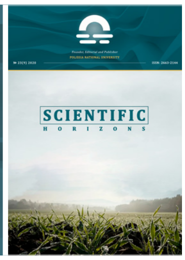
ISSN 2663-2144
e-ISSN 2709-8877

SCIENTIFIC HORIZONS

Journal homepage: https://sciencehorizon.com.ua

Scientific Horizons, 29(1), 66-78

UDC 636.3;519.85;004.94
DOI: 10.48077/scihor1.2026.66



The influence of agro- and meteorological factors on sunflower yield

Anatolii Kulyk*

PhD in Physics and Mathematics, Head of Department
Kyiv National Economic University named after Vadym Hetman
03057, 54/1 Beresteiskyi Ave., Kyiv, Ukraine
https://orcid.org/0000-0002-6629-0253

Valentyna Lisovska

PhD in Physics and Mathematics, Professor
Kyiv National Economic University named after Vadym Hetman
03057, 54/1 Beresteiskyi Ave., Kyiv, Ukraine
https://orcid.org/0000-0001-8675-3975

Olha Melnyk

PhD in Physics and Mathematics, Associate Professor
Kyiv National Economic University named after Vadym Hetman
03057, 54/1 Beresteiskyi Ave., Kyiv, Ukraine
https://orcid.org/0000-0002-4399-176X

Nadiia Shchekan

Senior Lecturer
Kyiv National Economic University named after Vadym Hetman
03057, 54/1 Beresteiskyi Ave., Kyiv, Ukraine
https://orcid.org/0000-0002-1784-6139

Article's History:
Received: 07.11.2025
Revised: 02.03.2026
Accepted: 25.03.2026
Published: 06.04.2026

Abstract. Sunflower is one of the leading oilseed crops in Ukraine, and the stability of its yield is of important economic and food importance. In conditions of increasing climate variability, the need for quantitative analysis of the influence of agrotechnical and meteorological factors on the development of the yield is becoming more urgent. The purpose of the study was to quantitatively assess the role of agrotechnical and climatic factors in the development of sunflower yield using statistical analysis methods. The empirical basis of the study was data for 2007-2024, including sunflower yield indicators, levels of mineral and organic fertilisers, and meteorological characteristics (soil temperature in May, precipitation, air moisture saturation deficit, Selyaninov hydrothermal coefficient, wind speed, number of clear days during the growing season). The study used descriptive statistics, the Shapiro-Wilk test, Pearson and Spearman correlation analysis, and multivariate linear regression. The results of the study showed that the average yield level for the period was 25.65 q/ha with a standard deviation of 5.91 q/ha. The most stable and statistically significant effect on sunflower yield was the level of mineral fertiliser application, for which a moderately strong positive relationship was recorded ($r = 0.656$). Among meteorological factors, the most noticeable positive relationship was found for wind speed ($r = 0.512$). The

Suggested Citation:
Kulyk, A., Lisovska, V., Melnyk, O., & Shchekan, N. (2025). The influence of agro- and meteorological factors on sunflower yield. *Scientific Horizons*, 29(1), 66-78. doi: 10.48077/scihor1.2026.66.

*Corresponding author

multicollinearity test using the variance inflation coefficient confirmed the correctness of the model, since the values for most variables did not exceed 4, and the maximum indicator was 5.17 for mineral fertilisers. The analysis emphasised the key role of agrotechnical management, since the influence of factors such as Selyaninov hydrothermal coefficient (r = 0.083) and moisture deficit (r = 0.092) turned out to be weak within the paired analysis. The practical value of the results lies in the possibility of using the developed regression models to predict sunflower productivity and optimise mineral nutrition systems in order to minimise risks caused by adverse meteorological factors

Keywords: agrometeorological indicators; Selyaninov hydrothermal coefficient; multicollinearity; correlation analysis; linear regression; variance inflation factor

INTRODUCTION

Sunflower has traditionally occupied the place of one of the leading oilseed crops of Ukraine, acting as a strategic resource for domestic consumption and export potential of the country. Its role as a key component of the world agricultural market has led to special attention of researchers to the stability of yield, since any fluctuations in production volumes had a direct impact on economic security and food stability. In current conditions of climatic instability, there has been an increase in the importance of both agrotechnical and meteorological factors, which together determined the dynamics of yield development and caused interannual variability in crop productivity.

Scientific studies have confirmed the complex nature of yield development under the influence of a complex of factors. In particular, D. Baranskyi (2024) substantiated that the temperature regime and the level of moisture supply acted in close interaction with soil cultivation systems, which determined the final productivity of the crop. In turn, J. Beteri *et al*. (2024) established that dynamic changes in air temperature and precipitation significantly adjusted the suitability of certain periods for the sowing campaign. The researchers also proved that the ecological parameters of the environment determined the limits of the potential yield level that the crop could approach under optimal conditions. Additionally, the study by F. Zabel *et al*. (2025) highlighted the role of solar insolation and mineral nutrition systems as factors that minimised the negative effects of climatic stresses. The importance of weather conditions as the main determinant of interannual yield variation has been extensively analysed in a number of international studies based on multi-year climate series. For example, S. Majumder & C.M. Mason (2025) focused on the analysis of historical data, which allowed them to identify a high predictive potential of temperature indicators precisely during critical phases of sunflower vegetation. Furthermore, C.O. Joseph *et al*. (2025) demonstrated that the amount of precipitation during the growing season was the main limiting factor, explaining up to 60% of yield variability in arid regions. These scientific results indicated the need for deeper integration of agrometeorological trends in the model for estimating future productivity.

Along with natural factors, the scientific community has actively investigated the role of anthropogenic and technological influences. The study by M. Zalai *et al.* (2025) showed that the negative effect of meteorological anomalies could be partially offset by the introduction of precise fertilisation systems. Moreover, E. Partal (2022) emphasised that the choice of tillage method directly modified the impact of precipitation on the water regime, creating a complex system of interaction between the agronomist's management decisions and the forces of nature. Thus, crop formation was considered not as a linear process, but as the result of the synergy of many variables. For the agricultural sector of Ukraine, this issue has become particularly acute. S.M. Shakalii & Ye.I. Kulyk (2025) stated in their study that the agroclimatic conditions of the last decade were characterised by a steady trend towards an increase in average annual temperatures and a shift in the zones of comfortable cultivation of oilseeds.

In view of the above, there was an objective need to conduct a comprehensive quantitative analysis of the impact of agrotechnical and meteorological factors on sunflower yield. The use of advanced statistical and econometric tools allowed considering the problem of multicollinearity of indicators, which previously often became an obstacle to obtaining reliable models. The use of distribution testing methods and regression analysis provided the opportunity not only to identify the most influential factors, but also to assess the degree of their contribution to the overall result. The purpose of this study was to assess the impact of agrotechnical and meteorological factors on sunflower yield based on statistical analysis of empirical data over a long period.

