Farmers' decision to use drought early warning system in developing countries

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Farmers' Decision to Use Drought Early Warning System in Developing Countries

Abstract

Drought is a persistent, sluggish natural disaster in developing countries that has generated a financial burden and an unstable climate. Farmers should adopt early warning systems (EWS) in their strategies for monitoring drought to reduce its serious consequences. However, farmers in developing countries are reluctant to use EWS as their management strategies. Hence, the aim of this study was to investigate the decision of farmers to use climate knowledge through the model of farming activity in Kermanshah Township, Iran. A surveyor questionnaire was used to gather data from 370 wheat farmers using random sampling methods in multi-stage clusters. Results revealed that the decision to use climate information is affected by personal factors, attitude towards climate information, objectives of using climate information, and external/physical farming factors. The result of this study has implications for drought management practitioners. To be specific, the results can aid policymakers to design early alert programs to minimize the risk of drought and thus move from conventional agriculture to climate smart agriculture.

Keywords: Climate information; Drought; Early warning system; Environmental risk; Response capacity.

1. Introduction

Drought as the most damaging and the least understood natural hazard (Pulwarty and Sivakumar, 2014) causes a significant burden on people's lives. The drought event occurs in most regions of the world (such as North America, West Africa, and East Asia), along with socio-economic and psychological impacts (Huang et al., 2016). For example, African Sahel (Miyan, 2015) and other developing countries such as Afghanistan, Pakistan, Bangladesh, India, Iran, and Sri Lanka have also endured serious droughts in the last five decades (Miyan, 2015; Mafi-Gholami et al., 2019). The key argument is that droughts are growing in number and intensity in many arid and semi-arid areas, and the socio-economic and environmental costs and damages of these slow-onset occurrences are severe.

In addition, drought has severely affected natural resource-dependent sectors such as agriculture, causing huge economic losses (e.g., loss of food and feed production, increased livestock mortality, declining household farm incomes, and rising food prices) in this sector. It has also caused irreparable damage, including biodiversity loss, water security risk, reduced soil fertility, increased wind erosion, reduced plant fertility, increased disease incidence and pest control, increased fires, and lost canopies. As a result, drought will have many consequences such as reduced quality of life, food insecurity, migration, fragmented society, increased access to and use of water, reduced access to training, etc., especially in developing countries (Keshavarz and Karami, 2014; Keshavarz et al., 2013; Miyan, 2015; Sharafi, 2020a; Wang et al., 2015). In fact, due to the effects of wind and flooding, drought can cause soil erosion. In addition, soil drying causes cracks that decrease the volume of the soil (de Souza Machado et al., 2020). Soil defects can result in subsidence, which in turn causes buildings to be damaged. The soil and vegetation cover can suffer serious and permanent damage in regions with frequent or extensive dry periods (Chen et al., 2018).

Furthermore, changes in the amount and manner of rainfall play a major role in water erosion. In addition to rainfall, land use also affects water erosion (Lal and Pimentel, 2008). Destructive human activities such as deforestation and other vigorous agricultural activities have caused severe erosion and land degradation in large parts of the world. This is followed by drought, groundwater erosion, and sea level retreat and can threaten the consolidation and stability of local ecosystems and increase the sensitivity of water erosion to rainfall changes (Wei et al., 2010).

Drought danger to arid and semi-arid regions is a result of both exposures to the hazard event and the vulnerability to that hazard (Wilhite and Svoboda, 2000). Therefore, identical droughts with the same intensity and duration would have different impacts on drought-prone areas due to different levels of vulnerability. On the other hand, vulnerability is defined by multiple socio-economic and environmental variables like population growth and scale, as well as human properties in areas that are vulnerable to drought, land use habits, water usage, infrastructure, policy, and economic development (Karimi et al., 2018; Zhang et al., 2019; Bai et al., 2019). As an outcome, subsequent climate change-induced droughts are expected to increase the vulnerability of rural societies, especially in arid and semi-arid regions (IPCC, 2014). Therefore, mitigating the negative impacts of drought and reducing the vulnerability of communities are imperative. These require the provision of timely and reliable climate information to support the drought management strategies of vulnerable groups (Hurlbert et al., 2019).

Weather information structures consist of numerous sub-systems, including an interconnected risk evaluation and coordination and decision support systems, a vital component of which is early warning (Pulwarty and Sivakumar, 2014). An early warning system (EWS) is defined as "the set of capacities needed to generate and disseminate timely and meaningful warning information to at-risk individuals". This, in effect, will require them to plan and act reasonably and with adequate time to mitigate the risk of harm or failure (UNISDR, 2009). This means that the concept of EWS is much more than dissemination of forecast. Eventually, EWS is people and location-centered and consists of four interrelated elements, including i) risk knowledge, ii) monitoring and warning service, iii) dissemination and communication of warnings, and iv) response capacity (Pulwarty and Sivakumar, 2014; SU and Yu, 2020; Wang et al., 2020).

