Determining the factors affecting the climate-friendly innovative technology usage levels of sheep farms

Cennet Oğuz*, Aykut Örs**, Aysun Yener Öğür*, Yusuf Çelik*

DOI: 10.30682/nm2401d
JEL codes: Q16, Q54, Q55

Abstract

Climate-friendly smart agriculture (CSA) describes a set of interventions aimed at sustainably increasing productivity and reducing greenhouse gas emissions from agriculture. The aim of this study was to calculate the climate-friendly innovative technology usage indexes of sheep farms in Konya and to determine the affecting factors. Neyman allocation sampling method was used to determine the 151 sheep farms. As a result of the study, it has been determined that 5.96% of the enterprises are low level, 87.42% medium level and 6.62% high level climate-friendly innovative technology users. The general average of climate-friendly innovative technology usage index (CFITU) of the sheep farms is 52.88% and they are medium level climate-friendly innovative technology users. Ordinal logistic regression analysis was conducted to determine the factors influencing the level of CFITU in sheep farms. The results showed that the dependent variable was explained by 7 independent variables with a percentage of 32.5%. Providing education and financial support to farmers in the region regarding climate change perception and technology usage will enhance the level of CFITU in enterprises.

Keywords: *Sheep farming, Climate friendly smart agriculture, Innovative Technology Usage Index, Konya.*

1. Introduction

Regardless of the state of development, the agricultural sector is indispensable for countries. Although many technological and biological innovations have been developed in agriculture, agriculture is considered to be one of the most sensitive sectors to the negative impact of climate change. It is clear that climate change has a direct impact on agricultural production. Climate change can significantly reduce agricultural productivity, which can affect rural per capita income and poverty levels (Dellal *et al.*, 2011; Li *et al.*, 2013; Masud *et al.*, 2017; Uitto *et al.*, 2017; Azadi *et al.*, 2019; Foguesatto *et al.*, 2019; Ramborun *et al.*, 2020).

The impact of climate change on animal production varies from year to year and increases (Descheemaeker *et al.*, 2018). Changes in death rate, feed consumption rate, live weight gain, milk production and pregnancy rate are expected with the deterioration of the balance between heat production and use of heat in animals with temperature increase (Polat and Dellal, 2016).

* Selçuk University, Faculty of Agriculture Department of Agricultural Economics, Konya, Turkey.
** Agriculture and Rural Development Support Institution, Konya Provincial Coordination Unit, Turkey.
Corresponding author: aykutors@gmail.com

According to Food and Agriculture Organization (FAO, 2015), the global demand for animal products is projected to double by 2050 due to the rising standard of living and population pressure. Because, in parallel with the increase in population and income in the world, the demands for animal food are increasing (Speedy, 2003; Steinfeld, 2003; Godfray and Garnett, 2014; Khan and Sameen, 2018; Tarawali *et al.*, 2018; Lemaire *et al.*, 2019). Therefore, climate change is emerging as one of the biggest threats to the animal food supply (Reilly *et al.*, 1996; Nardone *et al.*, 2010; Gauly *et al.*, 2013).

Agriculture is an area of activity that causes climate change as much as it is affected by climate change. Industrial agriculture practiced worldwide disrupts fundamental ecological processes. This, triggers climate change and causs loss of biosphere integrity, destructive soil system changes, and pollution of the oceans with phosphorus and nitrogen fertilizers (Tilman *et al.*, 2001; West *et al.*, 2014; Liebman and Schulte, 2015; Steffen *et al.*, 2015; DeLonge *et al.*, 2016).

Livestock contributes to 14.5% of greenhouse gas emissions responsible for climate change (Barnes and Toma, 2012; Gerber *et al.*, 2013; Ardakani *et al.*, 2019). In the production of greenhouse gases, sheep and goats have a low rate (Görgülü *et al.*, 2009; Rojas-Downing *et al.*, 2017; Koluman *et al.*, 2017; Koluman and Silanikove, 2018). Ovine breeding has a very important place especially in arid or semi-arid regions (Sejian *et al.*, 2017). It is stated that the methane gas emission in Turkey is approximately 1 million tons and 76% of the total emission originates from cattle, 20.49% from sheep breeding and 2.98% from goat breeding (Görgülü *et al.*, 2009).

Reducing the negative effects of climate change will only be possible by adapting to these effects. The level of knowledge, recognition and perception of climate change by producers is also important in order to know what the effects of climate change are and to reduce these effects (Masud *et al.*, 2017; Somda *et al.*, 2017; Tripathi and Mishra, 2017; Chedid *et al.*, 2018; Wetende *et al.*, 2018). Because, to the extent that the producer has knowledge about climate change and its effects, it will endeavor to reduce the negative effects. It is stated that farmers define climate change knowledge in terms of how it affects them in the context of history, culture and local experiences (Velempini *et al.*, 2018). They develop place-based coping strategies and take part in adaptation studies to alleviate and maintain their livelihoods (Ashraf and Routray, 2013; Roco-Fuentes *et al.*, 2015; Hyland *et al.*, 2016; Daly-Hassen *et al.*, 2019; Ata *et al.*, 2021).

Climate-friendly smart agriculture (CSA) describes a set of interventions aimed at increasing productivity sustainably while helping farmers adapt their agricultural systems to the predicted effects of climate change and manage climate risk more effectively (Mutenje *et al.*, 2019). CSA is a new concept first proposed by the FAO at the Hague Conference on Agriculture, Food Security and Climate Change in 2010 to address the need for a strategy for managing agriculture and food systems under climate change (Saj *et al.*, 2017). Mutenje *et al.* (2019) used a mixed methodology approach (stochastic dominance) combined with cost-benefit analysis to determine the probability of investment in various CSA technology combinations in their study. As a result of their study, they found that CSA practices are economically viable and should be implemented. Azumah *et al.* (2020) also show that the adoption of CSA is profitable because the average benefits outweigh the average costs.

In their study, Long *et al.* (2016) discussed the barriers to the adoption and diffusion of CSA in Europe. They selected the countries of the Netherlands, France, Switzerland, and Italy as their study areas. The research concluded that there were barriers on both the demand and supply sides. It showed that traditional supply-focused innovation policies alone are unlikely to lead to a sufficient level of technological innovation adoption in CSA practices. Khatri-Chhetri *et al.* (2017b), on the other hand, evaluated CSA implementation options in Nepal in their study. They assessed CSA options that could be applied in different parts of the country and provided recommendations in four areas for the widespread adoption of these technologies. These headings are as follows: Knowledge-transfer approach, Market-based approach, Public-Private Partnership Approach, Community-based Climate-Smart Villages (CSVs) approach. In the study of Everest (2021), factors affecting the adaptation of CSA technologies among farmers in the northwestern Marmara region of Turkey were examined. The study identified factors influencing farmer decisions in this regard as education, participation in agricultural meetings, land size, and agricultural income. In the study by Biró *et al.* (2021), they worked on solutions offered by CSA technologies with farmers and farmer organizations in Hungary. They identified 27 CSA technologies that could be used in Hungary. They recommended integrating CSA goals into agricultural policies with regional characteristics in mind and including CSA technologies in the curriculum of digital agriculture academies.

The use of climate-friendly smart innovative technology by sheep farms is important for the management of agricultural enterprises. Agricultural enterprises have a privileged structure in terms of management. Especially in small-scale businesses, the business and the life of the business manager and his family are spatially integrated. In order for the resources to be used effectively in agricultural enterprises, the characteristics of the resources allocated to production should be known and they should be allocated to production in accordance with their characteristics. In addition, as a result of the activities carried out in the enterprise, income and expense status and profitability analyzes of the enterprise should be made. The importance of *making decisions based on information* is increasing day by day in order for businesses and countries to use their scarce resources effectively and consciously and to create a competitive advantage. That is why the utilization of emerging smart technologies in agricultural production is important (Oğuz and Çelik, 2020).

