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ARAŞTIRMA MAKALESİ **RESEARCH ARTICLE**

Evaluation and Potential Analysis of Saving Opportunities in Agricultural Enterprises

Tarım İşletmelerinde Tasarruf Fırsatlarının Değerlendirilmesi ve Potansiyel Analizi

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Abstract

The primary objective of this study is to assess potential savings opportunities in agricultural enterprises and to determine their feasibility. To this end, face-to-face interviews were conducted with 268 agricultural enterprises in Turkey, selected according to the stratified random sampling method. The results of the interviews revealed the amount of savings accrued by agricultural enterprises and the factors influencing the formation of savings. The data obtained was then used to determine the savings potential of agricultural enterprises using artificial neural networks. The classification analysis in the artificial neural network model enables the prediction of the savings potential of enterprises by classifying them according to all the variables included in the model, in comparison to the classification made with the existing data. This approach allows for the consideration of not only financial indicators but also socio-economic factors, personal factors and environmental factors in determining savings policies, thereby revealing the actual potential of the enterprises. To determine the savings potential of the analyzed enterprises, 29 different models in 9 model classes were tested. Consequently, the model class with the highest accuracy was identified as decision trees. The accuracy of decision trees varies between 82.5% and 85.1%. While 62.69% of the enterprises exhibited high savings because of the modelling process, this value was determined as 60.8% because of the prediction model. Furthermore, the proportion of enterprises with low savings, which was estimated at 32.84% in the data model, was found to be 35.8% in the prediction model. Additionally, the proportion of enterprises with negative savings was determined to be 4.48% in the data model and 3.4% in the prediction model. The study identified the structural, social and economic characteristics of enterprises according to their savings structures and evaluated potential for increasing savings. It was determined that agricultural enterprises should focus on ways to increase savings, increase income, keep expenses under control and make investments for the future. Efficient farming techniques, the formation of agricultural cooperatives and marketing associations, the reduction of energy and input costs, the effective utilization of agricultural machinery, and the investment in renewable energy sources could assist agribusinesses in increasing their economic security and sustainability. All these steps enable agricultural households to have a stronger and more sustainable financial structure and contribute to the economic development of rural areas.

Keywords: Savings, Agricultural enterprises, Artificial neural networks

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Öz

Bu çalışmanın temel amacı tarım işletmelerinde tasarruf fırsatlarının değerlendirilmesi ve potansiyellerinin belirlenmesidir. Bu amaca yönelik olarak Türkiye'deki tabakalı tesadüfi örnekleme yöntemine göre belirlenen 268 tarım işletmesiyle yüz yüze anket yöntemiyle mülakatlar yapılmıştır. Mülakatlar sonucunda tarım işletmelerinin tasarruf miktarları ve tasarrufların oluşumları üzerindeki etkili olan faktörler belirlenmiştir. Elde edilen veriler sonucunda tarım işletmelerinin tasarruf potansiyellerini belirlemek için yapay sinir ağları kullanılmıştır. Yapay sinir ağları modelinde sınıflandırma analizi mevcut verilerle yapılan sınıflandırmaya karşı modele dahil edilen tüm değişkenlerle birlikte işletmeleri sınıflandırarak işletmelerin tasarruf potansiyellerine yönelik tahminlerde bulunmaktadır. Böylece tasarruf politikalarının belirlenmesinde sadece finansal göstergeler değil aynı zamanda sosyo-ekonomik faktörler, kişisel faktörler ve çevresel faktörler de göz önünde bulundurularak gerçek potansiyeller ortaya çıkarılmıştır. İncelenen işletmelerde tasarruf yapma potansiyellerini belirlemek amacıyla 9 model sınıfında farklı 29 model test edilmiştir. Buna göre en yüksek doğruluk payına sahip model sınıfı karar ağaçları olarak belirlenmiştir. Karar ağaçlarının doğruluk payları %82,5-%85,1 arasında değişmektedir. Yapılan modelleme sonucunda işletmelerin %62,69'u yüksek tasarrufa sahip iken tahmin modeli sonucunda bu değer %60,8 olarak belirlenmiştir. Ayrıca veri modelinde %32,84 olarak belirlenen düşük tasarruflu işletmelerin oranı tahmin modelinde %35,8 olarak tespit edilmiş olup negatif işletmelerin oranı veri modelinde %4,48 ve tahmin modelinde %3,4 olarak bulunmuştur. Çalışmanın sonucunda tasarruf yapılarına göre işletmelerin yapısal, sosyal ve ekonomik özellikleri küme halinde gösterilerek tasarruf potansiyellerinin artırılmasına yönelik değerlendirmeler yapılmıştır. Çalışma sonucunda tarım işletmelerinin tasarrufu artırma yolları, gelir artırma, giderleri kontrol altında tutma ve geleceğe yönelik yatırımlar yapma üzerine odaklanması gerekliliği belirlenmiştir. Verimli tarım teknikleri kullanmak, tarım kooperatifleri ve pazarlama birliklerine katılmak, enerji ve girdi maliyetlerini azaltmak, tarım makinelerini etkili bir şekilde kullanmak ve yenilenebilir enerji kaynaklarına yatırım yapmak gibi stratejiler, tarım işletmelerinin ekonomik güvenliği ve sürdürülebilirliklerini artırmalarına yardımcı olabilir. Tüm bu adımlar, tarım hane halklarının daha güçlü ve sürdürülebilir bir finansal yapıya sahip olmalarını sağlar ve kırsal kesimin ekonomik kalkınmasına katkıda bulunabilir.

