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Space-time modeling and forecasting steppe soil fertility using geo-information systems and neuro-technologies

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Abstract

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The study presents the results of using geo-information systems and neuro-technologies for modeling spatial heterogeneity and forecasting changes in agro-chemical properties of steppe soil fertility exemplified by Kherson region of Ukraine. Modeling allowed determining general regularities of impacts of the current agricultural practices on changes in the content of macronutrients over the past 50 years that have caused the ongoing process of a gradual decrease in the content of humus, nitrogen, phosphorus and potassium in steppe soils. A lack of balanced crop rotations, regular, uniform and necessary supply of fertilizers, occurrence of water erosion, including irrigation erosion and deflation, and also long-term irrigation led to a drop in the content of macronutrients in 1970–2020: the content of humus – by 0.36% (from 2.56% to 2.20%) or by 14.1% in statistical relation; mobile phosphorus – by 34.2% (from 62.0 mg·kg^{-1} to 40.8 mg·kg^{-1}); exchangeable potassium – by 17.8% (from 442.4 mg·kg^{-1} to 363.8 mg·kg^{-1}); a decrease in the content of nitrifiable nitrogen – by 17.0% (from 23.0 mg·kg^{-1} to 19.1 mg·kg^{-1}) on the average in 2013-2020.

Geo-statistical analysis made it possible to determine spatial regularities of changes in the content of macronutrients in steppe soils. The method of autocorrelation analysis was used to measure the minimum and maximum radii of typicality of the formation of agro-chemical properties of steppe soils being from 2.5 to 12.5 km, respectively. It indicates considerable spatial heterogeneity in distribution of macronutrients within the contours of different soil types. The neuro-technological modeling resulted in the creation of three-layer artificial neural networks for space-time modeling of the content of macronutrients in steppe soils.

The reliability of approximation of neuro-models on test samples equaled 92.4–94.8%. An irreversible process of gradual depletion of steppe soils is forecasted under the current agricultural practices: a drop in the content of humus – by 0.01% per year on non-irrigated lands, by 0.03% per year on the average on irrigated lands; nitrifiable nitrogen – by 0.04 mg·kg^{-1} of soil on non-irrigated lands, by 0.06 mg·kg^{-1} of soil per year on the average on irrigated lands; mobile phosphorus – by 0.16 mg·kg^{-1} of soil per year on non-irrigated lands, by 0.18 mg·kg^{-1} of soil per year on the average on irrigated lands; exchangeable potassium – by 1.9 mg·kg^{-1} of soil per year on non-irrigated lands, by 3.1 mg·kg^{-1} of soil per year on the average on irrigated lands. The obtained result determines territorial priorities of the regional policies, making it possible to apply differential effectiveness of the soil-protecting block of agricultural systems.

Keywords: steppe soil fertility; humus; nitrogen; phosphorus, potassium; modelling; forecasting; GIS-technologies; neuro-technologies

Introduction

Under conditions of increased anthropogenic impacts, it is necessary to find optimal interaction between a farm, an individual and nature for efficient nature management, i.e. a balanced relationship between exploitation of geo-system components, protection for them and purposeful transformation (Dudiak et al., 2019, 2020; Jensena et al., 2020). The task to achieve balanced use of land resources under the current negative production and economic conditions can become unsolvable, if land use is not an immanent component of balanced nature management (Lasanta et al., 2019; Dudiak et al., 2021, Buryak et al., 2022). Heterogeneity of space-time changes in soil fertility is largely caused by natural and climatic conditions of the region and agricultural practices (Lisetskii et al., 2017; Liab et al., 2020). In agricultural nature management, the main indicators determining the direction of changes in natural soil fertility are their agro-chemical properties including the content of humus (organic substance), nitrogen, phosphorus and potassium (Breus et al., 2021). Availability of these macronutrients in a mobile form for plants determines the necessity of additional application of fertilizers and productivity of agricultural crops (Domaratskiy et al., 2018, 2019).

Many scientists consider space-time investigation of changes in agro-chemical properties as one of the most important and objective procedures for measuring effectiveness of agricultural systems, especially in terms of soil-protection and programming agricultural crop yields. Under conditions of global and regional climate change (Lisetskii et al., 2016; Pichura et al., 2019), nature-related changes in agro-chemical properties and the rate of their renewal are indicators of space-time heterogeneity of climate energy supply for soil-formation processes (Lisetskii et al., 2014) and formation of new bio-climatic conditions (Pichura et al., 2021) of the territories. Nutrient supplies and their availability to plants, and also supplies of productive moisture are strongly dependent on natural and climatic conditions of zonal agro-landscapes (topographic features, parent rocks, climate, hydrogeological conditions, etc.) and agricultural systems applied (Lisetskii et al., 2016, 2020; Martsinevskaya et al., 2018; Zelenskaya et al., 2018). It determines high spatial heterogeneity in distribution of soil fertility characteristics within the boundaries of similar soil groups and agricultural fields (Medvedev, 2006; Levers et al., 2016).

Therefore, examination of regularities of the impact of the current anthropogenic-climatic conditions on the formation of soil fertility, thorough understanding of the processes of retrospective changes in soil properties on agricultural lands, their spatial differentiation and accurate forecasts of possible consequences require application of modern approaches, methods and instruments for space-time research of changes in soil fertility. The main instruments for increasing informational value of the research, analysis, modeling and obtaining reliable results on retrospective changes and creating situational forecasts of soil fertility are geo-information systems and nonlinear methods of neuro-technology. It will ensure collection of objective, highly accurate space-time information for developing soil-protecting measures and optimization of agricultural nature management.

The purpose of the research is to determine space-time regularities of changes in steppe soil fertility under conditions of the current agricultural practices using geo-information systems and neuro-technologies.

Materials and Methods

The research was conducted in typical steppe soils of Kherson region in Ukraine. The total area of the region equals 2846.1 thous. ha, including farmlands – 1971.0 thous. ha (69.25%), arable lands – 1777.6 thous. ha (90.2%). In the territory of the region there are 20% of irrigated lands of Ukraine occupying the area of 426.8 thous. ha (21.65% of the area of farmlands). According to the latest data of the State Agency of Water Resources of Ukraine (2020), irrigated lands used in irrigation regime comprise 312.4 thous. ha (73.2%), and 114.4 thous. ha (26.8%) of them are not used. The area of rice irrigation systems equals 8.1 thous. ha (Pichura et al., 2021). The main soil types of Kherson region are southern black soils occupying 43.7% of the total area of agricultural lands and dark chestnut soils – 30.7% (Figure 1).

Analysis of changes in agro-chemical properties and creation of neural network models for nonlinear forecasting for steppe soil fertility on the territory of Kherson region in Ukraine were based on the data of 1970-2020 obtained from the research conducted on 25 stationary monitoring plots of Kherson branch of the state organization "Institute of Soil Conservation of Ukraine" distributed on all types of steppe soils. Cartograms of the detailed assessment of the current state of steppe soil fertility were made on the basis of the data obtained from 296 stationary monitoring plots for five years (2013-2017) of the complex fife-year examination of agricultural lands in Kherson region. The research on agro-chemical state was carried out for the upper fertile layer of 0…20 cm of steppe soils by the main macronutrients – the content of humus (%), nitrifiable nitrogen ($mg \cdot kg^{-1}$), mobile phosphorus ($mg \cdot kg^{-1}$) and exchangeable potassium ($mg \cdot kg^{-1}$). The error of spatial interpolation models (cartograms) was determined by means of distribution of a standard error of calculated data with the actual data of the field research. Reliability of the spatial modeling was the following: the content of humus – 92.0%, nitrifiable nitrogen – 85.8%, mobile phosphorus – 87.8%, exchangeable potassium – 91.4%. The spatial modeling of heterogeneity in distribution of agro-chemical properties of steppe soils was performed using the method of radial basis functions (Kamińska et al., 2014; Kamińska et al., 2018) of the working module Geostatistical Analyst of ArcGis.

