International Journal of Design & Nature and Ecodynamics
Vol. 18, No. 2, April, 2023, pp. 449-455
Journal homepage: http://iieta.org/journals/ijdne

System Analysis and Forecast of Yield Time Series Based on Neural Network Technologies

Gailya F. Aubakirova[1*], Yuliya V. Gerassimova[1], Victor P. Ivel[1], Tetiana V. Arestenko[2], Svitlana Prymyska[3]

[1] Department of Energy and Radioelectronics, M. Kozybayev North Kazakhstan University, 86 Pushkin Str., Petropavlovsk 150000, Republic of Kazakhstan
[2] Department of Marketing, Dmytro Motornyi Tavria State Agrotechnological University, 18 B. Khmelnitsky Ave., Melitopol 72310, Ukraine
[3] Department of Organic Chemistry and Technology of Organic Substances, National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute", 37 Peremohy Ave., Kyiv 03056, Ukraine

Corresponding Author Email: gailya.aubak@yahoo.com

https://doi.org/10.18280/ijdne.180224

Received: 28 December 2022
Accepted: 15 March 2023

Keywords:
the least-squares method, crops, nonlinear trend, difference series, vegetation index, neural networks

ABSTRACT

With the help of neural networks, it is possible to automate the processes of pattern recognition, adaptive control, forecasting, creating expert systems, etc. Neural networks can successfully solve problems that traditional methods cannot cope with, relying on incomplete, noisy or modified information. In its pure form, neural network modelling is based solely on data without using a priori theories. The North Kazakhstan region is the object of the study. The paper uses the theory of random processes and high-order Markov chains, allowing to build a model of a series; statistics and econometrics, which are used to select a plurality of lagged variables that affect predictive indicators, and to estimate the probability matrices of transitions between states; nonlinear optimisation methods to construct a nonlinear trend model with harmonic components aimed at predicting the low-frequency component of a time series. The artificial neural network will be implemented using Matlab. Studies have shown that the yield time series are persistent, that is, they have the effect of "long-term memory". Autoregressive models cannot act as an adequate tool for modelling and forecasting such series. The practical significance of the study lies in the possibility to use the results to enhance plant yield at agricultural enterprises.

1. INTRODUCTION

Time series modelling is a dynamic research field that has invited the attention of scientists over the past decades. In this field, the main goal of researchers is to carefully collect and study past observations of time series to develop an appropriate model describing the structure inherent in this series. This model is then used to generate future data for the series, that is, to forecast. Thus, time series forecasting can be called an act of predicting the future by understanding the past. Due to the indispensable importance of forecasting some time series in many practical areas, such as business, economics, finance, science and engineering, and the like, it is obvious that successful forecasting of time series depends on the correct configuration of the model. Over the years, researchers have done a lot of work to develop effective models to improve the accuracy of forecasting. As a result, various important time series forecasting models have appeared in the literature. A time series is a sequential set of data points, measured, as a rule, over several consecutive time periods. Mathematically, it is defined as a set of vectors $x(t)$, t=0, 1, 2, ... where t is the time elapsed. The variable $x(t)$ is considered as a random variable. The measurements taken during an event in a time series are arranged in a properly sorted form [1].

Time series is called univariate if it contains records of a single variable. But, if we consider records of more than one variable, then it is called multivariate. Time series can be continuous or discrete. In continuous time series, observations are measured at each specific time instance, while discrete time series contain observations measured at discrete time points. For example, temperature indicators, river flow, chemical process concentration, etc. can be recorded as continuous time series. On the other hand, the population of a particular country, a city, the production of a company, the exchange rates between two different currencies can be examples of a discrete-time series. Usually, consecutive observations are recorded in discrete time series, at the same time intervals, such as an hour, a day, a week, a month or a year [2, 3].

According to the study of Marko et al. [4], a variable that is observed in a discrete-time series is the following, which is supposed to be measured as a continuous variable using a scale of real numbers. In addition, the researcher [5] believes continuous time series can be easily converted into discrete time series by combining data over a specific time interval. According to the study of Wei et al. [6], in many cases, crop yield modelling has a sufficiently high estimation error for a linear model, which allows us to assume that the nature of the dependence y=f(x) is nonlinear. Scientists in the research [7] claim that linear regression with coefficients calculated based on the least squares method is observed only when the model variables are random variables distributed according to a normal constant variance. If the assumption of normality is not fulfilled, then the linear model will make a significant error [8]. Nonlinear estimation refers to complex and time-consuming tasks, requires professional knowledge of mathematical statistics, since a researcher must obtain a model of crop yield formation with sufficiently high accuracy as a result of modelling [9]. This makes it possible to use nonlinear models in production processes to obtain highly reliable forecasts of yield design.

