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Original article

The Impact of Agricultural Mechanisation on Production and Labour in Türkiye: 2005–2024

Ecehan Kazancı Yabanova *

Department of Labour Economics and Industrial Relations, Institute of Social Science, Süleyman Demirel University, Isparta, Türkiye

Abstract

Food supply security in agricultural production is becoming an increasingly important issue for societies. In this context, developed and developing countries are creating stronger investment areas for machinery and equipment used in agricultural activities. Particularly in the last quarter of a century, the increase in the production of these tools, the reduction in their costs, and the provision of their affordability have enabled their acquisition by a greater number of people within the agricultural sector. Recent developments in technologies such as artificial intelligence, robotics, autonomous systems, and unmanned vehicles have also found extensive application in the field of agricultural machinery. This entire mechanisation process is explained by agricultural mechanisation. The aim of this study is to reveal the effects of changes in agricultural mechanisation between 2005 and 2024, covering the last 20 years of data in Türkiye, on agricultural production and labour. To this end, data on agricultural mechanisation, tractors, combine harvesters, and other agricultural tools were converted into a mechanisation index using Principal Component Analysis and analysed using linear regression with agricultural production and labour force data. Agricultural production was analysed using statistics on cereals and other crop products, as well as fruit, beverage, and spice crop production. Labour force data registered under insurance types 4-A and 4-B were also analysed. The study found that agricultural mechanisation has a positive and very strong effect on the production quantities of cereals and other plant products, as well as fruits, beverages, and spice plants, which are indicators of agricultural production. It was determined that it has a very strong and negative effect on the labour force.

Keywords: Agricultural Mechanisation, Agricultural Production, Labour Force.

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* **Corresponding author:**

Ecehan Kazancı Yabanova, completed her doctorate in Isparta Süleyman Demirel University, Department of Labor Economics and Industrial Relations. She works in the fields of labor law, Employee training and occupational health and safety.
Email: ecehankazanci@gmail.com

INTRODUCTION

Agriculture, one of the most fundamental and strategic areas in human history, has been shaped by agricultural activities since the beginning of the Neolithic Age, with the cultivation of the land and the domestication of certain plant and animal species in different and limited regions of the world (Mazoyer & Roudart, 2006). Following the Industrial Revolution, the widespread adoption of agricultural mechanisation and the integration of scientific developments into production led to a transformation in agriculture and increased productivity (Ali et al., 2024; Kortak & Çakır, 2025). Agriculture, one of the oldest livelihoods in human history, has undergone changes and developments over time. In this regard, traditional farming methods based on human and animal power were replaced by the widespread mechanisation of production with the Industrial Revolution, leading to increases in agricultural productivity and production capacity (Tutar et al., 2025). The agricultural sector is indispensable to human life, relying on various basic inputs ranging from seed selection to fertilisation, agricultural mechanisation to energy use in plant and animal production processes. At this point, the effective use of these inputs also contributes to increasing yield per hectare or per animal (Özkan & Dilay, 2025).

In Türkiye, as a result of the support provided under the Marshall Plan after the 1950s, agricultural mechanisation gained momentum, and the widespread use of tractors reduced the agricultural workforce while enabling the expansion of cultivated areas (Sezer, 2025). Between 1949 and 1952, known as the Green Revolution and Marshall Aid Plan, synthetic fertilisers and pesticides, as well as tractors, contributed to the modernisation of agricultural production in Türkiye. These innovations have helped to expand agricultural areas and increase productivity within geographical diversity (Öztürk & Çelik, 2024; Sabancı, 1990). The decline in the agricultural workforce in Türkiye, rural migration, rising input costs, and the negative effects of climate change have made investments in agricultural mechanisation even more critical. In this regard, "agricultural mechanisation" stands out as an important policy tool in terms of both increasing production capacity and reducing labour costs (Özpınar, 2020).

Due to global population growth, rising food demand, the various effects of climate change, and declining labour in rural areas, ensuring sustainability in agricultural production has become an important issue worldwide. In this context, agricultural mechanisation has become a strategic tool for the more effective use of production processes, transformation of the labour force structure, and sustainability of productivity (FAO, 2025). The growing world population, the climate crisis, wars, global warming, migration movements, and developments on a global scale are causing both problems in accessing food and the risk of rapid depletion of natural resources (Aslan & Yavuzer-Aslan, 2025). The Food and Agriculture Organisation (FAO) predicts that the world population will reach 9.1 billion by 2050 and that this increase will bring with it problems related to access to food and nutrition ( ) (FAO, 2025).

Agricultural mechanisation refers to the replacement of human and animal labour in production processes with machinery and equipment (Yılmaz & Sümer, 2018). This transformation not only reduces the need for physical labour but also saves time, thereby reducing costs and increasing agricultural productivity (Ertekin et al., 2021; Ertuğrul, 2025). The fundamental aim of agricultural mechanisation is to reduce dependence on human labour, thereby accelerating field operations, increasing farm productivity, reducing costs, and increasing producer income (Chi et al., 2021). Mechanisation refers not only to an increase in the number of tractors but also to the integration of technological innovations into all stages of production, such as soil cultivation, sowing, maintenance, harvesting, transportation, and storage (Sims & Kienzle, 2017). The increased use of machinery in agricultural production leads to a reduction in workload and an increase in agricultural productivity and profit margins (Altıkat & Çelik, 2011). Developments in agricultural technologies have led to diversity in tractor and agricultural machinery combinations, making both productivity and the selection of the right equipment important (Saygılı & Çakmak, 2023). One of the most important parameters used to express the information of tractors and tool and machine systems, which are one of the basic power sources used in agricultural enterprises, is the level of "agricultural mechanisation" (Akbaş & Aydoğan, 2025; Gül et al., 2023).