The method of artificial neural networks (ANN) of the three-layer Perceptron architecture was used for space-time forecasting to determine agro-chemical state of soils (Haykin, 2005; Pichura et al., 2015) (Figure 2).

In order to create neural networks for forecasting changes in agrochemical properties of soil fertility, the data of the field research on 25 stationary monitoring plots in the course of 1970-2020 were used. The dataset for training and testing neural networks by each agro-chemical index comprised 1250 values. Reliability of approximation of the models and forecasting was determined on the basis of division of time series at the ratio 0.68 and 0.32 by two subsets: training (68% – 850 values) and testing (32% – 400 values). The following

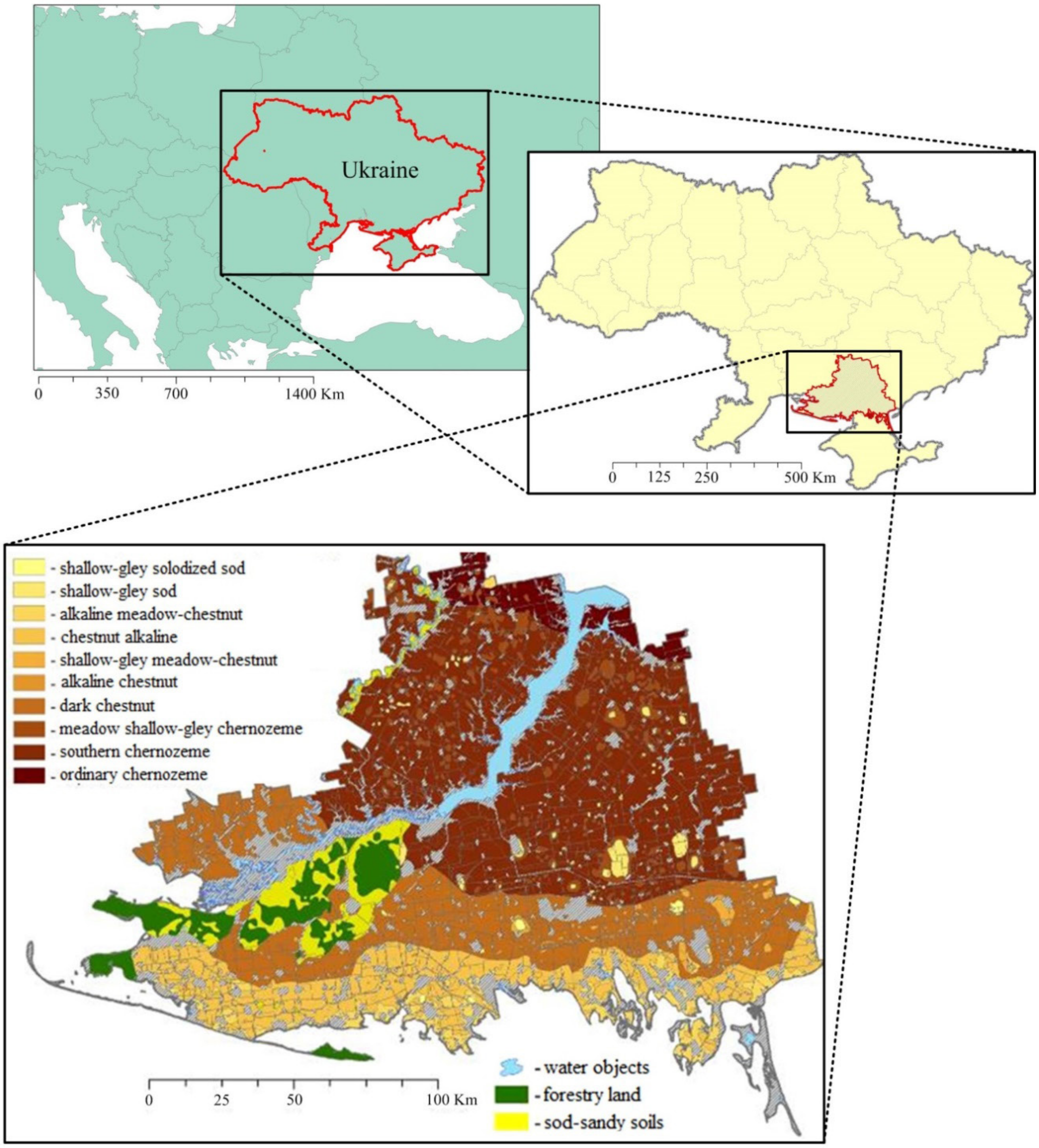
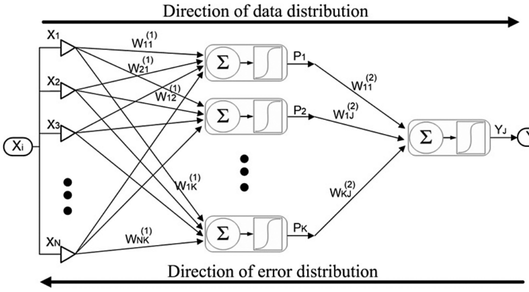


Fig. 1. Location of the research territory (Kherson region, Ukraine)



a

$$y_i(t) = f(\sum_{j=1}^{J} w_j^{(2)}(t) f(\sum_{n=1}^{N} w_n^{(1)}(t) x_n^{(t)}))$$

b

$$E(w(t)) = \frac{1}{2}(\sum_{i=1}^{I}(f(\sum_{j=1}^{J} w_j^{(2)}(t) f(\sum_{n=1}^{N} w_n^{(1)}(t) x_n^{(t)})) - d_i^{(t)})^2)$$

c

$$w_{ni}(t+1) = \eta\delta_i x_n(t) + \alpha(w_{ni}(t) - w_{ni}(t-1))$$

d

Fig. 2. Hardware implementation (identification) of artificial neural network: *a* – architecture of ANN; *b* – response function of ANN; *c* – correction function of weighing coefficients of ANN; *d* – training function of ANN

Note: t – time series discrete value; *w* – weighting coefficient matrix; $x_n^{(t)}$ – n-th coordinate of the input vector at a given time moment t; $y_i(t)$ – i-th coordinate of the output vector that is developed by the neural network at a certain time moment *t*; $d_i^{(t)}$ – i-th coordinate of the actual output vector at the time moment *t*; *f(si)* – hidden layer neurons activation function: $f(s)\frac{e^s - e^{-s}}{e^s + e^{-s}}$ – sinusoidal-hyperbolic tangent with data conversion range [-1, 1]; $w_{ni}(t)$ – weight from neuron *n* or from the element of the incoming signal *n* to the neuron *i* at the moment of time *t*; x_n – neuron output n or n-element of the incoming signal; η – coefficient of a learning rate; α – inertia coefficient; δ_i – error value for the neuron *i*.

methods were used as an optimization method: the method of inverse distribution and the method of conjugate gradients. Cross-validation of forecasting models was performed using statistical criteria of reliability: expected value of error, standard deviation of error, expected value of absolute error (in physical terms and percent), correlation value (Pichura et al., 2015). Three-layer models of neural networks were created using the module Statistics Neural Networks (SNN) of the software product STATISTICA Advanced + QC for Windows v.10 Ru