Many countries have developed EWSs which will help decision-makers raise the effects of repeated extreme droughts. However, a few studies (e.g., Horita et al., 2018; Matere et al., 2019) have shown that despite the development of drought EWSs, effective communication with end-users, i.e., farmers, has not been achieved. In theory, effective communication of drought EWSs should improve the productivity of agricultural systems and the economic welfare of farm families. As climate change increases the frequency and severity of drought events, the value of climate information for farmers should increase (Kusunose and Mahmood, 2016). Under an ideal drought management scenario, farm families should rapidly accept drought related warnings and adopt appropriate adaptive strategies at the farm level (Khanian et al., 2019). However, some farmers do not adopt drought EWSs and change their decisions according to early warnings (Sharifzadeh et al., 2012). Studies indicate that farmers' reluctance to utilize EWSs is related to their crisis management behavior. In other terms, lack of a coordinated regional drought strategy, that requires robust surveillance, early warning, and information systems, impacts evaluation processes, risk reduction measures, drought preparedness strategies, and disaster response services.

Drought EWS assumes that farmers are interested in maximizing their products and profits. This method of agriculture reduces the vulnerability of local farmers to drought and allows farmers to diversify and improve their incomes, which helps increase drought resilience and adaptation. However, adaptation strategies applied by farmers may primarily serve their interests in minimizing drought risk and maximizing economic benefits, but it can also undermine social benefits. To maintain agricultural sustainability, a strong adaptive strategy must balance environmental and economic benefits with social interests. Hence, the tendency of farmers to use early warning systems as one of the adaptation strategies is increasing (Willock et al., 1999; Güth and Kliemt, 2004). While farmers' decisions are aimed at profit maximization, the complex set of socio-psychological, natural, physical, and structural factors have significant effects on their decision-making process too (Feng et al., 2017; Keshavarz and Karami, 2014). Agriculture as a major source of livelihood for rural residents in developing countries is inherently sensitive to drought and is regarded as a significant threat to farming systems and rural family livelihood security (Lillemets and Viira, 2019). Vulnerability of farmers' livelihoods also includes a set of financial, physical, social, and natural capitals, so farmers will be willing to use the early warning system to avoid the negative effects of drought and financial constraints. Therefore, to understand farmers' behavior toward the adoption of drought EWSs, investigating the drivers and impediments of EWS adoption is imperative.

Several studies (Basher, 2006; Wilhite and Svoboda, 2000; Wilhite et al., 2014; Buurman et al., 2014; Hou et al., 2017; Li et al., 2017) have suggested that EWSs are still treated as a linear, centralized, and one-way process, and multiple factors limit the application of drought EWSs. For example, limitations in modeling the climate system's complexities (Basher, 2006), providing decision support systems in groundwater resources management for the purpose of sustainable development (Aliyari et al., 2018; Chang et al., 2017), comparative analysis of agricultural water pricing (Momeni et al., 2019), drought early warning system for impacts, especially in the food and nutritional security (Akwango et al., 2017; Choularton and Krishnamurthy, 2019; Rembold et al., 2019; Nuñez, 2020), early warning of agricultural drought and forewarning of crop vigor (Das et al., 2019; Vyas et al., 2020), insufficient meteorological and hydrological data density and accuracy (Liu et al., 2018; Wicklung and Raum, 2006), and insufficient indices for early onset and end of drought prediction (Shamano, 2010; Pendergrass et al., 2020) have hampered the application of EWSs.

In addition, the high cost of EWS data and the insufficient exchange of data between government agencies (Sharifzade et al., 2012) have restricted the applicability of EWSs among farmers. Some other scholars have pointed out that lack of knowledge precision generated by predictions, low credibility and reliability of EWS information, ineffective dissemination of

EWS data, and low user accessibility (Pulwarty and Sivakumar, 2014) tended to reduce the application of EWSs adoption. Finally, the poor understandability of EWS data for people at risk, perceived insufficient capacity to use EWS information, negative attitude towards drought management, perceived low severity of drought, and the cognitive structure of farmers (i.e., their personality, beliefs, and values) have demotivated their adoption of drought EWSs (Buurman et al., 2014; Kusunose and Mahmood, 2016; Sharafi et al., 2020).

This implies that EWSs should consider a reasonable technical and scientific basis and vigorously focus on the needs, priorities, and capacities of vulnerable communities. Therefore, comprehensive recognition of how farmers make decisions to use drought EWS information is imperative.