According to the definition of the Food and Agriculture Organisation of the United Nations, agricultural mechanisation is defined as "a broad umbrella term covering mechanical, electro-mechanical and digital machines used in all stages of production." In this context, agricultural mechanisation includes irrigation systems, logistics vehicles and automation technologies, as well as tractors and harvesting machines. One of the most fundamental indicators of agricultural development is the level of agricultural mechanisation in countries (FAO, 2025; Mrema et al., 2018). Tractors, which are used as the primary power source in agricultural production, are the most critical indicator in determining the level of mechanisation (Eryılmaz et al., 2014; Saygılı & Şen, 2022). In this regard, criteria such as tractor power per unit (kw/ha), number of tractors per 1000 hectares, and number of tractors per hectare indicate the mechanisation levels of regions (Koçtürk et al., 2007). These indicators used to determine the level of mechanisation are based on two fundamental variables: tractor power and the area cultivated, and various levels of mechanisation are defined by the different combinations of these variables. At this point, the accurate calculation of the variables mentioned above enables a more sound and realistic presentation of the level of mechanisation (Gökdoğan, 2012).

Agricultural mechanisation increases the effectiveness of innovations in other agricultural technologies, enhances economic efficiency, and enables more favourable working conditions in terms of labour (Kara & Arslan, 2025). In this regard, the effective and correct use of agricultural mechanisation contributes to higher yields from agricultural areas (Özgüven et al., 2010). Agricultural productivity is defined as "the amount of output obtained per unit of input". At this point, the impact of agricultural mechanisation on productivity manifests itself in areas such as time efficiency, work quality, reduction of harvest losses, and energy efficiency (Pingali, 2007). One of the most critical inputs in agriculture is the use of modern production techniques and agricultural tools and machinery, i.e., agricultural mechanisation, which plays an important role in carrying out agricultural activities in a high-quality and rational manner and obtaining higher yields per unit area (Akbaş and Aydoğan, 2025; Korucu et al., 2015).

The development of agricultural mechanisation, which is of critical importance in increasing Türkiye's agricultural production capacity, began in the 1950s with the use of tractors. During this period, policies developed to promote the widespread use of modern machinery and equipment led to rapid mechanisation in the agricultural sector and a corresponding increase in productivity (Aydın et al., 2024; İnci, 2022). In terms of agricultural labour, while the need for labour is greater in small-scale family businesses, demand for labour may decrease in large-scale modern businesses with developments in mechanisation and technology (Şeyranlıoğlu & Han, 2025). Agricultural mechanisation has a two-way effect on labour. The first is a quantitative effect due to the reduced need for labour, and the second is a qualitative transformation in the workforce, with workers becoming more technical and knowledgeable in the use of machinery (Diao et al., 2020).

Smart agricultural technologies within agricultural mechanisation contribute to increasing agricultural productivity and optimising resource use by reducing environmental impacts and ensuring stability in production (Severoğlu, 2025). It is important to widely use digital technologies and mechanisation in all areas in order to strengthen sustainability and maximise productivity in the agricultural sector (Dayıoğlu & Turker, 2021; Yıldız & Veziroğlu, 2025). Thanks to the use of machines in agriculture, time-consuming plant production processes such as sowing, planting, maintenance, and harvesting are carried out more quickly and efficiently. Thus, all work required within the scope of agricultural techniques can be performed at the right time and effectively (Özkan & Dilay, 2024). Mechanisation increases productivity by replacing human and animal power in production processes with modern tools and machinery, while also enabling agricultural work to be carried out more comfortably, quickly and on time. This makes difficult agricultural activities easier to implement (Ateş & Çay, 2024). The level of agricultural mechanisation in countries is assessed according to criteria such as the suitability of tractors in different power groups, the numerical density of tools and machines used with tractors, and the size of the operating areas (Altuntaş & Aslan, 2009).

Significant advances in agricultural technologies over the last 20 years, the reduction in the cost of access to machinery and equipment, and the widespread use of fully autonomous, robotic, and unmanned technologies in agriculture have brought about profound changes in the agricultural mechanisation process. The aim of this study is to analyse the effects of the changes in agricultural mechanisation between 2005 and 2024, which constitute the last 20 years of the agricultural sector in Türkiye, on agricultural production and labour.

MATERIALS and METHODS

In this study, a quantitative descriptive analysis approach was used to examine the effects of changes in agricultural mechanisation between 2005 and 2024 on agricultural production and labour. Quantitative descriptive research allows patterns, trends, and variable distributions to be interpreted clearly through various analyses (Neuman, 2009). In this context, the study seeks to answer the following questions:

RQ1. How did changes in agricultural mechanisation between 2005 and 2024 affect the production of cereals and other plant products?

RQ2. How did changes in agricultural mechanisation between 2005 and 2024 affect the production of fruits, beverages, and spice crops?

RQ3. How did changes in agricultural mechanisation between 2005 and 2024 affect the labour force?

Data Collection

Within the scope of the study, data from the Turkish Statistical Institute (TÜİK) on the Number of Agricultural Tools and Machinery and Plant Production Statistics were used to analyse agricultural mechanisation and agricultural production (TÜİK, 2025). To examine the impact of agricultural mechanisation on the labour force, data from the Insured and Workplace Statistics (4-A and 4-B) reports on insured workers published by the Ministry of Labour and Social Security were used as a data source (MLSS, 2025). For data prior to 2007, data from the Social Security Institution – SGK (2007), the predecessor organisation of the institution, was used.

Data Analysis

The data obtained within the scope of the study were first compiled in Excel. Proportional changes were calculated by year. In order to determine the effect of agricultural mechanisation through regression analysis, the data on tractors, combine harvesters and other agricultural equipment included in the Agricultural Equipment and Machinery Statistics were converted into a single parameter, the mechanisation index value, by applying Principal Component Analysis. The conversion of mechanisation indicators into a single index via PCA forms the methodological basis of this study in terms of both statistical validity and literature consistency. Linear Regression Analysis was applied using the JASP statistical analysis programme to analyse the effects of agricultural mechanisation on production and labour. It is known that 20 observations are sufficient for linear regression models and econometric analyses involving annual time series (Green, 1991; Gujarati & Porter, 2009; Wooldridge, 2016). In this context, the data set included in the analyses is of sufficient size for regression analysis.

