Journal of Agricultural Science and Technology (JAST), 28(4)
In Press, Pre-Proof Version

Sheep Farmers' Types and Efficiency in Konya

Cennet Oguz[1*], Aysun Yener Ögur[1], Aykut Örs[2], and Yusuf Çelik[1]

ABSTRACT

This study aims to identify farm typologies and evaluate resource use efficiency based on sheep farmers' perceptions of and adaptations to climate change in Konya Province, Turkey. The sample size was determined as 151 using Neyman's stratified random sampling method. Data were collected through face-to-face surveys with sheep rising enterprises. Farmers' perceptions and adaptive behaviors related to climate change were analyzed using SPSS. The Principal component analysis (PCA) and cluster analysis were applied to classify farmer typologies, which were categorized as *climate-friendly smart innovators*, *disengaged*, *concerned*, and *unconcerned*. The farms' resource use efficiency, economic efficiency, and pure technical efficiency were determined using Data Envelopment Analysis (DEA). The average technical efficiency (TE) of the farms was found to be 39.80%, indicating that farms could reduce input usage by 60.20% without compromising agricultural output. Resource use efficiency differed significantly across farm typologies. Specifically, allocative efficiency—closely linked to the identified farmer types—was found to be only 16.20%, indicating widespread inefficiencies in resource allocation and poor farm management. The findings also reveal that the majority of farmers demonstrated limited awareness and adaptation capacity concerning climate change.

Keywords: Climate change, sheep farming, farmer typology, resource use efficiency, Data Envelopment Analysis (DEA), Konya, Turkey.

INTRODUCTION

Climate change stands as one of the most urgent environmental issues confronting humanity today, with its effects being observed not only in certain areas but worldwide (Adams et al., 1990; Swart, 2008). Since 2007, global climate change—especially global warming—has gained significant prominence both on the international stage and within Turkey's national discussions.

Agriculture is both affected by and contributes to climate change. Industrial farming disrupts ecological processes, causing climate change, loss of biodiversity, land degradation, and marine pollution from fertilizers (Liebman and Schulte, 2015; Steffen et al., 2015; Tilman et al., 2001; West et al., 2014; De Longe et al., 2016). Climate change impacts crop and livestock

[1] Department of Agricultural Economics, Faculty of Agriculture, University of Selcuk, Konya, Turkey.
[2] Agriculture and Rural Development Support Institution, Konya Provincial Coordination Unit, Turkey.
*Corresponding author; e-mail: coguz@selcuk.edu.tr

production, with animal production suffering more severely over time (Descheemaeker et al., 2018). Livestock, particularly small ruminants, are critical for nutrition and have socio-economic importance, producing 1.5 million tons of meat and 25.6 million tons of milk annually (FAO, 2019). They also contribute to biodiversity and ecosystem protection (Marino et al., 2016; Patra, 2014; FAO, 2019). Small ruminant farming is especially important in arid and semi-arid regions (Sejian et al., 2017). Understanding farmers' awareness and perceptions of climate change is essential for mitigation (Masud et al., 2017; Somda et al., 2017; Tripathi and Mishra, 2017; Chedid et al., 2018; Wetende et al., 2018). Farmers with sufficient knowledge of climate change are more likely to act to reduce its impact (Velempini et al., 2018). In Turkey, where the Konya region is semi-arid, the Eleventh Development Plan emphasizes the need for climate-resilient species and advanced technologies in agriculture. Small ruminant farming could play a key role in climate change adaptation and mitigation. To date, no study has examined the direct and indirect effects of climate change on sheep farming in the research area. The primary objective of this study is to identify farm typologies and evaluate the resource use efficiency of sheep farmers in Konya Province, Türkiye, based on their perceptions of and adaptations to climate change. This research aims to fill that gap by providing insights for policymakers on how farmers currently utilize their resources, how they could optimize resource use in the face of climate change, and how production systems may need to evolve to support effective adaptation.

MATERIALS AND METHODS

This research is based on data from face-to-face surveys with sheep farms in Konya, Turkey, reflecting the 2021 production year. Secondary sources, including reports, academic studies, and online databases, were also used. The exchange rate applied was $1 = 14.12 Turkish Lira, the average rate during the fieldwork period (TCMB, 2022).

Sample Size and Survey Instrument

To define the study population, records from the Konya Province Sheep and Goat Breeders Association were utilized. According to these records, there are a total of 9,228 sheep rising farms in the province. The districts with the largest sheep populations—Karapınar, Ereğli, Cihanbeyli, Meram, Karatay, and Çumra—collectively account for 54.92% of Konya's total sheep population, which stands at 786,748 (Figure 1).