Anahtar Kelimeler: Tasarruf, Tarım işletmeleri, Yapay sinir ağları

1. Introduction

Agriculture, a basic sector, has always been strategic due to its direct contribution to the service sector and raw materials to industry. Although the share of the industrial and service sectors in national economies has increased with the new market conditions, agriculture provides nutrition and food sources for necessities in many areas. For this reason, as the economy becomes more globalized, the agricultural sector has begun to meet international standards, just like other sectors. This change has also affected the financing sources used by agricultural enterprises, which are the smallest structure in the agricultural sector (Njegomir et al., 2017; Sãžrbulescu et al., 2015).

Financing sources in the agricultural sector are examined in two sections: internal and external financing sources. Internal financing in agricultural enterprises consists of two components: auto finance and equity capital. Auto financing is the fund created with the income generated by the enterprises and their internal resources, and while reducing the demand for external financing sources, it also contributes to the independent decision-making of enterprises, ensuring their financial security and reducing the debt burden and interest costs. However, the structural issues in agriculture necessitate the inclusion of external financing sources in the development of financing strategies. To benefit from the financial benefits, particularly in the context of corporate development and expansion, it is essential to use foreign cash. Therefore, rational capital utilization necessitates a balance between financing models, with auto financing instruments being the primary choice due to their ability to manage interest burdens, financial risks, cash flow challenges, and safeguard the enterprise's credit rating (Naranchimeg et al., 2023; Гринюк et al., 2023).

Internal borrowing, stock increases, asset sales, and dividend sales are all commonly used as auto financing instruments. However, the auto financing instruments that enterprises can use may differ according to the size, sector, financial situation, and objectives of the enterprise. Considering the structural and economic characteristics of the agricultural sector, savings come to the forefront among self-financing instruments.

Savings in the agricultural sector refers to income that is not consumed in the current year but is held for future investment, consumption, or unforeseen circumstances (Bayramoğlu et al., 2023; Erdem, 2017; Karagöl and Özkan, 2014; Sancak and Demirci, 2012; Zengin et al., 2018). Savings serve as a strategy to mitigate unforeseeable future risks. Therefore, saving is a crucial economic practice for households to maintain their financial stability. Subsistence farmers make up a significant portion of agricultural enterprises. Subsistence farming enterprises have very limited capital and are defined as enterprises that use traditional methods in carrying out production activities and have low land and labor productivity. For this reason, the social purpose of subsistence farms takes precedence over the profit purpose. In recent years, there have been difficulties in meeting the basic needs of family members in enterprises due to increasing population pressure, climatic differences, market uncertainties, and input costs. Because of this, agricultural enterprises' income decreases, resulting in negative savings (Loiko et al., 2019; Uddin et al., 2014; Wang et al., 2009).

