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Assessing vulnerability to climate change among farmers in northwestern Iran: A multi-dimensional approach

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ABSTRACT

Assessing the vulnerability of farmers can strengthen their capabilities against climate change (CC). For this purpose, this study uses a multi-dimensional approach, integrating both quantitative and qualitative methods to assess the vulnerability of farmers to CC and subsequently to provide solutions to cope with or adapt to CC in rural districts (RDs) of Hashtroud city, northwestern Iran. Our findings reveal that the lowest vulnerability of farmers to CC in Solouk and Qarranqou RDs is due to their higher "net income from the farmlands," "labor force," "medical insurance" and "access to agricultural inputs." Also, the highest vulnerability of farmers to CC in the Nazar Kahrizi RD is due to their weaker "net income from the farmlands," "sale channels," "education" and "crop diversity." The experiences of farmers indicate that coping and adaptation strategies such as "weather forecasting," "changing planting date," "implementing agroforestry practices," and "pre-selling the products" have increased their adaptive capacity (AC). The acceptance of these strategies by local communities is critical, emphasizing the importance of aligning proposed solutions with farmers' preferences and capabilities. Results highlight the predominant role of AC in influencing vulnerability, consistent with similar studies in other regions. Higher AC is shown to mitigate the potential harm of CC, emphasizing the importance of farmers' capacity to transform resources into adaptive strategies. Overall, this study provides a comprehensive assessment of CC vulnerability, shedding light on the importance of AC and proposing context-specific coping and adaptation strategies to boost resilience in the face of climate challenges.

1. Introduction

Agriculture is a source of income in rural communities that are mostly smallholder farmers whose livelihoods depend heavily on agricultural production especially in developing countries (Antonelli et al., 2022). Smallholder farmers are responsible for 75% of farmlands in the world, accounting for 60% of the world's agricultural workforce and they produce ~80% of food consumed in developing countries. Also, they are recognized as the group with the highest vulnerability to climate change (CC) because of the following four main reasons: (i) They highly rely on goods and services provided by ecosystem; (ii) They have the least adaptive capacity (AC) to absorb the shocks; (iii) They have a high reliance on rainfed crops, which completely depends on climate condition; and (iv) They are located in fragile landscapes (e.g., hillsides and deserts) where they are exposed to drought, storm, flood, and other extreme events (Donatti et al., 2019). Smallholder farmers have limited resources to conserve or enhance agricultural productivity due to their poor financial capacity and physical lack of suitable land (Schwarz et al., 2011). They are also marginalized from social activities and development programs. Although smallholder farmers are vital to food security (Harvey et al., 2014), the well-being of these farmers is at risk due to the negative effects of CC (Sharafi et al., 2020).

Vulnerability is a multi-dimensional concept which is mostly affected by a wide range of economic, socio-cultural, geographic, demographic, institutional, and environmental factors (Li et al., 2015). The most comprehensive definition about vulnerability is provided by the intergovernmental panel on CC (IPCC, 2000):

> *"The degree to which a system is vulnerable to or capable of dealing with the negative consequences of CC, such as CC and extremes. Vulnerability is determined by the nature, amount, and pace of CC to which a system is exposed, as well as its sensitivity and adaptive capability."*

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Vulnerability assessment is a prerequisite to ensure the security of livelihood by limiting the negative effects of climatic hazards (e.g., flood and drought) on agricultural systems (Parker et al., 2019). In this regard, different methodologies and procedures have been applied to measure susceptibility to CC and adaptation in agriculture (e.g. Smith and Olesen, 2010; Finger et al., 2011; Graux et al., 2013; Li et al., 2019). For instance, Hahn et al. (2009) established the Livelihood Vulnerability Index (LVI) to evaluate the vulnerability of Mozambique to CC from aspects of water, food, and population. Mukherjee et al. (2019) used the LVI-IPCC to analyze the vulnerability of human communities in selected mouzas of Sagar Island, India. Additionally, the Climate Vulnerability Index (CVI) was designed to evaluate the vulnerability to CC (Sathyan et al., 2018). All three indices, namely LVI, LVI-IPCC, and CVI were used to evaluate the CC vulnerability in Guwahati City, India (Paul et al., 2019). Other methods such as the Livelihood Effect Index (LEI) were also used for vulnerability assessments (Urothody and Larsen, 2010). Weng et al. (2023) proposed a conceptual framework to evaluate the vulnerability of semi-arid pastoral social-ecological systems (SAPSES) to CC effects and environmental pressure in China. Trang Anh et al. (2023) investigated the short- and long-term impacts of CC on agriculture in Vietnam, revealing that CC poses a significant threat to the sector, impacting production and economic value, thus endangering global food security. Another framework for evaluating the vulnerability of agricultural systems to CC is introduced by Eza et al. (2015). In the study by Eza et al. (2015), an application platform was set up to analyze climate characteristics (occurrence of arid conditions), soils, and human management in order to evaluate vulnerability to CC. In addition, Gupta et al. (2022) introduced a model to simulate farmers' adaptation strategies to CC through climate-smart agriculture (CSA) practices. These strategies aim to improve crop and environmental estimation, field management, and decision-making (Gupta et al., 2022). Roshani et al. (2024) assessed the forest vulnerability map in India by considering three components: exposure (E), sensitivity (S), and adaptive capacity (AC). Moreover, studying the effects of CC on crop growth in Chinese farms has revealed that taking into account climatic factors like solar radiation, precipitation, temperature, and CO_2 levels can be beneficial for understanding how to adapt to CC (Wang et al., 2023). Other indices such as the Enhanced Vegetation Index (EVI) and Fractional Vegetation Coverage Index (FVC) were utilized to evaluate the susceptibility of vegetation cover to CC and human activities in Ethiopia (Yang et al., 2022). However, past studies have not apprehended various stressors of vulnerability. The existing literature on agriculture vulnerability has considered limited variables to assess E, S and AC. The frameworks of current studies are not available for different types of agricultural systems (Weng et al., 2023). Besides, answering the question "How agricultural systems cope or adapt to CC in a vulnerable situation" still requires quite some research. Also, these studies, while offering valuable insights into regional vulnerability trends, often fail to precisely identify vulnerable farmers and the extent of their susceptibility. As Eza et al. (2015) argued, (i) lack of integrated information systems, (ii) insufficient automation of composition and execution, and scalability of approaches are two main reasons for the absence of comprehensive and precise assessments of vulnerability to CC. Consequently, as a full-fledged method, it is crucial to apply an integrated analytical framework to understand vulnerability caused by multiple factors considering human, social, physical, natural and financial capital to provide multiple solutions.

As a developing country, Iran is currently experiencing unprecedented severe climate events such as severe declines in lakes and rivers, floods, storms, extreme temperatures, and drought (Nazari Nooghabi et al., 2020). It was implied that the agricultural sector of the country is drastically vulnerable to environmental, social, and economic consequences of CC (Karimi et al., 2018). Currently, about four million people in Iran, mostly from rural communities and smallholder farmers, suffer from food insecurity (FAO, IFAD, UNICEF, WFP, WHO, 2020). Therefore, there is an urgent need to design and implement sustainable strategies that increase the AC of smallholder farmers and reduce their sensitivity to CC, and thereby overcome the food security problem. Accordingly, identifying the most vulnerable areas to the impacts of CC should be considered as the first step of the implementation of a sustainable strategy (Sathyan et al., 2018).

In this study, we attempt to propose a novel analysis framework to evaluate vulnerability to CC among the smallholder farmers in northwest Iran. This analysis framework involves a range of techniques and models such as the Fuzzy-AHP method, the RClimDex software package, the LARS-WG software, and a survey questionnaire (using both quantitative and qualitative methods), realizing the sources of vulnerability of farmers to CC and subsequently provide solutions to cope with or adapt to CC at rural scale. Meanwhile, we also identify the coping and adaptation strategies that were believed by farmers as a successful solution to reduce vulnerability to CC. By adopting this innovative approach, the study not only advances the methodological landscape of vulnerability assessments but also provides valuable insights into the specific challenges faced by farmers in the region.

The objectives of this study are to (i) examine the vulnerability to CC among the smallholder farmers at rural scale considering a wide range of financial, physical, human, social, or natural capacities and to (ii) identify the effective coping and adaptation strategies to reduce vulnerability to CC. The most important hypothesis of this study is *"most of farmers are vulnerable to CC in different ways, but their level of vulnerability varies and, therefore, there is a high potential for increasing their AC and decreasing their vulnerability to CC."* Accordingly, this study seeks to answer the following research questions:

(1) Where is/are the most vulnerable area(s) to CC?
(2) What is/are the main cause(s) of vulnerability of farmers to CC?
(3) What coping and/or adaptation strategies can be adopted to deal with the CC consequences?

2. Materials and methods

This research was performed in the farmlands of Hashtroud, a city located in northwestern Iran occupying an area of 2000 km^2; about half of those areas are agricultural (Fig. 1). Hashtroud is located in the south of East Azerbaijan province with altitudes between 1340 and 2940 m above sea level and consists of two districts, seven rural districts (RDs), and 233 villages most of which are located near farmlands. Hashtroud has a cold and mountainous climate with an annual precipitation of ~270 mm and an annual mean temperature of 12 °C. The most important water resources of Hashtroud are the eight rivers of Qarranqou, Aydoqmoush, AjiChai, Qal'aChai, QuruChai, LeylanChai, Ajirlou, and QaraQaya. With the total population of 57,200 people, 70% of which living in rural areas, the study area is known as the most strategic region of East Azerbaijan province in terms of agricultural productions. The income of ~75% of rural households is directly and indirectly dependent on the agricultural products in Hashtroud. Also, wheat, barley, chickpea, and alfalfa are the major crops cultivated in this region.

2.1. Selecting indicators and collecting data

The vulnerability of any system is often defined as an interaction of three components consisting of (i) E: the level and extent of exposure of a system to CC, (ii) S: the effect of climate-related stimuli, either negatively or positively on a system, and (iii) AC: the capability of a system to absorb or adapt to the effects of CC with minimal disruption (Žurovec et al., 2017).

We have identified a set of indicators addressing the three components of vulnerability, namely E, S, and AC through literature review and expert knowledge (12 experts). Therefore, 12 experts who were aware of the concept of vulnerability were asked to select the important indicators affecting vulnerability accordingly. These experts were selected via snowball sampling method and from research institutions,