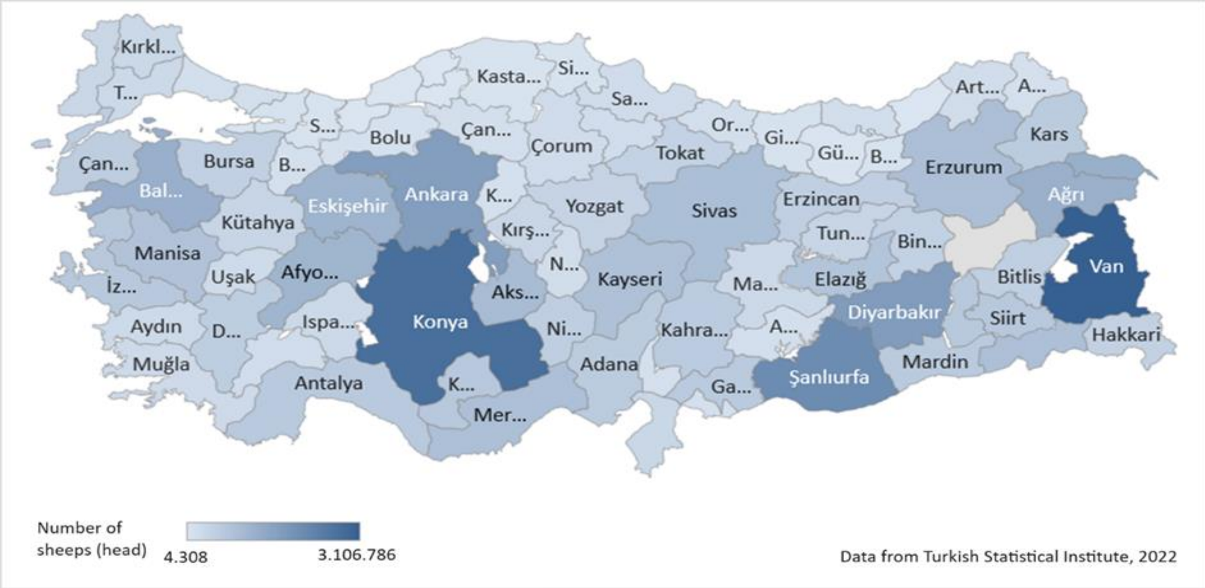


Figure 1. Map of the Research Area.

The selection of districts was based on several factors, including the number of sheep, drought and rainfall conditions, availability of pastureland, and prevailing production patterns that represent the region's ecological characteristics. The methodological framework of the study is illustrated in Figure 2, and the methods employed at each stage are comprehensively detailed below.

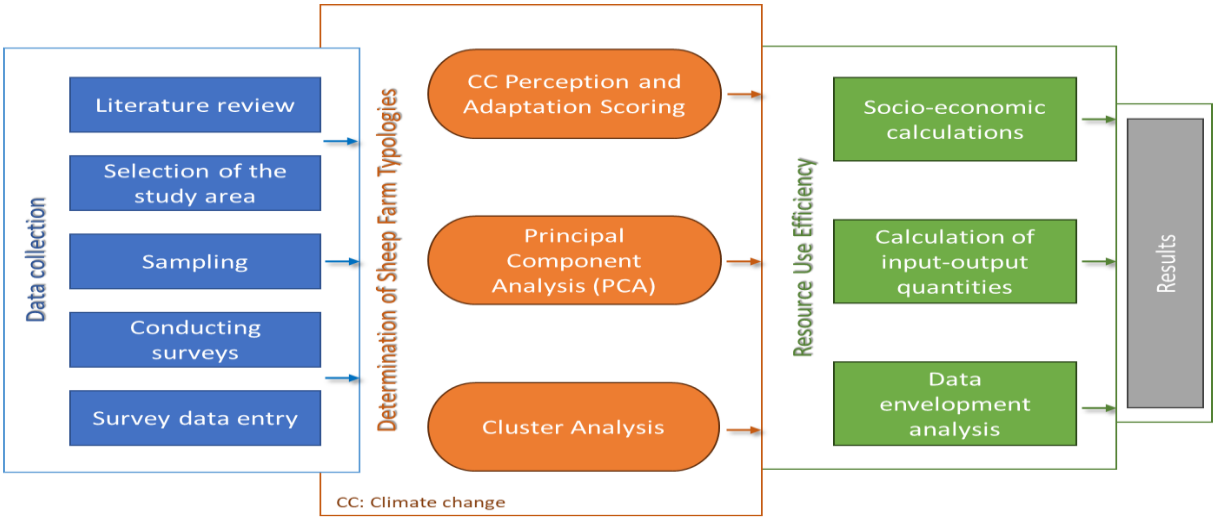


Figure 2. The methodological framework of the research.

Since the coefficient of variation of the population exceeded 75%, Neyman's stratified random sampling method was employed to calculate the sample size. With a 5% margin of error and a 95% confidence level, the sample size was determined to be 151.

$$n = \frac{[\sum(N_h S_h)]^2}{N^2 D^2 + \sum[N_h (S_h)^2]} \qquad \text{Where,} \qquad D^2 = d/z$$

In the formula:

n: sample size,

N: total number of farms in the population,

N_h: number of farms in the h-th stratum (frequency),

S_h: the standard deviation within the h-th stratum,

d: allowable error margin from the population mean,

z: z-value corresponding to the confidence level from the standard normal distribution (Yamane, 1967).

Farms were stratified according to their size, resulting in three strata based on frequency distributions. The strata boundaries were defined as farms with 1–100 heads, 101–250 heads, and 251 or more heads of sheep. The sample allocation to each stratum was performed using the formula (Yamane, 1967):

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

Accordingly, the distribution of sample farms across size groups (based on flock size) in the study area is presented in Table 1.