LITERATURE REVIEW

Based on the analysis of the current state of the agricultural market, I.V. Chekhova (2022) highlighted the specifics of the functioning of the oilseed market in Ukraine, argued the need to improve the state agrarian policy to support the diversification of production, expand the range of products, and stimulate producers to grow various oilseeds. The study by O.V. Sydiakina & V.V. Hamajunova (2023) was devoted to the analysis of the current state and prospects of sunflower seed production. The researchers considered the key factors affecting the efficiency of seed production and outline the areas of development of the industry based on contemporary scientific and practical achievements. K. Vasylkovska *et al.* (2022) investigated the dynamics of sunflower production in Ukraine and the world for the period 2000-2021 in the context of global climate change. The study emphasised that due to the adaptation of technologies and the selection of drought-resistant hybrids, the average yield in Ukraine increased by 2.5 times, which allowed the country to remain the world leader in sunflower oil exports despite adverse climatic challenges.

P. Debaeke *et al.* (2023) developed and evaluated methods for predicting sunflower yields at the field level using a combination of remote sensing (satellite imagery) and statistical modelling. The paper by K. Amankulova *et al.* (2023) explored methods for accurately estimating future sunflower yields. The researchers used remote sensing data to analyse vegetation indices in combination with phenological phases of plant development, which allowed creating reliable statistical models for predicting agricultural land productivity. The study by Z. Song *et al.* (2023) was devoted to the development of a method for automatic recognition of sunflower growth phases using deep learning technologies and multispectral images from unmanned aerial vehicles. The results of the study, tested on multi-year data, demonstrated the high efficiency of the approach for the needs of precision agriculture, providing farmers with operational information for making crop management decisions.

The study by V. Hnatiienko & H. Hnatiienko (2024) was devoted to the development of an intelligent system for accurate assessment of future yields within the framework of digital agronomy. The study analysed the methods of machine learning, deep learning, and computer vision applied to the processing of satellite data and other multivariate indicators. R. Karan *et al.* (2024) examined the application of artificial intelligence methods for yield prediction and early detection of oilseed diseases in the agriculture of the state of Tamil Nadu (India). The researchers proposed an AI-based model that combines agronomic, meteorological, and historical data to improve the accuracy of yield predictions and timely detection of plant diseases. It was shown that the use of machine learning can significantly improve the decision-making process of farmers, contribute to increasing productivity, reducing crop losses, and sustainable development of the agricultural sector of the region.

The study by M.A. Jabed & M.A.A. Murad (2024) was devoted to a comprehensive review of modern machine learning and deep learning approaches for crop yield forecasting, with a detailed analysis of the algorithms used, data sources (climatic, soil, remote sensing, etc.) and model performance indicators. The paper by S. Thavareesan *et al.* (2025) investigated the application of various machine learning methods to accurately predict crop yields in South Asian countries using historical data on yields, weather factors (rainfall, temperature) and pesticide use; the researchers compared the performance of regressor models, highlighting the potential of machine learning to support decision-making in agriculture and resource planning.

Recent research in the agricultural sector demonstrated the increasing use of regularisation methods (Lasso, Ridge, Elastic Net) in yield forecasting models and agricultural indicators, which allows improving the generalisation of estimates and reducing the impact of multicollinearity between variables. Z. Qiu (2022) proposed an algorithm for forecasting the gross domestic product of China's agricultural sector based on the Elastic Net method for working with multivariate economic data. The researchers analysed the impact of various macroeconomic and agricultural indicators on the dynamics of agricultural gross domestic product, reduced the problem of multicollinearity between variables, and improved the accuracy of forecasting. N. Acir (2025) applied regularised regression models (Ridge, Lasso, Elastic Net) to develop a model for predicting soil fertility in semi-arid agroecosystems based on limited data.

A review of the literature has shown that significant progress has been made in the application of cutting-edge technologies and methods for predicting the yield of oilseed crops, particularly sunflowers. The researchers were actively using remote sensing, machine learning, and statistical models to more accurately predict yields considering factors such as climate change, agronomic conditions, and technological adaptations. However, issues such as multicollinearity among variables and data limitations still restrict the accuracy of forecasts. Thus, this literature review demonstrates the importance of further improving yield forecasting methods for effective agricultural production management.

MATERIALS AND METHODS

The object of the study was the processes of sunflower yield development within the Vinnytsia Oblast, Ukraine. The choice of this region as a geographical coverage was conditioned by its key role in the agricultural sector of the state and its location in the Forest-Steppe zone, which was the most representative for analysing the impact of climate change on oilseed crops. Vinnytsia Oblast was characterised by a transition from sufficient to risky moisture, which enabled the most complete assessment of the sensitivity of modern sunflower hybrids to fluctuations in hydrothermal indicators. The empirical basis of the study was annual statistical and meteorological data for the period 2007-2024. The initial boundary of the study (2007) was determined by the availability and integrity of data, and it was from this year that a full array of open data was available.

Paired linear regression was used to analyse the relationship between sunflower yield and individual agro- and meteorological factors, which allowed assessing the area and strength of the influence of each explanatory variable separately. The research data on agro-factors was obtained from the website of the Main Department of Statistics in Vinnytsia Oblast of Ukraine (State Statistics Service of Ukraine, n.d.), and about meteorological factors – from the Sectoral State Archive of Hydrometeorological Observation Materials of the State Emergency Service of Ukraine (n.d.) for the period 2007-2024 and covered each year of the study in the interval from May to September (tables of meteorological observations are not publicly available). The covered 18-year cycle provided the necessary climatic variability, including a representative sample of weather extremes (droughts, temperature anomalies), which was important for high-quality modelling of the crop response to external stimuli. From a statistical standpoint, such a sample size (n = 18) was sufficient to confirm the normality of the distribution of variables according to the Shapiro-Wilk criterion and ensure high reliability of the obtained correlation and regression coefficients.

In this study, eight independent variables were used to model sunflower yield, covering both agronomic and meteorological factors. Agronomic factors included the amount of applied mineral and organic fertilisers in kg/ha, which were direct indicators of the level of agrotechnical support of crops and significantly affected the stability and development of plants, contributing to an increase in yield under the conditions of their balanced application. Meteorological factors included: soil surface temperature in May (soil_5), since thermal dynamics determine the rate of crop development and the passage of vegetation phases; average wind speed (wind), which can affect transpiration, moisture evaporation, and the spread of diseases and pollen; air moisture saturation deficit (saturation_deficit), which characterised atmospheric dryness and affects the water balance of plants; the total number of clear days (clear_days), which reflected the solar insolation necessary for photosynthesis; and the hydrothermal coefficient (HTC), which generally characterised the ratio of heat and moisture and was a critical indicator of the favourableness of meteorological conditions for crop growth and development. The choice of these indicators was substantiated by their key role in shaping sunflower yield. The involvement of both agro- and meteorological factors provided a comprehensive approach to yield forecasting, as it considered both controllable (technological) and uncontrollable (natural) components of agricultural production.