2. MATERIALS AND METHODS

The North Kazakhstan region was chosen as the object for forecasting using neural networks. The paper uses the theory of random processes and high-order Markov chains, allowing to build a model of a series; statistics and econometrics, which are used to select a plurality of lagged variables that affect predictive indicators, and to estimate the probability matrices of transitions between states; nonlinear optimisation methods to construct a nonlinear trend model with harmonic components aimed at predicting the low-frequency component of a time series. So, the proposed method involves using a combination of random processes, Markov chains, statistics, econometrics, and nonlinear optimization methods to build a model for forecasting yield time series. The specific steps of the method include:

(1) using the theory of random processes and high-order Markov chains to build a model for the time series;

(2) using statistics and econometrics to select a set of lagged variables that affect the predictive indicators, and estimate the probability matrices of transitions between states;

(3) using nonlinear optimization methods to construct a nonlinear trend model with harmonic components aimed at predicting the low-frequency component of the time series;

(4) using an artificial neural network (ANN) based on Matlab to perform the forecasting of the yield time series for the North Kazakhstan region.

The overall goal of the proposed method is to improve the information and analytical support system for agriculture in the region, by incorporating geoinformation technologies, precision farming technologies, and rational use of natural resources. The method aims to overcome the limitations of traditional statistical methods by using neural network technology, while also leveraging the benefits of established statistical and econometric approaches.

3. RESULTS

The main tasks that we want to perform in this study are the development of new methods for forecasting yields and comparing them with the current ones; a comparative assessment of the accuracy of various forecasting methods. All the methods discussed in this paper were tested based on time series of the average yield of spring wheat for the North Kazakhstan region.

(1) Harmonious model. An effective way to model time series with a cyclic effect is the polyharmonic yield model [10], based on the hypothesis that the Yield function is the sum of several harmonic and one random factor (noise):

$$x_t = a_i \times b_i sin(t) + E, i = 1 \times T_i \quad (1)$$

where, x_t is the actual yield values, a_i, b_i are the amplitudes of the i-th harmonic, E is an error term or noise, which represents random fluctuations or measurement errors that affect the value of x_t; i is an index that specifies the different harmonic components that are included in the model; T_i is the harmonic period, t is the current time, m is the number of fundamental waves.

According to estimates, the first three harmonics are the most significant. The i-th harmonic values (i =1, 2, 3, ..., m) were sequentially determined from the state of the minimum error of the model using the least-squares method in combination with a complete search of the period values.

$$\Psi = (x_t - a_0 - a_i \times cos(t) - b_i \times \sin(t)) \rightarrow min, i = 1 \times T_i \quad (2)$$

where, a_0 represents the mean value of the time series x_t, and a_i and b_i represent the amplitudes of the i-th harmonic component; min, i mean that the minimization is performed with respect to the values of a_i and b_i for each i, as well as the period values $T_{i.}$

An extrapolation of the three-harmonic trend was used to forecast the yield called the harmonic model.

(2) Analytical method for difference series. Studying and modelling a first difference series is an effective mechanism for forecasting a time series. The advantage of this approach is the correct reproduction of ups and downs, which is especially important for modelling the dynamics of a time series. If the time series is next to independent increments, the probabilities of increments and declines are the same. The persistence effect rejects this possibility. Therefore, the corresponding probabilities must be estimated for each specific time series. The authors implemented this approach within the framework of the method of statistical analysis of difference series. The algorithm of the method is as follows. A difference series is built based on an initial series, and a series that consists of one, two, three or more consecutive increases (declines). The following difference series are classified: i1 - a one-line increase (decrease (increase-decrease)), i2 - a series of two consecutive increments, i3 - a series of three consecutive increments, i4 - a series of four or more consecutive increments. The corresponding series of declines are denoted by d1, d2, d3, d4. The difference series is statistically analysed to identify the frequency of occurrence of each of the eight series highlighted above. On its basis, taking into account the type of the last series and the possible following scenarios of the system behaviour, the forecast is built:

$$x \times n + 1 = x_n + p_i \times \Delta i + p_d \times \Delta d \quad (3)$$

where, p_i is the probability of future growth, determined by the type of the last series, p_d is the probability of decline, Δi is the average value of growth, Δd is the average value of decline.