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

Enterprise Groups (number of sheep)	Nh	Sh	Ort	CV	Nh*Sh	Nh*(Sh)^2	Sample Size (n)
1-100	1636	22,27	64	33	36.429,03	811.170	22
101-250	2103	62,86	163	31	132.189,64	8.309.130	79
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

The demographic characteristics of the farms were examined based on the age, gender, and education levels of the farmers. To assess sheep farmers' attitudes and behaviors regarding climate change, multiple statements covering topics such as the environment, economics, and plant and animal production were presented. Farmers' agreement with these statements was measured using a five-point Likert scale. The Likert scale is a widely accepted method for quantifying and analyzing attitudes and behaviors. The response option with the highest mean score indicates the most preferred or agreed-upon attitude.The average rating was calculated as described by Oğuz and Karakayacı (2017). Farmers rated each statement on a five-point Likert scale with the following options: Strongly Disagree (1), Disagree (2), Moderately Agree (3), Agree (4), and Strongly Agree (5). Thus, the maximum score a farmer could assign to each statement was five. The validity and reliability of the nominal scale were assessed based on these average scores.

Determination of farm typologies and resource use efficiency

PCA was used to identify farm typologies based on sheep farmers' perceptions and adaptation to climate change (Abid et al., 2015; Hyland et al., 2016). It extracted factors related to climate change perceptions, adaptation, and technology use. Components with eigenvalues >1 were retained, and dataset suitability was confirmed with the KMO test (Kaiser and Rice, 1974; Tatlıdil, 1996; Hair, 1998; Kalaycı, 2006; Barnes and Toma, 2012; Nainggolan et al., 2012). KMO values exceeding 0.50 or 0.60 are considered indicative of an adequate dataset for PCA (Kaiser and Rice, 1974; Sharma, 1996; Pallant and Manual, 2010; Kalaycı, 2006).

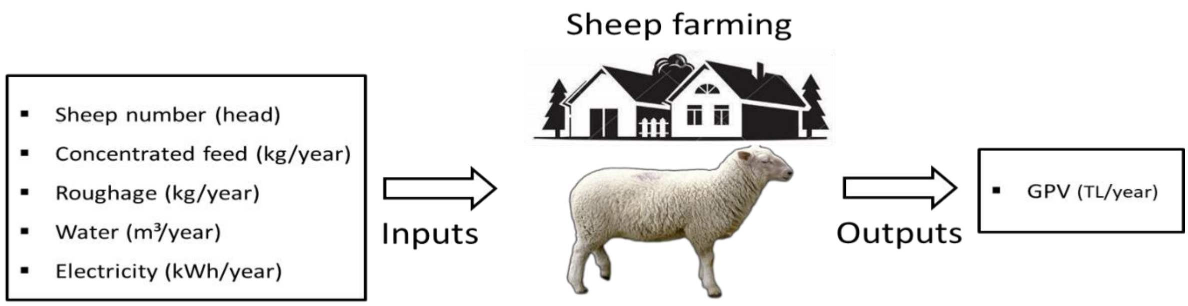
$$KMO = \frac{\sum_{i\neq j}\sum r^2 ij}{\sum_{i\neq j}\sum r^2 ij + \sum_{i\neq j}\sum a^2 ij}$$

Cluster Analysis

Farms, categorized based on climate change perceptions from PCA, were grouped into four clusters using cluster analysis: K1 (Awareness), K2 (Innovators using climate technologies and promoting environmental responsibility), K3 (Low-risk perception), and K4 (Livestock-related awareness). This method, used in similar studies (Bidogeza et al., 2009; Voss et al., 2009; Barnes and Toma, 2012; Morgan-Davies et al., 2012; Nainggolan et al., 2013), applied PCA-derived factor scores for hierarchical and non-hierarchical K-means clustering (Hall and Minns, 1999). The goal of K-means is to partition data by minimizing the sum of squared distances to the nearest cluster centroid, using Euclidean distance (Rao and Srivinas, 2006).

Determining resource use efficiency based on farmer typologies in sheep farms

To calculate resource use efficiency in sheep rising farming, relevant literature was reviewed (Theodoridis et al., 2014; Conradie and Piesse, 2015; Dalgıç et al., 2018). Inputs and outputs used are shown in Figure 3. Economic analysis was based on survey data, with input costs and gross production value calculated for each enterprise.



*GPV: Gross Production Value(TL/year)

Figure 3. Input-output scheme for sheep farming.

Data envelopment analysis (DEA)

The efficiency of resource utilization in sheep farms—grouped according to their perceptions and adaptations to climate change through cluster analysis—was assessed using Data Envelopment Analysis (DEA) via the DEAP software. DEA is a non-parametric approach grounded in linear programming that evaluates the performance of decision-making units (DMUs) by optimally assigning weights to multiple inputs and outputs. The primary efficiency indicator in DEA is the ratio between the weighted sum of outputs and the weighted sum of inputs (Cooper, 2004; Coelli et al., 2002).

$$TE\ (\emptyset) = \frac{U_1 Y_{j1} + U_2 Y_{2j} + \cdots \ldots\ldots\ldots + U_n Y_{nj}}{V_1 X_{j1j\iota} + V_2 X_{2j} + \cdots \ldots\ldots\ldots + V_n X_{nj}} = \frac{\sum_{r-1}^{n} + U_r Y_{rj}}{\sum_{s-1}^{m} + V_s X_{sj}}$$