The months of May, June, July, August, and September were chosen for meteorological observations, as they were the most representative of the growing season of sunflower. During this period, weather conditions had the maximum impact on the growth, development and yield of the crop. One of the key meteorological indicators included in the analysis was the HTC, which was used to assess the moisture content of an area during the growing season of agricultural crops. HTC was calculated using the Selyaninov equation:

$$\mathrm{HTC} = \frac{10 \cdot \sum P}{\sum T}, \quad (1)$$

where $\sum P$ – the sum of precipitation (mm) for the period when the average daily temperature exceeds +10°C, and $\sum T$ – the sum of average daily air temperatures (°C) for the same period.

The Selininov HTC reflects the complex influence of precipitation and temperature on soil water balance and crop development. The normality of the distribution of the studied variables was checked using the S.S. Shapiro & M.B. Wilk (1965) test and QQ-plots (Hu & Yu, 2016). The Shapiro-Wilk test determined the W statistic by the equation:

$$W = \frac{\left(\sum a_i x_{(i)}\right)^2}{\sum (x_i - \bar{x})^2}, \quad (2)$$

where $x_{(i)}$ – observations ordered in ascending order, x_i – variable value, $\bar{x}$ – average value, a_i – coefficients calculated based on the covariances of the normal distribution.

The p-value for a test determined the probability of observing this or a more extreme W-statistic, assuming the data were normally distributed. If the p-value >0.05, the null hypothesis of normality was not rejected. For all indicators, the p-value exceeded the significance level of 0.05, which formally allowed the use of parametric analysis methods, in particular the Pearson correlation coefficient:

$$r_{xy} = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}}, \quad (3)$$

where x_i and y_i – observations for variables X and Y, $\bar{x}$ and $\bar{y}$ – their average values.

Furthermore, given the small sample size (n = 18) and possible marginal effects, to increase the stability of the results, the Spearman correlation coefficient was additionally used, which was calculated using the ranks of the variables:

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)}, \quad (4)$$

where $d_i = R(x_i) - R(y_i)$ – difference in the ranks of observations for each pair of variables.

Comparison of the results obtained using both coefficients allowed assessing the reliability of the identified relationships between sunflower yield and agro- and meteorological factors. To quantitatively assess the impact of agro- and meteorological factors on sunflower yield, a classical linear regression model was used:

$$\hat{y} = \beta_0 + \sum_i \beta_i x_i, \quad (5)$$

where $\hat{y}$ – predicted yield, β_0 – free term, β_i – coefficients for traits, x_i – values of independent variables (agro- and meteorological factors).

The feasibility of using classical linear regression was substantiated by the results of multicollinearity analysis using the variance inflation factor (VIF) (O'Brien, 2007). For each explanatory variable X_i VIF was calculated using the equation:

$$\mathrm{VIF}_i = \frac{1}{1-R_i^2}, \tag{6}$$

where R_i^2 – coefficient of determination when regressing a variable X_i on all other variables.

All calculations and visualisations were performed using Jupyter Notebook (Python 3). A significance level of $p < 0.05$ was used throughout the study.

RESULTS AND DISCUSSION

The trends in sunflower yield in the Vinnytsia Oblast from 2007 to 2024 were examined. Figure 1 shows a generally upward but unstable dynamics of sunflower yield in Vinnytsia Oblast in 2007-2024. In 2007-2012, the yield was relatively low and fluctuated within approximately 14-22 q/ha, which may indicate less intensive cultivation technologies and higher dependence on weather conditions. Starting from 2013, there has been a sharp increase in yield (over 30 q/ha), after which a period of increased but variable values was established. In 2013-2019, the yield was mainly maintained at the level of 27-34 q/ha with a maximum around 2019, which may be a result of a combination of favourable meteorological conditions, the use of advanced hybrids and optimisation of the fertiliser system. However, noticeable decreases in yield were recorded in 2020 and 2022, which were likely associated with adverse weather conditions or stress factors in agricultural production. In 2023-2024, a partial recovery of yield was observed, but the level remains lower than the peak values of the previous period, which emphasised the high sensitivity of the crop to agro- and meteorological factors. In general, the dynamics indicate a long-term increase in sunflower productivity in the region with significant fluctuations, which justifies the feasibility of quantitative analysis of the impact of agrotechnical and climatic factors on yield.

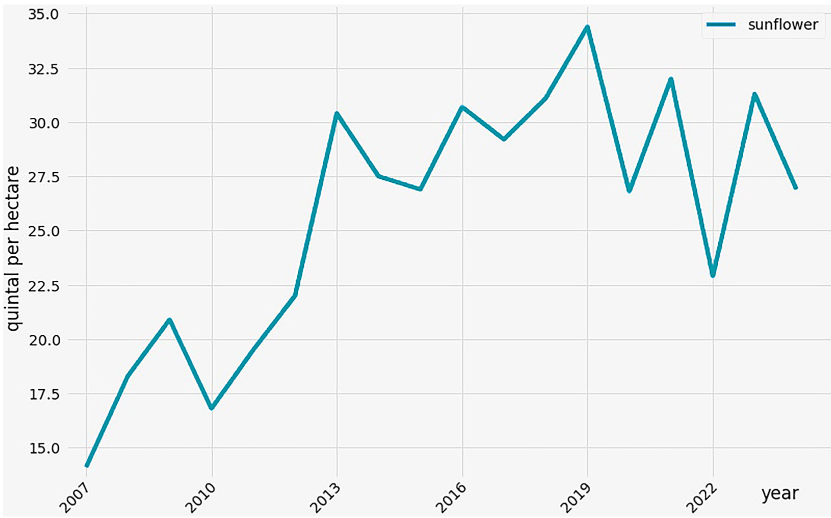


***Figure 1**. Dynamics of changes in sunflower yield in Vinnytsia Oblast from 2007 to 2024*
***Source:** compiled by the authors based on State Statistics Service of Ukraine (n.d.)*

The data in Table 1 were consistent with the graph of sunflower yield dynamics in Vinnytsia Oblast for 2007-2024. The average yield level is 25.65 q/ha, which corresponds to the predominance of values in the range of 25-30 q/ha on the graph in the second half of the period under study. The standard deviation of 5.91 q/ha indicates moderate annual fluctuations in yield, which are clearly manifested in the form of separate sharp declines and rises of the curve (in particular, a minimum of 14.1 q/ha at the beginning of the period and a maximum of 34.4 q/ha in 2019). The negative value of the asymmetry coefficient (Skew = -0.47) indicates a weak left-sided asymmetry of the distribution. The negative coefficient of kurtosis (Kurtosis = -0.88) reflects the absence of sharply expressed peak values and confirms the uniform nature of yield fluctuations. Table 1 presented statistical characteristics of sunflower yield.

