Toochi (2018), who highlighted that the C sequestration rate relies on the development traits of various tree species and the growth circumstances, also supports this assertion.

Based on the results, the plantation of the recommended trees in the study area as the agroforestry systems could lead to CO_2 sequestration of about 12.96 Mg yr^{-1} (Fig. 8f). In this regard, about 84.86%

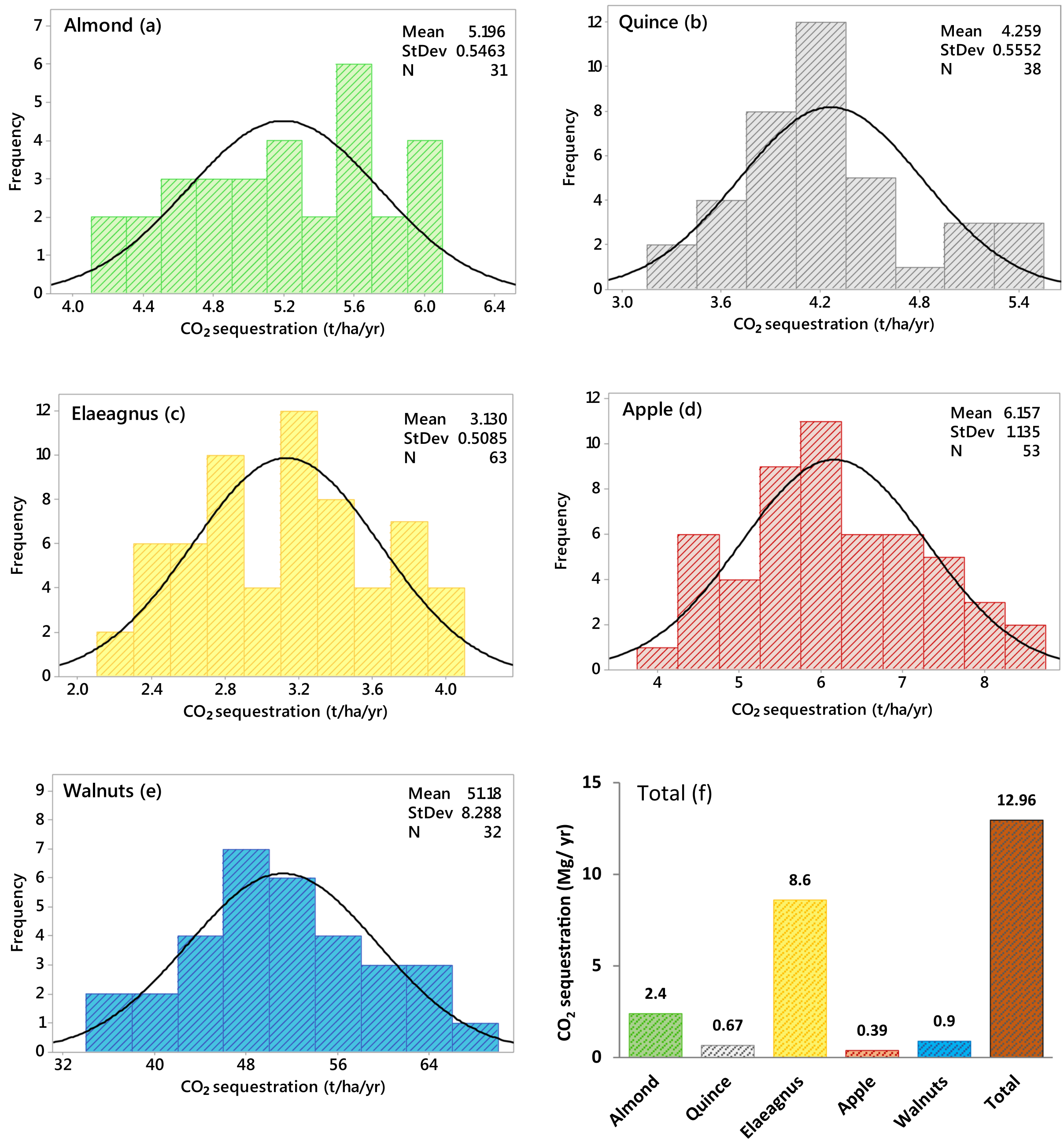


Fig. 8 The amount of CO_2 sequestration (t yr^{-1}) of the recommended trees per hectare (**a**–**e**) along with their total amount of CO_2 sequestration (Mg yr^{-1}) in the study area (**f**)