The aim of the research is to calculate innovative technology usage indexes of sheep farms based on climate-friendly smart technologies and to determine the affecting factors. Within the scope of the study, climate-friendly smart technologies are grouped under six headings and are given. These factors are water, energy, food, carbon, weather, and information-friendly smart technologies. Innovative climate-friendly smart technology usage indices have been calculated by scoring the technologies under the headings. In the research area, farmers who use climate-friendly innovative technology at a high level are defined as a "climate-friendly smart farmers" and are detailed in the research findings and results section below.

2. Materials and method

2.1. *Material*

2.1.1. *Study area*

As the research region, Konya has been chosen as the study area because it is one of the driest provinces in Turkey (Erkan *et al.*, 2009; Cebeci *et al.*, 2019; MGM, 2021), as well as having an important production potential in terms of both plant production and animal production. Konya meets 5% of Turkey's agricultural production

Figure 1 - Turkey sheep population density map.

value and constitutes 6.20% of Turkey in terms of the number of sheep (2,770,980). In the study, the records of the Konya Province Sheep and Goat Breeders' Association were used to determine the population. Districts with the highest number of sheep in the province are Karapınar, Ereğli, Cihanbeyli, Meram, Karatay and Çumra. These districts constituted the main frame of the research, as they constitute 54.92% of the total number of sheep (1,521,822) in Konya. In the selection of the districts, the presence of sheep, drought and precipitation, the presence of pasture land, and the representation of the current production pattern for the ecology of the region were taken into account.

2.1.2. *Data collection*

The main material of the research is the primary data collected from the sheep farms of Konya through a questionnaire. In addition to these data, the publications and websites of the relevant public institutions and organizations in the research region, as well as previous research findings and published statistical data on this subject were also used. In this study, $1 = 14.12 Turkish Liras calculated that was the average exchange rate of the dates of the field study was done.

2.2. *Method*

The methodological framework of the research has been schematized in Figure 2. The methods used at each stage of the research are comprehensively explained below.

2.2.1. *Sampling methods*

Neyman's "stratified random sampling method" was used to determine the sample size due to

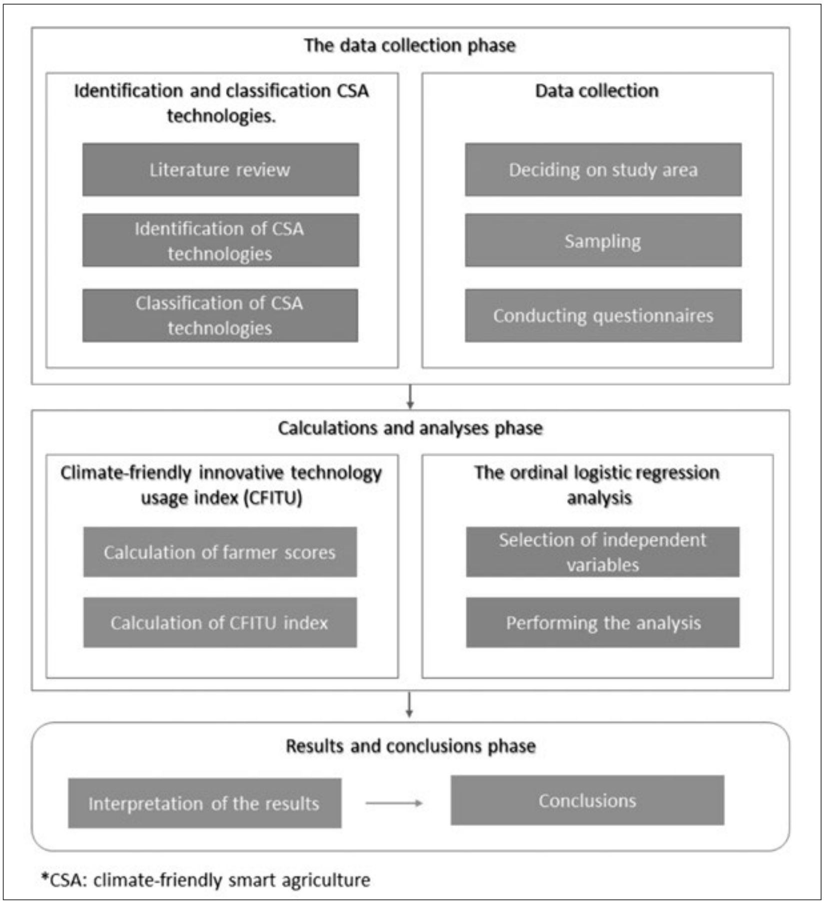


Figure 2 - The methodological framework of the research.

the coefficient of variation of the population was greater than 75%.

$$n = \frac{[\sum(N_h S_h)]^2}{N^2 D^2 + \sum[N_h (S_h)^2]}$$

$$D^2 = d / z$$

In formula; n = sample volume, N = total unit number belonging to the sampling frame, D = d / t, d = derivation from the average, t = standard normal distribution value (Yamane, 1967).

The size of the enterprise was examined by arranging various layers, and it was deemed appropriate to form 3 layers by taking into account the frequency distributions. The boundaries of these strata were determined as holdings with 1-100 head, 101-250 head, 251 head and more sheep. In determining the number of samples drawn from the main population, 5% error and 95% confidence limits were used and determined as 151. The distribution of sheep farms according to layer widths was made with the following formula (Yamane, 1967).

$$n_i = \frac{(N_h S_h)n}{\sum N_h S_h}$$

As a result, the distribution of the farms in the research area according to the size of the farms (number of animals) and the number of sheep farms to be surveyed are given in Table 1.

2.2.2. *Constructing a climate-friendly innovative technology usage index*

Since the diffusion and adoption of innovations requires a certain process, the stages that manufacturers go through during this process are important. These stages are; acquiring knowledge, persuasion, decision making, implementation and adoption. In the first stage, the manufacturer learns about the innovation and its functions. At the stage of persuasion, it evaluates the advantages and disadvantages of innovation for itself and shapes its attitude towards innovation. At the decision stage, it obtains additional information about the innovation and makes a decision to accept or reject the innovation. At this stage, the producer is particularly influenced by his peers around him. The fourth stage, implementation, takes place when the decision to adapt to innovation is made. In the final stage, the manufacturer validates and reinforces the compliance decision (Rogers, 1995). The time spent in each stage varies according to the innovation, the way it is presented and the characteristics of the person (Özçatalbaş and Gürgen, 1998). According to the speed of diffusion of innovations, manufacturers are classified as innovators (2.5%), early adopters (13.5%), early majority (34%), late majority (34%) and the laggards (16%) (Rogers, 1995). There are many factors that affect people's early or late adoption of innovations. These factors are socio-economic, personal and communication techniques (Özçatalbaş and Gürgen, 1998).

Khatri-Chhetri *et al.* (2017a) gathered climate-friendly smart technologies under six headings in their study titled "Farmers' prioritization of climate-smart agriculture (CSA) technologies". These topics are water, energy, nutrients, carbon, weather and information-friendly smart technologies (Table 2). Farmers were asked to provide one of three responses, "I don't know", "I know", or "I implement", regarding the following technologies and applications in the research field.

Scoring was made according to the farmers' knowledge and application of each of the 25 technologies and applications in the above list. If he knows the technology or application, 2 points are given, if he applies it, 3 points, if he does not know and does not apply it, 1 point is given. The maximum score a farmer can achieve if they know and implement all the technologies is a total of 75 points. After the scoring was completed for each

Table 1 - Distribution of sheep farm numbers by farm size groups.