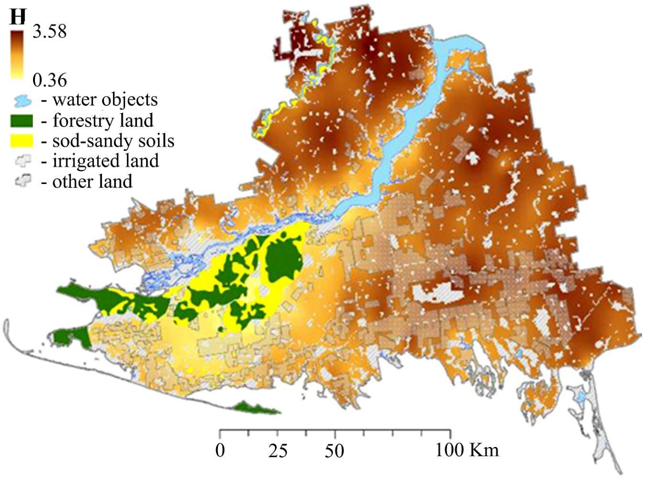
Results and Discussion

Humus supply (H). Humus is one of the main resources for potential soil fertility and an integral indicator of the effectiveness of the agro-technological block of agricultural systems. The topsoil of Kherson region which is a typical region of the Steppe zone, is characterized by low-humic soils with the humus content of 0.36–3.85%. Spatial heterogeneity of humus content is determined by the complexity of the topsoil structure depending, firstly, on zonal factors of soil formation and heterogeneity of hydrothermal conditions, secondly, on the development of gleization in soil hollows due to their sporadic excessive moisturizing by meltwater and rainwater, thirdly, on intensive manifestation of alkalinity and salinization under shallow groundwater occurrence (Pichura et al., 2021).

The specifics of topsoil determine the initial content of humus undergoing dynamic changes resulting from agricultural activities that depend on the intensity of farming operations within the boundaries of farmlands (fields, crop rotations) and land management. Under irrigated conditions the content of humus in different soil types in the region (in the layer of 0…20 cm) is by 0.1-0.5%, on the average, less than on rainfed lands that is caused by the intensity and technological characteristics of irrigation reclamations (water quality, irrigation norms, crop rotations etc.).

Dehumification of soils is caused by increased mineralization of organic matter resulting from intensive tillage and unbalanced productional and soil formation processes, insufficient supply of postharvest residues and organic fertilizers to a plowing horizon, an increase in the portion of arable crops, a decrease in the portion of perennial grasses and field crop rotations, long-term application of mineral fertilizers (especially physiologically acid forms), incomplete use of plant residues as fertilizers, stubble burning, straw residue burning, manifestation of water erosion, including irrigation erosion soil deflation and also long-term irrigation (Dudiak et al., 2019, 2020, 2021; Benauda et al., 2020; Li et al., 2020).

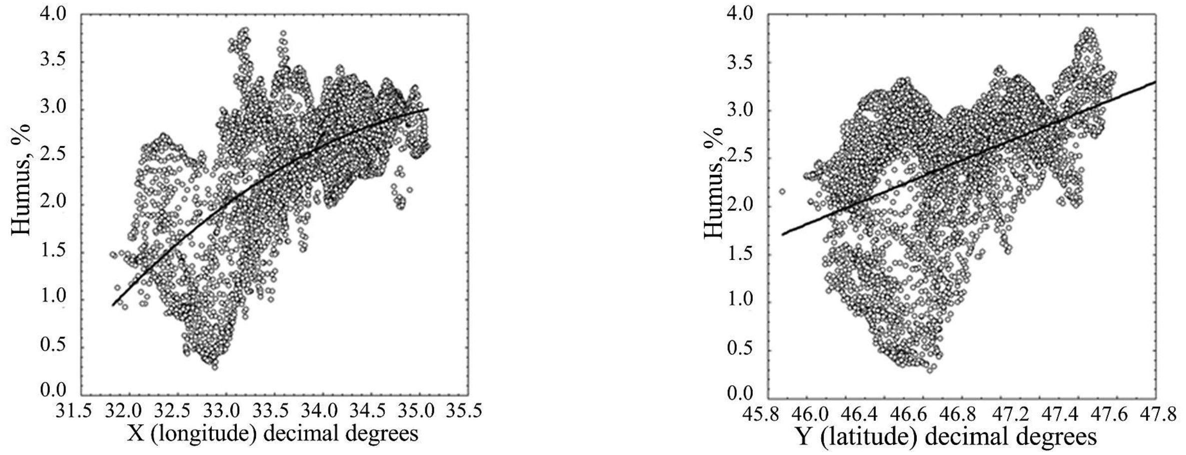
Intensive development of irrigation in 1970-1989 in the Steppe zone led to profile soil degradation, leakage of nutrients into a lower soil profile poorly accessible to plants and a significant reduction in humus content in the upper soil layer (the layer of 0…20 cm) – by 0.36% (from 2.56% to 2.20%) on the average or by 14.1% in statistical relation. The period of 1985-2020 was characterized by stable irrigation loading with insignificant dynamics of changes in humus content (V = 3.3%) and a negative direction of changes (trend, T) in its content over time (t): $T(H) = –0.0061 \cdot t + 2.2914$; $r^2 = 0.022$.



a

Mean value	2.40
Credible interval of the mean	0.02
Median	2.60
Mode	2.92
Minimum	0.30
Maximum	3.85
Percentile 10,0	1.25
Percentile 90,0	3.10
Level of variation	3.54
Dispersion	0.48
Standard deviation	0.69
Standard error of the mean	0.01
Asymmetry	-1.08
Excess	0.61

b



$H = -0.1284x^2 + 9.2215x - 162.5$; $R = 0.63$,
where x – value of geographic longitude in decimal degrees

c

$H = 38.469 Ln(y) - 145.47$; $R = 0.44$,
where y – value of geographic latitude in decimal degrees

d

Fig. 3. Spatial heterogeneity of humus distribution in steppe soils of Kherson region:
***a* – cartogram; *b* – statistical characteristics; *b* – west→east; *d* – south→north**

Graphical and statistical characteristics of spatial heterogeneity of humus distribution were examined (Figure 3) using the spatial raster model of humus distribution created on the basis of natural changes.

Spatial variability of soil properties mostly differs in non-stationary(non-typical) character of their distribution in agro-landscapes on different levels of observations that is mainly determined by agricultural practices and soil diversity. Application of the autocorrelation approach for this situation allows measuring the maximum distance of distribution and conservation of possible spatial energy of stationarity (typicality) of the process between the lags.

It also allows substantiating simultaneity of temporal changes in the indexes under study within a radius of stationarity lag. Autocorrelation research on spatial typicality of humus content in soil (in the layer of 0…20 cm) was conducted in the direction of an increase in the spatial trend from the south-west (the starting point –Lag 1) to the north-east of the region. The spatial distance between the lags was 2.5 km. A significant correlation on Lag 1 – 0.998 was determined on the basis of the research results, but the spatial correlation of Lag 3 dropped to 0.015, that is caused by significant non-stationarity of humus distribution in space.

In order to reduce the signal strength, we used the difference of Lag 1, and the main signal of the non-stationary process was preserved. As a result of data transformation, we measured the minimum (r = 0.391) and the maximum (r = 0.143) radii of typicality of humus formation equaling 2.5 km (Lag 1) and 12.5 km (Lag 5). Low strength of relationship between the lags indicates significant spatial variability (heterogeneity) of humus distribution within the boundaries of individual basins and within the contours of different soil types (subtypes).

The spatial function of humus distribution in steppe soils in the territory of Kherson region looks as follows:

$$f(H) = 25.14 \cdot x - 11.98 \cdot y + 0.07 \cdot x^2 - 0.63 \cdot x \cdot y + 0.36 \cdot y^2 - 168.97; \; r^2 = 0.58$$

where x – longitude, decimal degrees, y – latitude, decimal degrees.

Humus content in soils (Table 1), corresponding to quality gradations of medium and elevated contents (>2.1%) is characteristic of 72% of the area of agricultural lands in Kherson region. High spatial heterogeneity of humus distribution is observed in irrigated territories of dark-chestnut soils of the southern part of Kherson region (59.3% of the irrigated area) that is caused by considerable irrigation loads on agricultural lands. The highest value of humus content (3.85%) was registered in common black soils located in the northern part of the region, the humus content up to 5.0%, which is not typical for steppe soils, was registered in some cases, that is caused by additional agro-technological seasonal application of organic fertilizers. The least humus content can be found in peat-sandy soils in the south-west part of the region – 0.36%.