Validity and Reliability

The data set used in this study has been reported over many years by official institutions using the same statistical methods and techniques. As the statistics maintained by official institutions are produced continuously based on a common methodology, the measurements have strong temporal consistency and conceptual validity (OECD, 2011). Therefore, the long-term time series used in the study constitute a valid and reliable data set.

RESULTS and DISCUSSION

The study utilised data from the Turkish Statistical Institute (TÜİK, 2025) on the Number of Agricultural Tools and Machinery and Plant Production Statistics covering the 20-year statistical period from 2005 to 2024. At the same time, the Insured and Workplace Statistics (4-A and 4-B) published by the Ministry of Labour and Social Security (2025) and the registered labour force reports in the agricultural sector were analysed.

Changes in the number of agricultural tools and machinery were analysed by tractor, combine harvester, and other machinery and tools. Changes in the data compared to the previous calendar year were also analysed. Changes in the number of tools and machinery, which is an indicator of mechanisation in the agricultural sector, are shown in Table 1.

Table 1. Number of agricultural tools and machinery between 2005 and 2024

Year	Tractor		Combine Harvester		Other		TOTAL	
	Number	Change (%)	Number	Change (%)	Number	Change (%)	Number	Change (%)
2005	1.022.365	1,32	11.811	2,53	7.810.172	0,90	8.844.348	0,95
2006	1.037.383	1,47	12.359	4,64	7.946.831	1,75	8.996.573	1,72
2007	1.056.128	1,81	12.775	3,37	8.074.514	1,61	9.143.417	1,63
2008	1.070.746	1,38	13.084	2,42	8.221.639	1,82	9.305.469	1,77
2009	1.073.538	0,26	13.360	2,11	8.252.926	0,38	9.339.824	0,37
2010	1.096.683	2,16	13.799	3,29	8.450.395	2,39	9.560.877	2,37
2011	1.125.001	2,58	14.313	3,72	8.593.447	1,69	9.732.761	1,80
2012	1.178.253	4,73	14.813	3,49	8.781.517	2,19	9.974.583	2,48
2013	1.213.560	3,00	15.486	4,54	8.895.025	1,29	10.124.071	1,50
2014	1.243.300	2,45	15.899	2,67	9.023.930	1,45	10.283.129	1,57
2015	1.260.358	1,37	15.998	0,62	9.147.509	1,37	10.423.865	1,37
2016	1.273.531	1,05	16.247	1,56	9.280.457	1,45	10.570.235	1,40
2017	1.306.736	2,61	17.199	5,86	9.491.803	2,28	10.815.738	2,32
2018	1.332.139	1,94	17.266	0,39	9.666.593	1,84	11.015.998	1,85
2019	1.354.912	1,71	17.190	-0,44	9.821.082	1,60	11.193.184	1,61
2020	1.442.909	6,49	17.793	3,51	10.032.365	2,15	11.493.067	2,68
2021	1.481.461	2,67	19.274	8,32	10.366.303	3,33	11.867.038	3,25
2022	1.526.769	3,06	20.271	5,17	10.645.139	2,69	12.192.179	2,74
2023	1.566.045	2,57	20.786	2,54	11.194.482	5,16	12.781.313	4,83
2024	1.598.659	2,08	20.783	-0,01	11.471.579	2,48	13.091.021	2,42

The analysis revealed a 56% increase in the number of tractors, a 76% increase in the number of combine harvesters, and a 48% increase in the number of other tools and machinery over the 20-year statistical period. The highest increase was observed in combine harvesters. A high correlation was found between the numbers of tractors, combine harvesters, and other machinery representing agricultural mechanisation. Representing these variables separately in the regression model carries the risk of multicollinearity (Gujarati & Porter, 2009). Therefore, a single statistically weighted "mechanisation index" (PC1) was created using the Principal Component Analysis (PCA) Index. PCA is widely used to create a single component from highly correlated variables (Jolliffe, 2002). This method is suitable for the approach in agricultural economics literature of representing the level of mechanisation with a composite index (Pingali, 2007).

Table 2. Component Loadings

	PC1	**Uniqueness**
Tractor	0.998	0.004
Combine harvester	0.997	0.006
Others	0.997	0.006

As a result of the analysis, three variables were loaded onto a single component. The values of the three variables were multiplied by the factor loadings and summed to determine the Mechanisation PC1 value. Within the scope of the research questions, the effect of agricultural mechanisation was analysed using this value.

RQ1. How does the change in agricultural mechanisation between 2005 and 2024 affect the production of cereals and other crop products?

The study examined the effect of agricultural mechanisation on cereal production. For this purpose, data on cereals and other crop products from the Turkish Statistical Institute's crop production statistics were used. Production data for cereals and other crop products are presented in Table 3.

Table 3. Production quantities of cereals and other plant products between 2005 and 2024 (tonnes)

Year	Wheat	Barley	Maize	Sunflower	Cotton (raw)	Sugar beets	Total
2005	21.500.000	9.500.000	4.200.000	975.000	2.240.000	15.181.247	53.596.247
2006	20.010.000	9.551.000	3.811.000	1.118.000	2.550.000	14.452.162	51.492.162
2007	17.234.000	7.306.800	3.535.000	854.407	2.275.000	12.414.715	43.619.922
2008	17.782.000	5.923.000	4.274.000	992.000	1.820.000	15.488.332	46.279.332
2009	20.600.000	7.300.000	4.250.000	1.057.125	1.725.000	17.274.674	52.206.799
2010	19.674.000	7.250.000	4.310.000	1.320.000	2.150.000	17.942.112	52.646.112
2011	21.800.000	7.600.000	4.200.000	1.335.000	2.580.000	16.126.489	53.641.489
2012	20.100.000	7.100.000	4.600.000	1.370.000	2.320.000	14.919.940	50.409.940
2013	22.050.000	7.900.000	5.900.000	1.523.000	2.250.000	16.488.590	56.111.590
2014	19.000.000	6.300.000	5.950.000	1.637.900	2.350.000	16.743.045	51.980.945
2015	22.600.000	8.000.000	6.400.000	1.680.700	2.050.000	16.022.783	56.753.483
2016	20.600.000	6.700.000	6.400.000	1.670.716	2.100.000	19.592.731	57.063.447
2017	21.500.000	7.100.000	5.900.000	1.964.385	2.450.000	21.149.020	60.063.405
2018	20.000.000	7.000.000	5.700.000	1.949.229	2.570.000	17.436.100	54.655.329
2019	19.000.000	7.600.000	6.000.000	2.100.000	2.200.000	18.054.320	54.954.320
2020	20.500.000	8.300.000	6.500.000	2.067.004	1.773.646	23.025.738	62.166.388
2021	17.650.000	5.750.000	6.750.000	2.415.000	2.250.000	17.767.085	52.582.085
2022	19.750.000	8.500.000	8.500.000	2.550.000	2.750.000	19.253.962	61.303.962
2023	22.000.000	9.200.000	9.000.000	2.198.000	2.100.000	25.250.213	69.748.213
2024	20.800.000	8.100.000	8.100.000	2.195.000	2.243.000	22.413.967	63.851.967