***Table 1**. Statistical characteristics of sunflower yield, q/ha*

Metrics	Mean	Std.	Min.	Max.	Skew.	Kurt.
Yield	25.65	5.91	14.1	34.4	-0.47	-0.88

***Source:** compiled by the authors*

Thus, descriptive statistics and the shape of the time series indicate the absence of extreme outliers and the relatively stable nature of yield variation in the period under study. In order to correctly select further statistical methods of analysis, the assumption of normality of the distribution of the studied indicators was additionally checked. Table 2 showed the results of testing the normality of the distribution of variables using the Shapiro-Wilk criterion for agro- and meteorological factors.

***Table 2**. Shapiro-Wilk normality test results for yield, agro- and meteorological variables*

Variable	W_statistic	p_value
yield	0.942	0.312
mineral	0.942	0.310
organic	0.950	0.418
soil_5	0.915	0.106
saturation_deficit	0.948	0.393
HTC	0.952	0.458
wind	0.945	0.353
clear_days	0.917	0.117

***Source:** compiled by the authors*

For all variables, the *p-values* exceed the significance level of 0.05, which means there is no statistical reason to reject the null hypothesis of normal distribution. Figure 2 shows QQ-plots of the assessment of the normality of the distribution of the research variables.

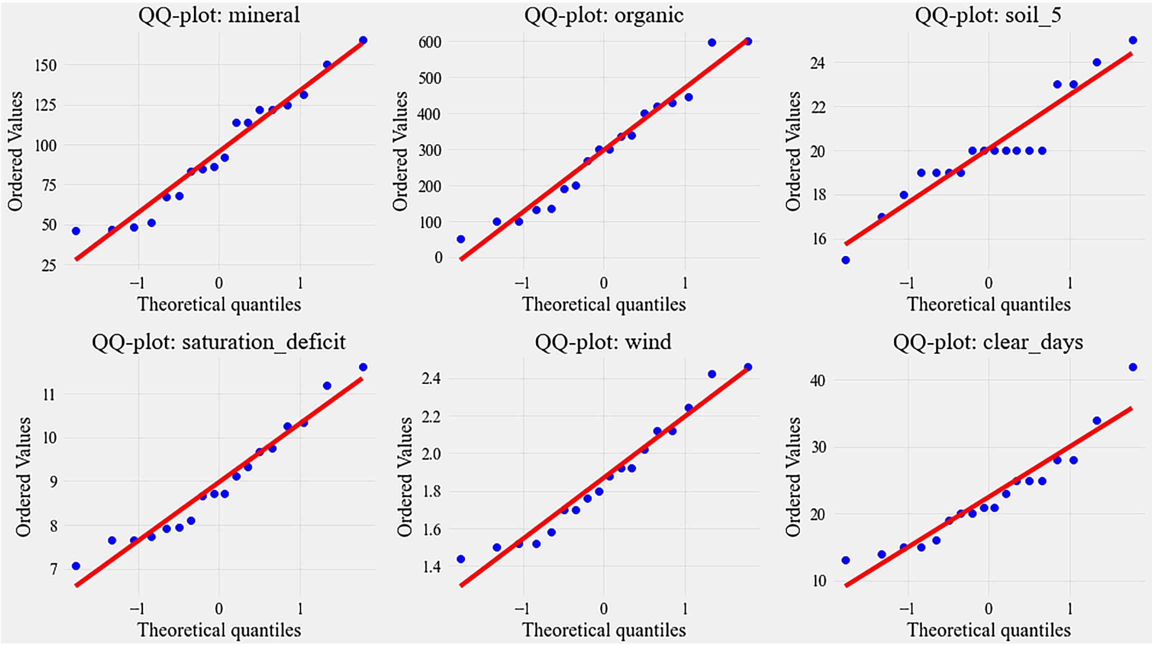


***Figure 2**. Visual assessment of the normality of the distribution of agro- and meteorological factors using QQ-plot*
***Source:** compiled by the authors*

The presented QQ-plots for agro- and meteorological variables allow visually assessing the correspondence of their empirical distributions to the theoretical normal distribution and logically complement the results of the Shapiro-Wilk test. QQ-plots for the variables mineral, organic, soil_5, saturation_deficit, wind, and clear_days generally demonstrated a linear arrangement of points without significant systematic deviations from the theoretical straight line. Minor deviations at the extreme quantiles, in particular for meteorological factors, may be conditioned by the small sample size (n = 18) and variability of weather conditions. Simultaneously, the central parts of the distributions are in good agreement with the normal law, which confirms the acceptability of the assumption of normality and the possibility of using parametric methods of analysis.

Considering the results of checking the normality of the distribution of variables and visual analysis of QQ graphs, to further assess the relationship between sunflower yield and agro- and meteorological factors, correlation analysis was applied using both the Pearson coefficient and the Spearman coefficient, which allows comparing linear and rank dependencies between indicators. Table 3 displays the values of the Pearson and Spearman correlation coefficients between sunflower yield and agro- and meteorological factors, which allows assessing both linear and monotonic relationships.

***Table 3**. Value of Pearson and Spearman correlation coefficients between sunflower yield and agro- and meteorological factors*

Variable	Pearson	Spearman
mineral	0.656	0.632
organic	0.074	0.102
soil_5	-0.190	-0.068
saturation_deficit	0.092	0.066
HTC	0.083	0.035
wind	0.512	0.569
clear_days	0.081	-0.043

***Source:** compiled by the authors*

The most pronounced and stable relationship with sunflower yield was recorded for mineral fertilisers ($r = 0.656$; $\rho = 0.632$), which indicates a moderately strong positive and predominantly linear dependence. A moderate positive relationship was also observed for the wind indicator ($r = 0.512$; $\rho = 0.569$), and a slightly higher value of the Spearman coefficient indicates a monotonic, but not strictly linear nature of the influence. Other agro- and meteorological factors demonstrated weak or absent pairwise correlations with yield, which indicates their indirect influence or manifestation in interaction with other variables. The weak negative correlation of soil temperature in May does not allow drawing unambiguous conclusions within the framework of the pairwise analysis. In general, the closeness of the values of the Pearson and Spearman coefficients confirmed the absence of significant nonlinearities and justified the feasibility of further multivariate regression analysis. Since pairwise correlation analysis reflects only two-dimensional relationships between indicators and does not consider the possible interdependence of explanatory variables, the next stage of the study was to assess the level of multicollinearity between agro- and meteorological factors. For this, the VIF was used, which helped to identify hidden linear dependencies between regressors and assess the feasibility of their simultaneous inclusion in the multivariate regression model (Table 4).