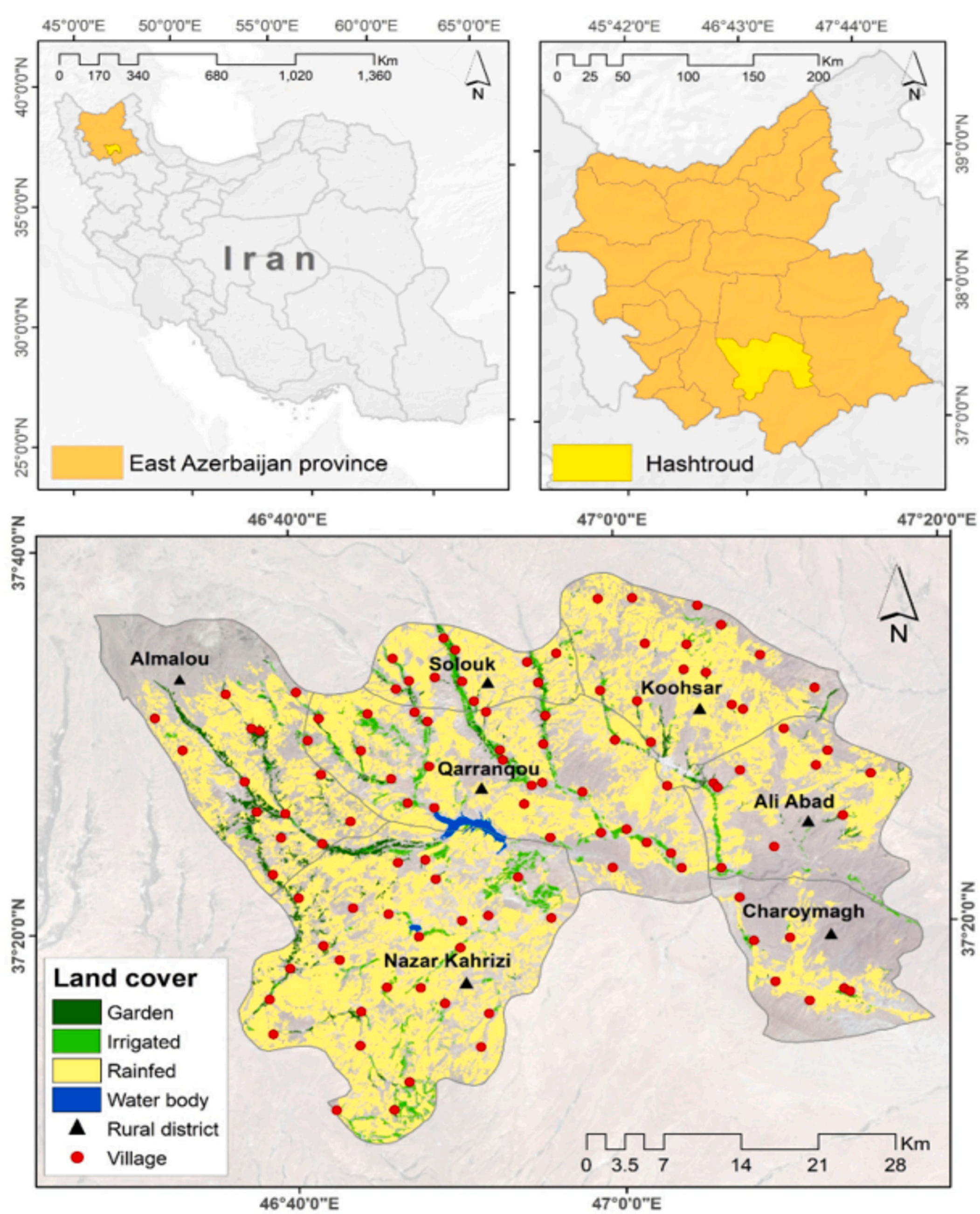

Fig. 1. Geographical position and land cover types of the study area along with the seven RDs.
Source: Study findings.

agencies, and universities. The snowball sampling method allowed us to get a higher response rate to the questionnaire (70.6%). Table 1 indicates the selected indicators and their relationships with vulnerability, along with the vulnerability components and the sub-components in which they were located.

To calculate the variables of E, the climatic information of six meteorological stations distributed around Hashtroud were gained from the Iranian Meteorological Organization (IMO) for the period 1990–2019 (Table 2). The information includes minimum, maximum and mean temperatures (°C), sunshine hours (h), relative humidity (%), precipitation (mm), and wind speed (m s^{-1}). Before using the information, the outlier detection test was applied to exclude outliers and the normality test was used to investigate the information homogeneity (Kheiri et al., 2021a).

In terms of the indicators of E, frequency of frostbite in the last 30 years (EE1), frequency of tropical nights in the last 30 years (EE2), consecutive dry days (EE3), consecutive wet days (EE4), ice days (EE5) and summer days (EE6) were calculated using the RClimDex software package which identifies and monitors extreme climatic events (Kouzegaran et al., 2020). The average annual cumulative precipitation (CV1), trends of variations of the annual mean temperature (CV2), and the annual cumulative precipitation (CV3) during 1990–2019 were also measured for the six selected meteorological stations. Furthermore, the future changes (2041–2060; denoted as the 2050s) in the annual mean temperature (CV4) and the annual cumulative precipitation (CV5) compared to the baseline (1990–2019), were investigated using the LARS-WG software. Fig. 2 indicates the variations of the weather variables for the six selected meteorological stations in the 2050s.

As shown in Eq. (1), the UNEP aridity indicator (CV6) was also applied to evaluate the variability of drought occurrence over the study

Table 1
The list of final selected indicators and their functional relationships with vulnerability in this study.

Components	Sub-components	Indicators	Symbols	Sources	Relationship	References
Exposure (E)	Extreme events	Frequency of frostbite in the last 30 years (defined as annual count when daily minimum temperature < 0 °C)	EE1	IMO	+	(Persitz et al., 2022)
		Frequency of tropical nights in the last 30 years (defined as annual count when daily minimum temperature > 20 °C)	EE2	IMO	+	(He et al., 2022)
		Consecutive dry days (maximum number of consecutive days with precipitation <1 mm)	EE3	IMO	+	(Sharafi et al., 2020)
		Consecutive wet days (maximum number of consecutive days with precipitation ≥1 mm)	EE4	IMO	−	(Sharafi et al., 2020)
		Ice days (defined as annual count when daily maximum temperature < 0 °C)	EE5	IMO	+	(Xu et al., 2020)
		Summer days (defined as annual count when daily maximum temperature > 25 °C)	EE6	IMO	+	(He et al., 2022)
	Climatic variables	Annual cumulative precipitation	CV1	IMO	−	(Jamshidi et al., 2019)
		Long-term trend of annual mean temperature	CV2	IMO	+	(Chimi et al., 2023)
		Long-term trend of annual precipitation	CV3	IMO	+	(Chimi et al., 2023)
		% changes in precipitation (base period compared to 2050s)	CV4	IMO	+	(Jamshidi et al., 2019)
		Change in mean temperature (base period compared to 2050s)	CV5	IMO	+	(Jamshidi et al., 2019)
		Long-term trend of annual UNEP aridity index	CV6	IMO	+	(Nazari Nooghabi et al., 2020)
Sensitivity (S)	Soil parameters	Soil organic carbon (SOC)	SP1	Soilgrids	−	(Baveye et al., 2020)
		Soil pH	SP2	Soilgrids	+	(Sun et al., 2023)
		Erosion	SP3	SWRI	+	(Eekhout and de Vente, 2022)
		Salinity	SP4	SWRI	+	(Nazari Nooghabi et al., 2020)
	Demographic	Work experience	D1	Survey	−	(Nazari Nooghabi et al., 2020)
		Number of unemployed members in family, aged 15 to 65 years old/ total number of family members	D2	Survey	+	(Fekete, 2009)
		Number of family members directly involved in agriculture / total number of family members	D3	Survey	+	(Jamshidi et al., 2019)
	Vulnerable social group	Number of family's children below 15 years old / total number of family members	VSG1	Survey	+	(Jamshidi et al., 2019)
		Number of family members above 65 years old / total number of family members	VSG2	Survey	+	(Hadipour et al., 2020)
	Farm operation	Total farmlands size owned / number of land pieces	FO1	Survey	−	(Jamshidi et al., 2019)
		Total irrigated lands size/total farmlands size	FO2	Survey	−	(Jamshidi et al., 2019)
		Total rainfed land size/total farmland size	FO3	Survey	+	(Sharafi et al., 2020)
		Uncultivated land area due to water shortage / total farmland size	FO4	Survey	+	(Jamshidi et al., 2019)
		Total farmland size owned / number of family members	FO5	Survey	−	(Jamshidi et al., 2019)
	Agricultural activity	Crop diversity index (CDI) = 1 / number of crops grown by a household +1	AA1	Survey	+	(Xu et al., 2020)
		Consumption of chemical fertilizer in a hectare	AA2	Survey	+	(Jamshidi et al., 2019)
Adaptive capacity (AC)	Economic capability	Net income from the farmlands (IRR)	EC1	Survey	−	(Jamshidi et al., 2019)
		% of farmland covered by crop insurance	EC2	Survey	−	(Zarafshani et al., 2012)
		Ownership of number of livestock units	EC3	Survey	−	(Jamshidi et al., 2019)
		% of income from agriculture	EC4	Survey	−	(Zarafshani et al., 2012)
		Households' farmland ownership (ha)	EC5	Survey	−	(Nazari et al., 2015)
	Social capability	The level of taking technical advice	SC1	Survey	−	(Sharafi et al., 2020)
		The level of participation in social communities	SC2	Survey	−	(Zarafshani et al., 2012)
		Sales channels	SC3	Survey	−	(Xu et al., 2020)
	Human resource Capability	Farmer education	HRC1	Survey	−	(Cutter et al., 2012)
		Adult family members aged 15 to 65/all family members	HRC2	Survey	−	(Jamshidi et al., 2019)
		Family members with medical insurance/all family members	HRC3	Survey	−	(Jamshidi et al., 2019)
	Institutional capability	Access to agricultural input (machinery, irrigation system, pesticide, and fertilizer)	IC1	Survey	−	(Zarafshani et al., 2012)
		Number of accesses to governmental credit during the last 5 years	IC2	Survey	−	(Jamshidi et al., 2019)
		Access to market (defined as the distance from the nearest city)	IC3	Survey	−	(Jamshidi et al., 2019)

Source: study findings.

Table 2
Geographical situation, elevation, and weather variables of the selected stations to calculate the exposure (E) indicators.

Stations	Latitude (N)	Longitude (E)	Altitude (m)	T mean (°C)	T maximum (°C)	T minimum (°C)	Precipitation (mm)	Time period
Maragheh	37.35	46.15	1344	13.7	19.3	8.2	276.5	1990–2019
Mianeh	37.45	47.72	1110	14.3	21	7.6	272.1	1990–2019
Sarab	37.93	47.53	1682	8.9	16.3	1.6	239.5	1990–2019
Tabriz	38.12	46.24	1361	13.5	19.1	7.8	250.1	1990–2019
Takab	36.39	47.09	1817	9.8	16.8	2.7	310.9	1990–2019
Zanjan	36.66	48.52	1659	11.5	18.6	4.5	287.7	1990–2019

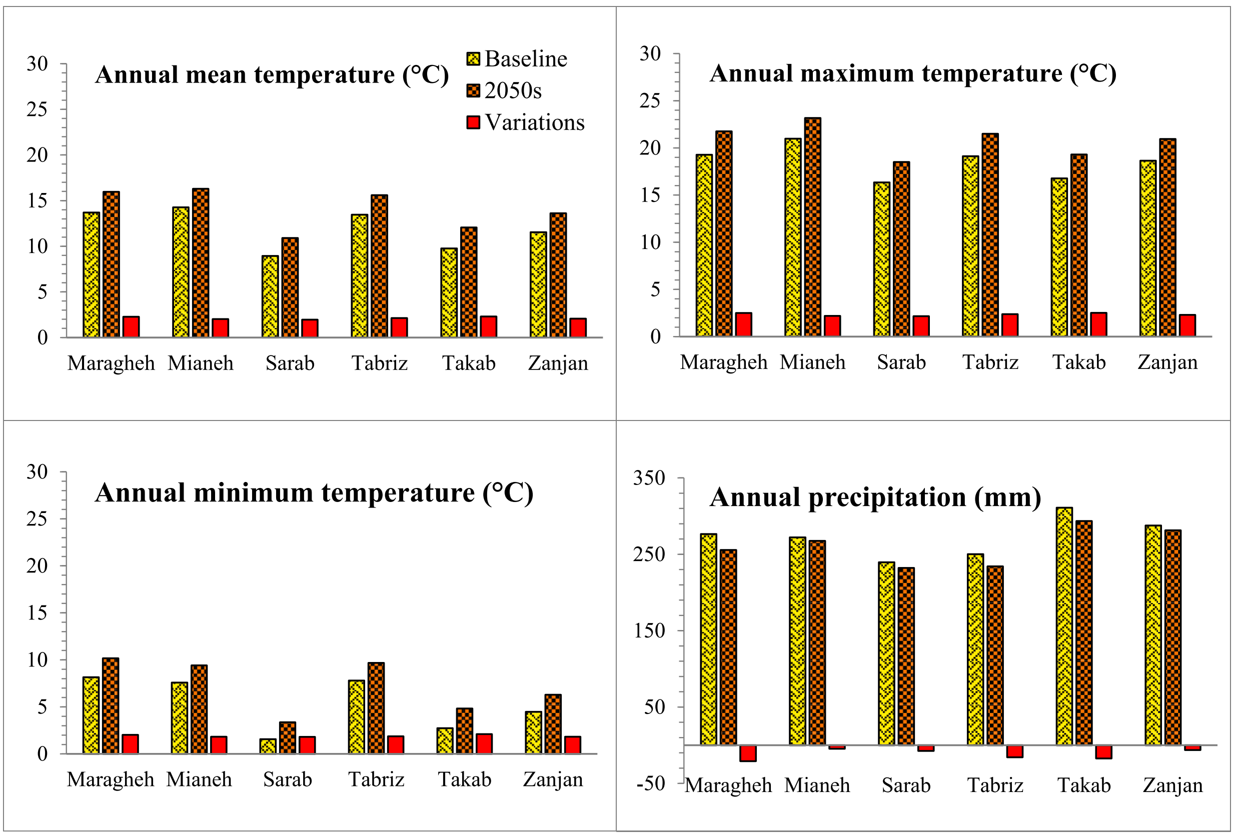

Fig. 2. The variations of the annual weather variables in 2050s compared to the baseline (1990–2019) in the selected stations for exposure (E) assessment of the study area. Source: study findings.