Many studies have been conducted so far to solve the paradox caused by the increase in income and decrease in savings. These studies have analyzed the saving behavior of rural and urban households and the factors affecting these behaviors. In particular, Hamaker and Patrick (1996), in their study in Indiana, showed that agricultural operators maintained their current behavior towards savings, while Spence and Mapp (1976) conducted a study to measure the savings behavior of farmers in Oklahoma. Léon and Rainelli (1976) found that climatic factors, natural disasters and uncertainty in agricultural markets force agricultural operators to save more than operators in other sectors. Jensen and Pope (2004) find a significant relationship between increased saving tendencies and greater income risk. Mapesa (2015) finds that the existence of financial programs increases savings, while Teshome et al. (2013) find that savings channels in the agricultural sector are informal sources. Nayak (2013) found that the lowest income groups (agricultural sector) have the highest marginal propensity to consume and therefore the lowest marginal propensity to save. Maheshwari (2016) stated that rural communities tend to save less. Gikonyo et al. (2022) argue that household savings provide an opportunity to build sufficient capital for farm investments and are useful for technology adoption. Argue that saving is the most important strategy to cope with risk in rural households in Nyando, while other studies (Abegunde et al., 2019; Aryal et al., 2018; Kurgat et al., 2020; Pagliacci et al., 2020; Sönmez and Artukoğlu, 2021; 2022) reveal that household savings in the agricultural sector are not sufficient. As can be understood from the literature, empirical models have been used to examine saving behavior and the factors affecting it and saving enterprises have been identified with the help of financial data. However, savings, which is the portion of income remaining from expenditures, is constantly changing due to the socio-economic and structural characteristics of agriculture and differs from firms in other sectors. Therefore, the main objective is to classify agricultural enterprises by taking these differences into account and the savings potential of agricultural enterprises has been quantitatively measured by considering economic, social and environmental factors.

2. Materials and Methods

Konya province, which is the research region, is considered the capital of agriculture due to its ecological and geographical characteristics. Konya, which is considered the province with the highest capital mobility due to its economic and structural characteristics, has a total population of 106,833 enterprises. For this reason, the stratified random sampling method was used for sampling. Consequently, (Yamane, 1967) determined the number of samples to be 268. After determining the number of samples, a model was created to determine the savings potential of agricultural enterprises. The most appropriate method for this model was determined to be artificial neural networks. As a matter of fact, artificial neural networks, which have advantages such as learning, generalization, nonlinearity, fault tolerance, adaptation, and parallelism, are used in medical applications such as image and signal processing, disease prediction, and in many different application areas such as engineering, production, finance, optimization, and classification (Altaş and Gülpınar, 2012; Karahan, 2011; Sabancı et al., 2012; Taner et al., 2015; Yüksek, 2007). In this study, the savings potential of agricultural enterprises was classified with the help of artificial neural networks.

Classification analysis in artificial neural networks model makes predictions about the savings potential of enterprises by classifying enterprises with all variables included in the model against the classification made with existing data (Akal and Umut, 2022; Baitu et al., 2023; Bayramoğlu et al., 2023; Kayabasi et al., 2018; Kujawa and Niedbała, 2021). For example, because of the classification of enterprises with savings potential with existing financial data using artificial neural network methodology, it can be determined that the savings potential will be low or non-existent. In this way, not only financial indicators but also socio-economic factors, personal factors and environmental factors are taken into consideration in determining savings policies and real potentials are revealed.

In order to assess the potential for cost reductions in the evaluated businesses, a total of 29 distinct models from 9 different model categories were examined (*Table 1*). Accordingly, the model class with the highest accuracy was determined as decision trees. The accuracy of decision trees varies between 82.5% and 85.1%. Decision trees are among the most widely used classification techniques (Aktürk et al., 2012; Alan, 2014; Altaş and Gülpınar, 2012; Edwards-Murphy et al., 2016; Kadirhanoğulları et al., 2021; Kavzoğlu and Çölkesen, 2010; Waheed et al., 2006; Wu et al., 2009). Decision trees are used to predict targets by applying many tests during data analysis. Each test creates a branch of the decision tree, and these branches continue the tests to form new subsets. The rules formed as a result of these tests, which continue until the last leaf node, have an if-then structure and are frequently used with decision trees to identify the items that can be members of a cluster, to classify various results in different categories, to predict the future, and to select the useful ones among many different variables (Bounsaythip and Rinta-Runsala, 2001; Emel and Taşkın, 2005).