***Table 4**. Value of the VIF for agro- and meteorological factors*

Variable	VIF
soil_5	1.602
organic	1.784
HTC	2.384
clear_days	2.665
saturation_deficit	3.863
wind	5.08
mineral	5.17

***Source:** compiled by the authors*

The values of the VIF indicate the absence of critical multicollinearity between agro- and meteorological factors. Most variables are characterised by a low or moderate level of interdependence (VIF < 4), which confirms their independent contribution to the model. For wind and mineral fertilisers, the VIF threshold values (≈ 5) were recorded, which indicate moderate multicollinearity, but do not exceed the permissible thresholds, enabling the use the least squares method. The results obtained confirm the correctness of the model specification and the feasibility of using the least squares method, providing the possibility of reliable interpretation of the influence of individual agro- and meteorological factors on sunflower yield. The applied approach preserves the transparency of the model and creates the basis for a well-founded economic and agronomic interpretation of the obtained estimates. The linear regression equation describes the average impact of agro- and meteorological factors on sunflower yield, assuming other variables are fixed:

$$\begin{gathered} \textit{yield} = 25.65 + 5.13\text{*mineral} - \\ - 0.81\text{*}\textit{organic} + 0.42\text{*soil\_5} - \\ - 0.18\text{*}\textit{saturation\_deficit} - 0.24\text{*}\textit{HTC} - \\ - 0.11\text{*wind} - 1.93\text{*clear\_days}. \end{gathered} \tag{7}$$

Analysis of equation (7) and data in Table 5 identified key patterns in the development of crop productivity. The most statistically significant positive contribution to yield was made by the application of mineral fertilisers (p = 0.03), where an increase in the rate of fertilisers per unit lead to an increase in yield by 5.13 q/ha. This confirmed the critical role of nutrition intensification as the main factor in stabilising production.

***Table 5**. Statistical parameters of the multiple linear regression model*

Coefficient	Value	Standard error	p-value
mineral	5.134	2.811	0.031
organic	0.810	1.651	0.354
soil_5	0.422	1.560	0.084
saturation_deficit	-0.183	2.433	0.413
HTC	-0.243	1.910	0.144
wind	-0.115	2.785	0.024
clear_days	-1.932	2.014	0.361

***Note:** coefficient of determination R^2 = 0.683*
***Source:** compiled by the authors*

High statistical significance was demonstrated by the indicator (p = 0.02). The negative coefficient for this parameter indicates the depressive effect of excessive wind activity, which may be associated with increased transpiration and the risks of crop drying in critical phases. The positive coefficient of soil temperature in May (p = 0.08) at the level of statistical trend confirms the importance of the thermal regime for the emergence of seedlings and the formation of the root system. Negative coefficients for moisture deficit, HTC, and number of clear days reflect the complex nature of plant response to hydrothermal stresses. In particular, the negative impact of a large number of clear days may indicate the risks of temperature stress and excessive solar insolation. In general, the obtained model with a high degree of probability (R^2 = 0.68) describes the dominant role of agrotechnical factors, which are the main lever of yield management against the background of changing climatic conditions of the region. Figure 3 shows paired scatter plots and linear regression lines between sunflower yield and selected factors. The presented visualisation clearly reflects the nature of the relationship between sunflower yield and individual agro- and meteorological factors and is in good agreement with the results of correlation and regression analyses.

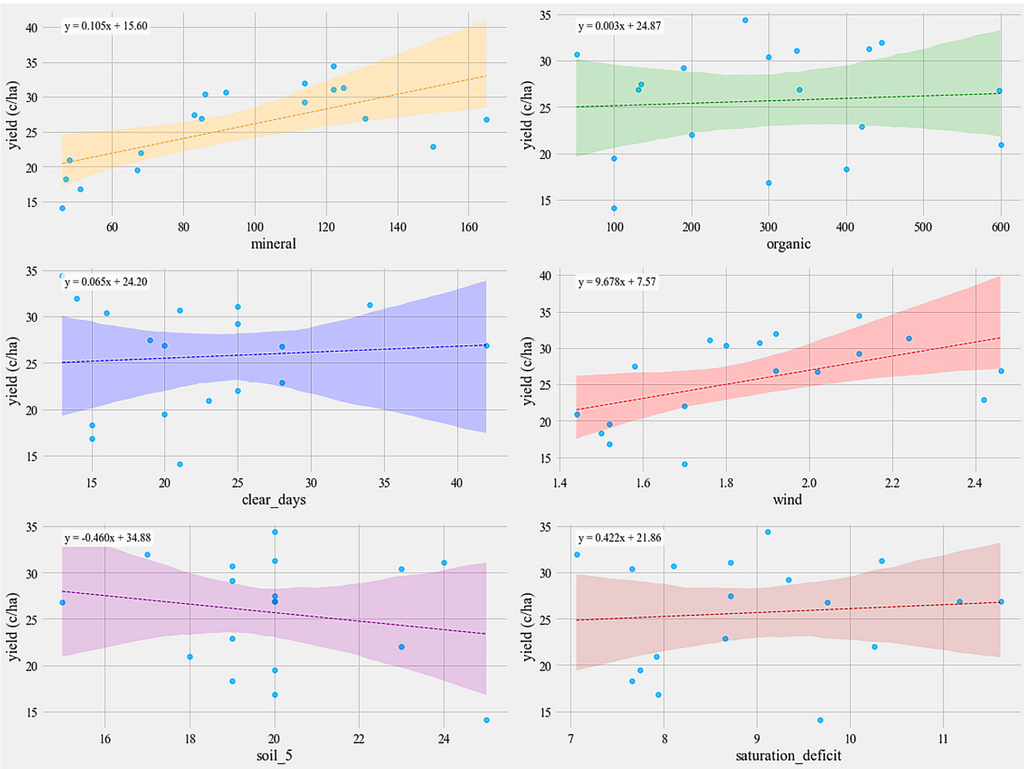


***Figure 3**. Linear relationship between sunflower yield and agro- and meteorological factors (pair analysis)*
***Source:** compiled by the authors*

The most pronounced positive linear dependence was observed for mineral fertilisers: the regression line has a pronounced increasing slope, and the confidence interval was relatively narrow in the central range of values, which indicates a stable and significant impact of this factor on yield. A positive trend is also observed for the wind indicator, but with a greater scatter of points, which indicates a moderate and contextual nature of its impact. The dependence of yield on organic fertilisers and the number of clear days is weak: the regression lines are almost horizontal, and the confidence intervals are wide, which indicates the absence of a clearly pronounced linear effect within the paired analysis. A similar situation was observed for the accumulation deficit, where the variation in yield largely overlaps the possible trend. Soil temperature in May was characterised by a weak negative trend, which may reflect a decrease in yield due to excessive soil warming in the early stages of vegetation, however, the significant scatter of observations does not allow interpreting this effect as dominant.In general, the graphs confirm that mineral nutrition was the main factor with a linear effect on sunflower yield, while meteorological factors mainly modify this effect and manifest themselves weaker or nonlinearly, which justifies the need for multifactorial analysis.