Wang et al. (2020) analyzed the predominant disaster factors caused by tropical cyclones and their impacts on early warning systems. Their results showed that predicting catastrophic tropical cyclone-related wind and rainfall is critical for preventing and mitigating tropical cyclone casualties and damage. Their results suggested that the minimum sea level pressure in tropical cyclones affected areas was the predominant disaster-warning factor and indicator for the resulting risks and damages of tropical cyclones between 1975 and 2017. Rovero and Ahumada (2017) argued that while there are well-established early warning systems for a number of natural phenomena, the current biodiversity crisis calls for an early warning system for biodiversity conservation. Hu et al. (2016) stated that although forecast characteristics have evolved over time, farmers' understanding of forecasts has not evolved, so there is a need to reflect on the driving factors. This point of view often recommends re-evaluating the impact of forecasts from the farmers' viewpoint, raising questions not only on how farmers interpret forecasts but also on how farmers evaluate such expectations. This shows that farmers' attitudes, values, perceptions, and personalities need to be better understood if the effective application of drought EWS should be considered. While internal drivers and motivators of the

EWS adoption can provide useful information, there has been only limited research about the psychological factors that might impact farmers' decisions about using the drought EWS. To fill this knowledge gap, this study aimed to investigate farmers' behavior toward the use of drought EWSs in Kermanshah Township, Iran. The objectives of this study are to: i) investigate farmers' decision to use EWS information and ii) explore the internal and external factors involved in farmers' decisions about the application of drought EWS. A better understanding of farmers' behavior in using drought EWS can help policymakers assess the needs and capacities of farm families and prioritize drought management programs while enabling farmers to build resilience to drought.

2. Theoretical framework

Behavioral approach has been recognized as a useful means for exploring the determinants of climate information usage. Many psychological experiments at the farm level have adapted the Theory of Rational Intervention (TRA) or the Theory of Organized Actions (TPB) to describe the activities of farmers (e.g., Alarcon et al., 2014; Ellis-Iversen et al., 2010; Sharifzade et al., 2011). It seems that application of TRA or TPB alone for prediction of farmers' behavior oversimplifies the complexities of decision making (O'Kane et al., 2017). For instance, TRA and TPB overlook the crucial role of personality and values, while previous studies (e.g., O'Kane et al., 2017; Willock et al., 1999) have supported the key role of such personality traits and emotional factors in decision making.

In order to investigate farmers' decisions about using EWSs, a model proposed by Willock et al. (1999) was adapted (Fig. 1). The model of Willock et al. (1999) suggests that the strength of decision for using climate information depends on the combination of i) farmers' attitude to use EWS information, ii) objectives to use EWS information, iii) personal factors such as personality traits, and iv) physical farm factors (Fig. 1). Attitudes represent the farmers' personal feelings towards implementation of climate information. They reflect the farmers' positive or negative perceptions about the effects of EWS adoption on improving farm productivity and maximizing on-farm income. Furthermore, they refer to farmers' evaluation of the impacts of EWS adoption. Many studies have shown that mindset is one of the key determinants of the probability that farmers use climate knowledge (e.g., Sharifzadeh et al., 2012; Mehta et al., 2013). Objectives to use climate information reflect the farmers' dominant values, including economic values (e.g., making maximum profit), social values (e.g., continuing farming traditions and optimizing interpersonal relationship), expressive values (e.g., pride of farmland ownership), and intrinsic values (e.g., enjoying work and independence) (Gasson, 1973). Personality traits show how farmers' personality differences might influence their decisions about using EWS information. It represents the farmers' motivation to comply with the information provided by early warning providers and agencies. Many studies have suggested that the personality of landholders has a major influence on their decision making (e.g., Byrne et al., 2015; Hirsh et al., 2008).

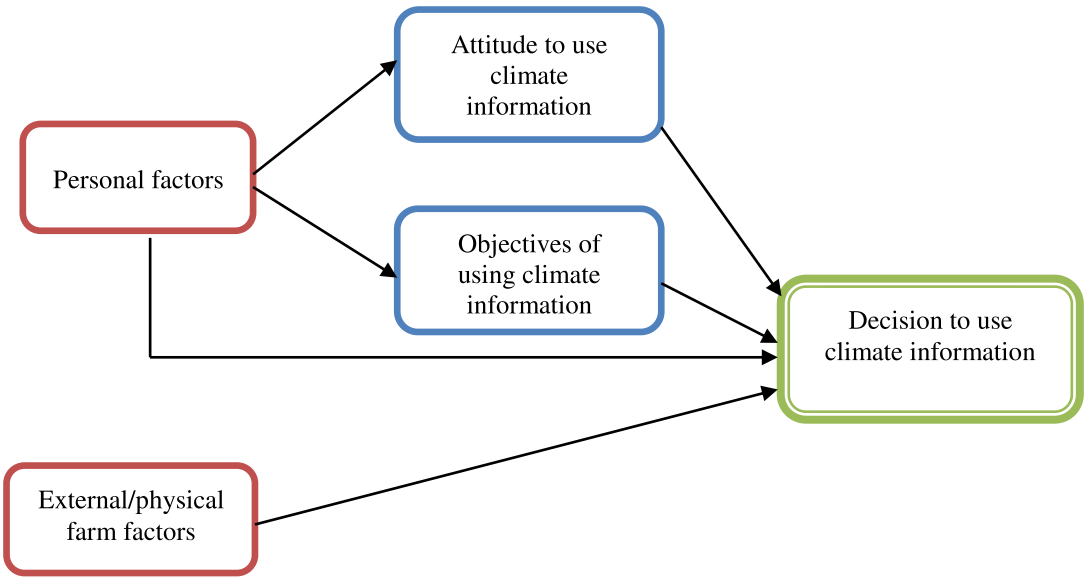

Fig. 1. Determinants of farmers' decisions on using drought EWS information (adapted from Willock et al., 1999).