Let, for example, the signs of the last two differences are as follows: "–+". If the next sign is "+", then the series i_2, i_3 or i_4 can be implemented. If the next sign is "–", then the series i_1 is implemented. The probability of future growth can be estimated as:

$$p_i = \frac{p_{i_2} + p_{i_3} + p_{i_4}}{p_{i_1} + p_{i_2} + p_{i_3} + p_{i_4}} \quad (4)$$

The probability of a future recession:

$$p_d = \frac{p_{i_1}}{p_{i_1} + p_{i_2} + p_{i_3} + p_{i_4}} \quad (5)$$

The significant dependence of the forecast value $x \times n + 1$ on the prediction base x_n is a certain disadvantage of the analytical method of difference series. In this regard, it is advisable to choose the average value of the last m elements of the series as the forecasting base, or the current average value of all the elements of the series. In this work, the authors have used the last option.

(3) The nearest neighbour method. Studies show that the grain production system belongs to the class of systems with chaotic dynamics [11]. A positive indicator reflects the sensitive dependence of the dynamic system on the initial data, which is one of the main signs of deterministic chaos. The horizon of predictability of a chaotic system is directly related to the indicator: during the time inversely proportional to the Lyapunov exponent, the system completely loses information about its initial state. Therefore, it is basically impossible to forecast the dynamics of a chaotic system for a time exceeding the horizon of predictability. The estimation of the senior Lyapunov exponent l_1=0.27 allows us to set the maximum horizon for forecasting the yield of spring wheat-4 years.

For systems with chaotic dynamics, an approach known as the "delay method" is used. It is based on the construction of a phase trajectory (attractor) in the reconstructed phase space. To restore the phase trajectory of the system from some observations of one variable x_i, it is necessary to form a sequence of vectors y_i according to the same principle as in autoregression problems:

$$y_n = (x_n, x_{n-1}, \ldots, x_n - D + 1)T \quad (6)$$

where, D is the minimum embedding dimension.

The theoretical justification of the delay method was given by F. Takens. According to Takens' theorem, a real attractor of a dynamical system and an attractor reconstructed in phase space from a time series of one of the parameters are topologically equivalent to an adequate choice of the embedding dimension and have the same generalised fractal dimensions, exponents and other numerical properties. If the time series is generated by a dynamic system, that is, the value $x(t)$ is a certain function of the state of such a system, then the immersion depth D occurs, which gives an unambiguous prediction of the next value of the time series. According to the authors' estimates, the cost of the investment measurement for the grain production system is D=4÷5 [11]. The nearest neighbours method is based on the idea of the proximity of phase vectors (Figure 1). Autocorrelation (AC) is a measure of the correlation between a time series and its own lagged values. Partial Autocorrelation (PAC) is a measure of the correlation between a time series and its own lagged values, after controlling for the effects of all intermediate lags.

The main idea is that close phase vectors evolve in the same way over a short period of time. The forecast problem in terms of phase vectors is formulated as follows. A sequence of phase vectors $\{yi\}$ $(i = 1 \ldots k)$ is given, it is necessary to simulate the vector $y_k + 1$. To estimate the change in the phase vector yk, it is necessary to find m vectors closest to it (nearest neighbours). Let us denote these vectors $y_{n_1}, y_{n_2}, \ldots, y_{nm}$. In the process of evolution, these vectors pass into the following vectors – sequences of neighbouring elements of the time series $y_{n1+1}, y_{n2+1}, \ldots, y_{nm+1}$. As the simplest model of the vector yk+1, we can use such a vector:

$$y_{k+1} = (y_{n1+1} + y_{n2+1} + \ldots + y_{nm+1}) \quad (7)$$

The authors used the value *m*=5.