Using the module Statistics Neural Networks (SNN) we created neuro-models of the three-layer Perceptron architecture to forecast the content of humus in steppe soils (in the layer 0–20 cm) in the territory of Kherson region on the basis

Table 1. Distribution of humus content in steppe soils of Kherson region

Humus content, %		Agricultural lands	
		thous.ha	%
Very low	< 1.10	124.4	6.3
Low	1.10 – 2.09	418.3	21.2
Medium	2.10 – 3.09	1182.3	60.0
Elevated	3.10 – 4.09	246.0	12.5
In total		1971.0	100

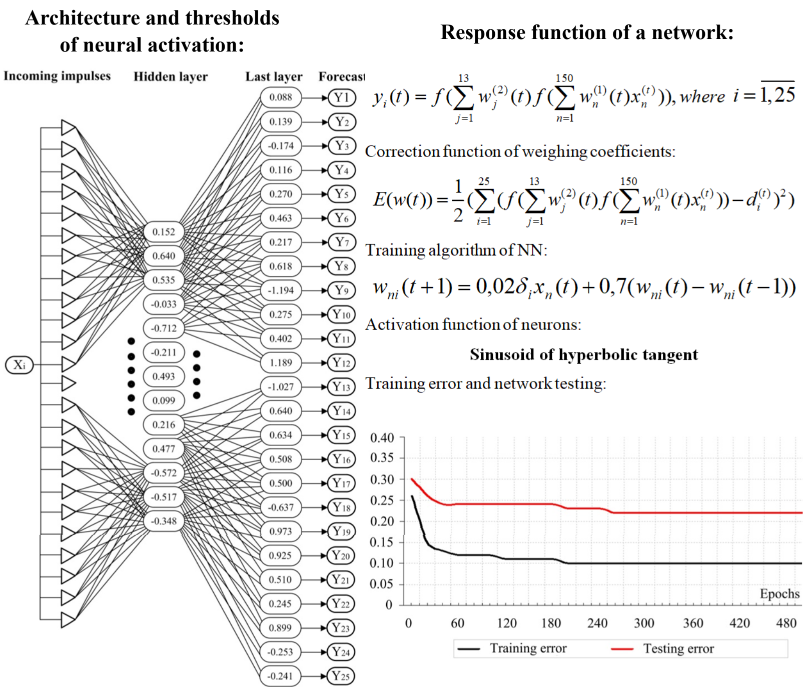


Fig. 4. Characteristic of a neural model for forecasting humus content in steppe soils

of observational data obtained from 25 stationary plots in 1970–2020. The model of a neural network is characterized by thirteen neurons in a hidden layer, the training method: inverse distribution (100 epochs) and connected gradients (355 epochs), matrix of the artificial neural network consisting of 2275 weighing coefficients (Figure 4).

Multilayer artificial neural networks made it possible to reflect the accurate data which were not used in the training process and forecast further changes in soil fertility with sufficiently high reliability. The final data on effectiveness of realizing neural networks on training and test samples are given in Table 2. Analysis of approximation of the three-layer network on the test sample indicates a high level of approximation of the model and obtaining reliable results on forecasting humus content in steppe soils (Figure 5).

The results on forecasting allow making a conclusion that under the current agricultural practices, an irreversible process of a gradual drop in humus content (dehumification) in steppe soils (in the layer of 0…20 cm) is predicted in the territory of Kherson region: on non-irrigated lands – by 0.01% per year on the average, on irrigated land – by 0.03% per year. It will lead to a reduction in the area of lands characterized by high and elevated humus contents.

Nitrogen supply (N). Nitrogen plays a leading role in raising agricultural crop yields. It is an important biological element in soil and plant life cycles. Nitrogen is a component of proteins, being a major element of cytoplasm and cell nucleus, amino acids, nucleic acids, chlorophyll, alkaloids, phosphatides, many vitamins, hormones and other biologically active substances. All ferments catalyzing the process of plant metabolism – protein substances, therefore, insufficient nitrogen supply in plants reduces protein formation. It causes retardation in biosynthesis processes, exchange of all groups of chemical compounds and a sharp reduction in photosynthesis intensity, that eventually reduces productivity by 30–45%. Its main sources are organic and mineral fertilizers, organic substances in soil, biological nitrogen, and also nitrogen from precipitation. This element can be used to manage plant development. It is especially important in the first half of a growing season when plants grow intensively (Domaratskiy et al., 2020). Therefore, nitrogen nutrition in plants is an important characteristic of soil fertility.

Over the past 7 years (2013–2020) the content of nitrifiable nitrogen in the layer of 0…20 cm in steppe soils of Kherson region fell by 17.0% (from 23.0 mg·kg^{-1} to 19.1 mg·kg^{-1}) and maintains a tendency for a decrease in its content: $T(N) = 0.053 \cdot t^2 + 0.966 \cdot t + 16.74$; $r^2 = 0.24$. Space-time differentiation of a reduction in nitrifiable nitrogen in steppe soils over the period of observations ranged from 2 mg·kg^{-1} to 12 mg·kg^{-1} (from 10% to 45%), that was caused by a lack of regular and uniform supply of nitrogen-con-

Table 2. Statistical characteristics of testing a neural network on the test sample (400 values) for forecasting humus content in steppe soils

Descriptive statistics	Test sample
Mean squared error	0.01
Mean absolute error	0.12
Maximum absolute error	1.08
Mean absolute relative error, %	5.24
Reliability estimation, %	94.76
Correlation coefficient, r	0.963
Determination coefficient, R	0.926

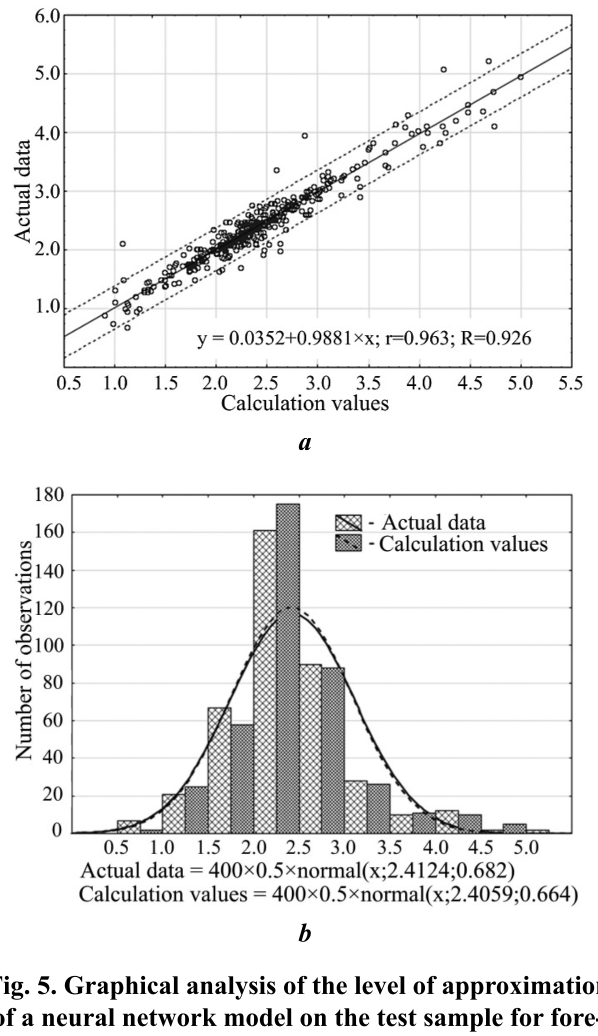


Fig. 5. Graphical analysis of the level of approximation of a neural network model on the test sample for forecasting humus content in steppe soils: *a* – graph of correlation coincidence of the actual and calculation-verification values; *b* – histogram of distribution of the actual and calculation-verification values

taining fertilizers, a negative balance caused by its removal with agricultural crop yields, a lack of grasses providing soil with nitrogen in crop rotations of legume grasses.