time period.

$$Aridity\ Index = \frac{P}{PET}\begin{Bmatrix} Humid & > 0.65 \\ Sub-humid & 0.5-0.65 \\ Semi-arid & 0.2-0.5 \\ Arid & 0.05-0.2 \\ Hyper-arid & < 0.05 \end{Bmatrix} \quad (1)$$

where P is the cumulative precipitation and PET is potential evapotranspiration. The UNEP aridity index ranges between 0 and $+\infty$, with higher values indicating wetter climatic conditions (Rodrigo-Comino et al., 2020). It should be noted that PET was calculated through the Penman-Monteith method using the CropWat8.0 software.

T mean: average annual mean temperature; T minimum: average annual minimum temperature; T maximum: average annual maximum temperature. Source: study findings.

In this study, soil organic carbon (SOC; SP1), pH (SP2), soil erosion (SP3), and soil salinity (SP4) were chosen as the four sub-indices of the SP component (Table 2). As reported by Roozitalab et al. (2018), soils of Iran have been faced with crucial challenges consisting of the absence of inadequate organic matter, water and wind erosion, and salinity and alkalinity. Assessing soil characteristics is an essential step in recognizing the extent of the fragility of an agricultural system and in implementing appropriate plans for mitigating CC and improving food security (Brevik, 2013). It should be noted that SP2 shows the alkalinity of the soils in this study because the amounts of this indicator were higher than 7 in the study area. In this study, the soil erosion and soil salinity maps with the scale of 1:100,000 were obtained from the Iranian Soil and Water Research Institute (SWRI). Also, maps of SOC and pH were downloaded from the open global database of SoilGrids which shares the soil property's data at 250 m spatial resolutions.

To gather information about the indicators of demography (D), vulnerable social group (VSG), farm operation (FO), agricultural activity (AA), economic capability (EC), social capability (SC), human resource capability (HRC) and institutional capability (IC) an in-house survey questionnaire was developed (Appendix 1). The questionnaire included both open and scaling questions. The questionnaire was validitychecked with the experts' judgments of the Agro-ecology Department of Environmental Sciences and Research Institute (ESRI). As mentioned earlier, household farmers who are the head of the household constitute the statistical population of this research. The study area has 11,950 farmers of which 368 households' head farmers (from 112 villages) were selected as a sample group using Cochran's formula (α <0.05). Accordingly, the sample size in each RD was determined based on the proportion of the number of farmers in that RD to total farmers of Hashtroud. Finally, the required socio-economic information was collected from the households' head farmers in the selected clusters. It should be noted that the households' head farmers in each cluster were recognized with the help of experts of Hashtroud Agricultural Jihad Administration. To do this, a face-to-face interview was conducted with the samples. At first, the purpose of the research was explained to them, and then they were asked to answer the questions carefully. Therefore, the sample sizes were determined as 32, 31, 70, 42, 30, 37, and 126 for Solouk, Ali Abad, Qarranqou, Koohsar, Charoymagh, Almalou, and Nazar Kahrizi, respectively. In order to determine the samples, a cluster random sampling method has been applied in this study. Therefore, within each RD, the villages were considered as the clusters. Then, the clusters were randomly selected to create the sample group in each RD. Finally, the required socio-economic information was collected from the households' head farmers in the selected clusters. It should be noted that the households' head farmers in each cluster were recognized with the help of experts of Hashtroud Agricultural Jihad Administration. To do this, a face-to-face interview was conducted with the samples. At first, the purpose of the research was explained to them, and then they were asked to answer the questions carefully. Regarding the respondents who were illiterate, the researcher asked the questions orally and recorded the answers. The reliability of the questionnaire was proved using the alpha Cronbach coefficient of 0.87. The processing of the information was done using the SPSS software version 26 and Microsoft Excel. After removing blanked surveys, the response rate to the questionnaire was about 43%, which can be related to the period in which the survey was conducted (from May 2021 to August 2021). It coincided with the outbreak of the Corona virus and some farmers did not tend to conduct interviews and complete questionnaires.

2.2. Calculating the vulnerability index (VI)

To make the indicators standardized and comparable, the normalization method was applied (Hadipour et al., 2020; Roshani et al., 2024). The study followed a min-max linear scaling approach, as illustrated in Eq. (2), to transform the indicators into a unit-less scale. In this approach, each indicator becomes normal in the range between 0 and 1 (Xu et al., 2020):

$$\begin{cases} NS_i = \dfrac{x_i - x_{\min}}{x_{\max} - x_{\min}} & \text{for positive indicators} \\ NS_i = \dfrac{x_i - x_{\max}}{x_{\min} - x_{\max}} & \text{for negative indicators} \end{cases} \tag{2}$$

where NS_i is the normalized score of the ith indicator and x_i, $x_{\min}$, and $x_{\max}$ are the actual, minimum, and maximum scores among the observations of ith indicator, respectively. Also, the positive and negative indicators refer to the relationships between the indicators of E, S, and AC, with the vulnerability that are indicated in Table 1.

After the calculation of the normalized scores, to map the spatial distributions of the indicators of E, an interpolation was applied using an inverse distance weighted (IDW) technique (Kheiri et al., 2021a). The reliability of the maps was confirmed by Kappa coefficient ranges between 0.64 and 0.83, indicating that the maps substantially represent the real conditions of the region (McHugh, 2012).

In terms of the S and AC indicators, before generating the maps, each indicator was averaged for the sample households of each RD. The SP indicators are themselves mapped and do not require further spatial processes. The spatial distributions of all the indicators were mapped using ArcGIS10.8.

In this study, the fuzzy-analytical hierarchical process (Fuzzy-AHP) method, which relies particularly on judgment of experts, was considered to determine the importance of the selected indicators, the sub-components, and the components of vulnerability. This method has been widely applied to weighting the indicators in vulnerability studies (Hadipour et al., 2020; Saha et al., 2021). Therefore, 12 experts who were aware of the concept of vulnerability were asked to judge the importance of the indicators. These experts were specialized in agro-ecology, social science, and geography, and they were selected from research institutions, agencies, and universities. See the supplementary material for detailed information on how the Fuzzy-AHP model works (Appendix 2).

The final relative weight of the indicator was calculated using the weighted linear combination (WLC) technique. To do this, the weights of each indicator and its related sub-component were multiplied by each other to obtain the final relative importance of that indicator. In the next step, the Eq. (3) was applied to measure the score of each vulnerability component:

$$VC = \sum_{i=1}^{n} NS_i \times W_i \tag{3}$$

where VC refers to the vulnerability component (E, S, or AC) score and NS_i and W_i represent the normalized score and the final relative weight, respectively, so that $W_i < 1$ and $\sum_{i=1}^{n} W_i = 1$. Furthermore, n is the number of indicators for each component, i.e., 12, 16, and 14 indicators for E, S, and AC, respectively.

Finally, once the scores of vulnerability components of E, S, and AC were obtained, the potential impact (PI) and the VI were calculated using the Eqs. (4) and (5), respectively, as follows (Žurovec et al., 2017):

$$PI = W_E E + W_S S \tag{4}$$

$$VI = PI - W_{AC} AC \tag{5}$$

where W_E, W_S, and W_{AC} are the weights of E, S, and AC, respectively.

2.3. Recognizing coping and adaptation strategies

After determining the VI of the study areas, the farmers who were less vulnerable to CC were asked to identify which coping and adaptation strategies they have adopted to combat CC. It should be noted that adaptation to CC involves reactive, concurrent or anticipatory long-term changes in behavior and practices aimed at reducing vulnerability to future CC. Also, the coping strategies are short-term and immediate efforts aimed at managing climate extreme risks (Yenglier Yiridomoh and Owusu, 2022). It was reported that the farmers' adaptation to CC could be obtained from the synergetic impacts of both coping and adaptation strategies (Ofgeha and Abshare, 2021). Accordingly, the farmers were asked to rate each strategy from 1 (very low) to 5 (very high) based on their importance. The score of 1 indicates that a strategy has the least effect on reducing their vulnerability, while the score of 5 indicates the greatest effect of a strategy on reducing their vulnerability. In the next step, the scores of each strategy were averaged to provide a reasonable ranking for the strategies based on their importance.

3. Results

3.1. Vulnerability components analysis

The weights of the components, the sub-components, and the final relative weights of the indicators applied to measure the vulnerability of the households' head farmers in Hashtroud are shown in Fig. 3. The consistency ratio (CR), which was calculated to demonstrate reliable consistency, was lower than 0.10 for all the comparisons. According to

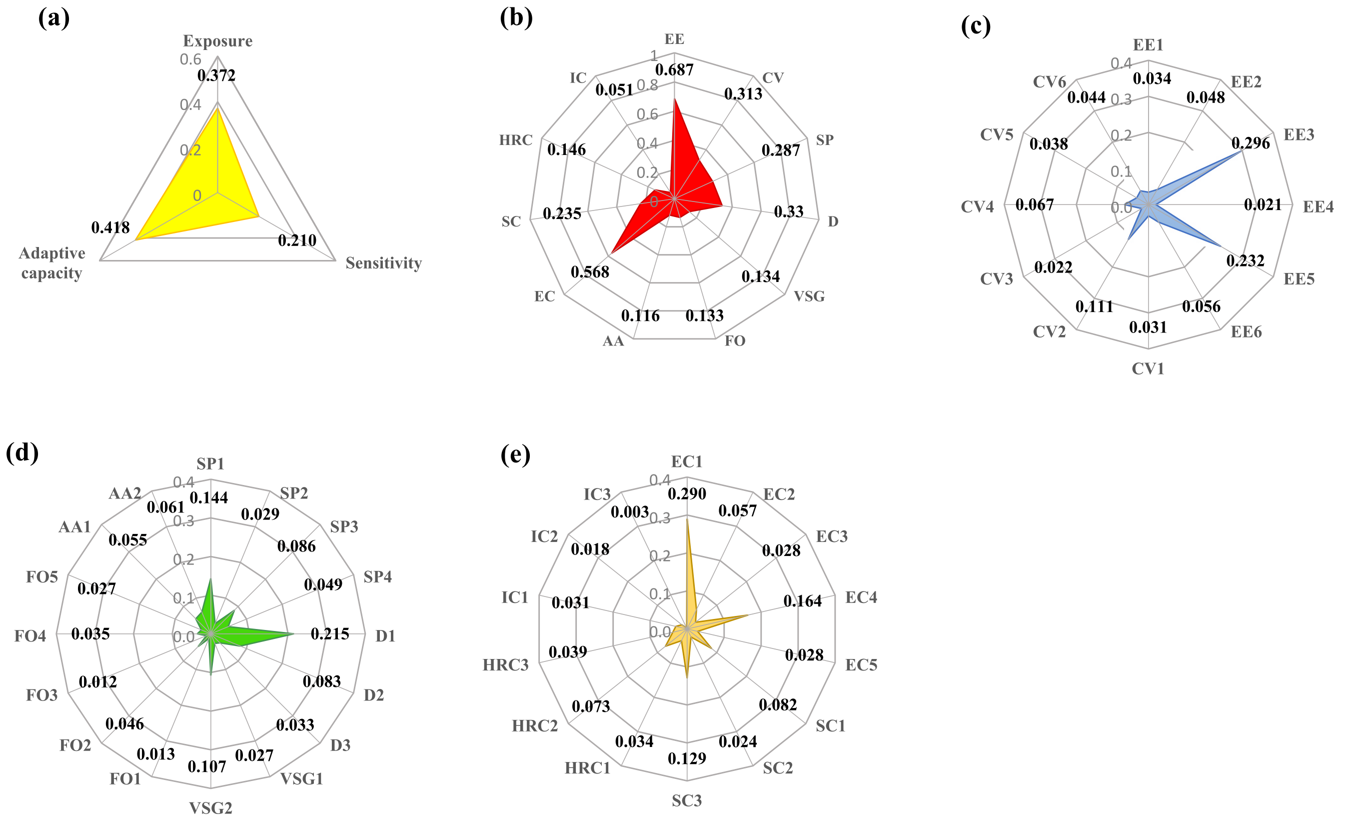

Fig. 3. The weights of the components (a) and the sub-components (b) and the final relative weights of the indicators of exposure (c), sensitivity (d), and adaptive capacity (e) obtained from Fuzzy-AHP. Source: study findings.