Farm Size Groups (number of sheep (Head))	*Nh*	*Sh*	*Ort*	*CV*	*Nh*Sh*	*Nh*(Sh)²*	*Sample Volume (n)*
1. Group (1-100)	1636	22.27	64	33	36,429.03	811,170	22
2. Group (101-250)	2103	62.86	163	31	132,189.64	8,309,130	79
3. Group (251 - +)	816	136.16	384	33	83,191.52	11,327,052	50
Total	4,555	221.28	172.72	86.30	251,810.19	20,447,353	151

Table 2 - Climate-friendly smart agriculture (CSA) technologies.

Water Friendly S.A.	*Energy Friendly S.A.*	*Nutrient Friendly S.A.*
Rainwater Harvesting	Zero Tillage/Minimum Tillage	Site Specific Integrated Nutrient Management
Drip Irrigation	Solar Energy Solutions for Agriculture	Green Manuring
Laser Land Levelling	Biofuel Use	Leaf Color Chart
Furrow Irrigated Bed Planting		Intercropping with Legumes
Drainage Management		
Cover Crops Method		
Carbon Friendly S.A.	*Weather Friendly S.A.*	*Knowledge Friendly S.A.*
Agro Forestry	Climate Smart Housing for Livestock	Contingent Crop Planning
Concentrate Feeding for Livestock	Weather Based Crop Agro-advisory	Improved Crop Varieties
Fodder Management	Crop Insurance	Seed and Fodder Banks
Integrated Pest Management		Farmer to Farmer Learning
		Farmer Organizations for Adaptation Technologies

**S.A.: Smart Applications.*

business, the climate-friendly innovative technology usage indexes (CFITU) were calculated with the score they received. By using the index, all businesses are divided into three subgroups as “those using high-level climate-friendly innovative technology”, “middle-level climate-friendly innovative technology users” and “low-level climate-friendly innovative technology users” (Oğuz and Yener, 2017). Climate-friendly innovative technology usage indexes (CFITU) were calculated using the formula below.

$$index_{CFITU} = \frac{\text{The total score received by the enterprise}}{\text{Maximum score the enterprise can get}} \text{ x } 100$$

$index_{CFITU}$: Climate-friendly innovative technology usage index (CFITU)

According to CFITU, index scores between 1% and 35% are classified as “low level climate friendly innovative technology users”; index scores between 36% and 70% are classified as “moderate climate friendly innovative technology users” and index scores 71% and above are classified as “enterprises using high level climate friendly innovative technology” (Oğuz and Yener, 2017; Örs and Oğuz, 2018). Within the scope of the study, those higher than 71% were called “climate friendly smart farmers”.

2.2.3. *Ordinal logistic regression analysis*

In determining the factors affecting the CFITU levels of farmers in the study, ordinal logistic regression analysis was used instead of linear regression due to the non-normal distribution of variables and the lack of homogeneity (equality) in group variance-covariance. Logistic regression analysis can be examined in three different groups based on the nature of the dependent variable: Binary Logistic Regression, Multinomial Logistic Regression, and Ordinal Logistic Regression (Akın and Şentürk, 2012). In the study, ordinal logistic regression analysis was used due to the categorical and ordinal nature of the dependent variable, CFITU level.

Ordinal logistic regression is a method used to examine the relationship between two or more ordered categories in a categorical response variable. The general representation of the Ordinal Logistic Regression model is based on the odds ratios of the categories and is as follows (McCullagh, 1980; Christensen, 2012):

$$\ln (Y_j) = \ln \left(\frac{P(Y \leq \frac{1}{X_1}, X_2, \dots, X_i)}{1 - P(Y \leq \frac{1}{X_1}, X_2, \dots, X_i)}\right) =$$

$$= \alpha_j - (\beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_i X_i)$$

The key features of the Ordinal Logistic Regression model can be listed as follows (Ding *et al.*, 2004):

- The dependent variable is a grouped and ordered categorical variable.
- It uses a cumulative function to describe the impact of the independent variables on the ordered and categorical dependent variable, eliminating the need for normality and constant variance assumptions.
- The model assumes that the relationship between the independent variables and the ordered dependent variable is independent of the specific categories. In the field of sheep farms, seven independent variables were considered to determine the factors affecting the level of climate-friendly smart innovative technology usage. These variables include education, perception of climate change, farming experience, livestock presence (in head), total farm land area, access to information, and agricultural income.

3. Results and discussions

3.1. *Climate-friendly innovative technology usage index results*

3.1.1. *Water-friendly smart innovative technology application cases*

Knowing and applying water-friendly smart applications of sheep farms are given in Table 3. It has been determined that 2.65% of the surveyed enterprises started rainwater harvesting practices, 46.36% used drip irrigation systems, 7.95% made laser land levelling, 1.32% made furrow ırrigated bed planting, 7.95% used drainage management, 0.67% applied cover crops method to protect the soil.

It has been determined that 41.06% of the enterprises do not practice rainwater harvesting, 45.03% drip irrigation, and 40.40% drainage management although they know about these methods. Some enterprises do not know these methods at all. When the unknown rates of the methods are examined; rainwater harvesting is 56.29%, laser land leveling is 64.90%, furrow ırrigated bed planting is 90.73%, cover crops management for soil protection is 82.78%, and drainage management is 51.66%.

3.1.2. *Energy-friendly smart innovative technology application cases*

The state of knowing and applying energy-friendly smart applications of the sheep farms is given in Table 4. It has been determined that 10.60% of the examined enterprises perform zero tillage/minimum tillage practices, and 1.99% use solar energy solutions for agriculture. There were no enterprises using biofuels. These rates show that the use of energy-friendly smart innovative technology applications is almost non-existent.

Considering the state of knowing the energy-friendly smart technologies of the enterprises, it is seen that 23.84% of them know zero tillage/minimum tillage, while 65.56% of them do not. These rates are 44.37% to 53.64% for solar energy solutions and 31.13% to 68.87% for biofuels.

3.1.3. *Nutrient-friendly smart innovative technology application cases*

The state of knowing and applying nutrient-friendly smart applications of sheep farms are given in Table 5. Implementation and aware-

Table 3 - Water-friendly smart innovative technology application cases of sheep farms.

Factors	*3**	*%*	*2**	*%*	*1**	*%*	*Total*	*%*
Rainwater Harvesting	4	2.65	62	41.06	85	56.29	151.00	100.00
Drip Irrigation	70	46.36	68	45.03	13	8.61	151.00	100.00
Laser Land Levelling	12	7.95	41	27.15	98	64.90	151.00	100.00
Furrow Irrigated Bed Planting	2	1.32	12	7.95	137	90.73	151.00	100.00
Drainage Management	12	7.95	61	40.40	78	51.66	151.00	100.00
Cover Crops Method	1	0.66	25	16.56	125	82.78	151.00	100.00

**1=I don't know, 2=I know, 3=I apply.*

Table 4 - Energy-friendly smart innovative technology application situations of sheep farms.

Factors	*3**	*%*	*2**	*%*	*1**	*%*	*Total*	*%*
Zero Tillage/Minimum Tillage	16	10.60	36	23.84	99	65.56	151.00	100.00
Solar Energy Solutions for Agriculture	3	1.99	67	44.37	81	53.64	151.00	100.00
Biofuel Use	0	0.00	47	31.13	104	68.87	151.00	100.00

**1=I don't know, 2=I know, 3=I apply.*

Table 5 - Food-friendly smart innovative technology application cases of sheep farms.