The table shows the 20-year changes in the production quantities of wheat, barley, maize, sunflower, cotton (raw) and sugar beets. When examining the change in total production quantity, it can be seen that production has increased by 19%.

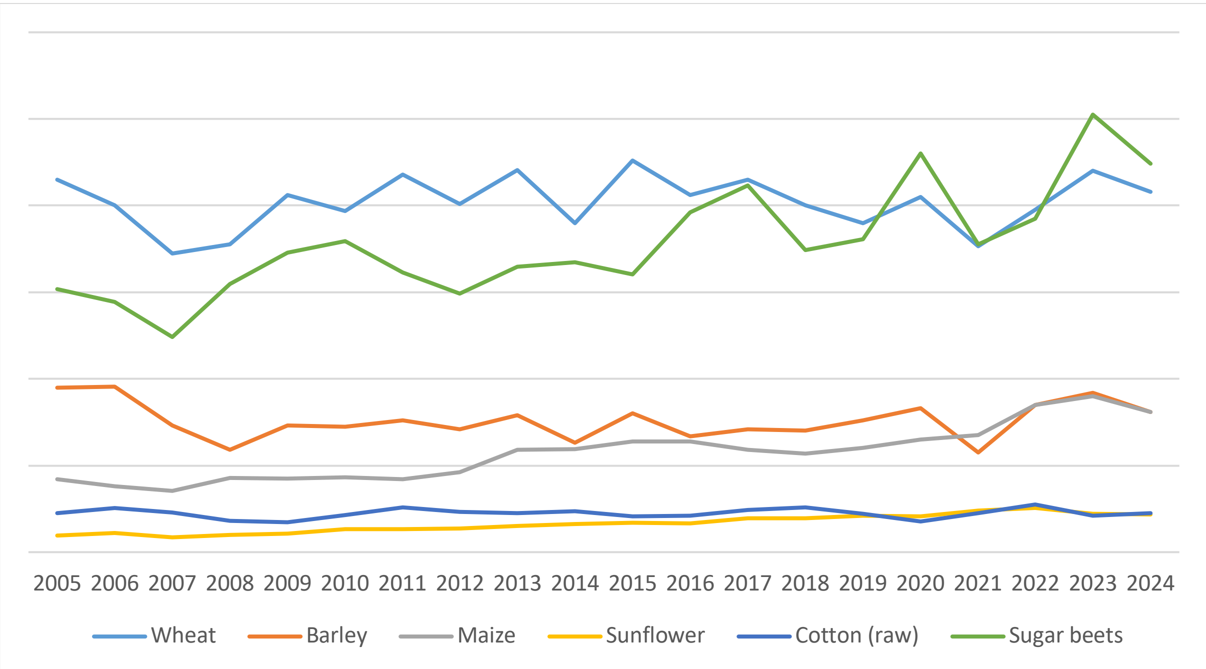

Figure 1. Production quantities of cereals and other plant products

When examining the graph of production quantities by product type, significant increases in sugar beet, sunflower and maize production are evident. Other product types show a fluctuating curve. Linear regression analysis was applied to determine the effect of agricultural mechanisation on the production quantities of cereals and other plant products.

Table 4. Model Summary – Cereals

Model	R	R²	Adjusted R²	RMSE
M_0	0.000	0.000	0.000	$6.031 \times 10^{+6}$
M_1	0.798	0.636	0.616	$3.738 \times 10^{+6}$

The analysis shows that the model mechanisation index has a very strong effect on grain production. Agricultural mechanisation explains 63.6% of the variance ($R^2 = .636$, Adjusted $R^2 = .616$). This result indicates that increases in the level of agricultural mechanisation have a strong and positive effect on grain production.

Table 5. Model fit ANOVA

Model		Sum of Squares	df	Mean Square	F	p
M_1	Regression	$4.396\times10^{+14}$	1	$4.396\times10^{+14}$	31.46	< .001
	Residual	$2.515\times10^{+14}$	18	$1.397\times10^{+13}$		
	Total	$6.910\times10^{+14}$	19			

The analysis results indicate that the regression analysis is significant for the model ($F(1,18) = 31.46$, $p < .001$). It was observed that 63.6% of the total variance was explained by regression, while the remaining 36.4% remained in the error term.

Table 6. Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p
M_0	(Intercept)	$5.526\times10^{+7}$	$1.349\times10^{+6}$		40.976	< .001
M_1	(Intercept)	$1.493\times10^{+7}$	$7.237\times10^{+6}$		2.063	.054
	Mechanization PC1	3.838	0.684	0.798	5.609	< .001

When examining the regression analysis coefficients, it is observed that agricultural mechanisation has a positive and strong effect on grain production ($B = 3.838$, $SE = 0.684$, $\beta = .798$, $p < .001$). These results reveal that agricultural mechanisation is a significant determinant of the increase in grain production.

