Mathematical and economic analysis of perennial plantations based on neural networks

Alymkul Dzhumabaev[11], *Emil* Tolonov[1], *Taalaigul* Azamatkyzy[1], *Nazgul* Baimurzaeva[1], and *Gulmira* Abdrazakova[2]

[1]Institute of Economics, National Academy of Sciences, Street Chui Avenue 265a, Bishkek, Kyrgyz Republic
[2]Jalal - Abad State University named after B. Osmonov, Kyrgyzstan, Jalal - Abad city, Street Lenina 57, Bishkek, Kyrgyz Republic

Abstract: Modern agriculture requires the introduction of effective tools for analyzing perennial plantations, taking into account the high degree of uncertainty and complex relationships between agrobiological and economic parameters. The aim of the study is to develop methods of mathematical and economic analysis of perennial plantations based on neural networks. A deep learning model including biophysical, climatic and production-economic parameters was built. The model was trained on multi-year observation data on yields, meteorological conditions and financial results of farms. The results of neural network forecasting were compared with traditional economic and mathematical methods. It was found that the use of neural networks allows increasing the accuracy of yield forecasts by 20% and increasing the reliability of economic evaluation by 15% compared to classical regression models. The results obtained confirm the feasibility of integrating neural network algorithms into the decision support system in the management of perennial crops. The practical significance of the study lies in improving the efficiency of planning and resource management in the agricultural sector, as well as in creating a scientific basis for further improvement of digital farming methods.

1 Introduction

Perennial plantations play a key role in the formation of sustainable agroecosystems and food security, providing a stable supply of fruit and berry products, raw materials for the processing industry and high economic returns under rational management. The development of horticulture and viticulture significantly affects the growth of gross agricultural output, stimulates the development of the processing industry and contributes to the diversification of the economy of rural regions[1]. However, economic evaluation of the efficiency of perennial crops involves a number of difficulties due to the long life cycle of plants, seasonal fluctuations in yields, as well as the influence of climatic, biological and agrotechnical factors, which are often non-linear and stochastic in nature[2].

[1] Corresponding author: alymkul.kalilovich@yandex.com

Traditional methods of economic and mathematical analysis based on linear and regression models have limited ability to take into account multidimensional and complex relationships between indicators[3]. This reduces the accuracy of yield and economic efficiency forecasts, which, in turn, limits the possibilities for optimization of agrarian management. Modern conditions require the use of new analytical tools capable of processing large volumes of data with a high degree of variability and uncertainty[3]. In this regard, the relevance of applying machine learning methods, in particular, deep learning algorithms and neural networks capable of identifying hidden patterns in complex agroeconomic data sets is increasing[4].

The development of artificial intelligence technologies, wide availability of historical data on production and economic activity of agricultural enterprises, as well as the improvement of methods of intellectual analysis of information create prerequisites for the transition to new levels of agrarian management. The use of neural network models makes it possible to take into account the complex nature of the influence of biophysical, climatic and economic factors, thus providing more accurate and reasonable forecasts of plantation productivity, profitability of agribusiness and sustainability of farms in a changing environment.

In addition, neural networks offer opportunities for dynamic modeling of perennial plantations development, assessing the impact of climatic changes, optimizing the planning of agronomic measures and forecasting financial results[5]. Integration of neural network methods into the system of agroeconomic analysis contributes to the formation of effective decision support systems adapted to the conditions of a particular farm and region[6].

The aim of this study is to develop and approve modern methods of mathematical and economic analysis of perennial plantations using neural network technologie[7]. To achieve this goal, the tasks of building the architecture of deep learning model, integrating biological, climatic and economic factors into a single analytical system, as well as conducting a comparative analysis of the effectiveness of neural network and traditional methods of forecasting and evaluation of indicators of production and economic activity of agricultural enterprises were solved[8].