Factors	*3**	*%*	*2**	*%*	*1**	*%*	*Total*	*%*
Site Specific Integrated Nutrient Management	7	4.64	13	8.61	131	86.75	151.00	100.00
Green Manuring	9	5.96	42	27.81	100	66.23	151.00	100.00
Leaf Color Chart	9	5.96	8	5.30	134	88.74	151.00	100.00
Intercropping with Legumes	8	5.30	59	39.07	84	55.63	151.00	100.00

**1=I don't know, 2=I know, 3=I apply.*

ness rates in this area are very low. The application rate of site-specific integrated nutrient management is 4.64%, green manuring is 5.96%, leaf color chart is 5.96%, and intercropping with legumes is 5.30%.

When the table is examined, it is seen that 27.81% of the enterprises have knowledge about green manuring and 39.7% of them have knowledge about intercropping with legumes. The rates of those who have not heard of these methods are 66.23% and 55.63%, respectively. The other two methods are unknown at a very high rate of 85%.

3.1.4. *Carbon-friendly smart innovative technology application cases*

The state of knowing and applying carbon-friendly smart applications of enterprises are given in Table 6. We do not have a enterprises that implements the first factor, agro forestry, among the enterprises we surveyed. The rate of those who make concentrated feeding is 57.2% and those who apply fodder management is 62.25%. Only 10.60% of enterprises implement integrated pest management.

While the number of enterprises that know the agro forestry method, which includes sustainable land use management and encourages carbon sequestration, is 31.13%, while the number of those who do not is as high as 68.87%. Concentrate feding and roughage management is widely known and practiced by enterprises. While 23.18% know but do not implement integrated pest management, 66.23% of the enterprises do not know at all.

3.1.5. *Weather-friendly smart innovative technology application cases*

The state of knowing and applying the weather-friendly smart applications of the sheep farms are given in Table 7. It has been determined that climate smart housing and weather-based crop agro-advisory are implemented at a very low rate of 5.30%. The rate of those who have product insurance is 30.46%.

The number of those who know climate smart housing and weather-based crop agro-advisory is very low, with ratios 30.46% and 23.18%. However, the rate of those who know crop insurance but do not apply, is very high with 47.02%.

3.1.6. *Knowledge-friendly smart innovative technology application cases*

Knowledge-friendly smart innovative technology application situations of sheep farms are given in Table 8. When the table is examined, it is seen that contingent product planning is used at very low rates such as 7.28%, improved product varieties 6.62%, and seed and fodder banks 6.62%. While the farmer-to-farmer learning application is applied at a high rate of 59.60%, the application of farmer organizations for adaptation technologies is 21.85%.

Table 6 - Carbon-friendly smart innovative technology application cases of sheep farms.

Factors	*3**	*%*	*2**	*%*	*1**	*%*	*Total*	*%*
Agro Forestry	0	0.00	47	31.13	104	68.87	151.00	100.00
Concentrate Feeding for Livestock	87	57.62	46	30.46	18	11.92	151.00	100.00
Fodder Management	94	62.25	43	28.48	14	9.27	151.00	100.00
Integrated Pest Management	16	10.60	35	23.18	100	66.23	151.00	100.00

**1=I don't know, 2=I know, 3=I apply.*

Table 7 - Weather-friendly smart innovative technology application cases of sheep farms.

Factors	*3**	*%*	*2**	*%*	*1**	*%*	*Total*	*%*
Climate Smart Housing for Livestock	8	5.30	46	30.46	97	64.24	151.00	100.00
Weather Based Crop Agro-advisory	8	5.30	35	23.18	108	71.52	151.00	100.00
Crop Insurance	46	30.46	71	47.02	34	22.52	151.00	100.00

**1=I don't know, 2=I know, 3=I apply.*

The rate of those who do not know the first three factors is 72.85%, 61.59% and 53.64%, respectively. The rate of those who do not know the application of farmer organization for adaptation technologies is relatively lower than the first three factors and is 45.03%. It is seen that the practice of learning from farmer to farmer is common among enterprises, and the rate of those who do not know this practice is only 19.87%.

3.1.7. *Climate-friendly innovative technology usage index (CFITU)*

Climate-friendly innovative technology usage indexes (CFITU) of sheep breeding enterprises are calculated and presented in Table 9.

When the table is examined, it is seen that 9 of the enterprises surveyed in the field are low level, 132 of them are medium level and 10 of them are high level innovative technology farmers. In terms of percentages, the rates are 5.96%,

Table 8 - Knowledge-friendly smart innovative technology application cases of sheep farms.

Factors	*3**	*%*	*2**	*%*	*1**	*%*	*Total*	*%*
Contingent Crop Planning	11	7.28	30	19.87	110	72.85	151.00	100.00
Improved Crop Varieties	10	6.62	48	31.79	93	61.59	151.00	100.00
Seed and Fodder Banks	10	6.62	60	39.74	81	53.64	151.00	100.00
Farmer to Farmer Learning	90	59.60	31	20.53	30	19.87	151.00	100.00
Farmer Organizations for Adaptation Technologies	33	21.85	50	33.11	68	45.03	151.00	100.00

**1=I don't know, 2=I know, 3=I apply.*

Table 9 - Climate-friendly innovative technology usage indexes (CFITU).

Description of farmers applying climate-friendly innovative technology	*1-100*	*101-250*	*251-+*	*Total*
Low-level climate-friendly innovative technology users (1-35%)	2	5	2	9
Middle-level climate-friendly innovative technology users (36-70%)	19	70	43	132
High-level climate-friendly innovative technology users (71-100%)	1	4	5	10
Total	22	79	50	151
Average CFITU (%)	51.27	51.68	55.49	52.88

Table 10 - Distribution of climate-friendly innovative technologies by CFITU groups.

	Average Score of Enterprises			
	Low-level CFITU	*Middle-level CFITU*	*High-level CFITU*	*Overall average*
Water Friendly S.A.	6.00	9.09	12.30	9.13
Energy Friendly S.A.	3.00	4.17	6.40	4.52
Nutrient Friendly S.A.	4.00	5.12	8.00	5.71
Carbon Friendly S.A.	4.00	7.88	9.30	7.06
Weather Friendly S.A.	3.00	4.76	7.40	5.05
Knowledge Friendly S.A.	5.00	8.39	13.00	8.80

**S.A.: Smart Applications.*

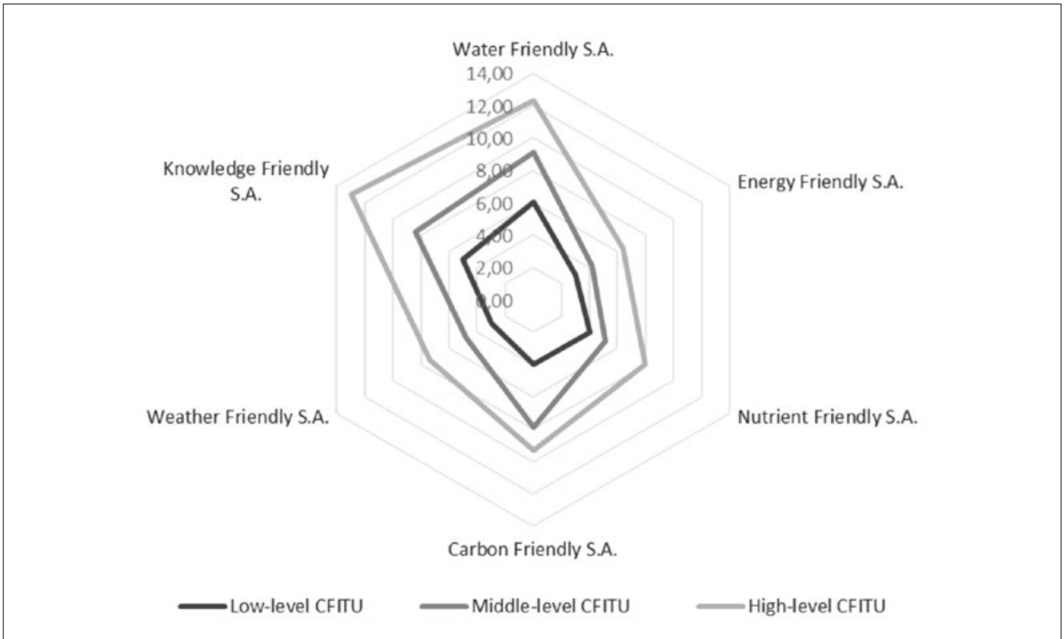
87.42% and 6.62%, respectively. When the averages of the CFITU (%) of the groups are examined, it is 51.27% for the 1-100 head group; 51.68% for the 101-250 head group and 55.49% for the 251+ head group. Sheep farms use moderately climate-friendly innovative technology with a general average of 52.88%.