the Fuzzy-AHP results, the weights of 0.372, 0.210, and 0.418 were assigned to E, S, and AC, respectively, which indicated that AC has the greatest significance on vulnerability (Fig. 3a).

In terms of the importance of the sub-components of E, the experts' judgments revealed the weights of 0.687 and 0.313 for EE and CV, respectively, which pointed to the higher significance of EE on vulnerability compared to CV (Fig. 3b). In addition, the weights of 0.287, 0.330, 0.134, 0.133 and 0.116 were assigned to the sub-components of SP, D, VSG, FO and AA, respectively (Fig. 3b). Accordingly, D had the most important role in vulnerability assessment among the sub-components of S. Finally, the results indicated the weights of 0.568, 0.235, 0.146 and 0.051 for the sub-components of EC, SC, HRC and IC, respectively, which emphasized that EC has the most important role in vulnerability assessment among the sub-components of AC (Fig. 3b).

The results of the Fuzzy-AHP model for the indicators of E are illustrated in Fig. 3c. Accordingly, the greatest weights belonged to consecutive dry days (EE3), ice days (EE5), and long-term trend of annual mean temperature (CV2), with the final relative weights of 0.296, 0.232, and 0.111, respectively.

The importance of the S indicators is illustrated in Fig. 3d. Accordingly, work experience (D1), SOC (SP1), and number of family members over 65 years / total number of family members (VSG2), with final relative weights of 0.215, 0.144 and 0.107, were judged to have the highest effect on S in Hashtroud.

The AC was evaluated based on 14 indicators from the four sub-components of economic capability (EC), social capability (SC), human resource capability (HRC), and institutional capability (IC). According to experts, the highest weights among the AC indicators were allocated to net income from agricultural land (EC1; 0.29), agricultural income to total income (EC4; 0.164), and sales channels (SC3; 0.129) (Fig. 3e).

3.1.1. *Exposure (E)*

According to the spatial distributions of the indicators of E, the frequency of frostbite (EE1) ranged between 74.5 days (in Almalou) and 143.6 days (in Koohsar) (Fig. 4). Also, the frequency of tropical nights (EE2) was between 2 days (in Koohsar) and 37.3 days (in Almalou). The results showed that the fluctuations of consecutive dry days (EE3) were between 62.2 days (eastern Hashtroud) and 101.8 days (western Hashtroud). Also, the highest consecutive wet days (EE4) were observed in Almalou (4.8 days) while the least EE4 belonged to Charoymagh (3.7 days). Ice days (EE5) indicated a similar spatial distribution to EE1 where the highest and the least EE5 were observed in Koohsar (27.4 days) and Almalou (12.5 days), respectively. The highest summer days (EE6) were observed in Charoymagh (156 days), while the least EE6 belonged to Koohsar (97.9 days) (Fig. 4).

According to the findings, the annual cumulative precipitation (CV1) was between 239 mm (in Nazar Kahrizi) and 310 mm (in Koohsar) (Fig. 4). Also, the results illustrated that the long-term trend of annual mean temperature (CV2) was between $+0.05$ °C yr^{-1} (in Solouk and Koohsar) and $+$ 0.12 °C yr^{-1} (in Charoymagh). However, the long-term trend of annual precipitation (CV3) was between -3.89 mm yr^{-1} (in Nazar Kahrizi) and $-$ 0.15 mm yr^{-1} (in Ali Abad). The spatial distribution of CV4 showed that compared to the baseline, the cumulative precipitation of the study region will be decreased by 7.6% (in western Hashtroud) to 1.7% (in eastern Hashtroud) up to 2050s. In addition, the spatial distribution of CV5 showed that, compared to the baseline, the mean temperature of the study region will be increased by $\sim$2 °C up to 2050s (Fig. 4).

3.1.2. *Sensitivity (S)*

According to the spatial distributions of the soil properties (SP) indicators of S, soil organic carbon (SP1) ranged between 0.76% and 2.1% throughout the study region (Fig. 4). Also, the results revealed that the soil pH (SP2) was from 7.4 to 8.1 in the study region. Based on Fig. 5, the

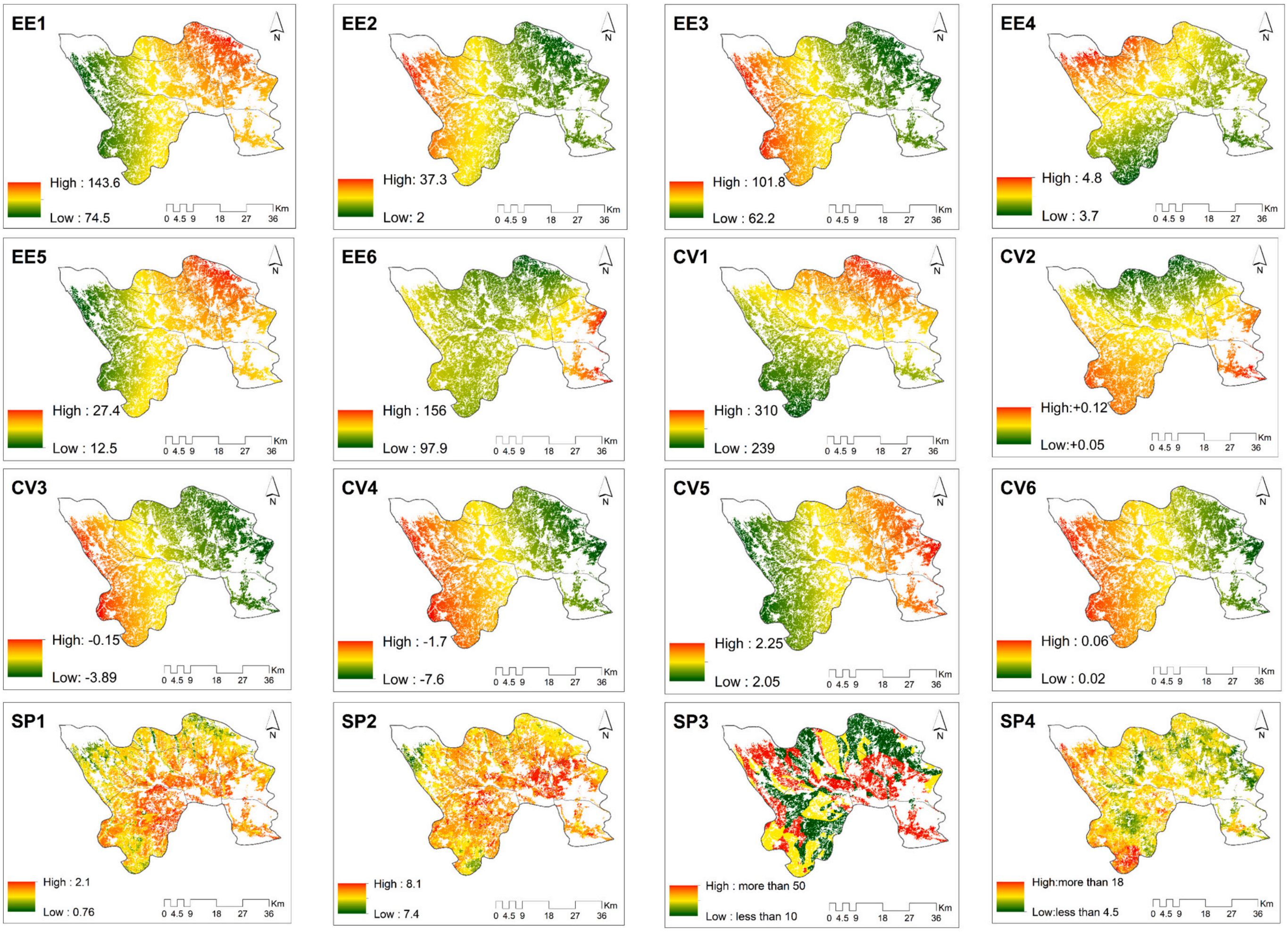

Fig. 4. The detailed environmental information that was used in the current study. Each indicator is named based on the symbol shown in Table 1. Source: study findings.

highest and the least amounts of soil erosion (SP3) were observed in Charoymagh (>50 t ha^{-1} yr^{-1}) and Koohsar (<10 t ha^{-1} yr^{-1}), respectively. Finally, the soil salinity (SP4) was in the range of 4.5–18 millimhos cm^{-1} (Fig. 4).

The results of the questionnaire survey indicated that the work experience (D1) was in the range of 33.6 years (in Almalou) to 36.4 years (in Nazar Kahrizi) (Table 3). According to Table 3, the number of unemployment member of family aged 15 to 65 / total number of family members (D2) ranged between 0.41 (in Solouk) and 0.57 (in Nazar Kahrizi). Also, the least and the highest number of family members directly involved in agriculture / total number of family members (D3) were observed in Ali Abad and Qarranqou by 0.29 and 0.36, respectively (Table 3).

The results investigated that the least and the highest number of family's children below 15 years old / total number of family members (VSG1) belonged to Nazar Kahrizi (0.11) and Solouk (0.21), respectively (Table 3). Also, the number of family members above 65 years old / total number of family members (VSG2) was in the range of 0.04 (Nazar Kahrizi) and 0.2 (in Koohsar).

In terms of farm operations indicators, the results of the questionnaire survey showed that the ratio of total farmlands size owned / number of land pieces (FO1) ranged between 1.76 (Nazar Kahrizi) and 4.7 (Almalou) (Table 3). In addition, the least and the highest ratio of the total irrigated lands size / total farmlands size (FO2) were observed in Koohsar and Charoymagh (0.21) and Almalou (0.11), respectively. According to Table 3, the total rainfed land sizes/total farmlands size (FO3) ranged between 0.92 (in Koohsar) and 0.74 (in Almalou). Also, the uncultivated lands area due to water shortage / total farmlands size (FO4) ranged between 0.02 (in Almalou, Solouk and Ali Abad) and 0.08 (in Charoymagh and Nazar Kahrizi). Our results also demonstrated that the total farmlands size owned / number of family members (FO5) was in the range of 4.32 (in Koohsar) and 7.48 (in Nazar Kahrizi) (Table 3).