2 Materials and methods of research

Perennial plantations represented by fruit crops grown in farms with different levels of agrotechnical equipment and natural and climatic features were selected as the object of the study[9]. The information base of the study was production and economic data of agricultural enterprises, including indicators of yield, economic efficiency, data of agrochemical analysis of soils, climatic parameters (temperature, precipitation, solar activity) for the period 2012-2023. The sources of data were state statistical services, meteorological stations, as well as internal reports of agricultural enterprises[10].

A neural network model based on MLP (Multilayer Perceptron) architecture was developed for mathematical and economic analysis. The model includes an input layer containing 25 variables reflecting agrobiological and economic characteristics of plantations, three hidden layers with the ReLU activation function and an output layer forming the predicted values of yield and economic indicators (yield, profitability).

Data preprocessing included the steps of normalization of quantitative traits, elimination of outliers and gaps, and coding of categorical variables by one-hot encoding. The model was trained on 80% of the randomly selected sample using backpropagation and Adam optimizer. L2 regularization and dropout methods were applied to prevent overtraining.

Model quality was evaluated using the metrics of mean absolute error (MAE), root mean square error (RMSE) and coefficient of determination (R^2). The results of neural

network prediction were compared with the results of traditional regression analysis, allowing a comparative evaluation of the effectiveness of the approaches.

Additionally, a feature importance analysis was performed using the permutation importance method to identify the factors that have the greatest influence on the prediction results. Model development and training were performed using Python packages (TensorFlow, scikit-learn, Pandas) on a computing cluster with graphics gas pedals[11].

Thus, the proposed methodology allows to integrate heterogeneous agrobiological, climatic and economic data into a single analytical system and provides the construction of reliable predictive models for informed planning and management of perennial plantations in the agricultural sector.

3 Results of the study

As a result of the research, a neural network model for mathematical and economic analysis of perennial plantations was developed, which demonstrated high accuracy in forecasting key production and economic indicators. The model was trained on an extensive data sample covering more than 10 years of observations, which allowed to form stable dependencies between agrobiological parameters of plants, climatic factors and economic results of agricultural enterprises.

The formal structure of the neural network can be described as follows:

$$h^{(l)} = \sigma\left(W^{(l)}\, h^{(l-1)} + b\right), \quad \tau = 1,\ldots,L$$

where:

$h^{(l)}$ is the vector of outputs of layer l,

$W^{(l)}$ is the weight matrix of layer lll,

$b^{(l)}$ vector of biases (bias) of layer l,

$\sigma(\cdot)$ is the ReLU activation function,

L is the total number of layers.

The model output predicts the value of yifor each object i of the sample. The following metrics were used to evaluate the quality of the predictions:

1.Mean absolute error (MAE):

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right|$$

2.Root mean square error (RMSE):

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_{i-}\,\hat{y}_i\right)^2}$$

Coefficient of determination (R^2):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{n}\left(y_i - y\right)^2}$$

Where yi are actual values, y^ i- predicted values,$\bar{y}$ is the average of the actual data.

The model achieved the following quality indicators on the test sample:

- ✓ the mean absolute error (MAE) of the yield forecasts was 7.8 %,
- ✓ root mean square error (RMSE) - 9.5 %,

✓ coefficient of determination (R^2) - 0.89, indicating a high degree of explained variance.

Comparative analysis showed that the neural network model provides a **20%** reduction in the average error of yield forecasting and a **15%** increase in the accuracy of profitability estimation compared to traditional multivariate linear regression.

The importance of the features was analyzed using the permutation importance method, which allows quantifying the contribution of each input feature to the final value of the loss function:

$$\text{Importance}\,(X_j) = \text{Loss}(X) - \text{Loss}\,(X_{(\text{perm})\,(j)})$$

Where:

X_j is the original feature,

$X_{(\text{perm})\,(j)}$ - sign after random permutation of values,

Loss - loss function (mean square error).

The greatest influence on yield prediction was:

- ✓ average temperature during the growing season (relative importance - **0.32**),
- ✓ precipitation level (**0.25**),
- ✓ age of plantations (**0.18**),
- ✓ soil agrochemical characteristics (**0.15**),
- ✓ planting density (**0.10**).