According to the CFITU score groups, the average scores obtained by the enterprises from each smart application are given in Table 10 and presented graphically in Figure 3.

When the table is examined, it is seen that sheep farms have the highest average score in water, carbon and knowledge friendly smart technology applications. Awareness and application rate are higher in these three areas. The average scores of energy, food and weather friendly smart technology applications of sheep farms are low. The rate of not having knowledge in this field or having knowledge but not applying it is higher.

Before the widespread availability of the internet, smartphones, and similar devices in rural areas, staying informed about innovative

Figure 3 - Distribution chart of climate-friendly innovative technologies by CFITU groups.



technologies often required economically demanding activities such as attending trade fairs or technical trips. However, in the current situation, internet and smartphone usage is high across all socio-economic groups. Therefore, thanks to the internet and social media, the awareness of innovative technologies among all farmers, regardless of their socio-economic background, is at a high level. However, as will be seen in the section on factors affecting the CFITU index, certain factors such as having a specific level of education, recognizing and understanding climate change, having experience, and having the agricultural income to purchase technology are necessary for these technologies to be applied in the field. Consequently, the levels of implementation remain significantly below the level of awareness.

The data in Table 10 are transferred to the radar chart in Figure 3. In the graph, it can be seen visually that all three groups have a higher tendency towards water, carbon and knowledge-friendly smart technology applications.

3.2. *Factors influencing the CFITU in sheep farming*

Ordinal logistic regression analysis was conducted to determine the factors influencing the level of climate-friendly smart innovative technology usage (CFITU). In the model, the dependent variable, CFITU levels, was examined together with the independent variables, and their relationships were explored and established. The relationships between the independent variables and CFITU levels were examined individually. The CFITU levels according to the independent variables are presented in Table 11.

Upon examining Table 11, it can be observed that there is a clustering of medium CFITU level for all independent variables. According to the education levels, it can be observed that farmers with a low CFITU level predominantly fall into the categories of primary-middle school and high school education. Farmers with a medium CFITU level are more prevalent, and as the education level increases, their CFITU levels tend to shift from medium to high. The percentages of farmers with a high CFITU level based on education categories are as follows: 3.45% for primary-middle school, 10.53% for high school, 12.50% for vocational school, 33.33% for bachelor’s degree, and 100% for master’s and above.

According to the perception levels of climate change, the percentages of farmers with a medium CFITU level are as follows: 91.30% for those with low perception, 86.67% for those with medium perception, and 87.50% for those with high perception. On the other hand, the percentages of farmers with a high CFITU level are: 8.70% for those with low perception, 5.83% for those with medium perception, and 12.50% for those with high perception.

According to the experience level, it can be observed that CFITU levels vary. However, there is no clear trend of CFITU levels increasing or decreasing proportionally with the increase in experience.

According to the livestock presence (head), there is an increase in CFITU level as the number of livestock increases. The percentages of farmers with a low CFITU level are 9.09% for the 1st group, 6.33% for the 2nd group, and 4% for the 3rd group. Correspondingly, as the number of livestock increases, the percentages of farmers with a high CFITU level also increase. The percentages of farmers with a high CFITU level are 4.55% for the 1st group, 5.06% for the 2nd group, and 10% for the 3rd group.

According to the total land area (decares), CFITU levels differ, but it can be said that CFITU level increases as the land size increases. The percentages of farmers with a high CFITU level are 5.32% for 0-250 decares, 4% for 251-500 decares, 10% for 501-750 decares, and 13.64% for 751 and above decares.

According to the agricultural income, there are farmers in all three CFITU levels at each income level. While there is no significant change in CFITU level in relation to low agricultural income, an increase in income is associated with an increase in CFITU level. As income increases, the CFITU level also increases. The percentages of farmers with a medium CFITU level based on income are 89.47%, 85.71%, and 75% respectively, while the percentages of farmers with a high CFITU level are 4.39%, 9.52%, and 18.75% respectively.

Table 11 - CFITU levels by independent variables.

Variables	*Categories*	*Climate-friendly smart innovative technology usage levels*		
		Low	*Medium*	*High*
Education	Can read and write (2)	0.00	100.00	0.00
	Primary-Middle School (3)	6.03	90.52	3.45
	High School (4)	10.53	78.95	10.53
	Vocational School (5)	0.00	87.50	12.50
	Bachelor's Degree (6)	0.00	66.67	33.33
	Master's and above (7)	0.00	0.00	100.00
Perception Level	Low	0.00	91.30	8.70
	Medium	7.50	86.67	5.83
	High	0.00	87.50	12.50
Experience	1-5 years (1)	0.00	87.50	12.50
	6-10 years (2)	11.11	88.89	0.00
	11-15 years (3)	4.35	82.61	13.04
	16-20 years (4)	0.00	100.00	0.00
	21-25 years (5)	7.69	80.77	11.54
	26-30 years (6)	6.90	82.76	10.34
	30 years (7)	7.69	92.31	0.00
Livestock Presence (head)	0-100	9.09	86.36	4.55
	101-250	6.33	88.61	5.06
	251+	4.00	86.00	10.00
Total Land Area (da)	0-250	7.45	87.23	5.32
	251-500	0.00	96.00	4.00
	501-750	0.00	90.00	10.00
	751+	9.09	77.27	13.64
Agricultural Income ($)	20,000 and below	6.14	89.47	4.39
	20,001-100,000	4.76	85.71	9.52
	100,000 and above	6.25	75.00	18.75
Access to Information Level	0-2.50	0.00	95.65	4.35
	2.51-4.00	9.18	83.67	7.14
	4.01 +	0.00	85.71	14.29

According to the access to information score, CFITU levels differ, but it can be said that CFITU level increases as the access to information score increases. The percentages of farmers with a high CFITU level are 4.35% for 0-2.50 points, 7.14% for 2.51-4.00 points, and 14.29% for 4.01 and above points.

The next stage after explaining the CFITU levels in terms of independent variables is modeling. Modeling was performed using the logistic link function. When examining the model fit, the model shows a good fit at a significance level of $p<0.05$ (X^2=33.096, p=0.045). The parallelism assumption was tested using the chi-square test (X^2=31.943, p=0.059), and since $p>0.05$, the parallelism assumption is satisfied. This means that the CFITU categories, which are the dependent variable, are parallel to each other, and the pa-

Table 12 - Expressing the significance of model parameters.