3. Research Method

3.1. Study area

This research was carried out in the Township of Kermanshah, Iran. Kermanshah is located in Western Iran (Fig. 2). With a population of 946,651 people and an area of 93,389 km2, the city is known as one of the metropolises centers in the west of Iran with a temperate mountainous climate (Sharafi et al., 2020). The city is located in the central part of Kermanshah with 47 degrees and 4 minutes east and 19 degrees and 34 minutes north and has an area of 24,500 km2 and an altitude of 1200 meters from the sea level (Aliyari et al., 2018). Climatic and ecological position of Kermanshah province according to the average annual rainfall and relative humidity is such that the slopes of the mountains and plains are generally covered with forests and pastures and in some places are irrigated and rainfed fields. The most important water resources of Kermanshah are Qarahsoo river, Abshouran river, Chambshir river, Taq Bostan lake, Khezr Elias mirage, and Niloufar mirage (Sharafi et al., 2020).

However, Kermanshah Township has experienced several droughts for the past 30 years; thus, it has become a recurrent incident (Sharafi et al., 2020). Due to the importance of the agricultural sector in this province and the occurrence of recent droughts, farmers' decisions to use early warning systems in this city are important.

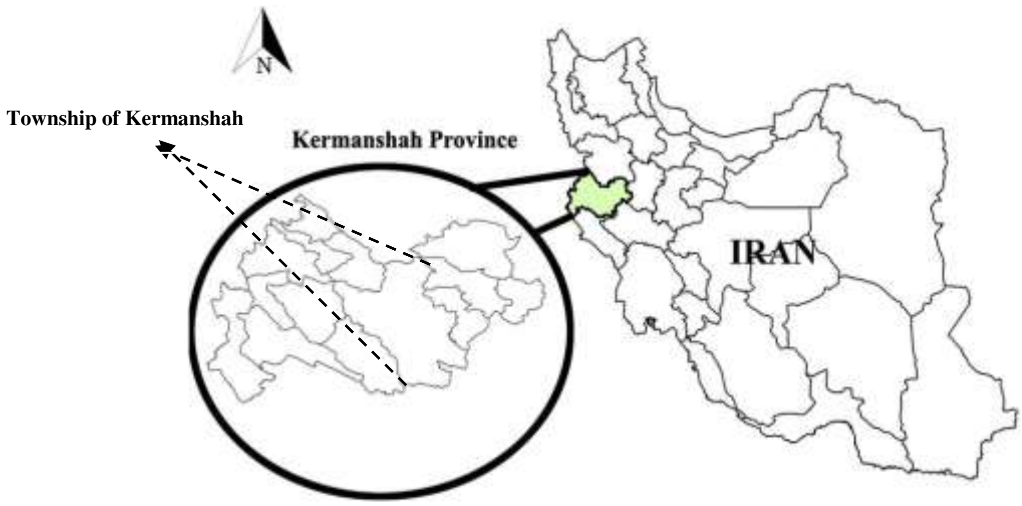

Fig. 2. Map of the study area.

3.2. Sampling and survey instrument

This cross-sectional study used a quantitative method and a descriptive-correlational research design which can be described based on different aspects. In terms of purpose, it is a type of quantitative applied to descriptive future research (Sajjad Kabir, 2016). The sampling method was multi-stage cluster random sampling method with proportional assignments. The statistical population comprised of wheat farmers in Kermanshah Township (N= 31,130). The sample size table proposed by Bartlett was used to determine the sample size (Bartlett et al., 2001). Finally, using multi-stage cluster random sampling, 370 farmers were selected out of whom the majority hold elementary education. A researcher-made questionnaire was used to collect quantitative data. After several revisions, the final version of the questionnaire was developed. The questionnaire included several Likert spectrum questions (from "completely disagree" to "completely agree"), which assessed the following variables: personality factors (13 questions), external or physical farming factors (7 questions), farmers' attitude towards using climate information (12 questions), farmers' objectives for using climate information (12 questions), and decision to use climate information (10 questions). The validity and reliability of the research instrument were respectively tested using a panel of experts and Cronbach's alpha coefficient (Annex 1). Overall, 293 questionnaires were completed showing a high response rate (RR = 79.2%).