In the study, the accuracy share was taken into account in deciding on the use of decision trees and it was determined that the model with the highest accuracy was decision trees. In explaining the decision tree method, the most appropriate socio-economic data obtained from agricultural enterprises were selected and the variable set created is shown in *Table 2*. In the variable set where the symbol, type and classification criteria of each variable are shown, the data are classified as continuous and categorical. Classification was made according to the savings potential of enterprises and savings were divided into 3 classes in the data model. Accordingly, if the savings rate is less than 0, it is classified as "No Savings", if it is between 0-50, it is classified as "Low Savings" and if it is between 50-100, it is classified as "High Savings".

Table 1. Accuracy Shares and Explanations of Models Available for Classification Analysis

Model Classification	Model	Share of Accuracy	Mean
Tree	Fine Tree	%85.1	Decision trees are the most widely used classification technique. This technique allows the data set to be divided into smaller clusters according to rules.
	Medimum Tree	%85.1	
	Coarse Tree	%82.5	
Discriminant	Linear Discriminant	%60.8	Discriminant analysis is the classification algorithm to try because it is fast, accurate and easy to interpret. Discriminant analysis is used for large datasets and assumes that different classes produce data based on different Gaussian distributions.
Naive Bayes	Kernel Naive Bayes	%66.8	Bayes' theorem is used in this classification algorithm, which assumes that predictors are conditionally independent.
SVM	Linear SVM	%75.0	Support Vector Machines (SVM) classify data by finding the best hyperplane that separates data points of one class from data points of another class. For an SVM, the best hyperplane means the one with the largest margin between the two classes.
	Quadratic SVM	%79.5	
	Qubic SVM	%78.7	
	Fine Gaussian SVM	%62.7	
	Medium Gaussian SVM	%75.4	
	Coarse Gaussian SVM	%62.7	
KNN	Fine KNN	%58.6	Nearest neighbor classifiers typically have good prediction accuracy in low dimensions but are not easy to interpret due to their high memory usage.
	Medium KNN	%68.3	
	Coarse KNN	%65.7	
	Cosine KNN	%67.2	
	Cubic KNN	%64.6	
	Weighted KNN	%67.9	
Ensemble	Boosted Trees	%62.7	Ensemble classifiers combine results from many weak learners into a single high-quality ensemble model. The qualities depend on the choice of algorithm.
	Bagged Trees	%84.7	
	Subspace Discriminant	%71.6	
	Subspace KNN	%79.9	
	RUSBoosted Trees	%76.9	
Neural Network	Narrow Neural Network	%75.7	Neural network models typically have good prediction accuracy and can be used for multi-class classification; however, they are not easy to interpret. Model flexibility increases with the size and number of fully connected layers in the neural network.
	Medium Neu. Net.	%78.7	
	Wide Neu. Net.	%83.6	
	Bilayered Neu. Net.	%79.1	
	Trilayered Neu. Net.	%73.5	
Kernel	SVM Kernel	%79.5	Kernel classification models are high-dimensional transformed predictive models using low-dimensional predictors.
	Logistic Regression Kernel	%72.0	

Table 2. Variable Set Used in the Classification Model

Variable Name	Type	Classification
Age	Continuous	Year
Education	Categorical	0: Illiterate, 1: Literate, 2: Primary school, 3: Secondary school, 4: High school, 5: University
Number of Households	Categorical	Number of People
Experience	Continuous	Year
Social Security	Categorical	0: None, 1: Social Insurance Institution, 2: Social Security Organization for Artisans and Self-Employed, 3: Pension Fund, 4: Green Card
Land Size	Continuous	Decare
GDP	Continuous	US $
Gross Profit	Continuous	US $
Disposable Agricultural Income	Continuous	US $
Non-Agricultural Income	Continuous	US $
Total Revenue	Continuous	US $
Household Expenditures	Continuous	US $
Loan Utilization Amount	Continuous	US $
Support Amount	Continuous	US $
TARSIM	Categorical	1: No Insurance, 2: Insurance
Contract Production	Categorical	1: No Contracted Production, 2: Contracted Production
Number of Organization Members	Continuous	Quantity
Health Status	Categorical	1: Not good at all, 2: Not good, 3: Fair, 4: Good, 5: Very good
Youth dependency ratio	Continuous	Percentage Rate
Elderly dependency ratio	Continuous	Percentage Rate
Farmer registration system	Categorical	1: Not registered with the FRS, 2: Registered with the FRS
Record Keeping	Categorical	1: No Records, 2: Keeps Records
Risk Perception	Categorical	1: Does Not Take Risk, 2: Takes Risk
Marketing Channels	Categorical	1: Broker, 2: Trader, 3: Cooperative, 4: Processing Plant, 5: Export, 6: Retail, 7: Direct Sales, 8: Regional Marketing (Store, Hotel, etc.)
Sales Methods	Categorical	1: Advance, 2: Term, 3: Mixed
Sales Times	Categorical	1: Immediately after harvest, 2: 1 month after harvest, 3: 3 months after harvest, 4: 6 months after harvest, 5: I use it in my own business
Social Assistance to Other Households	Continuous	US $