		Estimate (β)	*Std. Error*	*Wald*	*sd*	*Sig.*	e^{β}
The dependent variable	[The_technology_level = 1.00]	-26.938	2.223	146.830	1	0.000	
	[The_technology_level = 2.00]	-19.542	2.071	88.997	1	0.000	
The independent variables	Livestock_presence	0.002	0.001	3.731	1	0.053	
	[Education=2.00]	**-25.046**	**4.937**	**25.736**	**1**	**0.133×10^{-10}**	**0.000**
	[Education=3.00]	**-23.837**	**1.341**	**316.180**	**1**	**0.445×10^{-10}**	**0.000**
	[Education=4.00]	**-23.277**	**1.398**	**277.099**	**1**	**0.778×10^{-10}**	**0.000**
	[Education=5.00]	**-21.934**	**1.545**	**201.682**	**1**	**2.978×10^{-10}**	**0.000**
	[Education=6.00]	-20.604	0.000		1		
	[Education=7.00]	0^a			0		
	[Experience=1.00]	1.994	1.378	2.094	1	0.148	
	[Experience=2.00]	-0.367	1.211	0.092	1	0.761	
	[Experience=3.00]	**2.271**	**1.035**	**4.816**	**1**	**0.028**	**9.685**
	[Experience=4.00]	0.766	1.028	0.555	1	0.456	
	[Experience=5.00]	1.227	0.908	1.827	1	0.177	
	[Experience=6.00]	1.209	0.898	1.812	1	0.178	
	[Experience=7.00]	0^a			0		
	[Perception_level=1.00]	0.505	1.303	0.150	1	0.699	
	[Perception_level=2.00]	-0.091	1.158	0.006	1	0.938	
	[Perception_level=3.00]	0^a			0		
	[total_land_code=1.00]	0.800	1.032	0.600	1	0.439	
	[total_land_code=2.00]	0.645	1.099	0.345	1	0.557	
	[total_land_code=3.00]	1.185	1.335	0.788	1	0.375	
	[total_land_code=4.00]	0^a			0		
	[income_code =1.00]	**-1.776**	**0.794**	**5.005**	**1**	**0.025**	**0.169**
	[income_code =2.00]	-2.259	1.176	3.687	1	0.055	
	[income_code =3.00]	0^a			0		
	[info_acces_code =1.00]	-0.506	1.343	0.142	1	0.706	
	[info_acces_code =2.00]	-1.372	1.296	1.122	1	0.290	
	[info_acces_code =3.00]	0^a			0		

rameters are equal in each category. With this assumption satisfied, the next step is to examine the goodness-of-fit measures of the model. The probabilities associated with the test statistics (Pearson p=0.483; Deviance p=1.000) are greater than 0.05, indicating that the model fits well with the data. The goodness-of-fit of the model is also examined through R^2. R^2 indicates the percentage of the dependent variable explained by the independent variables. In the analysis, the Cox and Snell R^2 value is 0.197, while the Nagelkerke R^2 value, which overcomes the limitations of the former, is relatively high at 0.325. Additionally, the McFadden R^2 value is 0.235.

The significance of the model's parameters was evaluated based on the probability values. In this model, there are a total of 7 independent variables. To interpret these variables, the probability values, which are associated with the Wald Test for testing the significance of parameters, were examined. Only the variables with probability values less than 0.05 (statistically significant variables) were interpreted. However, before interpreting the estimated parameter values, these values were transformed by taking the exponent of "e" to facilitate interpretation (Kokthi *et al.*, 2015).

The ordinal logistic regression test is based on the principle of selecting a reference category and interpreting other categories relative to this reference category. In this study, the highest level of CFITU was chosen as the reference category. Similarly, for the independent variables, the last categories were selected as the reference categories. Therefore, the interpretations were made based on these reference categories using odds ratios. The odds ratios were calculated, and the model prediction results are presented in Table 12.

According to the data in the Table 12, out of the 7 independent variables, 3 of them (education, experience, agricultural income) are statistically significant at the $p<0.05$ level. Therefore, these 3 variables have been interpreted with their significant categories.

Education Level: This variable represents the education levels, and the reference category for this variable is the 7th and last category, "master's and above", where farmers have higher levels of CFITU. Looking at the estimate values of the education categories in Table 12, it can be observed that as the education level of farmers in sheep farming enterprises increases, the rates of using climate-friendly innovative technologies also increase. This result can be interpreted as higher education levels being associated with increased awareness of climate change and a higher inclination to adopt climate-friendly innovative technologies to adapt to the changes.

Experience: When looking at Table 12, it can be said that farmers with 11-15 years of experience have approximately 9.685 times higher CFITU levels compared to farmers with 30 years and more experience. Based on these results, it can be observed that young sheep farmers with more than 10 years of experience tend to have higher tendencies in using climate-friendly technologies compared to relatively older sheep farmers, generally aged 55 and above, with 30 years and more experience.

Agricultural Income: The reference category for this variable is farmers with agricultural income "above \$100,000". Significant differences can be observed in the income group with agricultural income "below \$20,000", where sheep farming enterprises with lower agricultural income have much lower CFITU levels compared to the reference category of those with agricultural income above \$100,000. The main reason for this difference is the potential additional cost associated with the establishment and implementation of climate-friendly innovative technologies in sheep farms.

4. Conclusions

As a result of the study, 10 of the sheep farms that made the survey fall into the enterprise class that uses high-level climate-friendly innovative technology. Within the scope of the study, these farmers were named as "climate-friendly smart farmers". The rate of climate-friendly smart farmers remained at a very low level at 6.62%. Similarly, the rate of the number of enterprises at low level is as low as 5.96%. The rate of those who use moderately climate-friendly innovative technology is as high as 87.42%, which is promising for the future. Medium-level enterprises can be transformed into climate-friendly smart farmers with necessary extension studies and support.

During the application of the Ordinal Logistic Regression Analysis, the dependent variable was the level of using climate-friendly innovative technologies (CFITU), and the independent variables education, perception level, experience, livestock presence (head), total land area (da), agricultural income (\$) and access to information level. The analysis results indicate that these 7 independent variables account for 32.5% (Nagelkarte R^2) of the variance in the dependent variable. When examining the categories, it can be observed that education, experience, and agricultural income have a significant impact on the CFITU level. The test results indicate a significant increase in the level of using climate-friendly innovative technologies as the education level of sheep farms increases. Sheep farms with low agricultural income have significantly lower investment and utilization rates in climate-friendly innovative technologies compared to those with high agricultural income. The test results also show that sheep farms with more than 10 years of experience have significantly higher levels of using climate-friendly innovative technologies compared to those with over 30 years of experience.

In order to minimize the negative effects of climate change on the agricultural sector, to take precautionary measures and to raise awareness of the agricultural sector on climate change adaptation and mitigation; universities, Ministry of Agriculture and Forestry, relevant institutions and organizations, farmers, farmer representatives, NGOs should develop strategies to enable farmers to use smart practices for adaptation by addressing the issue of climate change together. While there is a need to conduct a comprehensive extension study for each smart application method evaluated under six headings, priority should be given to studies on energy, nutrient and weather friendly smart technology applications where average scores are low.

Climate change, environment, biodiversity and sustainable agriculture are the priority topics within the scope of harmonization with the European Green Deal. These issues are also included as a separate heading in the Eleventh Development Plan of the Republic of Turkey. The Eleventh Plan emphasizes the creation of an efficient, environmentally sustainable agricultural sector *based on advanced technology*. In this context, it will be possible to include climate-friendly smart application technologies as a separate title among the many support tools currently implemented in the field of agriculture and to accelerate their spread with the financial support to be provided.

When we look at CSA technologies, it is clear that these technologies are readily accessible both globally and in our country. Here, the issue is not so much the accessibility of technologies but rather the awareness of the problem (farmers' awareness of climate change and their ability to adapt, which requires education), as well as financial factors. The primary responsibility here lies with national leaders and policymakers. Within the framework of the European Union's green economic development strategy and our country's sustainable agriculture policy, policies that promote digitalization in agriculture and the use of CSA technologies should be developed and urgently implemented.