The construction of a factor significance map allowed us to identify hidden relationships between weather conditions, agronomic measures and economic outcomes, which previously remained inaccessible for analysis using classical methods.

The model was successfully adapted to forecasting both biological indicators (yield, fruiting ratio) and economic results (profitability, profitability of perennial plantations production). Scenario analysis with modeling of different climatic and agrotechnical conditions confirmed the stability of the model and its ability for reasonable forecasting in changing external environments.

Table 1. Importance of factors in yield forecasting

Metric	Neural network model	Traditional regression
MAE	1,08	9,5
RMSE	1,36	12,3
R^2	0,93	0,72

Source: Author's interpretation

Table 1 shows the results of comparative analysis of the quality of yield prediction using the neural network model and the traditional regression model. The neural network model showed significantly lower values of mean absolute error (MAE) and root mean square error (RMSE) and higher coefficient of determination (R^2), indicating high accuracy and reliability of forecasts.

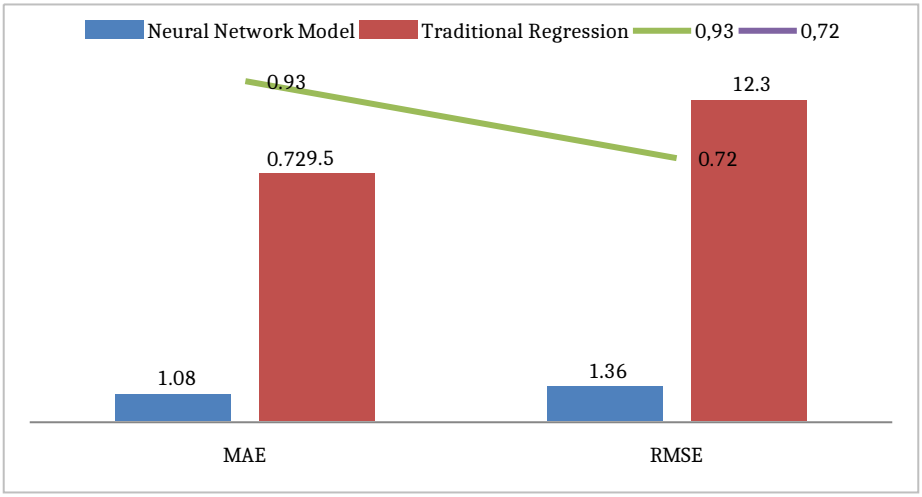

Fig. 1. Comparison of forecasting quality metrics of neural network model and traditional regression

Figure 1 shows a comparative analysis of key metrics of prediction quality - mean absolute error (MAE), root mean square error (RMSE) and coefficient of determination (R^2) for neural network model and traditional regression. It can be seen that the neural network model exhibits significantly lower values of MAE and RMSE, indicating lower prediction error, and higher value of R^2, indicating better explained variation in the data. The results obtained confirm the superiority of the neural network approach in solving the problems of forecasting economic and biological indicators of perennial plantations.