of the total CO_2 sequestration was attributed to elaeagnus and almond trees plantation in the rainfed lands. In addition, the remaining 15.14% was attributed to quince, apple, and walnut trees plantation in the irrigated lands. As the results showed, by allocating the recommended trees, AI can greatly mitigate the negative effects of CC and increase the adaptive capacity of the study area to CC. According to Torres et al. (2017), agroforestry systems decrease GHG emissions by trapping CO_2 from the atmosphere. In line with the findings of this study, Kay et al. (2019) reported that AI in the most suitable areas in European farmlands could mitigate between 7.7 and 234.8 million tons of CO_2 per year. They also revealed that converting the conventionally used farmland to agroforestry could capture between 1.4 and 43.4% of the European agricultural GHG emissions. The co-benefits and trade-offs of agroforestry for CC mitigation were examined by Tschora and Cherubini (2020) in West Africa. They showed that a large-scale deployment of agroforestry can sequester up to 135 Mg CO_2 yr1 over two decades, which is equivalent to 166% of the C emissions from fossil fuels and deforestation in their study area.

Conclusion

This study was carried out to assess the use of agroforestry using native trees in the Nazar Kahrizi district of Hashtroud city, situated in the northwest of Iran, with the purpose of reducing the vulnerability of local farmers. The implementation of agroforestry, despite its numerous proposed advantages, often encounters resistance and failure due to neglecting the interests of farmers and the natural capacities of a given region. Users will be able to identify the appropriate arboreal components for agroforestry implementation using the techniques presented in this study, taking into account socioeconomic and environmental factors.

According to the variables of “soil erosion,” “wind speed”, “drainage,” and “irrigation type,” the agricultural lands of the study area were divided into 16 classes. Based on the preferences of the local farmers, 19 native trees were identified. Furthermore, the PROMETHEE II method was used to compare and rank these trees in terms of seven criteria of “frostbite resistance”, “salinity resistance”, “drainage sensitivity”, “storm resistance”, “drought resistance”, “preventing soil erosion”, and “economic benefits”. The findings of this study showed that only 0.77% of the study area did not tolerate any environmental restrictions. In addition, elaeagnus and almond were the most appropriate trees for agroforestry implementation in the rainfed lands while apple, quince, and walnut were the most suitable trees for agroforestry implementation in the irrigated lands. Measurements showed that agroforestry implementation with the recommended trees will lead to CO_2 sequestration of about 12.96 Mg yr^{-1}.

The most challenging part of this research was to determine the number and type of variables for land evaluation, as well as selecting criteria for tree comparison. Moreover, the lack of access to information such as GHG emissions of the agricultural sector of the study area was another challenge of this study. However, this study cannot address all of the factors affecting the agroforestry establishment. For example, the current study did not take into account the retention of nutrients, water availability, ecophysiological features of allelopathy, biodiversity issues, natural dangers, or the vulnerability of the trees to pests and diseases; all of these elements might be addressed in further research.

There are a few limitations in this study that should be noted. Firstly, considering that the approach of this study regarding the selection of tree type for agroforestry implementation was based on the preference of local farmers, it was not possible to examine all native trees/shrubs. Secondly, in some cases, the farmers were not willing to change their land management practices and, therefore, were not willing to cooperate with the researcher in expressing their opinions. Thirdly, the lack of access to information such as soil organic carbon, flood risk map, reference evapotranspiration, topsoil and subsoil features, etc. was another limitation of this research. Overall, the method utilized in this study might be applied to other nations, particularly those sensitive to climate change. Based on the approach used in this study, researchers could confidently identify appropriate trees for agroforestry implementation. Policymakers and decision-makers in other locations with situations comparable to Iran can apply the research’s conclusions. The target audience for this study may be researchers in arid and semi-arid countries with unstable agriculture and frequently smallholder farmers.

Author contributions MK, and JK, conducted the study and developed the main text. RS, SS, AMD, and HA, contributed to the first draft manuscript and enriched it up to the final version.

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Data availability Raw data were generated at Shahid Beheshti University. We confirm that the data, models, and methodology used in the research are proprietary, and that derived data supporting the findings of this study are available from the first author on request.

Declarations

Conflicts of interest The authors declare no conflict of interest.

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