Acknowledgements

This article has been prepared by making use of the project numbered 121K885, "Determination of Typology of Sheep Enterprises in the Scope of Climate Change Perception and Adaptation, and Comparison of Resource Use Efficiency by Types of Enterprises", supported by The Scientific and Technological Research Council of Türkiye (TÜBİTAK).

References

Akın H.B., Şentürk E., 2012. Bireylerin mutluluk düzeylerinin ordinal lojistik regresyon analizi ile incelenmesi-Analysing levels of happiness of individuals with ordinal logistic analysis. *Öneri Dergisi*, 10(37): 183-193.

Ardakani Z., Bartolini F., Brunori G., 2019. Economic modeling of climate-smart agriculture in Iran. *New Medit*, 18(1): 29-40.

Ashraf M., Routray J.K., 2013. Perception and understanding of drought and coping strategies of farming households in north-west Balochistan. *International Journal of Disaster Risk Reduction*, 5: 49-60.

Ata M., Altarawneh M., Al-Masad M., 2021. Climate change perceptions and adaptations for dairy cattle farmers in Jordan: Case study in North East Region-Al-Dhulel Area. *New Medit*, 20(2): 97-105.

Azadi Y., Yazdanpanah M., Mahmoudi H., 2019. Understanding smallholder farmers' adaptation behaviors through climate change beliefs, risk perception, trust, and psychological distance: Evidence from wheat growers in Iran. *Journal of Environmental Management*, 250: 109456.

Azumah S.B., Adzawla W., Osman A., Anani P.Y., 2020. Cost-benefit analysis of on-farm climate change adaptation strategies in Ghana. *Ghana Journal of Geography*, 12(1): 29-46.

Barnes A.P., Toma L., 2012. A typology of dairy farmer perceptions towards climate change. *Climatic Change*, 112(2): 507-522.

Biró K., Szalmáné Csete M., Németh B., 2021. Climate-Smart Agriculture: Sleeping Beauty of the

Hungarian Agribusiness. *Sustainability*, 13(18): 10269.

Cebeci İ., Demirkiran O., Doğan O., Sezer K.K., Öztürk Ö., Elbaşi F., 2019. Türkiye'nin iller bazında kuraklık değerlendirmesi. *Toprak Su Dergisi*, Special issue: 169-176.

Chedid M., Tourrand J.-F., Jaber L.S., Hamadeh S.K., 2018. Farmers' perception to change and adaptation strategies of small ruminant systems in the West Bekaa of Lebanon. S*mall Ruminant Research*, 167: 16-21.

Christensen R., 2012. *Ordinal: Regression Models for Ordinal Data*. R Package, Version 2011.08-11.

Daly-Hassen H., Annabi M., King-Okumu C., 2019. Social and private profitability of tree-based adaptation options to climate change in a dryland area of Tunisia. *New Medit*, 18(2): 89-104.

Dellal İ., McCarl B.A., Butt T., 2011. The economic assessment of climate change on Turkish agriculture. *Journal of Environmental Protection and Ecology*, 12(1): 376-385.

DeLonge M.S., Miles A., Carlisle L., 2016. Investing in the transition to sustainable agriculture. *Environmental Science & Policy*, 55: 266-273.

Descheemaeker K., Zijlstra M., Masikati P., Crespo O., Tui S.H.-K., 2018. Effects of climate change and adaptation on the livestock component of mixed farming systems: A modelling study from semi-arid Zimbabwe. *Agricultural Systems*, 159: 282-295.

Ding J.H., Xu X., Yang D., Chu P.H., Dalton N.D., Ye Z., Yeakley J.M., Cheng H., Xiao R.P., Ross Jr J., 2004. Dilated cardiomyopathy caused by tissue-specific ablation of SC35 in the heart. *The EMBO Journal*, 23(4): 885-896.

Erkan O., Oğuz C., Kan A., Gültekin U., 2009. *Measuring the Effect of the Change in Climate Condition on Input Use in Agriculture in Konya*. Paper presented at the 1st International Symposium on Sustainable Development, June 9-1, Sarajevo, pp. 26-33. https://omeka.ibu.edu.ba/files/original/fb8e5d0ee7a6d7f92a0423829b18a61c.pdf.

Everest B., 2021. Farmers' adaptation to climate-smart agriculture (CSA) in NW Turkey. *Environment, Development and Sustainability*, 23(3): 4215-4235.

FAO, 2015. *The State of Food Insecurity in the World*. Rome: FAO. Accessed on 07.12.2022. http://www.fao.org/3/a-i4646e.pdf.

Foguesatto C.R., Borges J.A.R., Machado J.A.D., 2019. Farmers' typologies regarding environmental values and climate change: Evidence from southern Brazil. *Journal of Cleaner Production*, 232: 400-407.

Gauly M., Bollwein H., Breves G., Brügemann K., Dänicke S., Daş G., Demeler J., Hansen H., Isselstein J., König S., 2013. Future consequences and challenges for dairy cow production systems arising from climate change in Central Europe–A review. *Animal*, 7(5): 843-859.

Gerber P.J., Steinfeld H., Henderson B., Mottet A., Opio C., Dijkman J., Falcucci A., Tempio G., 2013. *Tackling climate change through livestock: a global assessment of emissions and mitigation opportunities*. Rome: Food and Agriculture Organization of the United Nations (FAO).

Godfray H.C.J., Garnett T., 2014. Food security and sustainable intensification. *Philosophical Transactions of the Royal Society. Biological Sciences*, 369(1639). https://doi.org/10.1098/rstb.2012.0273.

Görgülü M., Koluman Darcan N., Göncü Karakök S., 2009. *Goat production and global warming*. 5. National Goat Nutrition Congress, 30 September - 3 October, Çorlu, Turkey.

Hyland J.J., Jones D.L., Parkhill K.A., Barnes A.P., Williams A.P., 2016. Farmers' perceptions of climate change: identifying types. *Agriculture and Human Values*, 33(2): 323-339.

Khan M.I., Sameen A., 2018. *Animal Sourced Foods for Developing Economies: Preservation, Nutrition, and Safety*. Boca Raton, FL: CRC Press.

Khatri-Chhetri A., Aggarwal P.K., Joshi P.K., Vyas S., 2017a. Farmers' prioritization of climate-smart agriculture (CSA) technologies. *Agricultural Systems*, 151: 184-191.

Khatri-Chhetri A., Poudel B., Shirsath P.B., Chaudhary P., 2017b. *Assessment of climate-smart agriculture (CSA) options in Nepal*. CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS), New Delhi, India.

Kokthi E., Bermúdez I.V., Limón M.G., 2015. Origin or food safety attributes? Analyzing consumer preferences using Likert Scale. Empirical evidence from Albania. *New Medit*, 14(4): 50-57.

Koluman (Darcan) N., Silanikove N., Koluman A., 2017. Climate Change and Goat Agriculture Interactions in the Mediterranean Region. In: Simões J. Gutiérrez C. (eds.), *Sustainable Goat Production in Adverse Environments*, vol. I. Cham: Springer, pp. 393-405.

Koluman (Darcan) N., Silanikove N., 2018. The advantages of goats for future adaptation to Climate Change: A conceptual overview. *Small Ruminant Research*, 163: 34-38.

Lemaire G., Giroud B., Bathily B., Lecomte P., Corniaux C., 2019. Toward integrated crop-livestock systems in West Africa: a project for dairy production along Senegal river. In: Laire G., De Faccio Carvalho P.C., Kronberg S., Recous S. (eds.), *Agroecosystem Diversity*. Amsterdam: Academic Press, pp. 275-285.