3.3. Analysis of decision-making model

The data were analyzed using both descriptive and inferential statistics. In the descriptive part, the tables for mean and standard deviation were used. In the inferential part, structural equation modeling using SmartPLS 3 software was used to determine factors influencing farmers' decision to use climate information (EWS). PLS-SEM should be used when: 1) the aim is to forecast key constructs or define key constructs and 2) the conceptual model is complicated (Hair et al., 2017 Shiri quoted). In other words, it is a tool that enables researchers to estimate very complex models with several variables of constructs and indicators, particularly when estimation is the study target (Sarstedt et al., 2017). The multivariate analysis focused on Partial Least Squares (PLS) and SmartPLS 3 software was implemented, given that the goals of this study included predicting the decision to use climate knowledge among farmers in Iran and expanding an established structural theory besides the fact that the structural model is complex. Goodness of fit indices for measures of reliability and validity are Composite Reliability (CR) and Average Variance Extracted (AVE). For the composite reliability, a value of CR=0.70 or higher is recommended. AVE is estimated to be over or near the required level of 0.50 for all buildings. As seen in Table A1 (Appendix 1), all the constructs had composite reliabilities that surpassed 0.70. The findings also show the AVE value to be over or below the required level of 0.50 for all constructs (Sarstedt et al., 2017). This suggested strong indices for the structures used in this analysis.

4. Results

4.1. Farmer personality traits

Results of farmers' personality traits show that "perseverance in doing works" (M= 4.13), "committed and accountable to works" (M= 4.11), and "goal in life" (M= 4.01) were among the top three most prevalent characteristics of farmers. Overall, farmers in this study scored somewhat high (3.85) in personal characteristics (Table 1).

Table 1

Farmers' personality traits

Personality traits	Mean	Standard deviation	Rank
Perseverance in doing things	4.13	0.86	1
Committed and accountable	4.11	0.87	2
Goal in life	4.01	0.88	3
Independence in work and life	4	0.93	4
Self-confident	3.94	0.88	5
Self-motivated	3.94	0.95	6

Spirit of cooperation with others	3.93	0.93	7
Ability to make quick decisions	3.88	0.90	8
Prospect of doing things	3.86	0.91	9
Optimistic	3.71	0.96	10
Communication skills	3.69	0.98	11
Innovation and creativity in doing things	3.49	1.10	12
Risk taking propensity	3.32	1.19	13

Scales: (1 = Very Low) to (5 = Very High)

Total mean: 3.85 Total standard deviation: 0.23

4.2. Farmers' attitude towards using climate information

The results show that in general, farmers with a total mean of 3.91 have a positive attitude toward receiving climatic information. For example, the following items were selected by the majority of farmers: "receiving climatic information will lead to more success in agriculture" (M= 4.47), "receiving climatic information leads to better planning for cultivation" (M= 4.44), and "before sowing, we should collect information about drought" (M= 4.24) (Table 2).

Table 2

Farmers' attitude towards using climate information

Items	Mean	Standard deviation	Rank
Receiving climatic information will lead to more success in agriculture.	4.47	0.65	1
Receiving climatic information leads to better planning for cultivation.	4.44	0.68	2
Before sowing, we should collect information about drought.	4.24	0.77	3
Receiving climatic information leads to more hope for the future of agriculture.	4.22	0.83	4
Climatic information helps me determine the right planting date.	4.20	0.76	5
Receiving climatic information leads to a timely harvest.	4.20	0.85	6
Receiving climatic information makes me aware of new agricultural information.	4.15	0.86	7
Receiving climatic information helps me plan correct irrigation timing.	4.08	0.87	8

The government policy is to provide farmers with more information and warnings about droughts through various organizations.	4.06	0.96	9
Personal experience is better than using climate information.	3.31	1.16	10
Receiving climatic information is not important in selecting crop type and variety.	2.79	1.23	11
Receiving climatic information has nothing to do with increased income and reduced expenses.	2.72	1.33	12

Scales: (1 = Strongly Disagree) to (5 = Strongly Agree)

Total mean: 3.91 Total standard deviation: 0.58

4.3. Farmers' objectives towards using climate information

Farmers' objectives in using climate information are presented in Table 3. Based on the results, farmers' motivation to use climatic information can be summarized as economic, social, expressive, and intrinsic values. The mean values of the above values are relatively high. In terms of ranking, economic, intrinsic, expressive, and social values received the mean values of 4.50, 4.24, 4.10, and 3.96, respectively.