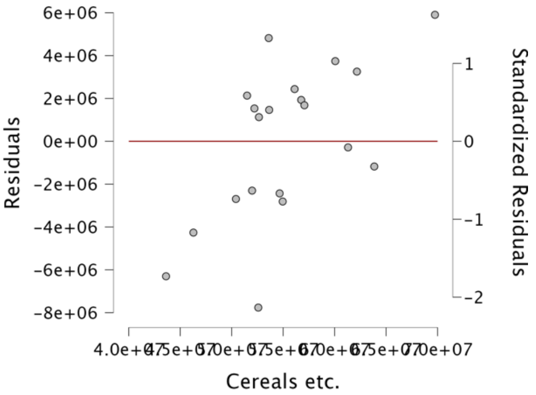

Figure 2. Residuals vs. Dependent Plots

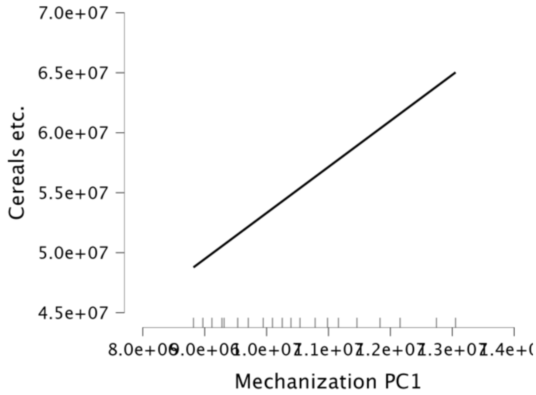

Figure 3. Marginal Effects Plots

The graph in Figure 2, which shows the relationship between grain production and residuals, reveals that the residuals are symmetrically distributed around the horizontal axis, with no systematic deviation, pattern, or directional error pattern. The graph indicates that the model works appropriately for linear regression analysis and that the residual behaviour is at an acceptable level. The Marginal Effects Plots in Figure 3 visually confirm the linear and positive relationship between grain production and mechanisation.

RQ2. How did changes in agricultural mechanisation between 2005 and 2024 affect the production of fruits, beverages, and spice plants?

Another important category in determining the effect of agricultural mechanisation on production is the analysis of the production quantities of fruits, beverages, and spice plants. The effect of mechanisation is particularly significant in this area, where the use of agricultural machinery is widespread. In this context, data on fruits, beverages, and spice plants from the Turkish Statistical Institute's (TÜİK) crop production statistics were used.

Table 7. Production quantities of fruits, beverages and spice plants between 2005 and 2024 (tonnes)

Year	Grapes	Apples	Olives	Oranges	Hazelnuts	Green tea	Total
2005	3.850.000	2.570.000	1.200.000	1.445.000	530.000	1.192.004	10.787.004
2006	4.000.063	2.002.033	1.766.749	1.535.806	661.000	1.121.206	11.086.857
2007	3.612.781	2.457.845	1.075.854	1.426.965	530.000	1.145.321	10.248.766
2008	3.918.442	2.504.494	1.464.248	1.427.156	800.791	1.100.257	11.215.388
2009	4.264.720	2.782.365	1.290.654	1.689.921	500.000	1.103.340	11.631.000
2010	4.255.000	2.600.000	1.415.000	1.710.500	600.000	1.305.566	11.886.066
2011	4.296.351	2.680.075	1.750.000	1.730.146	430.000	1.231.141	12.117.713
2012	4.234.305	2.888.985	1.820.000	1.661.111	660.000	1.250.000	12.514.401
2013	4.011.409	3.128.450	1.676.000	1.781.258	549.000	1.180.000	12.326.117
2014	4.175.356	2.480.444	1.768.000	1.779.675	450.000	1.266.311	11.919.786
2015	3.650.000	2.569.759	1.700.000	1.816.798	646.000	1.327.934	11.710.491
2016	4.000.000	2.925.828	1.730.000	1.850.000	420.000	1.350.000	12.275.828
2017	4.200.000	3.032.164	2.100.000	1.950.000	675.000	1.300.000	13.257.164
2018	3.933.000	3.625.960	1.500.467	1.900.000	515.000	1.480.534	12.954.961
2019	4.100.000	3.618.752	1.525.000	1.700.000	776.046	1.407.448	13.127.246
2020	4.208.908	4.300.486	1.316.626	1.333.975	665.000	1.450.556	13.275.551
2021	3.670.000	4.493.264	1.738.680	1.742.000	684.000	1.453.964	13.781.908
2022	4.165.000	4.817.500	2.976.000	1.322.000	765.000	1.269.546	15.315.046
2023	3.400.000	4.602.517	1.520.000	2.311.335	650.000	1.356.556	13.840.408
2024	3.468.000	4.420.185	3.750.000	1.610.000	717.000	1.450.034	15.415.219

The table shows the production quantities of grapes, apples, olives, oranges, hazelnuts and green tea. It can be seen that the total production quantity has increased by 43% over the 20-year statistical period.