In the analysis, efficiency measurements aimed at inputs were used, as agricultural farms generally tend to control inputs (Farrell, 1957). The CCR and BCC models were used to determine resource use efficiency in sheep rising farm created according to climate change perception. The CCR model assumes of constant returns to scale. The CCR model boundary is given below. In the DEA model, θ represents the efficiency score (Coelli et al., 2005).

$$E_0 = MinQ - \varepsilon\left(\sum_{i=1}^{m} S_i^- - \sum_{i=1}^{s} S_r^+\right)$$

Subject to:

$$\textstyle\sum_{j=1}^{n} X_{ij}\lambda_j + S_i^- - Qx_{i0}$$

$$\sum_{j=1}^{n} Y_{ij}\lambda_j + S_i^+ - Yx_{r0}$$

$$\lambda_j + S_i^-, S_i^+ \geq 0$$

j= 1,2,…..n

i= 1,2,…..m

r= 1,2,….s

The BCC model, introduced by Banker, Charnes, and Cooper, extends the CCR model by incorporating variable returns to scale instead of assuming constant returns. Consequently, the BCC efficiency frontier is positioned at or beneath the CCR frontier. This model also allows for determining the type of returns to scale for each decision-making unit (DMU), revealing whether a farm operates under increasing, decreasing, or constant returns to scale. The formulation of the BCC model is provided below (Cooper et al., 2000).

$$Max\ h_k \frac{\sum_{r=1}^{s} u_{rk} y_{rk} - u_o}{\sum_{i=1}^{m} v_{ik} x_{ik}}$$

Subject to:

$$\frac{\sum_{r=1}^{s} u_{rk} y_{rk} - u_o}{\sum_{i=1}^{m} v_{ik} x_{ik}} \leq 1$$

$u_r, v_i \geq \varepsilon > 0,$

$j = 1, 2, \ldots, n$

$i = 1, 2, \ldots, m$

$r = 1, 2, \ldots, s$

The input-oriented CCR model, developed by Charnes, Cooper, and Rhodes (1978), which assumes constant returns to scale, was applied to estimate the technical efficiency of sheep farms. This model is widely employed in agricultural efficiency studies (Coelli et al., 2005; Farrell, 1957). It assesses the capacity of each decision-making unit (DMU) to minimize input use while maintaining at least the current level of output. The following linear programming model was used:

minimize θ

Subject to:

$\sum (\lambda_j * x_{ij}) \leq \theta * x_{i0}$ for all $i = 1, 2, ..., m$

$\sum (\lambda_j * y_{rj}) \geq y_{r0}$ for all $r = 1, 2, ..., s$

$\lambda_j \geq 0$ for all $j = 1, 2, ..., n$

Where:

θ is the technical efficiency score of the decision-making unit (DMU) under evaluation.

x_{ij} and y_{rj} represent the i-th input and r-th output of the j-th DMU, respectively.

x_{i0} and y_{r0} refer to the inputs and outputs for the target DMU (DMU_0).

λ_j are the intensity variables (weights) assigned to peer DMUs.

An efficiency score (θ) of 1 indicates that the DMU is technically efficient under constant returns to scale, while a score less than 1 reflects technical inefficiency. This model was originally proposed by Charnes et al. (1978) and was later extended by Banker et al. (1984) to account for variable returns to scale in the BCC model.

Economic Efficiency (EE) = Pure Technical Efficiency (TE) *Allocative Efficiency (AE)

In the efficiency analysis, the Gross Production Value (GPV) obtained from sheep farming activities was used as the output. The input variables included: number of sheep (heads), concentrated feed (kg/year), roughage (kg/year), water (m^3/year), and electricity (kWh/year). For determining allocative efficiency, input prices were considered, including expenditures on veterinary services ($/year), concentrated feed ($/year), roughage ($/year), water ($/year), and electricity ($/year). All input and output prices were based on farmers' self-reported data. Since farms often use multiple types of concentrated and roughage feed, the total annual cost incurred for all types of concentrated feed was aggregated and used as a single input cost. The same approach was applied for roughage costs.

RESEARCH FINDINGS AND DISCUSSION

The socio-economic characteristics of the farmers

The socio-economic characteristics of the farmers were analyzed. In the study area, 52.91% of the farmers fall within the 15–49 age group, representing the economically active agricultural population. Approximately 68.47% of the farmers are primary school graduates, and 80.10% own agricultural land. The average Gross Production Value (GPV) per farm was calculated as $86,871.39 (Table 2).

Table 2. Socio-economic characteristics of farmers (n= 151).

Age Distribution of Population		
	Number	Percentage (%)
0-6	0.25	5.61
7--14	0.60	13.45
15-49	2.36	52.91
50-+	1.25	28.03
Total	4.46	100
Education Level		
No formal education	0.39	8.78
Primary-secondary school	3.04	68.47
High school	0.68	15.32
University	0.33	7.43
Total	4.44	100
Land Ownership (decare)		
Owned land	251.06	80.1
Rented	59.67	19
Shared cropping	2.71	0.9
Total land (decare)	313.44	100
Enterprise Income (GPV) ($/per farms)		
Value of Crop Production	55,613.03	64.02
Value of Animal Production	31,258.36	35.98
Total GPV ($/per farms)	86,871.39	100

Determining farmer typologies based on climate change perception and adaptation levels of sheep farming

Regional climate affects agricultural productivity, making farmers' adaptation vital for sustainability. Adaptation is classified as planned, transformative, or autonomous (Stokes and Howden, 2010). This study used factor analysis to identify farmer adaptation typologies (Barnes and Toma, 2012; Nainggolan et al., 2013). PCA revealed key perceptions of climate change, and reliable classification groups were formed, supported by Cronbach's alpha. From 66 variables, four with high communalities were selected for further analysis (Table 3).