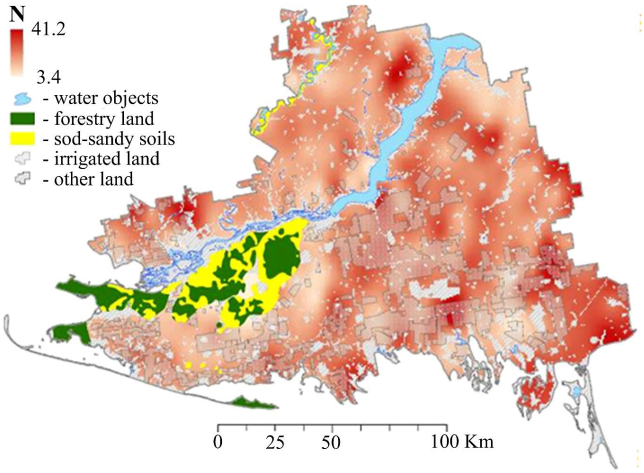
Graphical and statistical regularities of spatial distribution of the content of nitrifiable nitrogen in steppe soils are given in Figure 6. Autocorrelation analysis allowed determining the minimum (r = 0,095) and maximum (r = 0.044) radii of typicality of the formation of nitrifiable nitrogen content in steppe soils equaling 2.5 km and 5.0 km.

The spatial function of distribution of nitrifiable nitrogen in steppe soils in the territory of Kherson region looks as follows:

$$f(N) = 155.52 \cdot x + 149.83 \cdot y + 1.07 \cdot x^2 - 4.83 \cdot x \cdot y + 0.13 \cdot y^2 - 6129.06;\ r^2 = 0.43$$

where x – longitude, decimal degrees, y – latitude, decimal degrees.

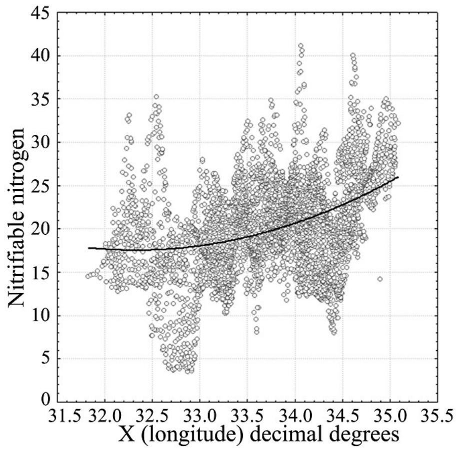
The content of nitrifiable nitrogen in soils (Table 3), corresponding to quality gradations from medium to elevated contents (21.0 mg·kg^{-1}), characterizes 47.4% of the area of agricultural lands of the region. The highest portion of agricultural lands with medium and high contents of nitrogen was registered in southern and common steppe black soils in the territory of the central and eastern parts of Kherson region.



a

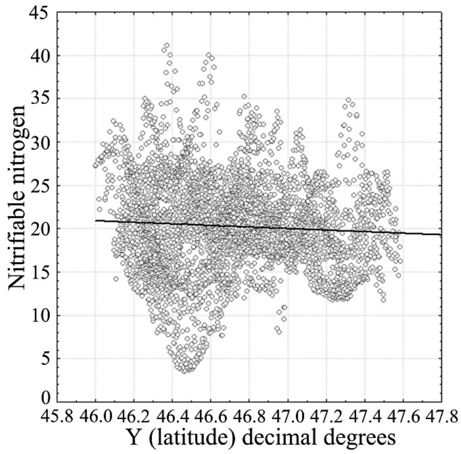
Mean value	20.25
Credible interval of the mean	0.16
Median	20.2
Mode	–
Minimum	3.4
Maximum	41.2
Percentile 10,0	13.61
Percentile 90,0	26.94
Level of variation	27.01
Dispersion	29.96
Standard deviation	5.47
Standard error of the mean	0.08
Asymmetry	0.03
Excess	0.44

b



$N = 1.111x^2 - 71.83x + 1178.5$; $R = 0.38$,
where x – value of geographic longitude in decimal degrees

c



$N = -41.956Ln(y) + 181.52$; $R = 0.06$,
where y – value of geographic latitude in decimal degrees

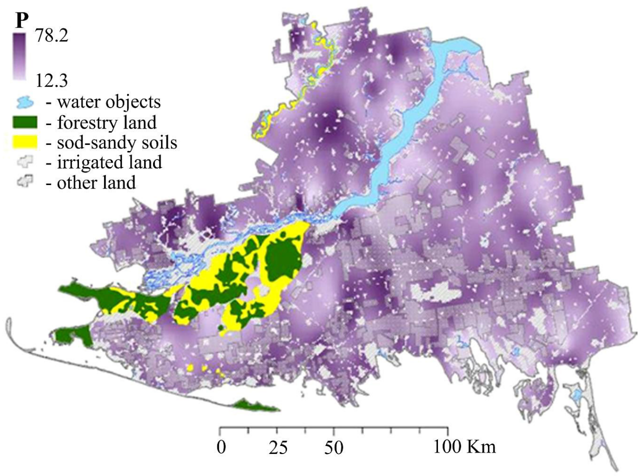
d

Fig. 6. Spatial heterogeneity of distribution of nitrifiable nitrogen (mg·kg^{-1}) in steppe soils of Kherson region: *a* – cartogram; *b* – statistical characteristics; *c* – west→east; *d* – south→north

Table 3. Distribution of nitrifiable nitrogen content in steppe soils of Kherson region

Nitrifiable nitrogen content, mg·kg^{-1}		Distribution	
		thous. ha	%
Very low	< 10,0	64.0	3.2
Low	11.0 – 20.0	972.1	49.3
Medium	21.0 – 30.0	881.5	44.7
Elevated	31.0 – 45.0	53.4	2.7
In total		1971.0	100.0

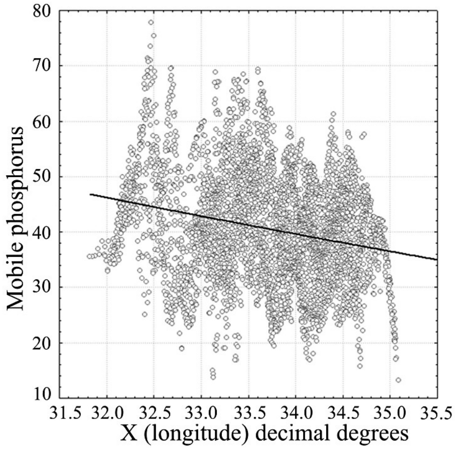
A lack of long series of observations made the process of training and creating neural network models more difficult for forecasting the content of nitrifiable nitrogen in steppe soils. The neural network models on small samples cannot consider space-time regularities of changes in the values of the properties of soil fertility to the full extent, that can lead



a

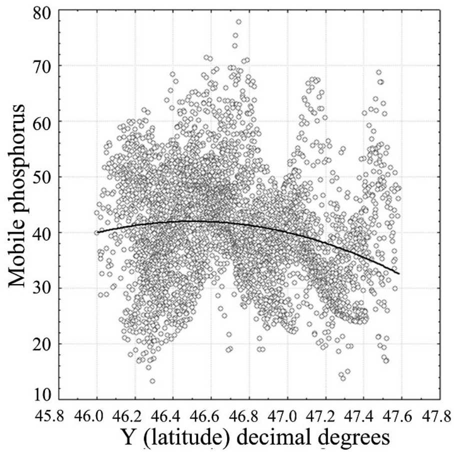
Mean value	40.55
Credible interval of the mean	0.57
Median	40,21
Mode	–
Minimum	12.3
Maximum	78.2
Procentile 10,0	27.71
Procentile 90,0	52.93
Level of variation	24.02
Dispersion	94.79
Standard deviation	9.74
Standard error of the mean	0.15
Asymmetry	0.25
Excess	0.07