3. Results and Discussion

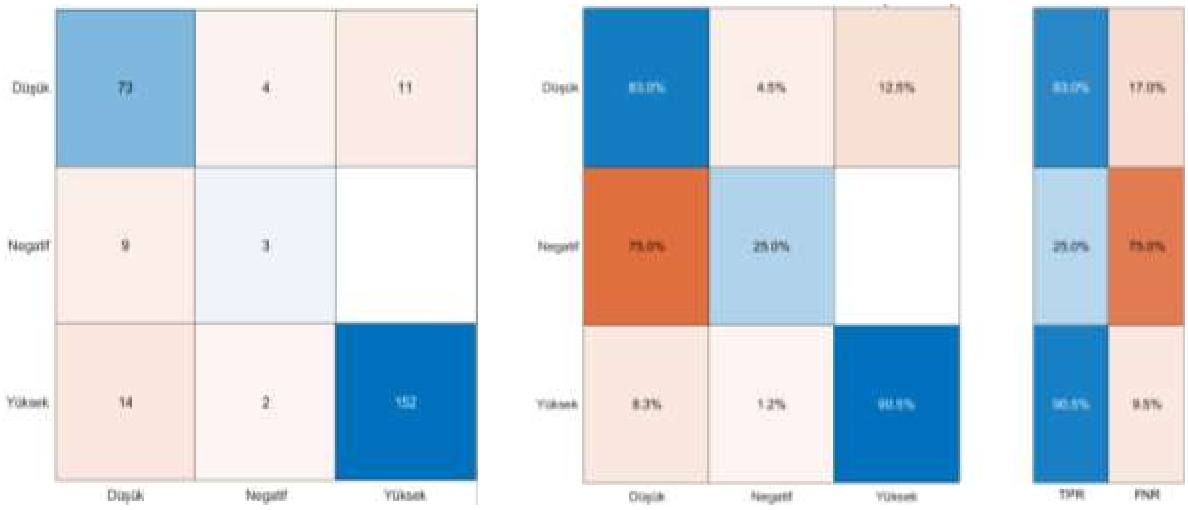
Agricultural enterprises calculate total income by calculating disposable agricultural and non-agricultural income from annual activity results, and then subtract consumption expenditures from this income to calculate savings amounts (Karaaslan et al., 2022; Kozera et al., 2016; Lidi et al., 2017; Strzelecka and Zawadzka, 2023; Zeng et al., 2023). Various theories test the obtained savings rates, concluding that the amount of savings varies with income. However, as is well known, countries or businesses are moving beyond traditional economic models and focusing on understanding the way people make economic decisions and their behavior. Traditional economics assumes that people are always rational, income-oriented, and perfectly informed. However, in real life, people's behavior does not conform to rational expectations and evolves in different ways depending on economic stability, social environment, cultural factors, and psychological thought patterns. Therefore, for a better understanding of saving behavior, it is necessary to examine it with a behavioral economics approach. This approach aims to explore the broader factors behind economic decisions by addressing people's emotional reactions, limited rationality, biases in decision-making processes, and behavioral patterns. As a result, it is unrealistic to consider only income and expenditures and measure saving behavior without considering other variables such as personal, financial, and environmental factors. Traditional economic behavior measures such a calculation, requiring integrated models to capture the complexity and unpredictability of people's decision-making in the real world. These models aim to adopt an approach that takes into account not only financial indicators, but also all indicators of behavioral, psychological, social, and environmental adaptation. For this reason, socio-economic and environmental criteria were utilized to determine the savings potential of agricultural enterprises, or, in other words, to reveal their real potential. With the help of the criteria determined, a classification model that takes into account all factors were used. The most widely used classification model in recent years has been artificial neural networks. This model classifies the data by utilizing the common features present in the data. The artificial neural network model classifies the enterprises using all model variables against the existing data classification, thereby estimating their savings potential. To determine the savings potential of enterprises, 29 different models were tested in 9 model classes. The model class with the highest accuracy was determined as a decision tree. The accuracy of decision trees ranged from 82.5% to 85.1%.