Table 3. Factor analysis.

Factors	Scale Items	Mean	Variance Ratio	Alpha (α) Coefficient
K1 Awareness	There have been 45 variable factors associated with farmers' perceptions of climate change awareness.	3.38	93.56	.996
K2 Climate Friendly Innovative Technologies and Environmental Responsibility	There have been 6 variables	2.85	99.87	.556
K3 Low Risk Perception	There were 5 variables factors	2.52	99.96	.762
K4 Awareness in Terms of Livestock	There were 2 variables factors	2.18	99.98	.783
The total variance			81.79	
The Kaiser-Meyer-Olkin Sample Adequacy Measure Statistic				**.950**
Bartlett's Test of Sphericity			**Chi-Square Value**	19492.389
			df	**2145**
			Sig.	**0.000**

Resource: Oğuz et al. 2024

The four factors extracted explained 81.79% of the variance, with a KMO value of 0.950, indicating high suitability for factor analysis. Varimax rotation was applied for clearer interpretation, and components with factor loadings >0.30 were retained. The factors were named: K1: Awareness (AW), K2: Innovative Technologies and Environmental Responsibility (ER), K3: Low Risk Perception (LRP), K4: Animal Husbandry Awareness (AAH). The Likert scale mean scores for farmers' perceptions, adaptations, and attitudes toward climate change in the study area were above 3, indicating a moderate level. This suggests that while farmers demonstrate some awareness and readiness, the adoption and implementation of effective climate change strategies may require additional time and support.

Identification of Farmer Types Based on Cluster Analysis

Farmer typologies were identified using non-hierarchical cluster analysis through the K-means clustering method, based on the factor scores derived from the PCA. The clusters were defined according to statistically significant differences in climate change perception scores at each cluster center (Table 4). The primary objective of the clustering process was to maximize intra-cluster homogeneity while maximizing inter-cluster heterogeneity. Based on the values presented in Table 4, the closest clusters were identified as Cluster 1 and Cluster 2, whereas the most distant clusters were Cluster 1 and Cluster 4. As a result of the cluster analysis conducted on farmer attitudes derived from factor analysis, four distinct farmer types were identified (Table 4).

Table 4. Farmer types identified in the surveyed farms using cluster analysis.

Clusters	Farmer Types			
	Environmentalist and Climate Friendly Smart Innovators (ECSFI)	Disengaged (D)	Concerned (C)	Unconcerned (U)
Awareness (AW)	0.22890	-1.20764	.94714	0.41896
Climate Friendly Innovative Technologies and Environmental Responsibility (ER)	1.17342	-0.66965	-0.71299	-0.34411
Low Risk Perception (LRP)	-0.17925	-0.66603	.09658	1.33796
Awareness in Terms of Animal Husbandry (AAH)	-.00174	-0.24531	1.14291	-0.95359

Based on the cluster distances, four farmer types were identified and labeled as follows: Environmentalist and Climate-Friendly Smart Innovators (ECSFI), Disengaged (D), Concerned (C), and Unconcerned (U). Similar typologies have been defined at both national and regional levels in previous studies to support climate change adaptation efforts (Barnes and Toma, 2012; Hyland et al., 2016; Shukla et al., 2019; Stringer, 2020; Islam et al., 2021). To visually illustrate the differences between these farmer types, radar charts were generated based on the distances from the cluster centers (Figure 4).