For the indicators of agricultural activity, the results of the questionnaire survey indicated that the least and the highest crop diversity index (AA1) were observed in Solouk and Nazar Kahrizi with the amounts of 0.31 and 0.42, respectively (Table 3). Also, based on the reports of household head farmers, the least and the highest consumption of chemical fertilizer in a hectare (AA2) belonged to Nazar Kahrizi (67.7 kg ha^{-1}) and Almalou (142.7 kg ha^{-1}), respectively.

3.1.3. Adaptive capacity (AC)

The results of the questionnaire survey for AC indicated that the net income from the farmlands (EC1) was between 42.8 mill IRR (in Nazar Kahrizi) and 56.3 mill IRR (in Qarranqou) (Table 3). Also, our findings indicated that 32.3% (in Charoymagh) to 49.2% (in Almalou) of farmland in the study region was covered by crop insurance (EC2). The ownership of the number of livestock units (EC3) was also in the range of 10.7 (in Almalou) to 17.6 (in Solouk) (Table 3). The results revealed that the ratio of the income from agriculture to all income (EC4) was between 56.6% (in Ali Abad) and 74% (in Qarranqou). According to Table 3, the least and the highest households' farmland ownership (EC5) were observed in Koohsar (13.91 ha) and Nazar Kahrizi (20.2 ha),

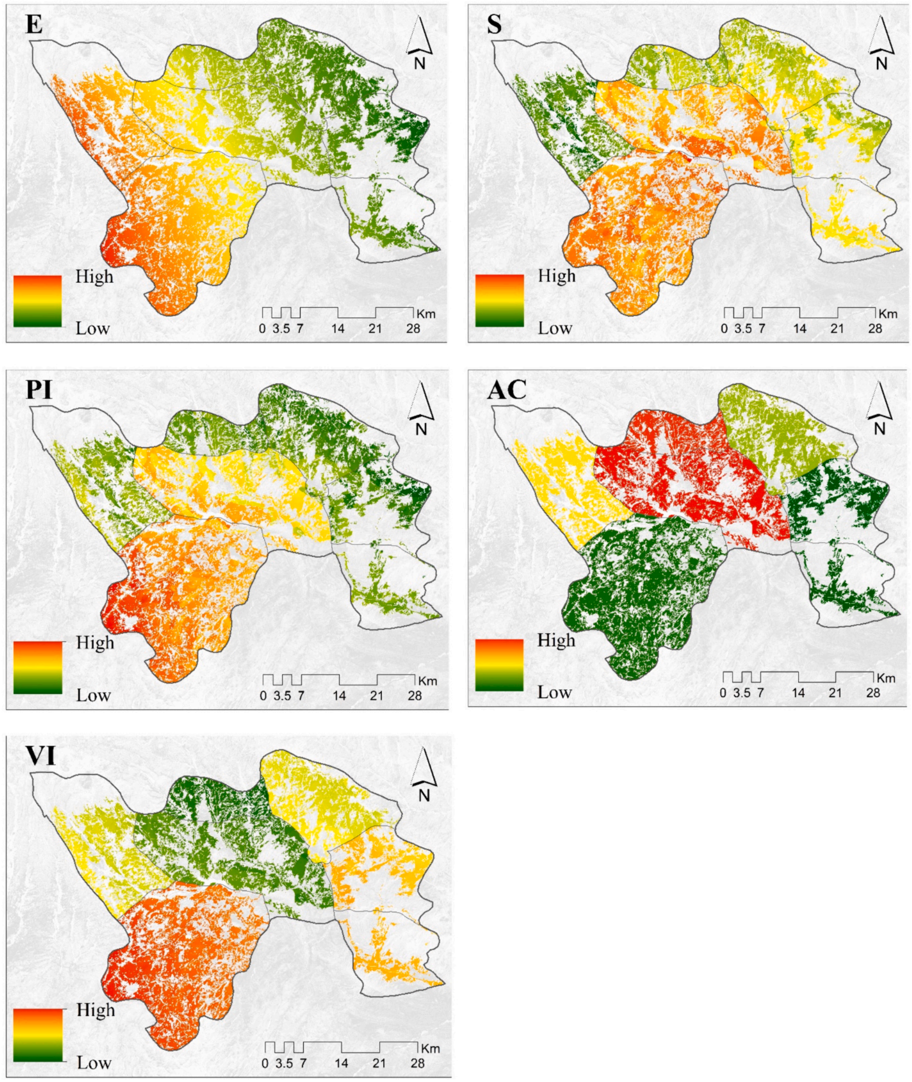

Fig. 5. Maps of the exposure (E), sensitivity (S), potential impact (PI), adaptive capacity (AC), and vulnerability index (VI) of the study area. Source: study findings.

respectively (Table 3).

According to Table 3, the level of taking technical advice consulting (SC1) was in the range of 0.51 (Solouk) and 2.09 (Almalou), while the level of participating in social communities (SC2) was in the range of 2.12 (Koohsar) and 3.26 (Ali Abad). In terms of sales channels (SC3), the least and the highest values belonged to Nazar Kahrizi (1.41) and Ali Abad (3.47), respectively (Table 3).

The results of the questionnaire survey for the human resource capability indicators illustrated that the least and the highest levels of literacy of farmers (HRC1) were observed in Qarranqou and Nazar Kahrizi (non-formal to middle school) and Ali Abad (high school to diploma), respectively (Table 3). Also, the ratio of the adult family members aged 15 to 65 / all family members (HRC2) was in the range of 0.34 (in Ali Abad and Nazar Kahrizi) and 0.87 (Qarranqou). In addition, the range of the family members with medical insurance / all family members (HRC3) was between 0.56 (in Charoymagh) and 0.84 (in Qarranqou) (Table 3).

The results of the questionnaire survey for the institutional capability indicators are shown in Table 3. Accordingly, the least and the highest access to agricultural input (IC1) were observed in Koohsar and Charoymagh (2.67) and Qarranqou (3.55), respectively. Also, the least and the highest access to governmental credit during the last 5 years (IC2) belonged to Solouk (0.48) and Almalou (1.28), respectively. Finally, in terms of market access (IC3), the study region was ranged between 2.97 (in Qarranqou) and 3.31 (in Almalou).

3.2. Determination of final vulnerability index (VI)

The E and S maps of the study region, which were measured using Eq. (3), are presented in Fig. 5. Based on the results, Nazar Kahrizi and Almalou (western Hashtroud) were exposed to CC much more severely than other RDs. However, the lowest level of E is observed in Ali Abad (eastern Hashtroud). Also, the sensitivity to CC was higher than the other RDs in Nazar Kahrizi and Qarranqou. However, the lowest level of sensitivity to CC belonged to Almalou.

In this study, PI was also measured via the arithmetic sum of E and S to obtain an overall index for these two components. Based on Fig. 5, an impressive difference was observed in the PI levels. In this regard, the highest level of PI was detected in Nazar Kahrizi and Qarranqou, while it was almost the same for the other RDs.

The map of the AC, which is reflected by a combination of the level of its sub-component indicators (Eq. (3)), is shown in Fig. 5. Accordingly, Solouk and Qarranqou were illustrated to have the highest AC, while Nazar Kahrizi, Charoymagh, and Ali Abad were categorized as the three RDs with the weakest AC.

To generate the VI map of the study area, we simply combined the PI and AC maps using Eq. (5) and the result is indicated in Fig. 5. In the study area, Nazar Kahrizi, Charoymagh, and Ali Abad show the greatest

Table 3
The detailed information obtained from questionnaire survey that was used in the current study. Source: study findings.

Component	Indicator	Rural District																				
		Almalou			Charoymagh			Solouk			Ali Abad			Qarranqou			Koohsar			Nazar Kahrizi		
		Min	Max	Avg.	Min	Max	Avg.	Min	Max	Avg.	Min	Max	Avg.	Min	Max	Avg.	Min	Max	Avg.	Min	Max	Avg.
	D1 (year)	15	65	33.6	10	60	34.2	10	65	34.9	15	55	35	4	75	35.9	15	65	33.7	6	50	36.4
	D2	0	0.8	0.45	0	0.8	0.49	0	0.75	0.41	0.2	0.8	0.48	0	0.8	0.44	0	0.8	0.43	0	0.8	0.57
	D3	0.17	0.5	0.30	0.17	0.67	0.3	0.17	0.67	0.35	0.2	0.67	0.29	0.17	1	0.36	0.2	0.6	0.34	0.2	1	0.33
	VSG1	0	0.5	0.19	0	0.5	0.13	0	0.67	0.21	0	0.5	0.12	0	0.5	0.13	0	0.5	0.15	0	0.5	0.11
	VSG2	0	1	0.14	0	1	0.14	0	1	0.16	0	0.4	0.09	0	1	0.13	0	1	0.2	0	0.5	0.04
Sensitivity (S)	FO1	0.56	5	4.70	0.53	14.8	1.9	0.5	4.67	4.58	0.3	12	2.56	0.45	13.2	2.46	0.36	8.88	3.24	0.91	12	1.76
	FO2	0	1	0.11	0	0.5	0.21	0.05	0.43	0.12	0	1	0.16	0	1	0.17	0	0.5	0.21	0	0.83	0.11
	FO3	0	1	0.74	0.33	1	0.83	0.57	0.95	0.75	0	1	0.8	0	1	0.79	0.5	1	0.92	0.17	1	0.8
	FO4	0	0.22	0.02	0	0.2	0.08	0	0.19	0.02	0	0.38	0.02	0	0.71	0.05	0	0.23	0.04	0	0.5	0.08
	FO5	0.83	18.3	7.42	1.3	80	4.59	0.83	20.4	5.75	0.1	30.6	4.44	0.4	57.5	6.38	0.75	25	4.32	0.18	86	7.48
	AA1	0.17	0.5	0.33	0.2	0.5	0.36	0.25	0.5	0.31	0.17	0.5	0.38	0.13	0.5	0.37	0.17	0.5	0.36	0.2	0.5	0.42
	AA2 (kg)	3	250	142.7	25	200	90.9	50	250	134.5	35	250	106.6	5	250	92	6	200	90.1	20	200	67.7
	EC1 (mill IRR)	10	100	43.5	10	150	44.1	10	85	56.7	13	270	41.5	5	200	56.3	10	100	47.1	10	100	42.8
	EC2 (%)	0	100	49.2	0	100	32.3	0	100	48.2	0	100	37.8	0	100	32.9	0	100	40.9	0	100	35.8
	EC3	0	80	10.7	0	180	10.9	0	45	17.6	0	30	17.6	0	150	13.5	0	52	14.2	0	125	15.3
	EC4 (%)	18.2	100	62.4	16.7	100	61.9	12.5	100	66.7	22.2	100	56.6	7.69	100	74	16.7	100	69.35	16.7	100	57.4
	EC5 (ha)	5	55	38.5	6.5	160	14.8	3.5	42	38.4	0.3	122.5	18.7	2	131	17.8	3	222	13.91	2	86	20.2
	SC1*	0	6	2.09	0	7	0.59	0	10	0.51	0	4	0.89	0	7	1.08	0	3	1.80	0	4	1
	SC2*	1	5	2.45	1	5	2.16	1	5	3.23	1	4	3.26	1	5	2.48	1	5	2.12	1	5	2.37
	SC3	1	4	3.43	1	4	2.47	1	4	3.34	1	3	3.47	1	4	3.04	1	4	1.46	1	4	1.41
	HRC1**	0	6	3.34	0	7	2.67	0	7	2.86	0	7	3.67	0	7	1.67	0	7	2.33	0	7	1.67
	HRC2	0.23	0.87	0.51	0.61	0.86	0.81	0.22	0.81	0.57	0.11	0.76	0.34	0.19	0.7	0.61	0.21	0.9	0.87	0.1	0.76	0.34
	HRC3	0.4	1	0.63	0	1	0.56	0	1	0.6	0.25	1	0.7	0.6	1	0.84	0	0.81	0.56	0	0.85	0.79
	IC1 (%)	1	5	3.00	1	5	2.67	1	5	2.93	1	4	3.1	1	5	3.55	1	5	2.67	1	5	3.37
	IC2	0	4	1.28	0	5	0.49	0	5	0.48	0	3	1.25	0	5	0.87	0	5	0.9	0	5	0.86
Adaptive capacity (AC)	IC3	2	5	3.31	1	5	3.08	3	5	3.25	2	5	3.26	1	5	3.15	2	5	2.97	1	5	3.01

[*] The classification is based on Likert scale (Very low: 1, Low: 2, Moderate: 3, High: 4 and Very high: 5).
[**] Illiterate: 0, Elementary/non-formal: 1, Middle school: 2, High school: 3, diploma: 4, Bachelor degree: 5, Master's degree: 6 and Doctorate: 7.

levels of vulnerability to CC, respectively. In addition, the farmers of Solouk and Qarranqou are recognized to have the least vulnerability to CC. However, the farmers of Almalou and Koohsar are identified as the group with a moderate vulnerability level in the study area (Fig. 5).