Table 3

Farmers' objectives towards using climate information

	Items	Mean	Standard deviation	Rank	Total mean
Economic values	My goal in using climate information is to increase the product.	4.57	0.62	1	4.50
	My goal in using climate information is to increase my income.	4.56	0.60	2	
	My goal in using climate information is to develop my farming.	4.45	0.75	3	
	My goal in using climate information is to reduce my farm risk.	4.42	0.68	4	
Social values	My goal in using climate information is to continue our traditional farming.	4.24	0.89	1	3.96

	My goal in using climate information is to gain up-to-date information.	3.84	1.11	2	
	I use climate information because other farmers use them.	3.79	1.16	3	
Expressive values	I feel overwhelmed by applying scientific information.	4.34	0.81	1	4.10
	My goal in using climate information is to be able to compete with other farmers.	3.87	1.17	2	
Intrinsic values	My goal in using climate information is to be able to stand on my own.	4.38	0.81	1	4.24
	My goal in using climate information is to stay and continue farming.	4.26	0.89	2	
	I enjoy using the advice of experts.	4.09	0.91	3	

Scales: (1 = Strongly Disagree) to (5 = Strongly Agree)

4.4. External/physical farm factors

External and physical farming factors are shown in Table 4. The average yearly income is 9425 USD (Min: 270 and Max: 35487 USD) with nearly 9.5 hectares of land holding (Min: 1 and Max: 25). Moreover, only a few land holdings were close to water resources (3 land holdings). The average experience of farmers in agricultural activities (nearly 29 years) reflects the relatively high experience of farmers. Furthermore, on average, 3 people work on each farm, and farmers own 4 agricultural machines.

Table 4

External and physical farming variables

Items	Mean	Standard deviation
Income	9425 $	28.78
Land size	9.28 Ha.	4.92
Number of land holdings	5.56	4.05
Distance from road	3.41 Km.	3.93
Number of land holdings near water resources	1.06	1.40
Number of labor force	3.10	2.74

Farmer' experience	28.50 Years	15.02
Number of agricultural machines	4.33	2.43

4.5. Decision to use climate information

The findings revealed that farmers' decision to use climate information is mainly influenced by statements such as "If I receive climate information from valid resources, I will certainly use them" (4.57), "If climatic information increases my income, I will certainly apply them" (4.43), and "If climate information is provided in simple language, I will certainly use them" (4.24), which were ranked first to third. The total mean of items was 3.45, indicating that farmers had a moderate tendency to use climate information (Table 5).

Table 5

Farmers' decision to use climate information

Items	Mean	Standard deviation	Rank
If I receive climate information from a valid source, I will certainly use it.	4.57	0.59	1
If climatic information increases my income, I will certainly use it.	4.43	0.72	2
If climate information is provided in simple language, I will certainly use it.	4.24	0.81	3
I will use climate information if drought continues in the region.	3.72	1.24	4
In most cases, the climate information provided by public organizations is not accurate and thus I prefer not to use it.	3.71	1.18	5
Without climatic information, I will not engage in any agricultural activities during drought.	3.62	1.36	6
I only use climate information provided by other sources if I am confident that my knowledge is insufficient.	3.61	1.43	7
I use climate information when I am sure that drought is causing severe damage to my farm and my family.	2.46	1.21	8
If I have easy access to climate information, I will use it.	2.19	1.10	9
If climate information helps me cope with drought well, I will use it.	1.95	0.98	10

Scales: (1 = Strongly Disagree) to (5 = Strongly Agree)

Total mean: 3.45 Total standard deviation: 0.89

4.6. Factors influencing farmers' decision to use climate information

Fig. 3 shows the results of Spearman's correlation coefficient. These results examine the relationship between the independent variables of the study (personality traits, attitudes toward the use of climate information, objectives of using climate information, and external or physical agricultural factors) and the dependent variable (farmers' decision to use climate information) (Table 6).

Table 6

Spearman correlation matrix

Variables	1	2	3	4	5
Personal factor	1	-	-	-	-
Attitude to use of climate information	0.145*	1	-	-	-
Objectives of using climate information	0.345**	0.394**	1	-	-
External/physical farming factors	0.082	0.026	0.014	1	-
Decision/behavior to use climate information	0.165**	0.296**	0.335**	-0.207**	1

**p<0.01 * p< 0.05

As shown in Table 6, there is a positive and significant relationship between personality traits, external/physical farming factors, attitude towards using climate information, and objectives towards using climate information. Farmers' decision to use climate information has a positive and significant relationship with personal factor, attitude to use climate information, and objectives of using climate information, but it has a negative and significant relationship with external/physical farming factors. The relational model integrates the proposed interactions in study process structures (see Fig. 1 and Annex 2).

As shown in structural equation model, attitude towards using climate information, objectives towards using climate information, and external/physical farming factors had a direct effect on farmers' decision to use climate information. However, personality trial had an indirect effect on farmers' decision to use climate information through farmers' attitudes towards using climate information and their objective in using climate information. Overall, the model explained a 23% variance in farmers' decision to use climate information (Fig. 3).