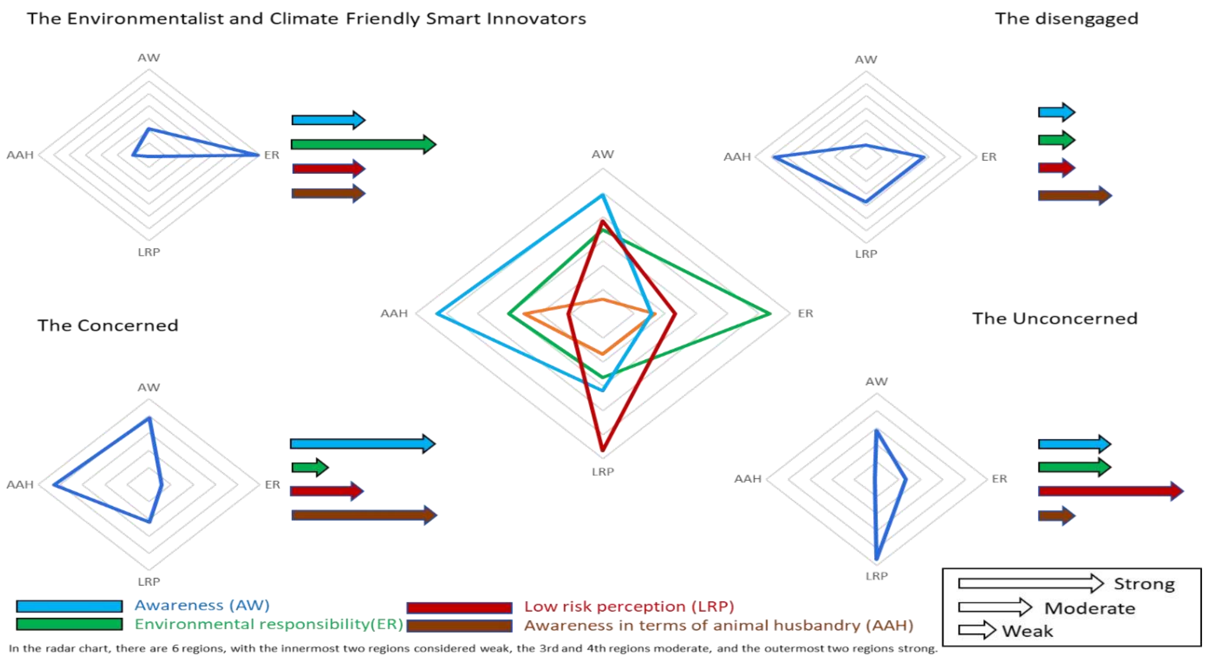


Figure 4. Identification of farmer types based on cluster center distances.

The Environmentalist and Climate Friendly Smart Innovators (ECSFI)

This group shows moderate awareness of climate change and strong environmental sensitivity. They emphasize reducing greenhouse gas emissions and using natural resources efficiently, favoring proactive environmental leadership. Their understanding of livestock farming's impact on climate change is moderate, and their risk perception is slightly above low, recognizing climate change as a real threat. They believe its effects are already visible, especially on ecosystems. Their high scores on the innovative technology index indicate strong knowledge and use of climate-smart technologies in water, energy, nutrition, carbon, and weather systems, making them moderate to high users of such technologies among farmers. Some studies on farmer typologies suggest that members of proactive groups are more likely to adopt recommended practices and technologies to mitigate the impacts of climate change compared to those holding negative perceptions. However, these technologies must also align with objectives of profit maximization and efficient resource use. Therefore, this group provides a strong rationale for promoting 'win-win' technologies, such as the adoption of best-practice guidelines for nitrogen application (Barnes et al., 2012; Hyland et al., 2016).

The Disengaged (D)

This group shows a limited awareness of environmental responsibility. Although their perception of climate and environmental issues is low, their risk awareness is similarly minimal, suggesting that they do not consider climate change to pose a significant threat to themselves or their farms. Their awareness related to livestock farming is slightly above minimal. In terms of innovative technology usage, this group scores the lowest among the four clusters. Most farmers classified as Disengaged lack knowledge of climate-friendly innovative technologies, and those who possess some knowledge rarely implement them. Consequently, they represent the most detached cluster in this study. Although this specific type has not been explicitly studied in the literature, similar groups have often been characterized as counterfactual or reference groups when evaluating participation in environmental and conservation programs (Wilson, 1996; Wilson and Hart, 2001; Mathijs, 2003). For instance, in the Environmentally Sensitive Areas scheme in Southwest England, a spectrum ranging from 'resistant non-adopters' to 'active adopters' was identified, with low belief in conservation as a legitimate land use cited as the primary reason for disengagement.

The Concerned (C)

This group shows little environmental responsibility, prioritizing economic wellbeing over environmental concerns. Their risk perception is moderate but low, believing climate change impacts are not yet evident but will emerge soon. According to the innovative technology usage index, they rank second after Environmentalists and Smart Innovators, being moderate to high adopters. In contrast, the Unconcerned farmers have moderate awareness and responsibility toward climate change.

The Unconcerned (U)

According to Figure 3, this group exhibits a notably high level of low-risk perception. They believe that climate change will primarily affect countries outside Turkey, impact urban areas more than rural ones, or influence future generations at least 50 years from now. Their awareness of the impact of livestock farming on climate change is nearly nonexistent. Based on the innovative technology usage index scores, they rank third in both awareness and adoption of climate-friendly innovative technologies. Overall, these farmers are moderate users of such technologies.

Comparing allocative efficiency based on farmer typologies in sheep rising farms

Farm performance is measured by productivity and market competitiveness. Farrell (1957) defined efficiency as maximizing output from inputs. Sheep farms showed 39.80% Pure Technical Efficiency, meaning they could reduce inputs by 60.20% without output loss. Efficiency varies with different farm typologies. The average allocative efficiency in the study area was calculated as 16.2%. Allocative efficiency is crucial as it reflects how well producers operate both technically and economically. In the region, sheep farming is predominantly pasture-based; however, during the winter season, animals are supplemented with concentrated and roughage feeds on the farm. Allocative efficiency was estimated using variable inputs such as costs of concentrated feed, roughage feed, water, and electricity. It indicates the ability of sheep farms to optimally utilize inputs while considering market prices and production technology (Farrell, 1957).

Table 5. Resource use efficiency of farms by farmer typologies.

Farmer Typologies	Number of Farms	Allocative Efficiency	Economic Efficiency	Pure Technical Efficiency	Efficient Farms		
					Efficient	Less Efficient	Inefficient
The Environmentalist and Climate Friendly Smart Innovators (ECSFI)	51	0.173	0.084	0.483	2	0	49
Disengaged (D)	43	0.280	0.157	0.561	4	0	39
Concerned (C)	31	0.419	0.333	0.794	4	0	27
Unconcerned (U)	26	0.388	0.317	0.818	1	1	22
Average (of 151 farms)	151	**0.162**	0.064	0.398	**3**	**0**	**148**

In other words, it reflects farmers' capability to select an input combination that yields optimal production at the lowest cost. On average, only three farms were found to be efficient in minimizing costs while maintaining optimal output, whereas 148 farms were identified as inefficient in resource utilization.