The level of farmers' vulnerability to CC in each RD was presented separately for the rainfed, irrigated, and total agricultural lands (Fig. 6a). It was found that 34% (33,360 ha) of the rainfed and 37% (2244 ha) of the irrigated farmlands were in the "very high" class in terms of vulnerability to CC. However, the detailed information on the agricultural land vulnerability class of each RD is shown in Fig. 6a. Based on the results, 34% (~35,902 ha) of the total farmlands, all of which are located in Nazar Kahrizi, showed a very high vulnerability to CC. Furthermore, 23% (~23,912 ha) of the farmlands located in Solouk and Qarranqou indicated very low vulnerability. In addition, 8% (~8460 ha), 24% (~25,514 ha), and 11% (~12,182 ha) of the farmlands showed low, moderate, and high vulnerability to CC, respectively.

3.3. Opportunities to reduce vulnerability to CC

As mentioned earlier, and according to the results of this study as the least vulnerable RDs, the farmers (164 farmers) of Solouk and Qarranqou were asked to identify the coping and adaptation strategies they adopted to reduce their vulnerability. Accordingly, we recognized 18 strategies as presented in Fig. 6b. These farmers believe that 'weather forecasting,' 'changing planting date,' 'implementing agroforestry practices,' and 'pre-selling the products' with average scores of 3.97, 3.31, 3.21, and 3.08, respectively, are the most important strategies in reducing their vulnerability. However, the least important strategies are 'changing harvested date' and 'using new irrigation technologies' with average scores of 0.69 and 0.86, respectively. It should be noted that although these strategies had the lowest score among the listed strategies, it does not mean that they are not appropriate for vulnerability reduction.

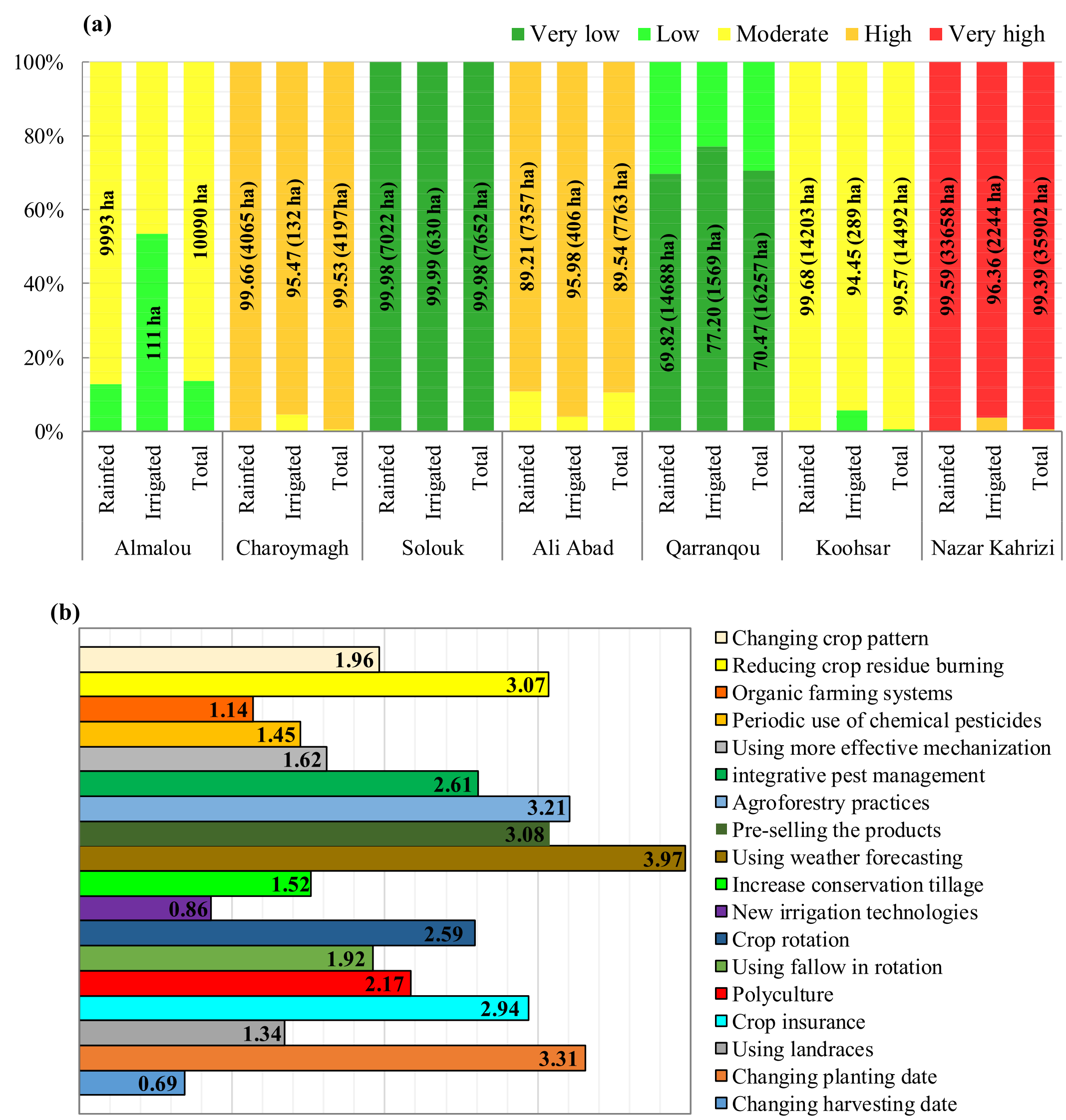

Fig. 6. (a) The vulnerability level of the rainfed, irrigated, and all agricultural lands of different RDs; the numbers in each column represent proportion (%), and the numbers within parentheses represent the extent (ha) of the corresponding vulnerability class. (b) The classification of the recognized coping and adaptation strategies to reduce vulnerability to CC in the study area based on their importance and according to the opinions of farmers who have the least vulnerability to CC. Source: study findings.

4. Discussion

This study evaluated farmers' vulnerability to CC in Hashtroud, located in the northwest of Iran. Our findings revealed that the study area became drier during the last decades. It was also predicted that the air temperature will increase by about 2 °C, while the cumulative precipitation will decrease by about 1.7–7.6% by the end of 2050s in this region. These changes in the climate will induce more severe effects on the agriculture sector of Hashtroud. These findings are in line with the previous reports (e.g. Kheiri et al., 2022; Zarghami et al., 2011) which illustrated the negative impacts of CC on agriculture section in this region. In this regard, Kheiri et al. (2021a) evaluated the response of dryland barley yield to climate variability in northwestern Iran during 1991–2010. Their results showed that the average annual air temperature has increased by 0.13 °C yr $^{-1}$ and the annual cumulative precipitation has decreased by 0.8 mm yr $^{-1}$ and therefore, the climate of this region has become drier drastically. Their results also showed that the change in the climate of this region has significantly decreased the yield of dryland barley. In another study, Kheiri et al. (2021b) assessed the response of rainfed chickpea yield to spatiotemporal variability of climate in the northwest of Iran during 1988–2017. They reported that the minimum temperature and maximum temperature have been increased by +0.05 °C yr $^{-1}$ and + 0.08 °C yr $^{-1}$, respectively. They also indicated that the chickpea yield has decreased by 1.8% per year during the studied period. The association between weather variables and dryland wheat yield in northwestern Iran was evaluated by Kheiri et al. (2017). Their results illustrated that this region became significantly drier during 1990–2004. In addition, the increased minimum, maximum and mean temperatures significantly decreased the dryland wheat yield in this region between 1990 and 2004.

4.1. Vulnerability to CC in the study region

According to the findings of this study, AC plays the most important role in vulnerability assessment compared to E and S. In consistent with our findings, Jamshidi et al. (2019) evaluated smallholder farmers' vulnerability to CC in Hamedan province, western Iran, utilizing 42 indicators derived from E, S, and AC components. They demonstrated that the degree of vulnerability of farmers to CC in their study region is more influenced by AC. Similar findings were also reported by Sharafi et al. (2020) and Parker et al. (2019). According to Roshani et al. (2024), AC of an ecosystem includes all the factors that contribute to its ability to make adaptive adjustments to the processes, practices and structure of its environment. Therefore, higher AC could mitigate the potential for harm of CC by taking synthetic action. Xu et al. (2020) defined AC of the agricultural systems as farmers' capacity to transform the existing and future resources, such as financial, physical, human, social, or natural capacities, into an opportunity to gain a future coping or adaptation strategy. As reported by Ofori et al. (2017), due to the nature of agricultural activities, farmers rely greatly on climate conditions and are more affected by CC effects, compared to other communities. However, higher AC strengthens the potential of this group to cope with or adapt to CC.

Generally, the Fuzzy-AHP model implied that "consecutive dry days," "ice days," "long-term trend of annual mean temperature," "work experience," "soil organic carbon," "number of family members over 65 years / total number of family members," "net income from agricultural land," "agricultural income / total income" and "sales channels" had the greatest final weights in the vulnerability assessment. According to Makoka and Kaplan (2005), vulnerability is a complicated term that is associated with a wide range of socio-cultural, environmental, economic, political, and institutional issues. Accordingly, the basic conditions must be examined in a particular area to identify the most vulnerable areas and social communities based on that condition (Zhang et al., 2019). In this regard, Jamshidi et al. (2019) found that "annual rainfall," "land size," "size of agricultural land for family members," and "net farm income" had the highest correlation with vulnerability. Furthermore, Xu et al. (2020) reported that "energy availability," "dependency ratio," and "land types," all of which classified as the S indicators in their study, were the most effective factors in vulnerability determination. In addition, according to Chinwendu et al. (2017), the most relevant indicators of vulnerability analysis are "access to resources (labor and land supply and traditional knowledge/ information)," "poor level of education," "gender," and "insufficient institutional capacity." However, depending on the scale of the study, the inclusion / exclusion criteria, the socio-cultural, economic, climatic, political and institutional status of a region and the method chosen to weigh the indicators, and the vulnerability indicators can be of different importance (Raufirad et al., 2022; Xu et al., 2020).

In this study, the rural districts of Solouk and Qarranqou exhibited the lowest vulnerability to climate change, whereas the rural district of Nazar Kahrizi demonstrated the highest vulnerability. Qarranqou is more exposed to CC and has the highest S to CC than other RDs. However, as expected, its high AC led to show the least vulnerability to CC. This means that the households in this area are in a vulnerable position but can still cope with CC without outside support (Mbakahya and Ndiema, 2015). In general, the higher AC in this area is attributed to higher "net income from the farmlands," higher "adult family member aged 15 to 65," higher "family members with medical insurance" and higher "access to agricultural inputs." These indicators have been widely reported as influential adaptive indicators in vulnerability assessments (e.g. Jamshidi et al., 2019; Parker et al., 2019; Xu et al., 2020). However, it is worth mentioning that due to different existing scales in vulnerability studies consisting of a regional/national/subnational/community/household level, each study should consider its scope and scale (Xu et al., 2020).