Table 3 displays the descriptive statistics of the variables used in the model. According to the obtained data, the average age of the operators is 52 years old, the majority are primary school graduates, there are 3.73 households, and they have been engaged in agriculture for an average of 28 years. Their land size is 281 decares, their total income is $56494.88, and their household expenditures are $10908.74

Table 3. Descriptive Statistics of the Model

	Minimum	Maximum	Average	Standard Deviation
Age	18.00	77.00	51.8209	13.40
Education	.00	4.00	1.7649	.96
Number of Households	1.00	10.00	3.7388	1.85
Experience	3.00	60.00	28.7649	13.39
Social Security	.00	3.00	1.3582	.55
Land Size	.00	4.200.00	281.6604	354.02
GDP	5.610.23	720.494.93	93.808.86	107.082.62
Gross Profit	5.972.32	530.322.04	64.375.24	85.721.92
Disposable Agricultural Income	9.303.82	516.498.65	5.3715.58	75.668.55
Non-Agricultural Income	0	58.605.17	2.779.30	5.293.95
Total İncome	2.631.60	530.756.24	56.494.88	76.018.04
Household Expenditures	1.198.65	30.642.51	10.908.74	6.575.23
Loan Utilization Amount	0	337.457.81	19.402.98	3.6315.79
Support Amount	0	158.098.98	4.049.37	14.522.08
TARSIM	.00	2.00	1.7500	.44
Contract Production	1.00	3.00	1.7388	.45
Number of Organization Members	1.00	5.00	2.6119	1.41
Health Status	1.00	5.00	3.4552	1.43
Youth dependency ratio	.00	50.00	7.4142	11.67
Elderly dependency ratio	.00	200.00	15.6604	25.90
Farmer registration system	1.00	2.00	1.0970	.29
Record Keeping	1.00	2.00	1.7537	.43
Risk Perception	1.00	5.00	3.2873	.82
Marketing Channels	1.00	8.00	2.4440	1.12
Sales Methods	1.00	3.00	1.2537	.59
Sales Times	1.00	4.00	1.2910	.57
Social Assistance to Other Households	.00	41.7257.00	34.792.3507	57.291.38

As a result of the classification analysis. it is known that 62.69% (168 enterprises) of the enterprises have high savings. 32.84% (88 enterprises) have low savings and 4.48% (12 enterprises) cannot save in the data model obtained from the available financial data (*Figure 1*). These data were obtained by subtracting total expenditures from total income. However. many studies have shown that there are many effective factors in the formation of savings in agricultural enterprises (Kozera et al., 2016; Mapesa, 2015; Nayak, 2013; Suresh et al., 2019) and in this context. the study tried to determine how effective many social. environmental and financial factors are in the formation of real savings potentials.



a b

Figure 1. Data Model Estimation (a) and Classification of Saving Potentials (b)

As a result of the modeling. 83% of the enterprises identified as low savings in the data model were correctly predicted. Of the 17% that were not predicted correctly. 4.5% do not save at all. while 12.5% have high savings potential. In the model. 75% of the enterprises with no savings were correctly estimated and 25% were incorrectly estimated. All the incorrect estimates were identified as enterprises with low saving tendency. Finally. because of the calculations. 90.5% of the enterprises classified as high savings were correctly estimated. while 9.5% were incorrectly estimated. Of those that were incorrectly estimated. 8.3% were low saving enterprises and 1.2% were enterprises with no savings at all. As a result of the evaluations made accordingly. it is seen that socio-economic factors have a significant effect on the formation of savings potentials. It is seen that enterprises with low savings have high savings potential or enterprises with high savings have low savings potential. Accordingly. it can be said that enterprises with low savings cannot use their real potential and the resources they have effectively and efficiently. It can be said that they can increase the amount of savings thanks to their knowledge and skills. Similarly. 25% of the enterprises with no savings are expected to have low savings. but it is seen that they cannot use their real potential. It can be said that external factors have an impact on the group that has high potential but is expected to have low savings. Climate. topographical structure. location of the enterprise and the high level of entrepreneurial ability. which is an endogenous factor. can be said to have a high level of savings because of these factors.