Time series usually serve as a basis to analyse, model, and forecast the future development of systems. The quality of the forecast depends on how well the system is evaluated in terms of its determinism. If the time series is a random process of the "random walk" type, then stochastic methods and estimates should be applied to its modelling [12]. Other approaches are used when the series detects long-term memory, that is, the corresponding system is largely deterministic [13].

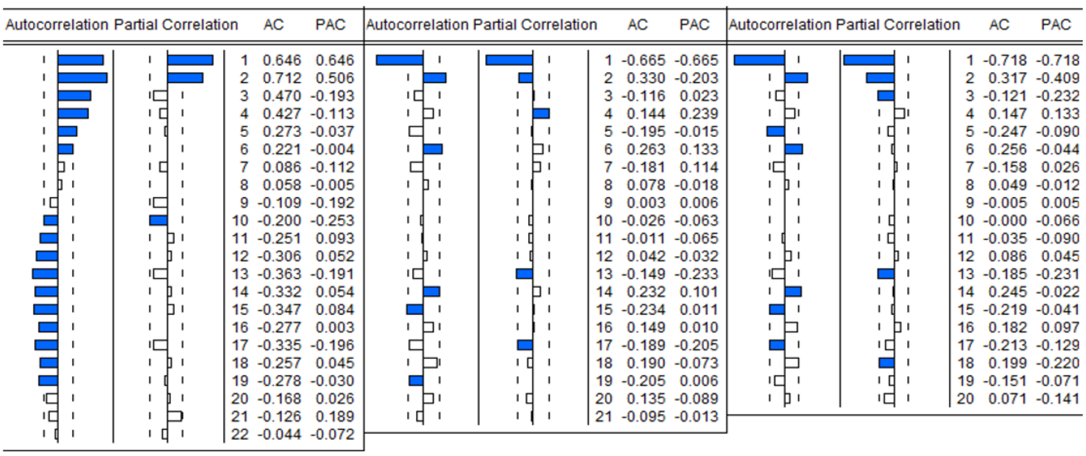

Figure 1. Obtained values of grain yield forecasting using neural networks, taking into account the correlation

4. DISCUSSION

Biophysical models, where remote sensing data are used as input variables to calibrate the model and adjust it, are used much less often. The need to specify numerous specific parameters for each crop is the main disadvantage of such models as well as soil characteristics, methods of crop processing, agrometeorological data of sowing dates. Increasingly, data obtained as a result of remote sensing are used to build models describing the dependence of crop yields on the number of nutrients introduced, the state of soils, and the influence of environmental factors. These methods are usually simple, and their implementation does not require setting a large number of parameters. However, it is necessary to take into account that the processes describing the yield of the main crops are usually non-stationary, and the yield indicators need to be worked out for a significant number of farms of certain soil and climatic zone [14-17].

Statistical methods of yield forecasting based on estimates of physical environmental factors are based on the assumption that there is a simple relationship between environmental properties and yield. In addition, quantitative indicators of photosynthetic activity of biomass i.e., vegetation indices are used to model plant productivity taking into account the determining role of the state of plant biomass formation at certain stages of development [18]. The normalised differential vegetation index (NDVI) is one of them i.e., a simple indicator of the amount of photosynthetically active biomass (the so-called vegetation index). In general, it is simple to obtain, which is the main advantage of the NDVI: to calculate the index, you do not need additional data and methods, except for the space survey itself and knowledge of its parameters. The NDVI dynamics of seasonal changes allows us to estimate the state of plants at different stages of development. The methods proposed for solving problems of this class are rarely used in practice due to the considerable complexity of the necessary soil measurements and the dependencies studied [19, 20].

Neural networks are computational structures aimed at modelling biological processes related to the processes of the human brain. NN are systems that can adapt and learn by analysing positive and negative consequences. An artificial neuron or an analogue of a biological neuron is an elementary converter in these networks. The current state of the theory and practice of creating artificial neural networks and neurocomputers has allowed us to develop fundamentally new algorithms and methods for forecasting; complex nonlinear dynamic objects. Most neural network forecasting schemes are based on the following approaches [13, 21, 22] To analyse these neural forecasting schemes, NN training algorithms and software models have been developed, on which studies are carried out of forecasting processes using dynamic objects. Forecasting values that change over time is one of the areas where ANNs may be applied. There are the following characteristic features of the expediency of using neural networks to complete the task at hand:

- There is no algorithm or principles for solving the problems, but a sufficient number of examples have been accumulated;
- The problem is characterised by large amounts of input information;
- The data is incomplete or redundant, noisy, partially contradictory.