In terms of Nazar Kahrizi, as Mbakahya and Ndiema (2015) argued, the households in such regions are situated at an almost irreversible point, but they can be resuscitated only by adopting the best possible coping and adaptation strategies. Accordingly, there will be very good strategies for this region, which should be tailored to local conditions. Many elements are categorized as ACs in a region, including distribution channels, farming techniques, technology, training, governmental assistance, second jobs, institutions, social equality, infrastructure, production costs social networks, etc. (Donatti et al., 2019). However, based on the results of this study, Nazar Kahrizi must be improved in terms of "net income from the farmlands," "sale channels," "education" and "crop diversity." As Xu et al. (2020) explained, the principle of poverty is the lack of a long-term plan for the future as well as neglecting the value of education. They also stated that the poverty problem of households can be solved by constantly boosting their education level. In addition, participation in rural cooperatives and organizations such as household associations have been shown to improve household adaptation to CC and facilitate product sales by expanding new sales channels (Kumar, 2019). Also, diversification will lead to strong resistance to climatic extreme events and will increase the stability of household food supplies, thus enhancing the diversity of income sources for households (Kher et al., 2020).

It should be noted that Nazar Kahrizi showed the highest "total farmlands size owned / number of family members." At the same time, the highest ratio of "the number of unemployment member of family aged 15 to 65 / total number of family members" were observed in this region. It means that although there are many agricultural lands for each household, the labor participation rate in the agricultural sector is weak, which can be due to their lack of enthusiasm for agriculture because of the negative consequences of CC. However, the governments' financial support for labor in agriculture can be a solution to these problems. As reported by Borda et al. (2023), the motivation of labor can be increased by creating innovations and making a positive difference in their income. In this regard, it is implied that promoting local cooperatives, improving the labor participation rate and strengthening social governance via developing financial supports can help to reduce vulnerability to CC (Weng et al., 2023).

4.2. Adopting coping and adaptation strategies

In this study, successful coping and adaptation strategies that farmers believed reduce vulnerability to CC were identified. Our findings illustrated that "weather forecasting," "changing planting date," "implementing agroforestry practices," and "pre-selling the products" were the most successful solutions to reduce vulnerability to CC. As Xu et al. (2020) argued, a fragile living environment will enhance the households' vulnerability in the face of CC; therefore, it is necessary to consider coping and adaptation strategies to reduce the threats of CC. In terms of the reason behind emphasizing the use of coping and adaptation strategies based on the beliefs of farmers, it should be considered that an essential problem is the admission of coping and adaptation strategies by local communities. A variety of coping and adaptation solutions can dramatically reduce vulnerability, but farmers must accept the solution. This finding is supported by Weng et al. (2023), indicating that the rise in susceptibility to CC is significantly mitigated by adaptation strategies, adaptive capital (natural and financial), the cultural organizational system, and collective action mechanisms. Eza et al. (2015) conducted a study on an application platform for adjusting strategies to climate change. They demonstrated that integrating climate time series into weather forecasting and determining planting dates can be included into the framework of agricultural, soil, and human management. As mentioned by Wang et al. (2023), it is better to focus on key factors (e.g., growth period, solar radiation, daily maximum temperature, daily minimum temperature, temperature difference between day and night, and precipitation) to enhance adaptation to CC. As stated by Azadi et al. (2021), many of the strategies recommended in climate-smart agriculture to cope with and adapt to CC have not been welcomed because the capabilities, preferences and limitations of farmers have not been considered. These strategies should ultimately improve farmers' incomes, reduce poverty, and alleviate the adverse effects of conventional agriculture on the environment (Makate et al., 2019). Therefore, it is essential to propose these strategies based on the acceptance of farmers.

5. Conclusion

In this study, a multi-dimensional assessment approach, including both quantitative and qualitative information, was expanded to investigate the farmers' vulnerability to climate change in seven rural districts of Hashtroud city, northwestern Iran. Our results show that the farmers are exposed to the severe impacts of climate change, including increased temperature, reduced rainfall and intensified drought. To answer the research question regarding the farmers who are more vulnerable to climate change, our findings reveal that all farmers are vulnerable to climate change, but their level of vulnerability varies. However, to improve the adaptation, they must have different coping and adaptation strategies tailored to their local conditions. It is worth noting that the level of vulnerability is intensified in Solouk, Qarranqou, Almalou, Koohsar, Ali Abad, Charoymagh, and Nazar Kahrizi. The lowest vulnerability to climate change in Solouk and Qarranqou is attributed to their higher "net income from the farmlands," higher "adult family members aged 15 to 65," higher "family members with medical insurance" and higher "access to agricultural inputs." Also, the highest vulnerability to climate change in Nazar Kahrizi is attributed to their weaker "net income from the farmlands," "sale channels," "education" and "crop diversity." Overall, the experiences of farmers in the least vulnerable regions (Solouk and Qarranqou) show that coping and adaptation strategies such as "weather forecasting," "changing planting date," "implementing agroforestry practices," and "pre-selling the products" have increased their AC. Therefore, these strategies could serve as an opportunity to reduce vulnerability to climate change in the most vulnerable regions (Nazar Kahrizi).

The main implication of this research is the need for the participation of the responsible agencies and the government organizations to reduce the farmers' vulnerability to CC in Hashtroud which is one of the main hubs of agricultural production in East Azerbaijan province. There were several limitations to the present study: (i) As discussed, an indicator-based method was used to assess the smallholder farmers' vulnerability to CC. This method has its own limitations, although it is a practical way in determining conceptual frameworks. Priority in selecting an indicator, weighting methods, availability of required information, and difficulty of measuring or testing the validity of constructions are examples of these limitations; (ii) Finding the experts familiar with the concept of vulnerability and the climatic and socio-economic conditions of the study area to judge the importance of the indicators was difficult; (iii) Due to the lack of access to roads in some villages or unsuitability of the route, it was not possible to survey some farmers; and (iv) Because the measurement of vulnerability was based more on data collected from government agencies, lack of available and reliable information on some indicators was problematic.

Future research might include expanding the methodology and results into a full, ready-to-use assessment strategy and evaluating its application in additional local contexts, both within the present case study in rural regions and in comparable situations across Iran and the world. It is offered that the findings of this research regarding the drivers of vulnerability to climate change as well as the determined successful coping and adaptation strategies in the study area be implemented in the most vulnerable areas. It is also suggested that other indicators involved in vulnerability, such as risks related to insects, pests and diseases, water resources, access to energy, etc. which were not considered in the current study, all be addressed in future studies.

In summary, this study provides useful results for planners, stakeholders, and decision-makers in rural regions, especially in Hashtroud, where the evaluation of vulnerability has not yet been carried out. Finally, the method used in this study can be transferred to other areas where agriculture is dependent on rural smallholder farmers and CC affects their livelihoods because they may face similar problems.

Disclosure statement

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

CRediT authorship contribution statement

Mohammad Kheiri: Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jafar Kambouzia:** Validation, Supervision, Investigation. **Saeid Soufizadeh:** Writing – review & editing, Visualization, Validation, Supervision. **Abdolmajid Mahdavi Damghani:** Writing – review & editing, Visualization, Investigation. **Romina Sayahnia:** Writing – review & editing, Supervision, Investigation. **Hossein Azadi:** Writing – review & editing, Visualization, Validation, Supervision.

Declaration of competing interest

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Data availability

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

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecoinf.2024.102669.

References

Antonelli, C., Coromaldi, M., Pallante, G., 2022. Crop and income diversification for rural adaptation: insights from Ugandan panel data. Ecol. Econ. 195, 107390.

Azadi, H., Movahhed Moghaddam, S., Burkart, S., Mahmoudi, H., Van Passel, S., Kurban, A., Lopez-Carr, D., 2021. Rethinking resilient agriculture: from climate-smart agriculture to vulnerable-smart agriculture. J. Clean. Prod. 128602.

Baveye, P.C., Schnee, L.S., Boivin, P., Laba, M., Radulovich, R., 2020. Soil organic matter research and climate change: merely re-storing carbon versus restoring soil functions. Front. Environ. Sci. 8, 579904 https://doi.org/10.3389/fenvs.2020.579904.

Borda, Á.J., Sárvári, B., Balogh, J.M., 2023. Generation change in agriculture: a systematic review of the literature. Econ 11 (5), 129. https://doi.org/10.3390/economies11050129.

Brevik, E.C., 2013. The potential impact of climate change on soil properties and processes and corresponding influence on food security. Agri 3 (3), 398–417.

Chimi, P.M., Mala, W.A., Abdel, K.N., Fobane, J.L., Essouma, F.M., Matick, J.H., Pokam, E.Y.N., Tcheferi, I., Bell, J.M., 2023. Vulnerability of family farming systems to climate change: the case of the forest-savannah transition zone, Centre region of Cameroon. Res. Global. 7, 100138 https://doi.org/10.1016/j.resglo.2023.100138.

Chinwendu, O.G., Sadiku, S.O.E., Okhimamhe, A.O., Eichie, J., 2017. Households vulnerability and adaptation to climate variability induced water stress on downstream Kaduna River Basin. Am. J. Clim. Chang. 6 (02), 247.

Cutter, S.L., Boruff, B.J., Shirley, W.L., 2012. Social vulnerability to environmental hazards. In: Hazards Vulnerability and Environmental Justice. Routledge, pp. 143–160. https://doi.org/10.1111/1540-6237.8402002.

Donatti, C.I., Harvey, C.A., Martinez-Rodriguez, M.R., Vignola, R., Rodriguez, C.M., 2019. Vulnerability of smallholder farmers to climate change in Central America and Mexico: current knowledge and research gaps. Clim. Dev. 11 (3), 264–286.

Eekhout, J.P., de Vente, J., 2022. Global impact of climate change on soil erosion and potential for adaptation through soil conservation. Earth Sci. Rev. 226, 103921 https://doi.org/10.1016/j.earscirev.2022.103921.

Eza, U., Shtiliyanova, A., Borras, D., Bellocchi, G., Carrère, P., Martin, R., 2015. An open platform to assess vulnerabilities to climate change: an application to agricultural systems. Ecol. Inform. 30 https://doi.org/10.1016/j.ecoinf.2015.10.009.

FAO, IFAD, UNICEF, WFP, WHO, 2020. The State of Food Security and Nutrition in the World 2020. Transforming Food Systems for Affordable Healthy Diets. FAO, Rome. https://doi.org/10.4060/ca9692en.

Fekete, A., 2009. Validation of a social vulnerability index in context to river-floods in Germany. Nat. Hazards Earth Syst. Sci. 9 (2), 393–403. https://doi.org/10.5194/nhess-9-393-2009.

Finger, R., Hediger, W., Schmid, S., 2011. Irrigation as adaptation strategy to climate change—a biophysical and economic appraisal for Swiss maize production. Clim. Chang. 105 (3), 509–528. https://doi.org/10.1007/s10584-010-9931-5.

Graux, A.I., Bellocchi, G., Lardy, R., Soussana, J.F., 2013. Ensemble modelling of climate change risks and opportunities for managed grasslands in France. Agric. For. Meteorol. 170, 114–131. https://doi.org/10.1016/j.agrformet.2012.06.010.

Gupta, D., Gujre, N., Singha, S., Mitra, S., 2022. Role of existing and emerging technologies in advancing climate-smart agriculture through modeling: a review. Ecol. Inform. 71 https://doi.org/10.1016/j.ecoinf.2022.101805.

Hadipour, V., Vafaie, F., Kerle, N., 2020. An indicator-based approach to assess social vulnerability of coastal areas to sea-level rise and flooding: a case study of Bandar Abbas City, Iran. Ocean Coast. Manag. 188, 105077.

Hahn, M.B., Riederer, A.M., Foster, S.O., 2009. The livelihood vulnerability index: a pragmatic approach to assessing risks from climate variability and change—a case study in Mozambique. Glob. Environ. Chang. 19 (1), 74–88.