This suggests that farmers in the study area are generally unable to use their resources effectively and that farm management practices are suboptimal. These findings highlight the need for tailored training programs for each farmer typology and the implementation of targeted interventions to improve resource management.

CONCLUSIONS AND RECOMMENDATIONS

This study evaluated production efficiency across farm typologies by analyzing pure technical efficiency, allocative efficiency, and economic efficiency. Allocative efficiency was found to be low at 16.20%. To improve input efficiency in sheep farming, policies and practical training programs for farmers are needed. Pure technical efficiency measures how effectively farm use inputs to achieve maximum output. The average pure technical efficiency of the farms was 39.80%, indicating a significant gap in efficient resource utilization. In the ECSFI group, 49 farms were inefficient; in the Disengaged group, 39; in the Concerned group, 27; and in the Unconcerned group, 22 farms were found to be inefficient. These findings suggest that most farmers fail to utilize their resources optimally, and farm management practices are suboptimal. Targeted training through agricultural extension programs is necessary to optimize resource use and improve input management.

ACKNOWLEDGEMENTS

This article was prepared using project number 121K885, titled "Determination of Typology of Sheep Farms in the Scope of Climate Change Perception and Adaptation and Comparison of Resource Use Efficiency by Types of Farms," supported by The Scientific and Technological Research Council of Türkiye (TÜBİTAK).

REFERENCES

1. Abid, M., Scheffran, J., Schneider, U. A., Ashfaq, M. J. E. S. D. 2015. Farmers' perceptions of and adaptation strategies to climate change and their determinants: the case of Punjab province, Pakistan. *Earth System Dynamics*, *6*(1), 225-243.
2. Adams, R. M., Rosenzweig, C., Peart, R. M., Ritchie, J. T., Mc. Carl, B. A., Glyer, J. D., Allen Jr, L. H. 1990. Global climate change and US agriculture. *Nature*, *345*(6272), 219.
3. Banker, R. D. (1984). Estimating most productive scale size using data envelopment analysis. *European journal of operational research*, *17*(1), 35-44.
4. Barnes A.P., Toma L., 2012. A typology of dairy farm er perceptions towards climate change. Climatic Change, 112(2): 507-522.
5. Bidogeza, J. C., Berentsen, P. B. M., De Graaff, J., Lansink, A. O. 2009. A typology of farm households for the Umutara Province in Rwanda. *Food Security*, *1*(3), 321-335.
6. Charnes, A., Cooper, W. W., Rhodes, E. 1978. Measuring the efficiency of decision making units. *European journal of operational research*, *2*(6), 429-444.
7. 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. *Small Ruminant Research*, *167*, 16-21.
8. Coelli, T., Rahman, S., Thirtle, C. 2002. Technical, allocative, cost and scale efficiencies in Bangladesh rice cultivation: a non-parametric approach. Journal of Agricultural Economics, 53(3), 607-626.
9. Coelli, T.J., Rao D.S.P., O'donnelL C.J., Battese G.E. 2005. An Introduction to Efficiency and Productivitiy Analysis, Springer, Second Edition, USA.
10. Conradie, B., Piesse, J., 2015. Productivity benchmarking of free-range sheep operations for Laingsburg, South Africa. Agrekon, 54, 2, 1-17.
11. Cooper, A. 2004. The inmates are running the asylum: [Why high-tech *products drive us crazy and how to restore the sanity]*. Indianapolis: Sams.
12. Cooper, W. W., Seiford, L. M., Tone, K. 2000. Data envelopment analysis. *Handbook on Data Envelopment Analysis, 1st ed.; Cooper, WW, Seiford, LM, Zhu, J., Eds*, 1-40.
13. Dalgıç, A., Demircan, V., Örmeci Kart, M.C., 2018. Technical Efficiency of Sheep Farming In Turkey: A Case Study of Isparta Province. Scientific Papers-Series Management Economic Engineering in Agriculture And Rural Development, 18, 3, 65-72.

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

15. 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.

16. FAO, 2019. http://www.fao.org/faostat/en/#data (Son erişim tarihi: 21.03.2019).

17. Farrell, M. J. 1957. The measurement of productive efficiency. Journal of the Royal Statistical Society: Series A (General), 120(3), 253-281.

18. Hair, J. F., Anderson, R. E., Tatham, R. L., William, C. 1998. Black (1998), Multivariate data analysis.

19. Hall, M. J., Minns, A. W. 1999. The Classification of Hydrologically Homogeneous Regions. Hydrological Sciences Journal, 44(5), 693-704.

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

21. Islam, A. R. M. T., Hasanuzzaman, M., Jaman, M., Alam, E., Mallick, J., Alam, G. M., ... Techato, K. 2021. Assessing farmers' typologies of perception for adopting sustainable adaptation strategies in bangladesh. Climate, 9(12), 167.