Along with this, it is possible to formulate the predictive properties of ANNs, which, in particular, include the following:

(1) The ability to make a multi-factor forecast.

(2) The efficiency of forecasting is necessary, which is achieved by the maximum parallelism of information processing.

(3) Insensitivity to the shortcomings of a priori information about the dynamics of the predicted object.

(4) The ability to process data presented in different types of scales.

(5) Due to the complete connectivity and a large number of artificial neurons, NNs retain their properties even when their separate parts are destroyed. As a result, NNs are highly reliable and tolerate the forecast results to distortions and interference in the input vectors.

(6) The ability to complete training.

(7) The ability to forecast jumps and events that were not observed earlier in training samples of other observed objects; it can be the choice or synthesis of such NN type able to produce a prototype and generalise precedents in their likeness.

The construction of models based on experimental data has a significant theoretical and practical basis. In particular, there is a wide arsenal of methods and tools for structural and parametric identification of the studied processes. In addition, these tools and methods can both have a universal character, and to a certain extent be focused on specific subject areas, different levels of formalisation of the task. Regression analysis methods are among the most widely used to analyse experimental data in economics, finance, sociology, biology, psychology, medicine, engineering, etc. [23]. The neuro-technological processes of modelling and forecasting the performance indicators of wheat cultivation management are based on nonlinear artificial neural networks. The neural network approach is based on the idea of building a computing device from a large number of simple elements working in parallel i.e., formal neurons. These neurons function independently of each other and are interconnected by unidirectional channels of information transmission. The neural network concepts are based on the idea that each neuron can be modelled using relatively simple functions, and the complexity of a brain, the flexibility of its function and other important properties are determined by the connections between neurons. Neural networks are widely used to construct predictive behavioural models of complex dynamic systems containing many parameters that change over time when interacting with various environmental characteristics [24-26].

Neural networks allow approximating any continuous function with any accuracy, despite the absence or presence of periodicity and cyclicity, that is, a neural network can be "taught" in such a way that it recognises any data set with high certainty and determines the further development of the studied process in agricultural production for a certain period of time. A neural network forecasting model is able not only to continuously process a large number of system parameters and predictive background factors but also to take into account heterogeneous information about the current and planned operating modes of objects and production processes [27]. A neural network forecasting system, in turn, takes into account information about the logic of the system, the reliability of its elements, as well as expert information. The ability of a neural network to work on the "black box" principle in many cases facilitates modelling agricultural production management systems. You just need to decide what your input source data are, systematise them and train your neural network [11]. Neural networks implement inductive and deductive approaches to solving complex problems, which allows us to reliably assess the situation and make a rational management decision to achieve a high economic effect of agricultural production. It is based on the principles that allow adjusting the answers as data (experience) accumulate. This means that you learn to make decisions in the process of actual decision-making [13].

The Bayesian network theory is based on the assumption that events are exhaustive and do not overlap. If this condition is not met, the results of the network application will be inconsistent (inaccurate). In the case when the events are exhaustive and do not overlap, the probability of event E can be calculated using conditional probabilities. The main advantage of Bayesian networks is their ability to handle complex probabilistic relationships in a transparent and interpretable way. Bayesian networks can be used for a variety of tasks, such as prediction, classification, diagnosis, decision-making, and risk assessment. They are also useful for identifying the most relevant variables and the causal relationships between them, and for updating the probabilities of events in light of new evidence or data. Taking into account the need to process significant amounts of statistical data on crops, NDVI indicators and weather factors, MatLab software was used for modelling and forecasting [28, 29]. To conduct the study, a method is proposed in the form of the following sequence:

- loading data;
- the data is divided into 2 subsamples: training (70%) and verification (30%);
- building models;
- comparison of models by statistical quality criteria;
- construction of a general report on the performed computational experiment.