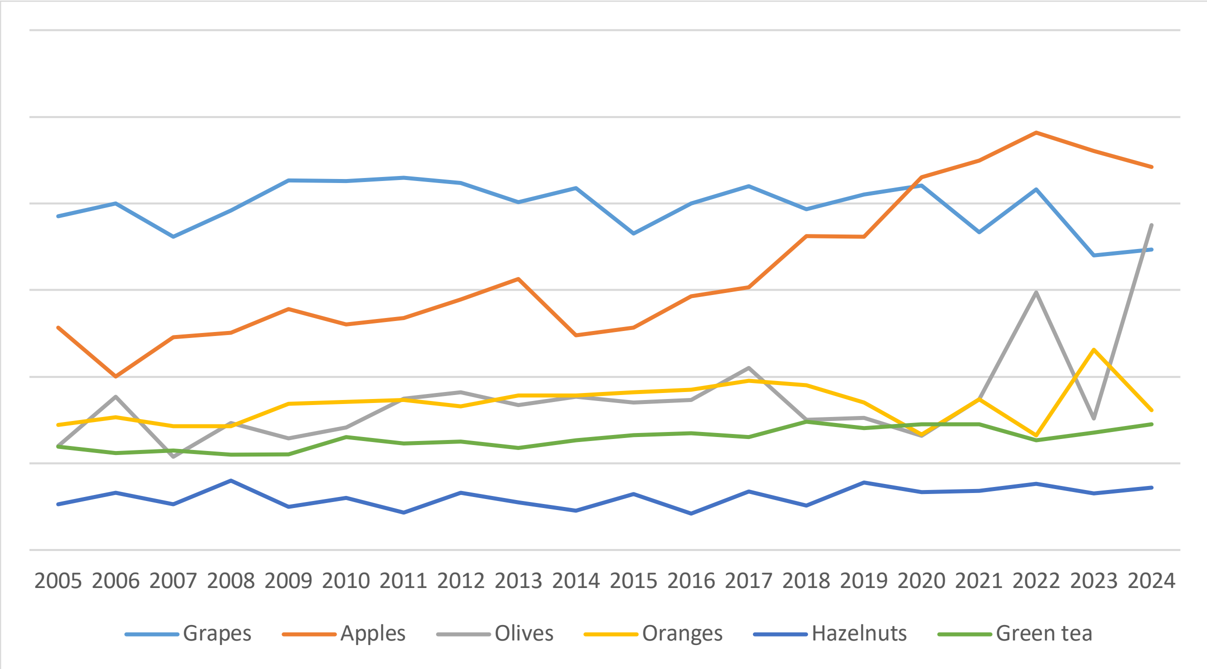

Figure 4. Production quantities of fruits, beverages, and spice plants

When examining the graph of production quantities by product type, the significant increase in apples is striking. Similarly, olive production has also seen major leaps, particularly in the last 3-4 years. Other product types show a fluctuating trend. Linear Regression analysis was applied to determine the effect of agricultural mechanisation on the production quantities of fruits, beverages, and spice plants.

Table 8. Model Summary – Fruits et al.

Model	R	R^2	Adjusted R^2	RMSE
M_0	0.000	0.000	0.000	$1.369x10^{+6}$
M_1	0.931	0.867	0.860	512139

The analysis shows that the model mechanisation index has a very strong effect on the production of fruits, beverages and spice crops. Agricultural mechanisation explains 86% of the variance ($R^2 = .867$, Adjusted $R^2 = .860$). This result indicates that increases in the level of agricultural mechanisation have a very strong and positive effect on the production of fruits, beverages and spice crops. The RMSE error margin data has a relatively low error margin value of 512 thousand tonnes compared to the total production.

Table 9. Model fit ANOVA

Model		Sum of Squares	df	Mean Square	F	p
M_1	Regression	$3.086\times10^{+13}$	1	$3.086\times10^{+13}$	117.7	< .001
	Residual	$4.721\times10^{+12}$	18	$2.623\times10^{+11}$		
	Total	$3.558\times10^{+13}$	19			

The analysis results indicate that the regression analysis is meaningful for the model (F(1,18) = 117.7, p < .001). It was observed that 86% of the total variance was explained by regression, while the remaining 14% remained in the error term.

Table 10. Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p
M_0	(Intercept)	$1.253\times10^{+7}$	306006.007		40.961	< .001
M_1	(Intercept)	$1.850\times10^{+6}$	991646.072		1.865	.079
	Mechanization PC1	1.017	0.094	0.931	10.847	< .001

When regression analysis coefficients are examined, it is seen that agricultural mechanisation has a positive and very strong effect on the production of fruits, beverages and spice crops (B = 1.017, SE = 0.094, β = .931, p < .001). These results reveal that agricultural mechanisation is a significant determinant of the increase in fruit, beverage and spice crop production. It is argued that the effect of agricultural mechanisation on fruit, beverage and spice crop production is much stronger than on cereal production.

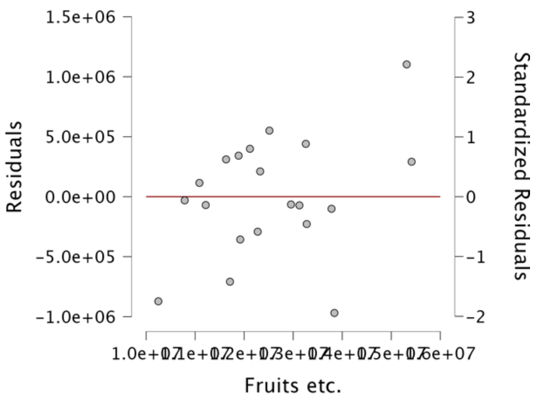

Figure 5. Residuals vs. Dependent Plots

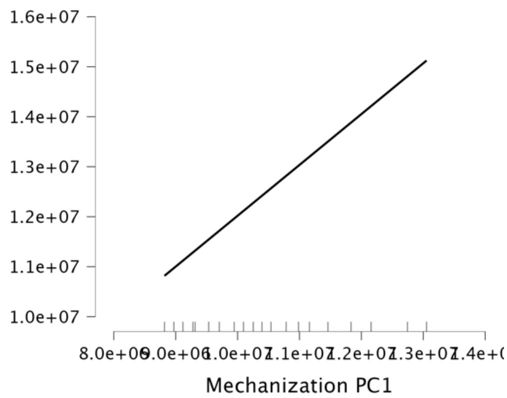

Figure 6. Marginal Effects Plots

The graph in Figure 5, which shows the relationship between cereal production and residuals, reveals that the residuals are distributed randomly along the horizontal axis, balanced around positive and negative values. This indicates that the model satisfies the assumptions of linearity and mean zero error. The marginal effects plots in Figure 6 visually confirm the linear and positive relationship between fruit, beverage and spice crop production and mechanisation.

RQ3. How did changes in agricultural mechanisation between 2005 and 2024 affect the labour force?

One of the most critical effects of agricultural mechanisation is the transformation it creates in the labour force. In this context, using CSGB statistics, the number of active workers registered under insurance types 4-A and 4-B, which constitute the labour force in the agricultural sector, and the rates of change over the years were analysed.