Li C., Tang Y., Luo H., Di B., Zhang L., 2013. Local farmers' perceptions of climate change and local adaptive strategies: a case study from the Middle Yarlung Zangbo River Valley, Tibet, China. *Environmental Management*, 52(4): 894-906.

Liebman M., Schulte L.A., 2015. Enhancing agroecosystem performance and resilience through increased diversification of landscapes and cropping systems. *Elementa: Science of the Anthropocene*, 3: 000041.

Long T.B., Blok V., Coninx I., 2016. Barriers to the adoption and diffusion of technological innovations for climate-smart agriculture in Europe: evidence from the Netherlands, France, Switzerland and Italy. *Journal of Cleaner Production*, 112: 9-21.

Masud M.M., Azam M.N., Mohiuddin M., Banna H., Akhtar R., Alam A.F., Begum H., 2017. Adaptation barriers and strategies towards climate change: Challenges in the agricultural sector. *Journal of Cleaner Production*, 156: 698-706.

McCullagh P., 1980. Regression models for ordinal data. *Journal of the Royal Statistical Society: Series B (Methodological)*, 42(2): 109-127.

MGM (Meteoroloji Genel Müdürlüğü), 2021. Accessed on 08.12.2022. https://mgm.gov.tr/veridegerlendirme/kuraklik-analizi.aspx?d=yillik#sfB.

Mutenje M.J., Farnworth C.R., Stirling C., Thierfelder C., Mupangwa W., Nyagumbo I., 2019. A cost-benefit analysis of climate-smart agriculture options in Southern Africa: Balancing gender and technology. *Ecological Economics*, 163: 126-137.

Nardone A., Ronchi B., Lacetera N., Ranieri M.S., Bernabucci U., 2010. Effects of climate changes on animal production and sustainability of livestock systems. *Livestock Science*, 130(1-3): 57-69.

Oğuz C., Çelik Y., 2020. *Technical Assistance for FADN project*. Farm Accounting Data Network (FADN) unpublished tutorials for NGOs and Farmers.

Oğuz C., Yener A., 2017. Konya İli Süt İşletmelerinin Ekonomik Faaliyet Sonuçları Ve Yenilikleri Benimseme Düzeyleri. Selçuk Üniversitesi Bilimsel Araştırma Projeleri Proje, 15401020.

Örs A., Oğuz C., 2018. The Comparison of Innovative Technology Usage Levels of Dairy Farms Supported and Non-Supported by IPARD Program; A Case Study of Konya. *Turkish Journal of Agriculture-Food Science and Technology*, 6(12): 1809-1813.

Özçatalbaş O., Gürgen Y., 1998. *Tarımsal Yayım ve Haberleşme*. Adana: Baki Kitabevi, 385 pp.

Polat K., Dellal İ., 2016. *İklim Değişikliği İle Mücadele Ve Uyumda Tarımın Rolü*. 12. Ulusal Tarım Ekonomisi Kongresi, Isparta.

Ramborun V., Facknath S., Lalljee B., 2020. Moving toward sustainable agriculture through a better understanding of farmer perceptions and attitudes to cope with climate change. *The Journal of Agricultural Education and Extension*, 26(1): 37-57.

Reilly J., Baethgen W., Chege F., Van de Geijn S., Iglesias A., Kenny G., Patterson D., Rogasik J., Rötter R., Rosenzweig C., 1996. Agriculture in a changing climate: impacts and adaptation. In: Watson R.T., Zinyowera M.C., Moss R.H. (eds.), *Climate change 1995; impacts, adaptations and mitigation of climate change: scientific-technical analyses*. Cambridge: Cambridge University Press, pp. 427-467.

Roco-Fuentes L., Engler A., Bravo-Ureta B., Jara-Rojas R., 2015. Farmers' perception of climate change in mediterranean Chile. *Regional Environmental Change*, 15: 867-879.

Rogers E.M., 1995. Diffusion of Innovations: Modifications of a model for telecommunications. In: Stoetzer Mw., Mahler A. (eds.), *Die Diffusion von Innovationen in der Telekommunikation*. Berlin-Heidelberg: Springer, pp. 25-38.

Rojas-Downing M.M., Nejadhashemi A.P., Harrigan T., Woznicki S.A., 2017. Climate change and livestock: Impacts, adaptation, and mitigation. *Climate Risk Management*, 16: 145-163.

Saj S., Torquebiau E., Hainzelin E., Pages J., Maraux F., 2017. The way forward: An agroecological perspective for Climate-Smart Agriculture. *Agriculture, Ecosystems & Environment*, 250: 20-24.

Sejian V., Kumar D., Gaughan J.B., Naqvi S.M., 2017. Effect of multiple environmental stressors on the adaptive capability of Malpura rams based on physiological responses in a semi-arid tropical environment. *Journal of Veterinary Behavior*, 17: 6-13.

Somda J., Zougmoré R., Sawadogo I., Bationo B.A., Buah S., Abasse T., 2017. Adaptation processes in agriculture and food security: Insights from evaluating behavioral changes in West Africa. In: Uitto J., Puri J., van den Berg R. (eds.), *Evaluating climate change action for sustainable development*. Cham: Springer, pp. 255-269.

Speedy A.W., 2003. Global production and consumption of animal source foods. *The Journal of Nutrition*, 133(11): 4048S-4053S.

Steffen W., Richardson K., Rockström J., Cornell S.E., Fetzer I., Bennett E.M., Biggs R., Carpenter S.R., De Vries W., De Wit C.A., 2015. Planetary boundaries: Guiding human development on a changing planet. *Science*, 347(6223). DOI: 10.1126/science.1259855.

Steinfeld H., 2003. Economic constraints on production and consumption of animal source foods for nutrition in developing countries. *The Journal of Nutrition*, 133(11): 4054S-4061S.

Tarawali S.A., Enahoro D.K., Pfeifer C., 2018. *Food of animal origin: Demand and diversity*. Presented at the Expert panel: "Food of Animal Origin 2030: Solutions to Consumption Driven Challenges", Global Forum for Food and Agriculture, Berlin, Germany, 18 January 2018. Nairobi, Kenya: ILRI.

Tilman D., Fargione J., Wolff B., D'Antonio C., Dobson A., Howarth R., Schindler D., Schlesinger W.H., Simberloff D., Swackhamer D., 2001. Forecasting agriculturally driven global environmental change. *Science*, 292(5515): 281-284.

Tripathi A., Mishra A.K., 2017. Knowledge and passive adaptation to climate change: An example from Indian farmers. *Climate Risk Management*, 16: 195-207.

Uitto J., Puri J., van den Berg R., 2017. Evaluating climate change action for sustainable development: Introduction. In: Uitto J., Puri J., van den Berg R. (eds.), *Evaluating Climate Change Action for Sustainable Development*. Cham: Springer, pp. 1-12.

Velempini K., Smucker T.A., Clem K.R., 2018. Community-based adaptation to climate variability and change: Mapping and assessment of water resource management challenges in the North Pare Highlands, Tanzania. *African Geographical Review*, 37(1): 30-48.

West J., Salter A., Vanhaverbeke W., Chesbrough H., 2014. Open innovation: The next decade. *Research Policy*, 43(5): 805-811.

Wetende E., Olago D., Ogara W., 2018. Perceptions of climate change variability and adaptation strategies on smallholder dairy farming systems: Insights from Siaya Sub-County of Western Kenya. *Environmental Development*, 27: 14-25.

Yamane T., 1967. *Elementary Sampling Theory*, 1th ed. Englewoods Cliffs, NJ: Prentice Hall, 405 pp.