b



$P = -108.04Ln(x) + 420.6$; $R = 0.24$,
where x – value of geographic longitude in decimal degrees

c



$P = -7.9263y^2 + 737.2y - 17099$; $R = 0.20$,
where y – value of geographic latitude in decimal degrees

d

Fig. 7. Spatial heterogeneity of distribution of mobile phosphorus (mg·kg^{-1}) in steppe soils of Kherson region: *a* – cartogram; *b* – statistical characteristics; *c*– west→east; *d* – south→north

to a wrong choice of a low-quality neural network model, a reduction in the forecast reliability and wrong results. Therefore, in order to ensure reliable results of the forecast, we performed cross-correlation analysis of the dependence of changes in the content of nitrifiable nitrogen on the variability of the content of humus, potassium and phosphorus. A significant correlation between nitrogen content and the differentiation of the content of exchangeable potassium in steppe soils was determined: $f(N) = 7.148 \cdot Ln(K) - 25.04$; $r = 0.68$. It allowed projecting a possible drop in the content of nitrifiable nitrogen in steppe soils on the basis of data on forecasting the content of exchangeable potassium: on non-irrigated lands – by 0.04 $mg \cdot kg^{-1}$ of soil per year on the average, on irrigated lands – by 0.06 $mg \cdot kg^{-1}$ of soil per year.

Phosphorus supply (P). Phosphorus is one of the most important plant nutrients. Apart from organic substance and nitrogen, there is often phosphorus deficiency for crop growth. It is a component of nucleoproteins, sugar phosphates, phosphatides and other compounds. Phosphorus actively participates in the processes of metabolism and protein synthesis, determines cellular energy and affects plant growth. A considerable part of available phosphorus in soil is in organic matter. When organic matter depletes due to intensive tillage, erosion, and also yield removal, phosphorus deficiency becomes an urgent problem. Parent rock contains a considerable part of it. Soil contains phosphorus in different forms: organic and non-organic, mobile and immobile. The content of mobile phosphorus in soil is one of the most important characteristics of its fertility. An inconsiderable amount of phosphorus comes with precipitation, space and atmospheric dust and anthropogenic activity. An effective way to replenish the supply of soil phosphorus is to add phosphorus to soil in the form of different fertilizers, to apply insecticides and fungicides (Makarova et al., 2021).

Over the past 50 years (1970-2020) the content of mobile phosphorus in the layer of 0…20 cm of steppe soils in Kherson region fell by 34.2% (from 62.0 $mg \cdot kg^{-1}$ to 40.8 $mg \cdot kg^{-1}$) and maintains a negative tendency for a decrease in its content: $f(N) = 7.148 \cdot Ln(K) - 25.04$; $r = 0.68$. Graphical and statistical regularities of spatial distribution of the content of mobile phosphorus in steppe soils are given in Figure 7. Autocorrelation analysis allowed determining the minimum ($r = 0.340$) and maximum ($r = 0.180$) radii of typicality of the formation of the content of mobile phosphorus in steppe soils equaling 2.5 km and 12.5 km.

The spatial function of distribution of mobile phosphorus in steppe soils in the territory of Kherson region looks as follows:

$$f(P) = 378.54 \cdot x + 1103.71 \cdot y - 1.92 \cdot x^2 - 5.43 \cdot x \cdot y - 9.90 \cdot y^2 - 31949.82; \; r^2 = 0.38$$

where x – longitude, decimal degrees, y – latitude, decimal degrees.

The content of mobile phosphorus in steppe soils (Table 4), corresponding to quality gradations from elevated to very high contents (>31.0 $mg \cdot kg^{-1}$), characterizes 87.3% of the area of agricultural lands. Most of the lands in the region (56.2%), mainly in the zones of irrigated lands, are characterized by high and very high contents of mobile phosphorus.

Using the module Statistics Neural Networks (SNN), we created the neuro-models of the three-layer perceptron architecture for forecasting the content of mobile phosphorus in steppe soils (in the layer of 0…20 cm) in the territory of Kherson region on the basis of the observation data obtained from 25 stationary plots in the period of 1970–2020. The neural network model is characterized by eleven neurons in a hidden layer, the training method: inverse distribution (100 epochs) and connected gradients (20 and 472 epochs), the matrix of the artificial neural network consists of 1650 weighing coefficients (Figure 8).

The final data on the effectiveness of realization of the neural networks on training and test samples are given in Table 5. Analysis of approximation of the tree-layer neural network on the test sample indicates a high level of approximation of the model and obtaining reliable results on forecasting the content of mobile phosphorus in steppe soils (Figure 9).

The results on forecasting allow making a conclusion that under the current agricultural practices, an irreversible process of a gradual reduction in the content of mobile phosphorus in steppe soils (in the layer of 0–20 cm) is forecasted in the territory of Kherson region: on non-irrigated lands –

Table 4. Distribution of the content of mobile phosphorus in steppe soils of Kherson region

Content of mobile phosphorus, $mg \cdot kg^{-1}$		Distribution of agricultural lands	
		thous. ha	%
Medium	16.0 – 30.0	250.0	12.7
Elevated	31.0 – 45.0	1064.4	54.0
High	46.0 – 60.0	599.7	30.4
Very high	> 60.0	56.9	2.9
In total		1971.0	100.0

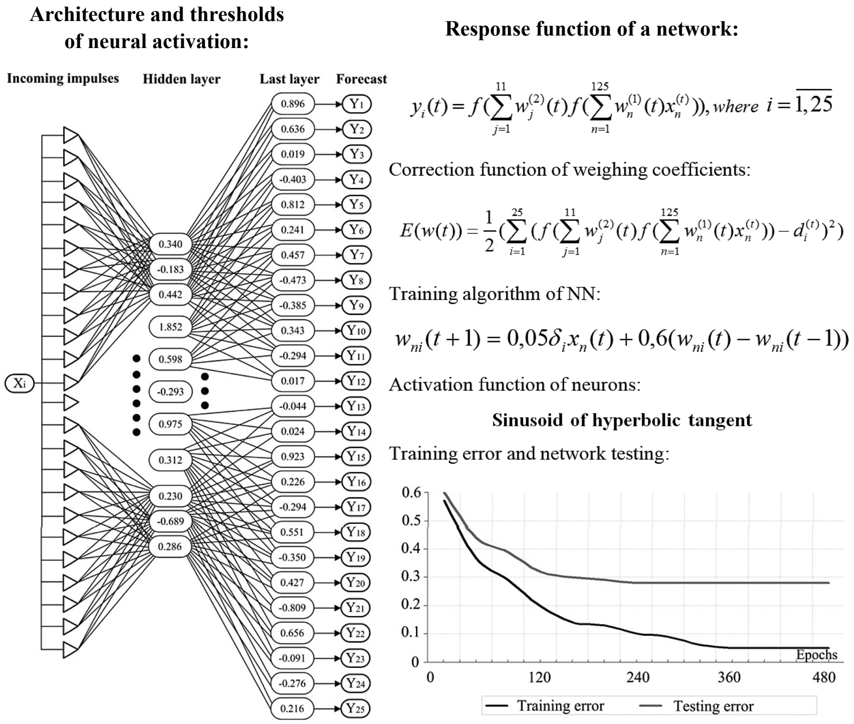


Fig. 8. Characteristic of the neural network for forecasting the content of mobile phosphorus in steppe spoils

Table 5. Statistical characteristics of the neural network on the test sample (400 values) for forecasting the content of mobile phosphorus in steppe soils

Descriptive characteristics	Test sample
Mean squared error	0.27
Mean absolute error	2.46
Maximum absolute error	16.36
Mean absolute relative error, %	5.60
Reliability estimation, %	94.40
Correlation coefficient, r	0.98
Determination coefficient, R	0.96

by 0.16 mg·kg^{-1} of soil per year on the average, on irrigated lands – by 0.18 mg·kg^{-1} of soil per year. The highest rate of a decrease in the content of mobile phosphorus is forecasted on irrigated lands with dark-chestnut soils in the south-west of Kherson region and the coastal territories of land-use.