Table 11. Labour force registered under 4-A and 4-B insurance types in the agricultural sector and its change

Year	4-A		4-B		TOTAL	
	Number	Change (%)	Number	Change (%)	Number	Change (%)
2005	178.178	0,83	1.011.333	1,34	1.189.511	1,26
2006	187.951	5,48	1.049.206	3,74	1.237.157	4,01
2007	215.340	14,57	1.079.785	2,91	1.295.125	4,69
2008	218.094	1,28	1.127.744	4,44	1.345.838	3,92
2009	178.541	-18,14	1.014.948	-10,00	1.193.489	-11,32
2010	152.802	-14,42	1.101.131	8,49	1.253.933	5,06
2011	124.911	-18,25	1.121.777	1,87	1.246.688	-0,58
2012	85.717	-31,38	1.056.852	-5,79	1.142.569	-8,35
2013	62.988	-26,52	928.454	-12,15	991.442	-13,23
2014	46.996	-25,39	864.468	-6,89	911.464	-8,07
2015	40.615	-13,58	797.334	-7,77	837.949	-8,07
2016	36.125	-11,06	717.876	-9,97	754.001	-10,02
2017	50.602	40,07	705.592	-1,71	756.194	0,29
2018	45.384	-10,31	696.175	-1,33	741.559	-1,94
2019	41.108	-9,42	600.787	-13,70	641.895	-13,44
2020	31.250	-23,98	547.075	-8,94	578.325	-9,90
2021	27.036	-13,48	511.923	-6,43	538.959	-6,81
2022	22.987	-14,98	512.966	0,20	535.953	-0,56
2023	17.408	-24,27	460.260	-10,27	477.668	-10,88
2024	14.676	-15,69	427.298	-7,16	441.974	-7,47

As seen in Table 11, there has been a significant decline in the agricultural workforce across all insurance categories. In the 20-year analysis period, there has been a significant decline of 82% in 4-A insurance, 58% in 4-B insurance, and 63% overall in the workforce data. Linear Regression analysis was applied to determine the effect of agricultural mechanisation on this transformation in the agricultural sector labour force.

Table 12. Model Summary – Labour Force

Model	R	R^2	Adjusted R^2	RMSE
M_0	0.000	0.000	0.000	311429
M_1	0.948	0.899	0.894	101492

The analysis shows that the model mechanisation index has a very strong effect on agricultural labour. Agricultural mechanisation explains 89.9% of the variance ($R^2 = .899$, Adjusted $R^2 = .894$). This result indicates that increases in the level of agricultural mechanisation are a strong determinant that reduces labour demand.

Table 13. Model fit ANOVA

Model		Sum of Squares	df	Mean Square	F	p
M_1	Regression	$1.657\times10^{+12}$	1	$1.657\times10^{+12}$	160.9	< .001
	Residual	$1.854\times10^{+11}$	18	$1.030\times10^{+10}$		
	Total	$1.843\times10^{+12}$	19			

The analysis results indicate that the regression analysis is meaningful for the model ($F(1,18) = 160.9$, $p < .001$). It was observed that 89.9% of the total variance was explained by regression, while the remaining 10.1% was retained in the error term.

Table 14. Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p
M_0	(Intercept)	905584.650	69637.565		13.00	< .001
M_1	(Intercept)	$3.382\times10^{+6}$	196516.775		17.21	< .001
	Mechanization PC1	-0.236	0.019	-0.948	-12.68	< .001

When examining the regression analysis coefficients, it is seen that agricultural mechanisation has a negative and very strong effect on labour ($B = -0.236$, $SE = 0.019$, $\beta = -.948$, $p < .001$). This result indicates that an increase in the level of agricultural mechanisation is associated with a significant decrease in the amount of labour in the agricultural sector. The high value of the standardised coefficient indicates that the change in labour is largely explained by mechanisation. It is also seen that the effect of agricultural mechanisation on labour is higher than its effect on agricultural production indicators such as grain and fruit production.

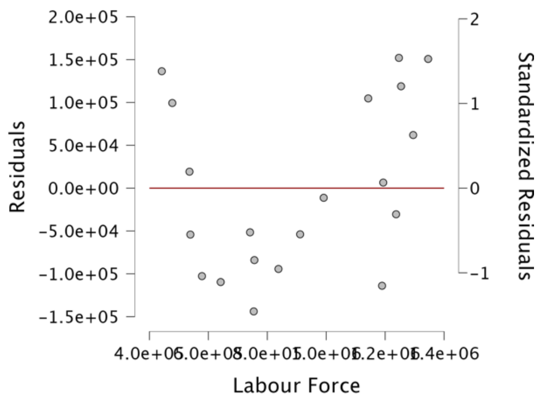

Figure 7. Residuals vs. Dependent Plots

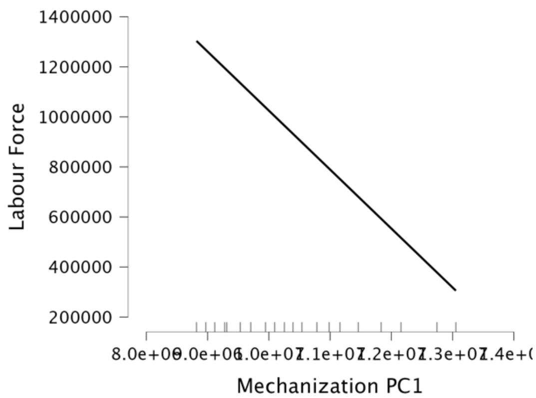

Figure 8. Marginal Effects Plots

The graph in Figure 7, which shows the relationship between grain production and residuals, reveals that the residuals generally show a balanced distribution around the zero line and that the linear regression assumptions are largely satisfied. This indicates that the model satisfies the assumptions of linearity and mean zero error. The marginal effects plots in Figure 8 show that agricultural labour decreases significantly as the level of agricultural mechanisation increases.

Table 15. The Impact of Agricultural Mechanisation

Model	Direction of Effect	R^2	Effect (β)	Result
Cereals, etc.	Positive	.636	.798	Mechanisation increases production
Fruits, etc.	Positive	.867	.931	Mechanisation is much more effective for fruits, etc.
Labour	**Negative**	**.899**	**–.948**	**Mechanisation significantly reduces labour**

The effects of agricultural mechanisation on the research questions analysed within the scope of the study are shown in Table 15. According to this, its effect on the production processes of fruits, beverages and spice crops is stronger than that on cereals and other plant products. Its effect on labour is stronger than both production indicators, but this effect has been determined to be negative.