Table 4. Comparison of Data and Forecasting Models According to Enterprise Size Groups

Enterprise Sizes		**0-50**	**51-150**	**151-500**	**501-+**	**Average**
Total Revenue ($)		4.991,16	7.673,48	23.760,14	107.221,52	18.643,40
Household Consumption Exp. ($)		4.878,31	6.900,83	11.364,15	21.211,62	10.621,60
Savings Amount ($)		112.84	772.65	12.395,99	86.009,90	8.021,79
Savings Ratio		2.26	10.07	52.17	80.22	43.03
Low Saving Enterprises. Ratio	**Data Mod.**	33.33	42.31	31.72	11.11	39.80
	Estimation Mod.	50.00	46.15	32.41	11.11	34.70
High Saving Enterprises. Ratio	**Data Mod.**	55.56	46.15	68.28	85.19	55.22
	Estimation Mod.	44.44	44.87	66.90	85.19	53.36
Negative Saving Enterprises. Ratio	**Data Mod.**	11.11	11.54	0.00	3.70	12.69
	Estimation Mod.	5.56	8.97	0.69	3.70	11.94

Table 4 shows the comparison of data and estimation models according to enterprise size groups. Accordingly. while the amount of savings in enterprises with a land size between 0-50 decares was 112.84 dollar. the savings rate was determined as 2.26%. While this rate was 10.07% in enterprises with 51-150 decares. it was 52.17% in enterprises with 151-500 decares and 80.22% in enterprises with 501 and more land. Therefore. according to the

average of enterprises. the saving rate of agricultural enterprises in Konya province was determined as 43.03%. In this direction. data model and estimation models were compared according to enterprise size groups. The enterprise group with high saving rates was determined as enterprises with a land size of 501 and above in both data and estimation models. In addition. it is seen that the rate of enterprises with negative and low savings decreases as the size of the enterprise increases.

Table 5. Structural. Social and Economic Characteristics of Enterprises by Savings Structure

İndicators	Negative Saving	Low Saving	High Saving
Age	47.18	52.72	54.60
Education	2.00	2.23	2.77
Number of Households	3.27	3.17	3.09
Experience	24.73	26.85	28.99
Social Security	1.27	1.40	1.34
Land Size	128.09	181.43	346.45
GDP	26.803,82	37.811,36	130.623,70
Gross Profit	7.500,66	17.361,95	95.325,37
Disposable Agricultural Income	5.439,94	11.721,70	81.190,79
Non-Agricultural Income	2.302,18	3.164,45	2.589,38
Total Revenue	7.742,14	14.886,15	83.780,17
Household Expenditures	2.817,59	3.013,60	2.873,53
Loan Utilization Amount	6.544,63	15.249,62	22.665,92
Support Amount	139.13	95.26	159.93
TARSIM	1.64	1.48	1.34
Contract Production	1.32	1.48	1.71
Number of Organization Members	2.51	2.63	3.27
Health Status	3.13	3.48	3.82
Youth dependency ratio	9.82	7.46	7.23
Elderly dependency ratio	5.45	16.16	16.06
Farmer registration system	1.18	1.27	1.40
Record Keeping	1.33	1.58	1.74
Risk Perception	3.07	3.27	3.30
Marketing Channels	2.27	2.53	2.70
Sales Methods	1.36	1.22	1.16
Sales Times	1.27	1.35	1.66
Social Assistance to Other Households	837.28	1.848,28	5.312,32

Table 5 compares the structural. social and economic characteristics of agricultural enterprises according to their savings structure. This comparison was prepared in line with the data obtained according to the saving prediction models of the enterprises. Accordingly. when the characteristics of the enterprises according to their savings structure are analyzed. it can be said that the enterprises with negative savings are managed by young operators and have low education levels and land sizes. In addition. while their income is lower than other enterprises. their per capita household expenditures are lower. It can be said that institutional skills such as contracted production. agricultural insurance and membership to organizations are weak in this group of enterprises. which are seen to be inadequate in the use of financial resources. Enterprises with low savings show higher economic and social adaptation flexibility than enterprises with negative savings. These enterprises show higher resilience against possible risks than the enterprises in the first group. However. their sustainability is likely to be jeopardized in case of a crisis. High-savings enterprises. on the other hand. are characterized by the presence of highly educated managers. effective cost management. high profitability and efficient supply chains. while having more experienced managers than other enterprises. High-savings businesses are those that manage costs effectively and develop strategies to increase revenues. These enterprises balance the production and supply process by carefully evaluating their investments and projects through cost-performance analysis. At the same time. they show high sensitivity to potential risks by using technology effectively and implementing risk strategies. They continuously develop their workforce by emphasizing the training and development of households. They focus on income-enhancing strategies and are careful in debt management. They avoid the accumulation of idle