Potassium supply (K). Potassium plays an important role in the life cycle of agricultural crops. It indirectly participates in nitrogen exchange, affects accumulation of amino acids and energy processes, regulates breathing. Availability of different forms of potassium in soils is related to primary and secondary minerals, and also to the specificity of their transformations. Gross potassium content in steppe soils largely depends on the content of clay fraction in soil granulometric composition (Pichura, 2015).

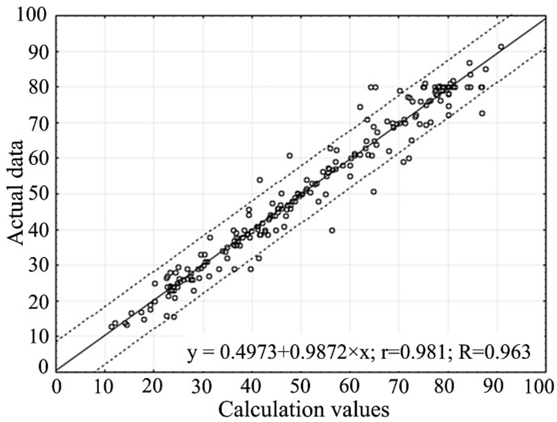
Over the past 50 years (1970–2020) the content of exchangeable potassium in the layer of 0…20 cm of steppe soils in Kherson region fell by 17.8% (from 442.4 mg·kg^{-1} to 363.8 mg·kg^{-1}) and maintains a tendency for a decrease in its content: . Space-time differentiation of a drop in potassium con and uniform supply of mineral fertilizers, manifestation of water erosion and soil deflation, including profile-irrigation erosion on irrigated lands.

Graphical and statistical regularities of spatial distribution of the content of exchangeable potassium in steppe soils are given in Figure 10. Autocorrelation analysis made it possible to determine the minimum (r = 0.413) and maximum (r = 0.170) radii of typicality of the formation of exchangeable potassium content in steppe soils equaling 2.5 km and 12.5 km (Figure 10).

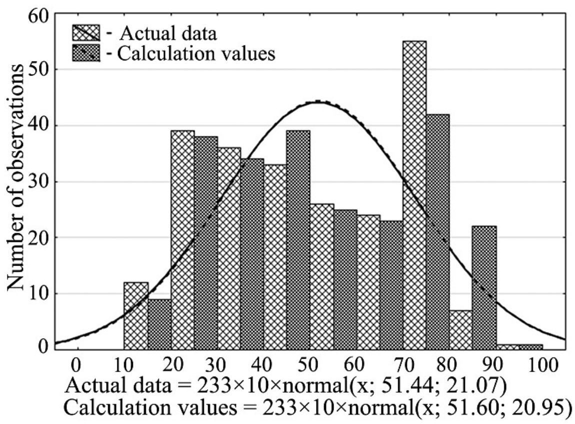
The spatial function of distribution of exchangeable potassium in steppe soils of Kherson region looks as follows:

$$f(K) = 9628.88 \cdot x - 3150.26 \cdot y + 11.05 \cdot x^2 - 220.27 \cdot x \cdot y + 112.49 \cdot y^2 - 88216.68; \; r^2 = 0.46$$

where x – longitude, decimal degrees, Y – latitude, decimal degrees.



a



b

Fig. 9. Graphical analysis of the level of approximation of the neural network model on the test sample for forecasting the content of mobile phosphorus in steppes soil: *a* – graph of correlation coincidence of the actual and calculation-verification values; *b* – histogram of distribution of the actual and calculation-verification values

Table 6. Distribution of the content of exchangeable potassium in steppe soils of Kherson region

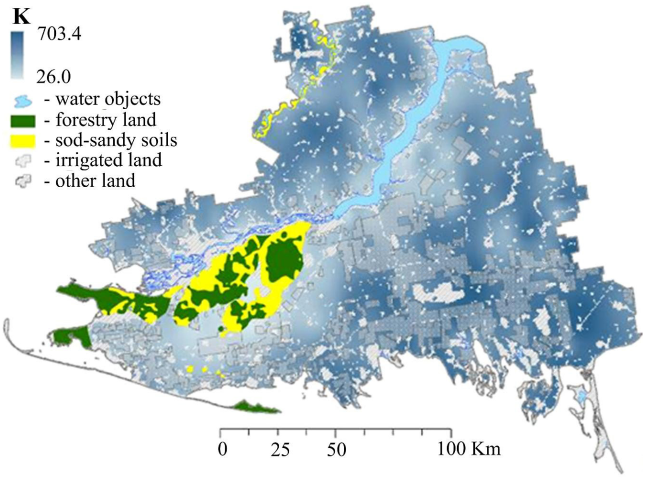
Content of exchangeable potassium, mg·kg^{-1}		Distribution of agricultural lands	
		thous. ha	%
Very low	< 100	70.6	3.6
Low	101 – 200	211.2	10.7
Medium	201 – 300	459.8	23.3
Elevated	301 – 400	572.6	29.1
High	401 – 600	596.3	30.3
Very high	> 600	60.5	3.1
In total		1971.0	100.0

The content of exchangeable potassium in soil (Table 6), corresponding to quality gradations from medium to very high contents (> 200 mg·kg^{-1}), characterizes 85.8% of the area of agricultural lands. A high value of the content of exchangeable potassium of more than 400 mg·kg^{-1} of soil was registered in the north-west and the south-east of the region.

Using the module Statistics Neural Networks (SNN) we created neuro-models of the three-layer Perceptron architecture for forecasting the content of exchangeable potassium in steppe soils (in the layer of 0–20 cm) in the territory of Kherson region on the basis of the observation data obtained from 25 stationary plots in the period of 1970–2020. The neural network model is characterized by twelve neurons in a hidden layer, the training method: inverse distribution (100 epochs) and connected gradients (20 and 596 epochs), the matrix of the artificial neural network consists of 1800 weighing coefficients (Figure 11).

The final data on effectiveness of the realization of neural networks on training and test samples is given in Table 7. Analysis of approximation of the three-layer neural network on the test sample indicates a high level of approximation of the model and obtaining reliable results on forecasting the content of exchangeable potassium in steppe soils (Figure 12).