The obtained results of the quantitative analysis of the influence of agro- and meteorological factors on sunflower yield in Vinnytsia Oblast are consistent with contemporary studies on the role of agrotechnical factors under climatic conditions. The most stable and statistically significant positive relationship was found between sunflower yield and the level of mineral fertiliser application, which was confirmed by both correlation analysis ($r = 0.656$, $\rho = 0.632$) and linear regression results. Similar conclusions were obtained in studies by M.J. Mokgolo *et al.* (2024) and M. Furmanets & Y. Furmanets (2025), who showed that adequate mineral nutrition significantly increases sunflower productivity regardless of variations in weather conditions, especially in areas of risky farming. In particular, according to M.J. Mokgolo *et al.* (2024), the combined use of organic and mineral fertilisers increased yield by 38.9%. Furthermore, the weak or statistically insignificant pairwise relationship between yield and organic fertilisers obtained in this study is consistent with the findings E. Partal (2022), who noted the prolonged and contextual nature of their impact, depending on the timing of application, soil conditions, and interaction with other agrotechnical measures. The significant influence of meteorological conditions on sunflower productivity was further confirmed in the multi-year study by F.G. Anton *et al.* (2025), conducted across nine counties of Romania in 2022-2024. The researchers established that the year factor had a statistically highly significant effect on seed yield ($F = 1397.87$, $p < 0.001$). This confirmed that even under conditions of applied agrotechnical measures, extreme heat and moisture deficit during the growing season can critically reduce sunflower yield, which was consistent with the pattern of weak but negative relationship between temperature and yield identified in this study. In the context of projected climate change, the findings of J. Junk *et al.* (2024) were particularly relevant: based on phenological modelling of winter oilseed rape the researchers showed that rising temperatures accelerate crop development and introduce new agroclimatic risks.

Among meteorological factors, the most noticeable positive relationship with yield was demonstrated by average wind speed. Similar results were presented by H. Gürkan (2023) and V. Georgieva *et al.* (2024), who showed that moderate wind regime can contribute to the development of a favourable microclimate for crops. Simultaneously, significant scatter of data indicates the contextual nature of this influence and its dependence on the combination with temperature and hydrothermal conditions. The results obtained regarding meteorological factors are also consistent with the study by J. Beteri *et al.* (2024), who showed a strong positive relationship between precipitation and sunflower productivity for Tanzanian conditions ($r \approx 0.65 - 0.75$) and a negative effect of high temperatures ($r \approx -0.60...-0.77$). These numerical indicators confirmed that it is rain and water supply (similar to the Selyaninov hydrothermal coefficient and moisture deficit) that are more important for the establishment of favourable conditions for sunflower growth, while high temperatures during critical phases of development can have a restraining effect.

Weak pairwise correlations between yield and such indicators as the number of clear days, air moisture saturation deficit, and hydrothermal coefficient do not contradict the literature data. C.O. Joseph *et al.* (2025) emphasised that climatic factors usually affect productivity not in isolation, but through interaction with each other and with agrotechnical factors, which limits the possibilities of pairwise analysis. The results obtained also correspond to the general conclusions regarding the increasing sensitivity of sunflower to climatic fluctuations, given by D. Baranskyi (2024) and F. Zabel *et al.* (2025). Similarly to these studies, the Vinnytsia Oblast is characterised by noticeable interannual fluctuations in yield against the background of a general increase in its average level. Compared to approaches based on machine learning methods (Cvejić *et al.*, 2023; Seck *et al.*, 2025; Nazir *et al.*, 2025), the linear regression used in this research has a lower predictive potential, but provides high interpretability of the results. This allows for clear identification of key influencing factors and is important for agro-economic analysis and practical recommendations.

In general, the results of the study confirmed that sunflower yield is formed under the influence of a complex interaction of agrotechnical and meteorological factors, with mineral nutrition playing a leading role under conditions of increasing climatic variability. Statistical analysis highlighted the critical importance of the hydrothermal regime and wind load, which significantly adjusted crop productivity within the Forest-Steppe zone. It was found that the stabilisation of yields during periods of weather anomalies is achieved mainly by intensification of nutrition systems, which eliminates part of the risks of product shortages. The results obtained emphasise the need to transition to adaptive cultivation technologies that consider not only standard agricultural applications, but also the dynamics of local meteorological indicators.

CONCLUSIONS

The conducted study quantitatively assessed the impact of agrotechnical and agrometeorological factors on sunflower yield in Vinnytsia Oblast for 2007-2024 and established the nature and strength of the relationship between the variables under consideration. The normality test using the Shapiro-Wilk test confirmed the absence of statistically significant deviations from normal distribution for all variables ($p > 0.05$), which justified the use of parametric analysis methods. Multicollinearity analysis using VIF did not reveal any critical violations: VIF values for most variables did not exceed 4, which confirmed the independent contribution of each factor to the model. Correlation analysis revealed that the most stable and statistically significant relationship with yield was characteristic of mineral fertilisers ($r = 0.656$; $\rho = 0.632$), which showed a moderately strong positive linear relationship. A moderate positive relationship was also recorded for the average wind speed indicator ($r = 0.512$; $\rho = 0.569$).

Other meteorological factors – the number of clear days, air humidity deficit, and the Selyaninov hydrothermal coefficient – demonstrated weak or indirect pairwise relationships with yield, which was consistent with the literature data on the predominantly nonlinear and interdependent nature of the influence of climatic factors. The constructed regression model demonstrated high predictive ability, describing 68% of the variability of yield was conditioned by the selected set of factors. Analysis of regression coefficients confirmed the leading role of mineral nutrition ($p = 0.03$): an increase in the rate of mineral fertiliser application per unit was accompanied by a statistically significant increase in crop productivity. A probable negative contribution was recorded for the wind regime indicator ($p = 0.02$): excessive wind activity was associated with a decrease in yield due to increased transpiration and the risks of crop drying out in critical phases of development.