stocks by effectively managing idle labor and capital with rational resources. All these characteristics help high-saving enterprises to achieve sustainable success and gain competitive advantage.

4. Conclusions

The use of savings in agricultural enterprises is critical for financial security and sustainable development. Agribusinesses save money by finding a balance between income levels and costs. Increasing agricultural incomes, controlling expenses, and efficiently using resources enable agribusinesses to achieve savings. These savings provide financial security against emergencies and build strong resilience to fluctuations in agricultural activities. Simultaneously, savings fuel long-term objectives like enhancing household members' education and health, as well as modernizing agribusinesses. Therefore, we should analyze the savings potential of agricultural enterprises to ensure a more stable development of rural areas.

The studies conducted so far have evaluated the enterprises' savings potential based on the data obtained from the activity results. However, we should evaluate agricultural enterprises alongside households, incorporating all personal, environmental, and economic factors to uncover the true potential of the operators. According to the data model, 62.69% of the enterprises had high savings, but the estimation model determined this value to be 60.8%. Additionally, the estimation model determined the rate of enterprises with low savings from 32.84% in the data model to 35.8%, while the data model found the rate of negative enterprises to be 4.48% in the data model and 3.4% in the estimation model. The study also compared the data and estimation models based on enterprise size groups. Accordingly, the difference between the data and prediction models was high in small-scale agricultural enterprises, but the deviations between the models decreased as the enterprise scale increased. Especially in the fourth group of agricultural holdings, no deviation was observed. This provides another indication of enterprise record consistency. As a matter of fact, as the scale of the enterprise increases, it is easier to measure the real potential of the enterprise with increasing specialization and registration.

In the study, after determining the savings potential of agricultural enterprises, the structural, social, and economic characteristics of the enterprises were clustered according to their savings structures. As a matter of fact, structures and patterns in the data sets were discovered by bringing together data points with similar characteristics in agricultural enterprises shown in three clusters. The evaluations provided information such as the demographic, structural, production, and marketing strategies of the enterprises, which contributed to the improvement of the decision-making process. As a result, ways to increase savings in agricultural enterprises are important in terms of ensuring economic security, conducting sustainable agricultural activities, and making investments for the future. Agricultural enterprises should utilize alternative income models for this purpose. Increasing productivity, growing quality products, and improving marketing strategies will contribute to achieving higher savings. At the same time, by joining agricultural cooperatives and marketing associations, they can increase their savings by taking advantage of collective marketing. Second, keeping costs under control is important. Steps such as waste management, efficient energy and water use, and optimizing input costs help to reduce expenses. Furthermore, reducing fuel and maintenance costs and avoiding idle expenditures through the effective use of agricultural technologies will also be effective in achieving savings. Third, agribusinesses can use savings to make future investments. Investing in education and skilled labor can increase the productivity of agribusinesses, while investing in modern agricultural equipment improves production processes and reduces costs.

As a result, the ways in which agribusinesses can increase savings focus on increasing income, keeping expenses under control, and investing for the future. Strategies such as using efficient farming techniques, joining agricultural cooperatives and marketing associations, reducing energy and input costs, using farm machinery effectively, and investing in renewable energy sources help agricultural households increase their economic security and sustainability. Savings for future-oriented investments are critical for modernizing agribusinesses and increasing their competitiveness. All these steps enable agricultural households to have a stronger and more sustainable financial structure and contribute to the economic development of rural areas.

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Ethical Statement

This study was prepared under the permission numbered E.85699. dated 17/06/2021. from the Ethics Committee of Selcuk University." One of the phrases must be used.

Conflicts of Interest

We declare that there is no conflict of interest between us as the article authors.

Authorship Contribution Statement

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