Considering the classical linear regression model, the least-squares method (LSM) gives the best linear unbiased estimates when a certain number of prerequisites are met only. Homoscedasticity is one of these prerequisites: for all observations i, i=1, 2, ..., n. In turn, integrated processes are divided into processes with a deterministic and a stochastic trend. A deterministic trend is a trend that does not contain a random component and its coefficients remain unchanged for a long period of time. This linear trend is an example of a deterministic trend that has this form:

$$Y = a + b_t, \tag{8}$$

where,

Y is the level of the measured indicator; a is the initial level of the trend at the moment or for the period at the beginning of time t; b is the average change per unit of time, that is, the rate of change or the trend constant.

A linear trend can be considered as a generalised expression of the actions of a factor complex, that is, the trend acts as a result of this factor complex. The parabolic trend is another example, which also applies to deterministic processes, but is already an example of a nonlinear trend:

$$Y = a + b_t + c_t^2 , \tag{9}$$

where,

c is the constant of the parabolic trend, its quadratic parameter equal to half the acceleration of the process.

There are many examples of nonlinear trends related to deterministic processes, in particular: a logarithmic trend reflects indicators that are increasingly difficult to improve; an indicative trend may be used to display processes with varying degrees of proportionality of changes over time; a hyperbolic trend reflects processes limited by value levels and many other types of nonlinear trends.

The following are examples of heteroscedastic processes, processes with time variables: autoregressive conditional heteroscedastic (ARCH) processes, generalized autoregressive conditional heteroscedastic (GARCH) processes, exponential generalized autoregressive conditional heteroscedastic (EGARCH) processes and others. Variance and standard deviation are often used as a measure of risk, so it is convenient to use heteroscedastic processes when analysing and forecasting risks. Nonlinear processes are those processes that cannot be described by a linear function. They are divided into non-linearity in variables and non-linearity in parameters. The polynomial regression can be an example of non-linearity in variables:

$$y(k) = a_0 + a_1 x(k) + a_2 x^2(k) + a_3 x^3 (k) + \varepsilon(k) \tag{10}$$

The coefficients of this equation can be estimated using the usual least squares method with the correct design of the measuring matrix. Non-linearity in parameters is due to the coefficients of products in the model, for example, in the form:

$$y(k) = a_0 + a_1 a_2 x(k) + a_2 \exp\big(-bx(k)\big) + \varepsilon(k) \tag{11}$$

The coefficients (parameters) of such a model cannot be estimated using the conventional LSM, so the nonlinear LMS, the maximum likelihood method or other methods of nonlinear estimation are used to solve this problem. The most successful forecasts are realised when an adequate mathematical object model is built. Methods aimed at building a model are divided into two large groups:

1. Construction of linear stochastic models (autoregression and moving average models are the most popular types of them). This direction has received a special name of “system identification”.
2. Construction of nonlinear dynamic models (reflections or ordinary differential equations). This technique is based on the ideas and methods of nonlinear dynamics. It was called “reconstruction of dynamic systems”.

However, it is not known whether there is an adequate model, and how it should be built in many real cases. Reconstruction of a real system requires considerable effort, and its predictive capabilities may be limited due to the spread of phase trajectories.

5. CONCLUSIONS

Despite the disadvantages of ANNs, the use of intelligent methods based on neurotechnologies is considered as a rather promising direction in modelling and forecasting indicators of the efficiency of agricultural production management. Modelling of yield dynamics is complicated by severe crop failures, which turn out to be accidental and are usually associated with meteorological factors. Studies have shown that the yield time series are persistent, that is, they have the effect of "long-term memory". This means that autoregressive models cannot act as an adequate tool for modelling and forecasting such series.

REFERENCES

[1] Bou-Rabee, M., Sulaiman, S.A., Saleh, M.S., Marafi, S. (2017). Using artificial neural networks to estimate solar radiation in Kuwait. Renewable and Sustainable Energy

Reviews, 72: 434-438. https://doi.org/10.1016/j.rser.2017.01.013

[2] Kar, S., Tanaka, R., Iwata, H., Kholova, J., Durbha, S.S., Adinarayana, J., Vadez, V. (2020). Multi-scale time series analysis of evapotranspiration for high-throughput phenotyping frequency optimization. International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences – ISPRS Archives, 42(3/W12): 425-430. https://doi.org/10.5194/isprs-archives-XLII-3-W12-2020-425-2020

[3] Li, X.X, Kang, Y.F, Li, F. (2020). Forecasting with time series imaging. Expert Systems with Applications, 160: 113680. https://doi.org/10.1016/j.eswa.2020.113680