Harvey, C.A., Rakotobe, Z.L., Rao, N.S., Dave, R., Razafimahatratra, H., Rabarijohn, R.H., Rajaofara, H., MacKinnon, J.L., 2014. Extreme vulnerability of smallholder farmers to agricultural risks and climate change in Madagascar. Philosoph. Trans. Royal Soc. B: Biol. Sci. 369 (1639), 20130089.

He, C., Kim, H., Hashizume, M., Lee, W., Honda, Y., Kim, S.E., Kinney, P.L., Schneider, A., Zhang, Y., Zhu, Y., Zhou, L., 2022. The effects of night-time warming on mortality burden under future climate change scenarios: a modelling study. Lancet Planet. Health 6 (8), 648–e657. https://doi.org/10.1016/S2542-5196(22)00139-5.

IPCC, 2000. Nakicenovic, N., Alcamo, J., Davis, G., Vries, B.D., Fenhann, J., Gaffin, S., Gregory, K., Grubler, A., Jung, T.Y., Kram, T., La Rovere, E.L., 2000. Special report on emissions scenarios. In: Nakicenovic, Nebojsa, Swart, Robert (Eds.), Special Report on Emissions Scenarios. Cambridge University Press, Cambridge, UK, p. 612.

Jamshidi, O., Asadi, A., Kalantari, K., Azadi, H., Scheffran, J., 2019. Vulnerability to climate change of smallholder farmers in the Hamadan province, Iran. Clim. Risk Manag. 23, 146–159.

Karimi, V., Karami, E., Keshavarz, M., 2018. Climate change and agriculture: impacts and adaptive responses in Iran. J. Integrat. Agri. 17 (1), 1–15.

Kheiri, M., Soufizadeh, S., Ghaffari, A., AghaAlikhani, M., Eskandari, A., 2017. Association between temperature and precipitation with dryland wheat yield in northwest of Iran. Clim. Chang. 141, 703–717.

Kheiri, M., Kambouzia, J., Deihimfard, R., Movahhed Moghaddam, S., Anvari, S., 2021a. Assessing the response of dryland barley yield to climate variability in semi-arid regions, Iran. J. Arid Land. 13 (9), 905–917.

Kheiri, M., Kambouzia, J., Deihimfard, R., Yaghoubian, I., Movahhed Moghaddam, S., 2021b. Response of Rainfed chickpea yield to Spatio-temporal variability in climate in the Northwest of Iran. Int. J. Plant Prod. 15 (3), 499–510.

Kheiri, M., Deihimfard, R., Kambouzia, J., Moghaddam, S.M., Rahimi-Moghaddam, S., Azadi, H., 2022. Impact of heat stress on Rainfed wheat growth and yield under semi-arid, semi-humid and Mediterranean climates in Iran condition. Int. J. Plant Prod. 16, 29–40.

Kher, J., Aggarwal, S., Punhani, G., Saini, S., 2020. Urbanization, climate linked water vulnerability as impediments to gender equality: A case study of Delhi, India. In: Leal Filho, W. (Ed.), Handbook of Climate Change Resilience. Springer, Cham.

Kouzegaran, S., Mousavi Baygi, M., Babaeian, I., Khashei-Siuki, A., 2020. Future projection of the effects of climate change on saffron yield and spatial-temporal distribution of cultivation by incorporating the effect of extreme climate indices. Theoret. Appl. Climatol. 141, 1109–1118.

Li, Y., Huang, H., Ju, H., Lin, E., Xiong, W., Han, X., Wang, H., Peng, Z., Wang, Y., Xu, J., Cao, Y., 2015. Assessing vulnerability and adaptive capacity to potential drought for winter-wheat under the RCP 8.5 scenario in the Huang-Huai-Hai Plain. Agric. Ecosyst. Environ. 209, 125–131.

Makate, C., Makate, M., Mango, N., Siziba, S., 2019. Increasing resilience of smallholder farmers to climate change through multiple adoption of proven climate-smart agriculture innovations. Lessons from southern Africa. J. Environ. Manag. 231, 858–868.

Makoka, D., Kaplan, M., 2005. Poverty and Vulnerability: An Interdisciplinary Approach. Centre for Development Research, University of Bonn. Online at: http://mpra.ub.uni-muenchen.de/6964/.

Mbakahya, G., Ndiema, A., 2015. Farming households' vulnerability and resilience to climate change in Nambale sub-county of Kenya. Int. J. Environ. Sci. Technol. 4, 1608–1617.

McHugh, M.L., 2012. Interrater reliability: the kappa statistic. Biochem. Med. 22 (3), 276–282.

Mukherjee, N., Siddique, G., Basak, A., Roy, A., Mandal, M.H., 2019. Climate change and livelihood vulnerability of the local population on Sagar Island, India. Chin. Geogr. Sci. 29, 417–436.

Nazari Nooghabi, S., Fleskens, L., Sietz, D., Azadi, H., 2020. Typology of vulnerability of wheat farmers in Northeast Iran and implications for their adaptive capacity. Clim. Dev. 12 (8), 703–716.

Nazari, S., Rad, G.P., Sedighi, H., Azadi, H., 2015. Vulnerability of wheat farmers: Toward a conceptual framework. Ecol. Indic. 52, 517–532.

Ofgeha, G.Y., Abshare, M.W., 2021. Local adaptation and coping strategies to global environmental changes: portraying agroecology beyond production functions in southwestern Ethiopia. PLoS One 16 (8), e0255813. https://doi.org/10.1371/journal.pone.0255813.

Ofori, B.Y., Stow, A.J., Baumgartner, J.B., Beaumont, L.J., 2017. Influence of adaptive capacity on the outcome of climate change vulnerability assessment. Sci. Report. 7 (1), 1–12.

Parker, L., Bourgoin, C., Martinez-Valle, A., Läderach, P., 2019. Vulnerability of the agricultural sector to climate change: the development of a pan-tropical climate risk vulnerability assessment to inform sub-national decision making. PLoS One 14 (3), e0213641.

Paul, A., Deka, J., Gujre, N., Rangan, L., Mitra, S., 2019. Does nature of livelihood regulate the urban community's vulnerability to climate change? Guwahati city, a case study from North East India. J. Eviron. Manage. 251, 109591.

Persitz, J., Essa, A., Ner, E.B., Assaraf, E., Avisar, E., 2022. Frostbite of the Extremities–Recognition, Evaluation and Treatment. Injury. https://doi.org/10.1016/j.injury.2022.07.040.

Raufirad, V., Heidari, Q., Ghorbani, J., 2022. Comparing socioeconomic vulnerability index and land cover indices: application of fuzzy TOPSIS model and geographic information system. Ecol. Inform. 72, 101917 https://doi.org/10.1016/j.ecoinf.2022.101917.

Rodrigo-Comino, J., Terol, E., Mora, G., Giménez-Morera, A., Cerdà, A., 2020. Vicia sativa Roth. can reduce soil and water losses in recently planted vineyards (*Vitis vinifera* L.). Earth Syst. Environ. 4 (4), 827–842.

Roozitalab, M.H., Siadat, H., Farshad, A., 2018. Introduction. In: Roozitalab, M., Siadat, H., Farshad, A. (Eds.), The Soils of Iran. World Soils Book Series. Springer, Cham. https://doi.org/10.1007/978-3-319-69048-31.

Roshani, Sajjad H., Rahaman, A.H., Masroor, M., Sharma, Y., Sharma, A., Saha, T.K., 2024. Vulnerability assessment of forest ecosystem based on exposure, sensitivity and adaptive capacity in the Valmiki Tiger Reserve, India: a geospatial analysis. Ecol. Inform. 80 https://doi.org/10.1016/j.ecoinf.2024.102494.

Saha, S., Kundu, B., Paul, G.C., Mukherjee, K., Pradhan, B., Dikshit, A., Abdul Maulud, K. N., Alamri, A.M., 2021. Spatial assessment of drought vulnerability using fuzzy-analytical hierarchical process: a case study at the Indian state of Odisha. Geomat. Nat. Hazards Risk. 12 (1), 123–153.

Sathyan, A.R., Funk, C., Aenis, T., Winker, P., Breuer, L., 2018. Sensitivity analysis of a climate vulnerability index-a case study from Indian watershed development programmes. Clim. Change Res. 5 (1), 1–14.

Schwarz, A.M., Béné, C., Bennett, G., Boso, D., Hilly, Z., Paul, C., Andrew, N., 2011. Vulnerability and resilience of remote rural communities to shocks and global changes: empirical analysis from Solomon Islands. Glob. Environ. Chang. 21 (3), 1128–1140.

Sharafi, L., Zarafshani, K., Keshavarz, M., Azadi, H., Van Passel, S., 2020. Drought risk assessment: towards drought early warning system and sustainable environment in western Iran. Ecol. Indic. 114, 106276.

Smith, P., Olesen, J.E., 2010. Synergies between the mitigation of, and adaptation to, climate change in agriculture. J. Agric. Sci. 148 (5), 543–552. https://doi.org/10.1017/S0021859610000341.

Sun, W., Li, S., Zhang, G., Fu, G., Qi, H., Li, T., 2023. Effects of climate change and anthropogenic activities on soil pH in grassland regions on the Tibetan Plateau. Global Ecol. Conserv. 02532 https://doi.org/10.1016/j.gecco.2023.e02532.

Trang Anh, D.L., Anh, N.T., Chandio, A.A., 2023. Climate change and its impacts on Vietnam agriculture: a macroeconomic perspective. Ecol. Inform. 74 https://doi.org/10.1016/j.ecoinf.2022.101960.

Urothody, A.A., Larsen, H.O., 2010. Measuring climate change vulnerability: a comparison of two indexes. Banko. Janakari. 20 (1), 9–16.

Wang, Y., Liu, S., Shi, H., 2023. Comparison of climate change impacts on the growth of C3 and C4 crops in China. Ecol. Inform. 74 https://doi.org/10.1016/j.ecoinf.2022.101968.

Weng, C., Bai, Y., Chen, B., Hu, Y., Shu, J., Chen, Q., Wang, P., 2023. Assessing the vulnerability to climate change of a semi-arid pastoral social–ecological system: a case study in Hulunbuir, China. Ecol. Inform. 76 https://doi.org/10.1016/j.ecoinf.2023.102139.

Xu, X., Wang, L., Sun, M., Fu, C., Bai, Y., Li, C., Zhang, L., 2020. Climate change vulnerability assessment for smallholder farmers in China: an extended framework. J. Environ. Manag. 276, 111315.

Yang, S., Song, S., Li, F., Yu, M., Guangming, Yu G., Zhang, Q., Cui, H., Wang, R., Wu, Y., 2022. Vegetation coverage changes driven by a combination of climate change and human activities in Ethiopia, 2003–2018. Ecolo. Inform. 71 https://doi.org/10.1016/j.ecoinf.2022.101776.

Yenglier Yiridomoh, G., Owusu, V., 2022. Do women farmers cope or adapt to strategies in response to climate extreme events? Evidence from rural Ghana. Clim. Dev. 14 (7), 678–687.

Zarafshani, K., Sharafi, L., Azadi, H., Hosseininia, G., De Maeyer, P., Witlox, F., 2012. Drought vulnerability assessment: the case of wheat farmers in Western Iran. Glob. Planet. Chang. 98, 122–130.

Zarghami, M., Abdi, A., Babaeian, I., Hassanzadeh, Y., Kanani, R., 2011. Impacts of climate change on runoffs in East Azerbaijan, Iran. Glob. Planet. Chang. 78 (3–4), 137–146.

Zhang, Q., Bilsborrow, R.E., Song, C., Tao, S., Huang, Q., 2019. Rural household income distribution and inequality in China: effects of payments for ecosystem services policies and other factors. Ecol. Econ. 160, 114–127.

Žurovec, O., Čadro, S., Sitaula, B.K., 2017. Quantitative assessment of vulnerability to climate change in rural municipalities of Bosnia and Herzegovina. Sustain 9 (7), 1208.