22. Kaiser, H. F., Rice, J. 1974. A second generation Little Jiffy. Psychometrika, 35, 401-4

23. Kalaycı, Ş. 2006. SPSS Uygulamalı Çok Değişkenli İstatistik Teknikleri (2. Baskı). Ankara:Asil Yayın Dağıtım.

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

25. Marino, R., Atzori, A. S., D'Andrea, M., Iovane, G., Trabalza-Marinucci, M., Rinaldi, L. 2016. Climate change: Production performance, health issues, greenhouse gas emissions and mitigation strategies in sheep and goat farming. *Small Ruminant Research*, *135*, 50-59.

26. 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.

27. Mathijs E (2003) Social capital and farmers' willingness to adopt countryside stewardship schemes. Outlook Agric 32:13–16

28. Morgan-Davies, C., Waterhouse, T., Wilson, R. 2012. Characterisation of farmers' responses to policy reforms in Scottish hill farming areas. *Small Ruminant Research*, *102*(2-3), 96-107.

29. Nainggolan, D., de Vente, J., Boix-Fayos, C., Termansen, M., Hubacek, K., Reed, M. S. 2012. Afforestation, agricultural abandonment and intensification: competing trajectories in semi-arid Mediterranean agro-ecosystems. *Agriculture, ecosystems & environment*, *159*, 90-104.

30. Nainggolan, D., Termansen, M., Reed, M. S., Cebollero, E. D., Hubacek, K. 2013. Farmer typology, future scenarios and the implications for ecosystem service provision: a case study from south-eastern Spain. *Regional Environmental Change*, *13*, 601-614.

31. Oğuz, C., Örs, A., Yener Ögür, A., Çelik, Y. 2024. Determining the factors affecting the climate-friendly innovative technology usage levels of sheep farms. New Medit, DOI: 10.30682/nm2401d. JEL codes: Q16, Q54, Q55.

32. Oğuz, Yener Ögür, A., Örs, A., Çelik, Y. 2024. Koyunculuk Yapan Çiftçilerin İklim Değişikliği Algısı ve Adaptasyonlarına Göre İşletmelerinTipolojilerinin ve Kaynak Kullanım Etkinliklerinin Belirlenmesi. Atlas akademi, ISBN 978-625-8101-80-5. Konya.

33. Oğuz, C., Karakayacı, Z. 2017. Tarım Ekonomisinde Araştırma ve Örnekleme Metodolojisi. Atlas Akademi, ISBN: 978-605-827852-3 1. Basım Konya.

34. Pallant, J., Manual, S. S. 2010. A step by step guide to data analysis using SPSS. *Berkshire UK: McGraw-Hill Education*.

35. Patra, A. K. 2014. A meta-analysis of the effect of dietary fat on enteric methane production, digestibility and rumen fermentation in sheep, and a comparison of these responses between cattle and sheep. Livestock Science, 162, 97-103.

36. Rao, A., Srivinas, V. V. 2006. Regionalization of watersheds by fuzzy cluster analysis. Journal of Hydrology, 318, 57-79.

37. 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.

38. Sharma, S. 1996. Applied Multivariate Techniques. John Wiley and Sons Inc., New York, 512p.

39. Shukla, P.R., Skea, J., Slade, Van Diemen, R., Haughey, E., Malley, J., Pathak, M., Portugal Pereira, J., 2019. Technical Summary. Climate Change and Land: an IPCC special report on climate change, desertification, land degradation, sustainable land management, food

security, and greenhouse gas fluxes in terrestrial ecosystems, Intergovernmental Panel on Climate Change.

40. 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 *Evaluating Climate Change Action for Sustainable Development* (pp. 255-269). Springer, Cham.

41. Steffen, W., Richardson, K., Rockström, J., Cornell, S. E., Fetzer, I., Bennett, E. M., Folke, C., 2015. Planetary boundaries: Guiding human development on a changing planet. Science, 347(6223).

42. Stokes, C., Howden, M. (Eds.). 2010. *Adapting agriculture to climate change: preparing Australian agriculture, forestry and fisheries for the future*. CSIRO publishing.

43. Stringer, L. C., Fraser, E. D., Harris, D., Lyon, C., Pereira, L., Ward, C. F., Simelton, E. 2020. Adaptation and development pathways for different types of farmers. Environmental Science & Policy, 104, 174-189.

44. Swart, R. 2008. Impacts of Europe's changing climate-2008 indicator-based assessment, European Environment Agency (EEA).

45. Tatlıdil, H. 1996. Uygulamalı Çok Değişkenli İstatistiksel Analiz, Ankara: Cem Web Ofset Ltd.

46. TCMB. 2022. Döviz kurları. https://www.tcmb.gov.tr/bilgiamackur/kur2021_tr.html

47. Theodoridis, A., Ragkos, A., Roustemis, D., Arsenos, G., Abas, Z., Sinapis, E. 2014. Technical indicators of economic performance in dairy sheep farming. Animal: an International Journal of Animal Bioscience, 8, 1, 133.

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

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

50. 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.

51. Voss, U., Holzmann, R., Tuin, I., Hobson, A. J. 2009. Lucid dreaming: a state of consciousness with features of both waking and non-lucid dreaming. *Sleep*, *32*(9), 1191-1200.

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

53. 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.

54. Wilson GA (1996) Factors influencing farmer participation in the environmentally sensitive areas scheme. J Environ Manag 50:67–93

55. Wilson GA, Hart K (2001) Farmer participation in agri-environmental schemes: towards conservation orientated thinking? Sociol Rural 41:254–274

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