Thus, sunflower yield was developed under the complex influence of controlled agrotechnical and uncontrolled meteorological factors, with the level of mineral nutrition playing a decisive role. The obtained regression equations can be used to predict sunflower productivity and optimise nutrition systems to minimise the risks of climate variability. Prospects for further research are related to expanding the geographical coverage of the sample, including nonlinear and regularised models (Lasso, Ridge, Elastic Net), and analysing interactions between factors to more fully consider the complex nature of crop development in a changing climate.

ACKNOWLEDGEMENTS

The research was carried out as parts of the following R&D project: (0123U101895) Mathematical methods and models in applied economic research.

FUNDING

None.

CONFLICT OF INTEREST

None.

REFERENCES

[1] Acir, N. (2025). Predicting soil fertility in semi-arid agroecosystems using interpretable machine learning models: A sustainable approach for data-sparse regions. *Sustainability*, 17(16), article number 7547. doi: 10.3390/su17167547.

[2] Amankulova, K., Farmonov, N., Mukhtorov, U., & Mucsi, L. (2023). Sunflower crop yield prediction by advanced statistical modeling using satellite-derived vegetation indices and crop phenology. *Geocarto International*, 38(1), article number 2197509. doi: 10.1080/10106049.2023.2197509.

[3] Anton, F.G., Joița-Păcureanu, M., Contescu, L., Cergan, M., Partal, E., & Pintilia, S. (2025). Sunflower production of some genotypes in years 2022, 2023 and 2024, in Romania. *Scientific Papers. Series A. Agronomy*, 68(1), 246-253.

[4] Baranskyi, D. (2024). Managing sunflower growth in the changing climate and fluctuating moisture levels of the Western forest-steppe. *Bulletin of Lviv National Environmental University. Series Agronomy*, 28, 57-66. doi: 10.31734/agronomy2024.28.057.

[5] Beteri, J., Lyimo, J.G., & Msinde, J.V. (2024). The influence of climatic and environmental variables on sunflower planting season suitability in Tanzania. *Scientific Reports*, 14, article number 3906. doi: 10.1038/s41598-023-49581-5.

[6] Chekhova, I.V. (2022). Peculiarities of oilseeds market functioning in Ukraine. *Scientific and Technical Bulletin of the Institute of Oilseed Crops NAAS*, 32, 154-161. doi: 10.36710/IOC-2022-32-15.

[7] Cvejić, S., Hrnjaković, O., Jocković, M., Kupusinac, A., Doroslovački, K., Gvozdenac, S., Jocić, S., & Miladinović, D. (2023). Oil yield prediction for sunflower hybrid selection using different machine learning algorithms. *Scientific Reports*, 13, article number 17611. doi: 10.1038/s41598-023-44999-3.
[8] Debaeke, P., Attia, F., Champolivier, L., Dejoux, J.F., Micheneau, A., Al Bitar, A., & Trépos, R. (2023). Forecasting sunflower grain yield using remote sensing data and statistical models. *European Journal of Agronomy*, 142, article number 126677. doi: 10.1016/j.eja.2022.126677.
[9] Furmanets, M., & Furmanets, Y. (2025). Productivity of sunflower under different tillage and fertilization systems in the Western Forest-Steppe of Ukraine. *Agro-Business Today*. Retrieved from https://agro-business.com.ua/agro/ahronomiia-sohodni/item/31616-produktyvnist-soniashnyku-za-riznykh-system-obrobitku-gruntu-i-udobrennia-v-zakhidnomu-lisostepu-ukrainy.html.
[10] Georgieva, V., Kazandjiev, V., Georgiev, S., Rashev, S., Valkova, D., Mihova, G., Valchev, D., & Dobreva, V. (2024). Agro-climatic conditions for growing of sunflower in different climatic area in Bulgaria. *Scientific Papers. Series A. Agronomy*, 67(2), 224-231.
[11] Gürkan, H. (2023). Evaluation of the impacts of climate change on sunflower with aquacrop model. *Journal of Tekirdag Agricultural Faculty*, 20(4), 933-947. doi: 10.33462/jotaf.1240401.
[12] Hnatiienko, V., & Hnatiienko, H. (2024). Integration of machine learning and deep learning methods for sunflower yield prediction. *Management of Development of Complex Systems*, 59, 225-234. doi: 10.32347/2412-9933.2024.59.225-234.
[13] Hu, Y., & Yu, J.y. (2016). Quantilequantile plot compared with stabilized probability plot in figure on the distribution of the test research. *American Journal of Applied Mathematics*, 4(2), 110-113. doi: 10.11648/j.ajam.20160402.17.
[14] Jabed, M.A., & Murad, M.A.A. (2024). Crop yield prediction in agriculture: A comprehensive review of machine learning and deep learning approaches, with insights for future research and sustainability. *Heliyon*, 10(24), article number e40836. doi: 10.1016/j.heliyon.2024.e40836.
[15] Joseph, C.O., Kambwily, K., & Emmanuel, S.M. (2025). Effects of planting window on grain yield and oil yield under rainfed sunflower (*Helianthus annuus* L.) in Kilwa District, Lindi, Tanzania. *Discover Agriculture*, 3, article number 8. doi: 10.1007/s44279-025-00155-1.
[16] Junk, J., Torres, A., El Jaroudi, M., & Eickermann, M. (2024). Impact of climate change on the phenology of winter oilseed rape (*Brassica napus* L.). *Agriculture*, 14(7), article number 1049. doi: 10.3390/agriculture14071049.
[17] Karan, R., Ramkumar, M.O., & Yokesh, M. (2024). Revolutionizing tamilnadu agriculture: AI-powered crop yield forecasting and disease prediction for oil seed crops. In *2024 Ist international conference on cognitive, green and ubiquitous computing* (pp. 1-10). Piscataway: IEEE. doi: 10.1109/IC-CGU58078.2024.10530710.
[18] Majumder, S., & Mason, C.M. (2025). Sunflower yield modeling with explainable artificial intelligence: Historical weather impacts across half a century of American production. *Agronomy Journal*, 117(6), article number e70204. doi: 10.1002/agj2.70204.
[19] Mokgolo, M.J., Zerizghy, M.G., & Mzezewa, J. (2024). Sunflower growth and grain yield under different tillage systems and sources of organic manure on contrasting soil types in Limpopo Province of South Africa. *Agronomy*, 14(4), article number 857. doi: 10.3390/agronomy14040857.
[20] Nazir, A.A., Rubaiat, E., Saiful, I., & Al Sohan, M.F.A. (2025). Evaluating machine learning models for crop yield prediction. In *2025 international conference on quantum photonics, artificial intelligence, and networking* (pp. 1-6). Piscataway: IEEE. doi: 10.1109/QPAIN66474.2025.11171630.
[21] O'Brien, R.M. (2007). A caution regarding rules of thumb for variance inflation factors. *Quality & Quantity*, 41, 673-690. doi: 10.1007/s11135-006-9018-6.
[22] Partal, E. (2022). Sunflower yield and quality under the influence of sowing date, plant population and the hybrid. *Romanian Agricultural Research*, 39, 463-470. doi: 10.59665/rar3944.
[23] Qiu, Z. (2022). An elastic net based algorithm for China agriculture GDP prediction. In *2022 international conference on economics, smart finance and contemporary trade* (pp. 843-849). Paris: Atlantis Press. doi: 10.2991/978-94-6463-052-7_96.
[24] Seck, N.K.G., Ngom, A., Ngom, P., & Noba, K. (2025). Crop yield forecasting in Senegal: Application of machine learning methods. *Discover Agriculture*, 3(1), article number 192. doi: 10.1007/s44279-025-00381-7.
[25] Sectoral State Archive of Hydrometeorological Observation Materials of the State Emergency Service of Ukraine. (n.d.). Retrieved from https://cgo-sreznevskyi.kyiv.ua/uk/struktura-fondiv/21-hda-mhs.
[26] Shakalii, S.M., & Kulyk, Ye.I. (2025). Impact of weather and climatic factors on sunflower seed quality. In *Current directions and challenges in crop production technologies: Proceedings of the 5th international scientific and practical internet conference* (pp. 27-29). Poltava: Poltava State Agrarian University.
[27] Shapiro, S.S., & Wilk, M.B. (1965). An analysis of variance test for normality (complete samples). *Biometrika*, 52(3-4), 591-611. doi: 10.1093/biomet/52.3-4.591.