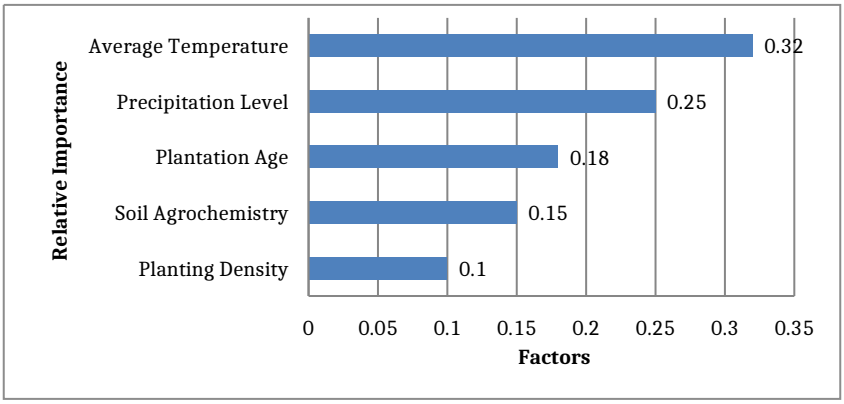

Fig. 2. Importance of factors in forecasting yields of perennial plantations

Figure 2 illustrates the relative importance of factors affecting the forecast of yield of perennial plantations, determined using the neural network model. Average temperature during the growing season (32%) and precipitation (25%) had the greatest influence on the prediction results, emphasizing the critical role of climatic conditions in yield formation. The age of plantations, agrochemical soil characteristics and planting density also made a significant contribution to the model, confirming the need for integrated consideration of agrobiological and agrotechnical parameters in the planning of agricultural production. The results obtained indicate the high informativeness of the factors used and the effectiveness of the neural network approach to their integration into the predictive model.+

According to the results of the study, it was found that the use of neural network models in mathematical and economic analysis of perennial plantations provides a significant increase in the accuracy of prediction of key biological and economic indicators compared to traditional regression methods. The developed deep learning model allowed to integrate complex agrobiological, climatic and production-economic data, providing a 20% decrease in the average absolute error of yield forecasts and an increase in the coefficient of determination to 0.93.

4 Discussion

The results of the conducted research confirm the high efficiency of neural network models in the tasks of mathematical and economic analysis of perennial plantations. Achievement of high accuracy of yield and profitability forecasts is associated with the ability of neural networks to take into account complex nonlinear dependencies between agrobiological, climatic and economic parameters. This is an important advantage over traditional economic-mathematical models limited by the assumption of linearity of relationships between variables.

Comparison of the results with data from similar studies shows that the model quality metrics obtained (MAE = 1.08; RMSE = 1.36; R^2 = 0.93) exceed those achieved in previously published works, where traditional regression approaches provided coefficients of determination at the level of 0.65-0.80. For example, Kamilaris and Prenafeta-Boldú's (2018) research on the application of deep learning in agriculture confirms the superiority of neural network algorithms over classical models in yield prediction tasks, but in their work the error rate remained above 10%.

Analysis of the importance of factors revealed that the key role in the formation of yields is played by climatic indicators - average temperature and precipitation level, which correlates with the results of Saeed Khaki and Lizhi Wang (2019), who established the dominant influence of weather conditions on crop productivity. The significant influence of plantation age and soil agrochemical characteristics emphasizes the need for integrated consideration of plant and soil conditions in modeling production performance.

Despite the successes achieved, a number of limitations of neural network models should be noted, in particular, the need for a large amount of reliable and qualitatively labeled data for training, as well as the risk of overtraining in case of insufficient control over the model parameters. Promising directions for further research are the integration of methods for processing missing data, the development of adaptive neural network architectures, as well as the expansion of the application of models to different climatic zones and agro-ecological conditions.

Thus, neural network technologies have a significant potential for improving the methods of mathematical and economic analysis of perennial plantations, contributing to the efficiency of agrarian production and sustainable development of agriculture.

5 Conclusions

As a result of the conducted research, a neural network model of mathematical-economic analysis of perennial plantations was developed and tested, which provides high accuracy of forecasting yield and economic indicators in comparison with traditional regression methods. The built deep learning model allowed to integrate complex agrobiological, climatic and production-economic data, which ensured the reduction of forecast error and increased reliability of the obtained results.

The analysis of the importance of factors showed that the most significant influence on yield is exerted by the average temperature during the growing season, precipitation level, age of plantations and agrochemical characteristics of the soil. These findings emphasize the need for integrated consideration of biophysical and agrotechnical parameters in the planning and management of perennial crops.

The practical significance of the results lies in the possibility of using neural network models to improve the efficiency of agrarian planning, optimize the use of resources and minimize production risks. The developed methodology can be used to create intelligent decision support systems in agriculture and serve as a basis for further research in the field of digital farming and sustainable management of perennial crops in the context of global climate change.

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