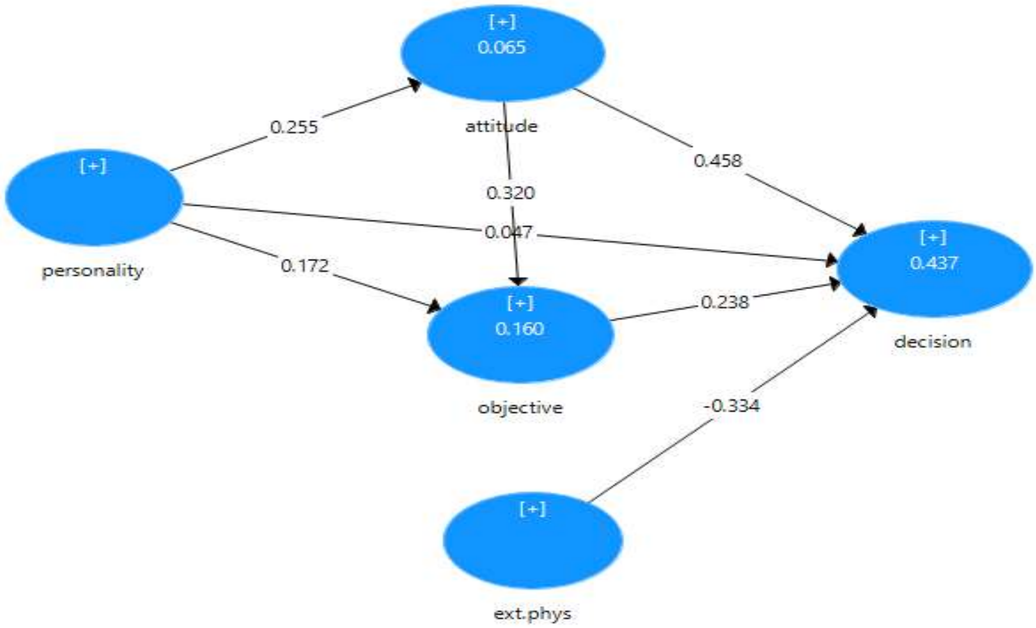

Fig. 3. Path model with Standardized Factor Loadings.

Given that "personality" and ext.phys" are among the external factors, other factors have no impact on them and this is the reason why no coefficients have been determined for them.

5. Discussion

5.1. Personality trial

Overall, results revealed that farmers' personality traits had an indirect relationship with farmers' decision to use climate information. This is in line with the results of Willock et al. (1999), showing that personality traits influence farmers' behavior and decision-making process. This implies that farmers' personality characteristics such as perseverance, commitment, and being responsible play a major role in farmers' motivation to use climate information on one hand, and adapting to drought conditions on the other hand.

5.2. Attitude towards using climate information

Attitude towards climate information had a direct and positive relationship with farmers' decision to use climate information. Ajzen (1991), Taylor and Todd (1995), and Davis et al. (1989) showed that attitude is a strong predictor of behavior in several socio-psychological studies. This clearly indicates that farmers believe that receiving climatic information will lead to more success in agricultural production. For example, accurate planning and being there at the right time and right place are the benefits of using climatic information as perceived by farmers. Some case studies show that attitude is a concept that changes over time and location (Sayuti et al., 2004; McCrea et al., 2005; Sharifzadeh et al., 2012). Among others, Iran is constantly exposed to natural disasters. In this regard, drought is one of the most important natural disasters that has led to huge damage to water resources and farmers' livelihoods. This creeping disaster has affected most of Iranian farmers. Given that in the study area, drought is a chronic event, farmers are somewhat adapted to and have developed a hands-on attitude towards drought. This indicates that farmers are willing to take proactive measures when coping with this climate incident (Sharafi, 2017; Sharafi et al., 2020).

This incident has caused a higher price for agricultural water (Grossi, 2017). Yet, it seems that increasing the price of agricultural water will never be effective in reducing water consumption in the study area unless the price adjustment is accompanied by the development of the necessary infrastructure and government support. Drought has increased economic problems among rural communities, which are often poor and dependent on agriculture for a living. Furthermore, drought makes rural farmers vulnerable to the high costs of damage, pollution, crop performance problems, maintenance, and drought (Tulare County, 2017). In fact, as in other businesses, drought EWSs assume that farmers are interested in maximizing production and profit (Willock et al., 1999; Güth and Kliemt, 2004). While farmers' decisions are aimed at profit maximization, the complex set of socio-psychological, natural, physical, and structural factors have significant effects on their decision-making process as well (Feng et al., 2017; Keshavarz and Karami, 2014). Therefore, farmers prefer to use adaptive behaviors to cope with climate change, especially drought, despite government support, in order to achieve better yields, higher incomes, and reduced costs of damage.

5.3. Objectives of using climate information

Farmers' economic, social, expressive, and intrinsic values are also affected by their use of early warning systems. Income and profit-making were emphasized by many farmers in the study area. For example, they stated that their goal in agricultural business is mainly profit-making and access to more resources. This was also highlighted by Willock et al. (1999) indicating that the majority of farmers' behavior is mainly objective-based behavior. However, other researchers stated that profit is not the only factor that influences farmers' decision making. For example, Keshavarz and Karami (2014) and Karali et al. (2011) believe that other factors may also influence farmers' decision making.