[4] Marko, O., Brdar, S., Panic, M., Lugonja, P., Crnojevic, V. (2016). Soybean varieties portfolio optimisation based on yield prediction. Computers and Electronics in Agriculture, 127: 467-474. http://dx.doi.org/10.1016/j.compag.2016.07.009

[5] Filippi, P., Jones, E.J., Wimalathunge, N.S., Somarathna, P.D.S.N., Pozza, L.E., Ugbaje, S.U., Bishop, T.F.A. (2019). An approach to forecast grain crop yield using multi-layered, multi-farm data sets and machine learning. Precision Agriculture, 20: 1015-1029. https://doi.org/10.1007/s11119-018-09628-4

[6] Wei, J., Jiang, G.Q., Liu, X. (2017). Parameterization of typhoon-induced ocean cooling using temperature equation and machine learning algorithms: An example of typhoon Soulik (2013). Ocean Dynamics, 67: 1179-1193. https://doi.org/10.1007/s10236-017-1082-z

[7] Zhang, S., Tao, F., Zhang, Z. (2017). Spatial and temporal changes in vapor pressure deficit and their impacts on crop yields in China during 1980-2008. Journal of Meteorological Research, 31: 800-808. https://doi.org/10.1007/s13351-017-6137-z

[8] Jafari, F., Ponnambalam, K., Mousavi, J., Karray, F. (2020). Yield forecast of california strawberry: Time-series models vs. ML tools. In 2020 IEEE International Conference on Systems, Man, and Cybernetics (SMC), pp. 3594-3598. https://doi.org/10.1109/SMC42975.2020.9283138

[9] Aubakirova, G., Gerassimova, Y., Ivel, V. (2023). Neural network system of grain (wheat) yield forecasting in risky agricultural conditions on the example of the North Kazakhstan region. International Journal of Design & Nature and Ecodynamics, 18(1): 189-194. https://doi.org/10.18280/ijdne.180123

[10] Ioffe, S., Szegedy, C. (2015). Batch normalization: Accelerating deep network training by reducing internal covariate shift. Proceedings of Machine Learning Research, pp. 448-456. https://arxiv.org/pdf/1502.03167.pdf, accessed on Nov. 11, 2022.

[11] He, K., Zhang, X.Y., Ren, S.Q., Sun, J. (2016). Deep residual learning for image recognition. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 770-778. https://doi.org/10.48550/arXiv.1512.03385

[12] Crossa, J., Yang, R.C., Cornelius, P.L. (2004). Studying crossover genotype × environment interaction using linear-bilinear models and mixed models. Journal of Agricultural, Biological, and Environmental Statistics, 9: 362-380. https://doi.org/10.1198/108571104X4423

[13] Gall, M., Gall, J., Borg, R. (2007). Educational Research: An Introduction. New York: Pearson Education.

[14] Reddy, P.C.S., Sureshbabu, A. (2020). An applied time series forecasting model for yield prediction of agricultural crop. Advances in Intelligent Systems and Computing, 1118: 177-187. https://doi.org/10.1007/978-981-15-2475-2_16

[15] Baibatsha, A.B., Kembayev, M.K., Mamanov, E.Z., Shaiyakhmet, T.K. (2020). Remote sensing techniques for identification of mineral deposit. Periodico Tche Quimica, 17(36): 1038-1051. https://doi.org/10.52571/PTQ.v17.n36.2020.1053_Periodico36_pgs_1038_1051.pdf

[16] Ismailova, A.A., Kanaev, A.T., Zhalgassuly, N., Aisijiang, M., Kogut, A.V. (2018). Studying the technology and methods of increasing the yield of cultivated plants on strongly saline soils. Ecology, Environment and Conservation, 24(4): 1666-1670. http://www.envirobiotechjournals.com/article_abstract.php?aid=9198&iid=265&jid=3.