CONCLUSION

The significant increase in the world population in the current century has made food supply security one of the most important issues for countries. This situation has led to the use of more efficient agricultural production tools and the replacement of human labour with machines and other equipment. Within the scope of this study, mechanisation in the Turkish agricultural sector over a long 20-year statistical period and the effects of this transformation on agricultural production and labour force were analysed. The study concluded that agricultural mechanisation caused a very strong increase in production and had a very strong negative impact on the labour force.

The effects on agricultural production were analysed in terms of changes in the production of cereals and other plant products, as well as fruits, beverages and spice crops. The cereals and other plant products category represents production where large-scale agricultural machinery is widely used, particularly in large-scale cultivation areas, while the production of fruits, beverages and spice plants is important in that it represents a type of production where smaller and functional agricultural tools are used compared to cereals. Agricultural mechanisation has been shown to have a strong positive effect in the cereals and other plant products category. This result supports previous studies in the field. A study by Liu and Li (2023) found that agricultural mechanisation significantly increased grain production capacity and productivity. Another study by Gebiso et al. (2024) concluded that farms with high levels of mechanisation achieved 26–48 per cent higher yields in wheat production than farms with low levels of mechanisation. A study conducted by Hussain et al. (2023) in Pakistan revealed that the use of tractors and harvesters supported both an increase in cultivated area and yield per unit area in rice and wheat production.

It has been concluded that agricultural mechanisation has a positive and very strong impact in the production of fruits, beverages and spice crops. There are studies in the literature that support this conclusion. A systematic review conducted by Srinivas and colleagues (2024) revealed that mechanised harvesting and maintenance practices reduce labour costs in horticultural crops and significantly increase yield and production intensity. Another study conducted by Kaur et al. (2023) reported that the use of mechanised harvesting equipment in fruit and spice crops reduces product losses and that timely harvesting directly contributes to increased yields. This type of production, in particular, requires a high level of human labour during the harvesting process. Therefore, it is quite natural that agricultural mechanisation in this category has effects such as increased productivity and reduced labour.

Perhaps the most powerful effect of agricultural mechanisation is the transformation it creates in the workforce. The study found a very strong negative relationship between agricultural mechanisation and labour. While agricultural labour is an area that requires high physical strength and low education levels, agricultural mechanisation is leading to the development of an area that requires a more qualified and technical workforce. Accordingly, processes such as production, sowing, spraying, irrigation, harvesting, etc. can be carried out on larger areas with fewer workers. Studies revealing the negative relationship between agricultural mechanisation and labour statistically confirm the labour-substituting and labour-reducing nature of mechanisation (Baudron et al., 2019; Caunedo & Kala, 2021; Yücel & Çalışkan, 2020; Zou et al., 2024). The positive effects of mechanisation in agricultural production, such as its contribution to increased production, its labour-reducing effect, the reduction of agricultural production costs, the increase in production volume, and the increase in labour-time efficiency, indicate that mechanisation in agricultural production will continue to advance. However, its negative impact on the labour force also brings some problems. The contraction of agricultural employment (Agarwal, 1981), the deepening of inequalities in the sector among agricultural workers employed at low wages (Brownstone, 2025; Caunedo & Kala, 2021), weakening income security for seasonal workers (Baudron et al., 2019), and rising regional unemployment rates (Pingali, 2007). Of course, the agricultural labour force is a sector where real labour force data is difficult to obtain due to reasons such as undeclared work, family members working in family businesses, seasonal and part-time work, etc., which also limits the ability to accurately understand the real impact of mechanisation on the labour force. Nevertheless, it is clear that agricultural mechanisation will significantly reduce the labour force, and this reduction will be felt more sharply in the near future with the falling costs of purchasing agricultural equipment and the spread of technologies such as artificial intelligence, robotics, drones, and unmanned vehicles. At this point, policymakers need to plan measures such as redirecting workers in the shrinking agricultural labour market to different sectors and increasing job opportunities through technical training in agricultural mechanics.

Robotic and autonomous systems, together with artificial intelligence–based technologies, have experienced remarkable development over the last decade. The reduction in production costs of these systems and their increasing accessibility for medium-sized enterprises have led to their widespread adoption within the agricultural sector. In agriculture, robotic systems have been shown to enhance productivity by reducing human error, particularly in fruit and vegetable production (Bechar & Vigneault, 2016). These systems also contribute to the optimization and reduction of input costs through more efficient applications of fertilizers, pesticides, and water (Shamshiri et al., 2018). Although such technologies entail significant investment costs in the short term, they reduce unit production costs in the medium and long term by increasing productivity and lowering input expenses (Lowenberg-DeBoer et al., 2020).

Looking ahead, it is suggested that agricultural production will increasingly transition toward a predictive and data-driven structure through the integration of artificial intelligence–based agricultural applications, big data, and Internet of Things technologies (Wolfert et al., 2017). Moreover, artificial intelligence and robotic technologies are expected to mitigate production fluctuations by addressing climate-induced challenges in agricultural production (Shamshiri et al., 2018). The use of autonomous tractors for GPS-based cultivation of large-scale agricultural land, artificial intelligence–supported drone technologies for efficient and precise pesticide application, and big data–driven production modeling, among other developments, indicate that the future of agricultural mechanization will lead to significant transformations in labor structures and machinery configurations in agricultural production.

Additional Declaration

Author Contributions

This study carried out by a single author.

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This study was not funded by any institution or organization.

Responsible Artificial Intelligence Statement

In this study, artificial intelligence tools ChatGPT were used in literature review stages. The artificial intelligence tool was used to provide the colophon information of current related resources in the literature review. We declare that we, as the authors, take full responsibility for the problems that may arise from the content produced by artificial intelligence.

Conflicts of Interest

The authors declare that there are no conflicts of interest related to the publication of this study.

Ethics Approval

In all processes of this study, the principles of Pen Academic Publishing Research Ethics Policy were followed. This study does not require ethics committee approval as it does not involve any direct application on human or animal subjects.

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