Small scale farming in Iran has shown that economic incentives are a major driving force for farmers to stay in business even during harsh times such as drought. Gilmor (1986) claimed that life-style priorities could be mirrored in the farm business system, as certain commercial farmers seem to be a little more concerned with economic interests, whereas small-scale farmers seem to be more concerned with the autonomous lifestyle offered by farming.

5.4. External/physical farming factors

The results of this study indicate that farming external and physical factors influenced farmers' decision to use climatic information. Studies by Willock et al. (1999) and Ali and Kumar (2011) are in line with our results. In the present study, external variables such as income, land size, number of land holdings, distance from the road, distance from water resources, number of labor force members, farmers' experience, and number of agricultural machines were investigated. Results revealed that external and field factors were negatively significant in the study. This means that lower incomes, more land holdings, long distance from the road, less number of agricultural machines, and long distance from water resources affected the farmers' decision to use more information. Simply, farmers who were in poor conditions in terms of these indicators were more interested in using climate information.

In fact, weak economic and physical capital influences farmers' decision to use climate information. Interestingly, this finding is inconsistent with that of innovation scholars in that they believe that farmers with higher socio-economic characteristics are more likely to adopt innovations (Rehman et al., 2013). This study also showed that farmers' attitude towards seeking climate information was positive. Perhaps this positive attitude towards climate information by farmers is another reason why small-scale farmers were more intended to use climate information. Moreover, McCrea et al. (2005) showed that farmers' attitude towards the usefulness of weather predictions is a key factor in using information.

According to Table 4, the lowest score of intrinsic values is the experts' advice. This could be due to farmers' lack of confidence in specialists, especially public sector experts, which could be due to the following factors:

1) failure to meet farmers' expectations from experts; 2) ineffectiveness and incompatibility of technical recommendations given by experts with farmers' experiences and existing climatic, soil, and land conditions, which ultimately lead to reduced yields and reduced product quality; 3) agricultural staff's lack of information and not enough contacts and communications between the farmers and experts; 4) lack of belief in the effectiveness of the application of science in crop production and expert's lack of experience and skills; and 5) lack of timely presence in the field and farms (Rezaei-Moghaddam and Fatemi, 2020; Ansari et al., 2019).

6. Conclusions

In accordance with the findings of the present study, we concluded that farmers' decision to use climate information is affected by their personality traits, farm factors, and their attitude, as well as their objectives towards climate information. In the context of climate change education, these conclusions help to shed light on farming vocational behavior. Farmers are engaged in a range of pertinent behaviors such as profit maximization, diversification, conservation, adoption of new technologies, and off-farm work. However, knowledge collection is one specific activity that connects both risk and creativity. The result of this study provides a deeper understanding of the role of socio-economic and psychological factors in determining farmers' decision to use climate information. In contrast to economic behavioral models which assume that all farmers are benefit maximizers, the model presented in this study adds to the current literature that the climate information seeking behavior of farmers is not driven only by the maximization of profit. Farmers' actions are more the product of dynamic mechanisms that are affected by a variety of socio-economic and psychological factors. The result of this study has some limitations. We recognized that our focus on wheat farmers serves as a limitation for generalizability. Furthermore, as this study was conducted in only one township, the results cannot be generalized beyond wheat farmers and Kermanshah Township. This study recommends, however, that additional research be conducted with other farmers in general and rain-fed farmers in particular to develop a firmer grasp of climate information seeking behavior with this type of population. Moreover, further studies are needed to examine other socio-psychological models to assess the predictors of farmers' information seeking behavior. As another recommendation for future research direction, future studies should distinguish between rain-fed farmers and irrigated farmers to have a more accurate analysis of the farmers' information about climate change and adaptation strategies.

Finally, this study used a quantitative methodology to assess farmers' decision to use DEWS information using a socio-psychological model; however, the socio-psychological nature of farmers' decisions may require a qualitative measure. Therefore, a mix method design should be considered in future studies.

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Appendix:

Annex 1

Measures of reliability and validity

Variables	Cronbach's alpha coefficients	Composite Reliability (CR)	Average Variance Extracted (AVE)
Decision/behavior to use climate information (EW)	1.00	1.00	1.00
Personality factors	1.00	1.00	1.00
Farmers' attitude to use of climate information	1.00	1.00	1.00
Objectives of using climate information	0.924	0.946	0.815
External/ physical factors	0.801	0.883	0.723

Annex 2

Direct, indirect, and total effects of predictive variables on decision to use climate information

Dependent variable	Predictive variables	Direct effect	Indirect effect	Total effect
Decision to use climate information (R^2=0.44)	Personal factors	0.05	0.18**	0.22**
	Attitude towards using climate information	0.46**	0.08**	0.53**
	Objectives towards using climate information	0.24**	-	0.24**
	External/physical farming factors	-0.33**	-	-0.33**

**p<0.01 * p< 0.05