[28] Song, Z., Wang, P., Zhang, Z., Yang, S., & Ning, J. (2023). Recognition of sunflower growth period based on deep learning from UAV remote sensing images. *Precision Agriculture*, 24, 1417-1438. doi: 10.1007/s11119-023-09996-6.

[29] State Statistics Service of Ukraine. (n.d.). *Main Department of Statistics in Vinnytsia Region*. Retrieved from https://vn.ukrstat.gov.ua/index.php/statistical-information/.

[30] Sydiakina, O.V., & Hamajunova, V.V. (2023). Current state and prospects of sunflower seed production. *Taurida Scientific Herald*, 131, 196-204. doi: 10.32782/2226-0099.2023.131.25.

[31] Thavareesan, S., Sriranganesan, J., & Nishatharan, T. (2025). Exploring machine learning techniques for accurate crop yield prediction. *Annals of Agricultural Science and Technology*, 8(1), 1-7.

[32] Vasylkovska, K., Andriienko, O., Malakhovska, V., & Moroz, O. (2022). Analysis of changes in comfortable sunflower growing areas using the example of Ukraine. *Helia*, 45(77), 175-189. doi: 10.1515/helia-2022-0010.

[33] Zabel, F., Knüttel, M., & Poschlod, B. (2025). CropSuite v1.0 – a comprehensive open-source crop suitability model considering climate variability for climate impact assessment. *Geoscientific Model Development*, 18(4), 1067-1087. doi: 10.5194/gmd-18-1067-2025.

[34] Zalai, M., Bojtor, C., Nagy, J., Széles, A., Monoki, S., & Illés, Á. (2025). Challenges in precision sunflower cultivation: The impact of the agronomic environment on the quality of precision sowing techniques and yield parameters. *AgriEngineering*, 7(5), article number 145. doi: 10.3390/agriengineering7050145.

Вплив агро- і метеофакторів на урожайність соняшника

Анатолій Кулик
Кандидат фізико-математичних наук, завідувач кафедри
Київський національний економічний університет імені Вадима Гетьмана
03057, просп. Берестейський, 54/1, м. Київ, Україна
https://orcid.org/0000-0002-6629-0253

Валентина Лісовська
Кандидат фізико-математичних наук, професор
Київський національний економічний університет імені Вадима Гетьмана
03057, просп. Берестейський, 54/1, м. Київ, Україна
https://orcid.org/0000-0001-8675-3975

Ольга Мельник
Кандидат фізико-математичних наук, доцент
Київський національний економічний університет імені Вадима Гетьмана
03057, просп. Берестейський, 54/1, м. Київ, Україна
https://orcid.org/0000-0002-4399-176X

Надія Щекань
Старший викладач
Київський національний економічний університет імені Вадима Гетьмана
03057, просп. Берестейський, 54/1, м. Київ, Україна
https://orcid.org/0000-0002-1784-6139

Анотація. Соняшник є однією з провідних олійних культур України, а стабільність його врожайності має важливе економічне та продовольче значення. В умовах посилення кліматичної мінливості актуалізується потреба в кількісному аналізі впливу агротехнічних і метеорологічних факторів на формування врожаю. Метою дослідження була кількісна оцінка ролі агротехнічних і кліматичних чинників у формуванні урожайності соняшника з використанням статистичних методів аналізу. Емпіричну базу дослідження становили дані за 2007-2024 рр., що включали показники урожайності соняшника, рівні внесення мінеральних і органічних добрив, а також метеорологічні характеристики (температура ґрунту у травні, кількість опадів, дефіцит насичення повітря вологою, гідротермічний коефіцієнт Селянінова, швидкість вітру, кількість ясних днів у вегетаційний період). У роботі застосовано описову статистику, критерій Шапіро-Вілка, кореляційний аналіз Пірсона і Спірмена, а також багатофакторну лінійну регресію. Результати дослідження свідчили, що середній рівень урожайності за період становив 25,65 ц/га зі стандартним відхиленням 5,91 ц/га. Найбільш стабільний і статистично значущий вплив на урожайність соняшника мав рівень внесення мінеральних добрив, для якого зафіксовано помірно сильний позитивний зв'язок (r = 0,656). Серед метеофакторів найбільш помітний позитивний зв'язок виявлено для швидкості вітру (r = 0,512). Перевірка на мультиколінеарність за допомогою коефіцієнта інфляції дисперсії підтвердила коректність моделі, оскільки значення для більшості змінних не перевищували 4, а максимальний показник склав 5,17 для мінеральних добрив. Аналіз підкреслив ключову роль агротехнічного управління, оскільки вплив таких факторів, як гідротермічний коефіцієнт Селянінова (r = 0,083) та дефіцит вологи (r = 0,092), виявився слабким у межах парного аналізу. Практична цінність результатів полягає у можливості використання розроблених регресійних моделей для прогнозування продуктивності соняшника та оптимізації систем мінерального живлення з метою мінімізації ризиків, зумовлених несприятливими метеорологічними чинниками

Ключові слова: агрометеорологічні показники; гідротермічний коефіцієнт Селянінова; мультиколінеарність; кореляційний аналіз; лінійна регресія; коефіцієнт інфляції дисперсії