[17] Kotenko, S., Nitsenko, V., Hanzhurenko, I., Havrysh, V. (2020). The Mathematical Modeling Stages of Combining the Carriage of Goods for Indefinite, Fuzzy and Stochastic Parameters. International Journal of Integrated Engineering, 12(7): 173-180. https://doi.org/10.30880/ijie.2020.12.07.019

[18] Kondratenko, Y.P., Kozlov, O.V., Kondratenko, G.V., Atamanyuk, I.P. (2018). Mathematical model and parametrical identification of ecopyrogenesis plant based on soft computing techniques. Studies in Systems, Decision and Control, 125: 201-233. https://doi.org/10.1007/978-3-319-69989-9_13

[19] Sen, R., Klüppelberg, C. (2019). Time series of functional data with application to yield curves. Applied Stochastic Models in Business and Industry, 35(4): 1028-1043. https://doi.org/10.1002/asmb.2443

[20] Tang, J.-G., Mukhambetzhanov, S., Nulahemaiti, B., Baishemirov, Z. (2014). Method of an evaluation of formation exposing with preliminary data. Life Science Journal, 11(10 SPEC. ISSUE): 321-326. https://doi.org/10.7537/marslsj1110s14.59

[21] Mukhamedshina, D.M., Mit, K.A., Beisenkhanov, N.B., Dmitriyeva, E.A., Valitova, I.V. (2008). Influence of plasma treatments on the microstructure and electrophysical properties of SnO x thin films synthesized by magnetron sputtering and sol-gel technique. Journal of Materials Science: Materials in Electronics, 19(SUPPL. 1): S382-S387. https://doi.org/10.1007/s10854-008-9695-0

[22] Abadi, M., Barham, P., Chen, J.M., Chen, Z.F., Davis, A., Dean, J., Devin, M.,Ghemawat, S., Irving,G., Isard, M., Kudlur, M., Levenberg, J., Monga, R., Moore, Sh., Murray, D.G., Steiner, B., Tucker,P., Vasudevan, V., Warden, P., Wicke, M., Yu, Y., Zheng, X.Q. (2016). TensorFlow: A system for large-scale machine learning. In: OSDI'16: Proceedings of the 12th USENIX conference on Operating Systems Design and Implementation, Berkeley: USENIX Association, pp. 265-283. https://doi.org/10.48550/arXiv.1605.08695

[23] Mustafin, A.T., Volkov, E.I. (1984). The role of lipid and antioxidant exchanges in cell division synchronization (mathematical model). Biological Cybernetics, 49(3): 149-154. https://doi.org/10.1007/BF00334460

[24] Wankhade, M.O. (2020). Trend and forecasts analysis of yield of jowar in India using sarima method of time series. International Journal of Scientific and Technology

Research, 9(1): 3555-3557. http://www.ijstr.org/final-print/jan2020/Trend-And-Forecasts-Analysis-Of-Yield-Of-Jowar-In-India-Using-Sarima-Method-Of-Time-Series, accessed on Nov. 13, 2022.

[25] Bekbauov, B., Berdyshev, A., Baishemirov, Z. (2016). Numerical simulation of chemical enhanced oil recovery processes. CEUR Workshop Proceedings, 1623: 664-676. https://ceur-ws.org/Vol-1623/paperapp1.pdf.

[26] Chuzlov, V.A., Nazarova, G.Y., Dolganov, I.M., Dolganova, I.O., Seitenova, G. (2019). Calculation of the optimal blending component ratio by using mathematical modeling method. Petroleum Science and Technology, 37(10): 1170-1175. https://doi.org/10.1080/10916466.2019.1578800

[27] Baibatsha, A.B., Muszynski, A. (2020). Geological-geophysical prospecting indicators of the arganaty district predictive blocks (Eastern Balkhash). News of the National Academy of Sciences of the Republic of Kazakhstan, Series of Geology and Technical Sciences, 2(440): 31-39. https://doi.org/10.32014/2020.2518-170X.28

[28] Glorot, X., Bengio, Y. (2010). Understanding the difficulty of training deep feedforward neural networks. In Proceedings of the thirteenth international conference on artificial intelligence and statistics, JMLR Workshop and Conference, pp. 249-256. http://proceedings.mlr.press/v9/glorot10a, accessed on Nov. 13, 2022.

[29] Sansyzbayeva, G., Ashirbekova, L., Nurgaliyeva, K., Ametova, Z., Asanova, A. (2020). Realities and prospects of using green technologies in Kazakhstan. E3S Web of Conferences, 159: 07002. https://doi.org/10.1051/e3sconf/202015907002