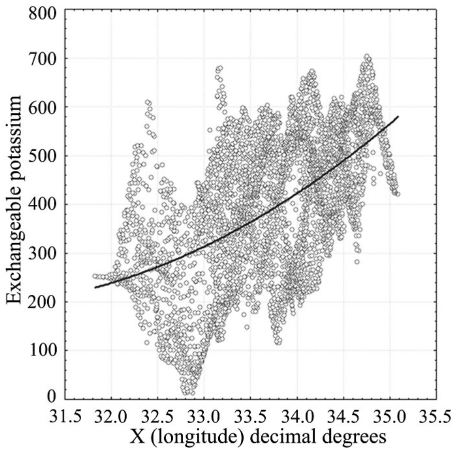
The results on forecasting allow making a conclusion that under the current agricultural practices, an irreversible process of a gradual reduction in the content of exchangeable potassium is forecasted in steppe soils (in the layer of 0-20 cm) in the entire territory of Kherson region: on non-irrigated lands – by 1.9 mg·kg^{-1} of soil per year on the average, on irrigated lands – by 3.1 mg·kg^{-1} of soil per year. The highest rate of a decrease in the content of exchangeable potassium is forecasted on irrigated lands with dark-chestnut soils in the southern part of Kherson re-



a

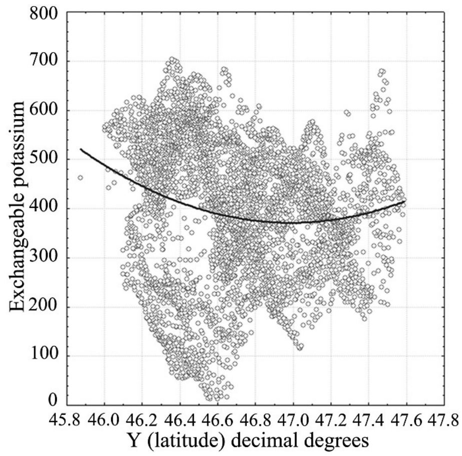
Mean value	396.78
Credible interval of the mean	4.24
Median	414.94
Mode	–
Minimum	26.0
Maximum	703.4
Procentile 10,0	199.63
Procentile 90,0	572.48
Level of variation	36.23
Dispersion	20 670
Standard deviation	143.77
Standard error of the mean	2.16
Asymmetry	-0.37
Excess	-0.64

b



$K = 17.079x^2 – 1035.5x + 15885$; $R = 0.56$,
where x – value of geographical longitude in decimal degrees

c



$K = 120.09y^2 – 11285y + 265508$; $R = 0.18$,
where y – value of geographical latitude in decimal degrees

d

Fig. 10. Spatial heterogeneity of distribution of exchangeable potassium (mg·kg^{-1}) in steppe soils of Kherson region: *a* – cartogram; *b* – statistical characteristics; *c* – west→east; *d* – south→north

Table 7. Statistical characteristic of testing the neural network on the test sample (400 values) for forecasting the content of exchangeable potassium in steppe soils

Descriptive statistics	Test sample
Mean squared error	2.71
Mean absolute error	28.12
Maximum absolute error	217.0
Mean absolute relative error, %	7.62
Reliability estimation, %	92.38
Correlation coefficient, r	0.955
Determination coefficient, R	0.911

gion. A relatively stable situation and a slight decrease in the content of exchangeable potassium is forecasted in the central (southern black soils) and northern (common black soils) parts of the region.

Conclusion

The results on space-time modeling allow drawing a conclusion that the current agricultural practices over the past 50 years have caused deterioration of steppe soil fertility in Ukraine, including a decrease in the content of humus by 14.1% on the average, mobile phosphorus – by 34.2%, ex-

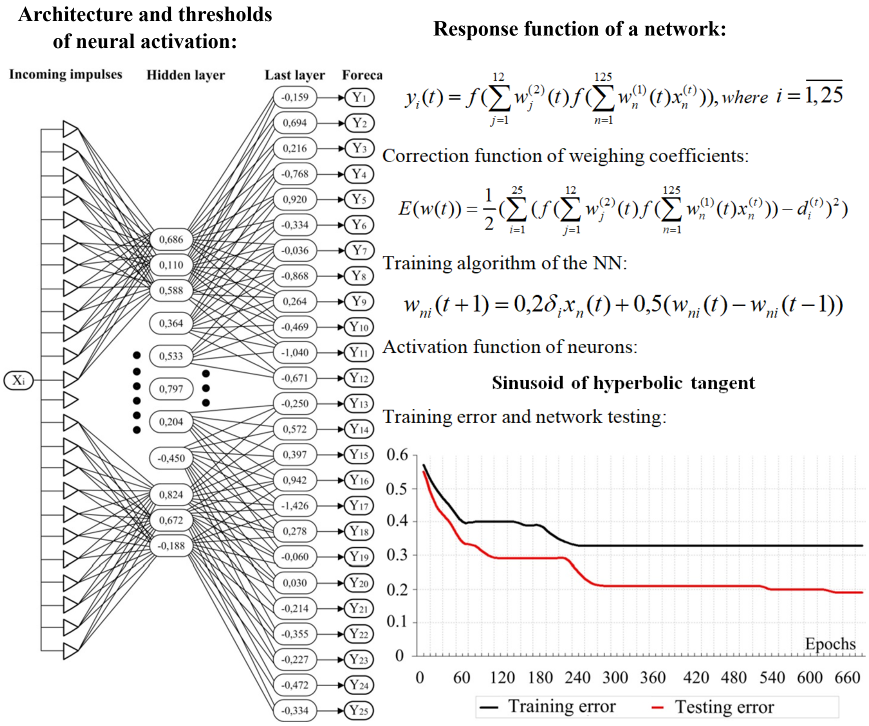


Fig. 11. Characteristic of the neural model for forecasting the content of exchangeable potassium in steppe soils

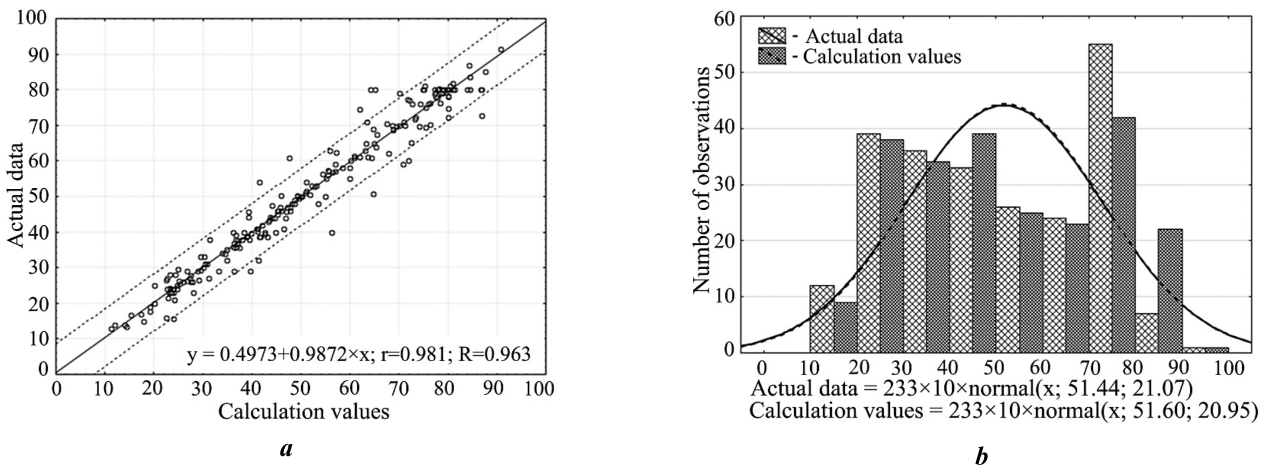


Fig. 12. Graphical analysis of the level of approximation of the neural network model on the test sample for forecasting the content of exchangeable potassium in steppe soils: *a* – graph of correlation coincidence of the actual and calculation-verification values; *b* – histogram of distribution of the actual and calculation-verification values

changeable potassium – by 17.8% and a drop in the content of nitrifiable nitrogen – by 17.0% over the past 7 years. The results on forecasting on the basis of neural network models confirm the process of a further reduction in the content of macronutrients in the upper fertile layer (0…20 cm) of steppe soils, including a drop in the content of humus – by 0.01-0.03% per year, on the average, nitrifiable nitrogen – by 0.04-0.06 mg·kg^{-1} soil per year, mobile phosphorus – by

0.16-0.18 mg·kg^{-1} of soil per year, exchangeable potassium by 1.9-3.1 mg·kg^{-1} of soil per year.

The highest rate of a reduction in the content of macronutrients is forecasted on irrigated lands with dark-chestnut soils in the southern part of Kherson region that is caused by additional irrigation-profile soil degradation, leakage of nutrients into a lower soil profile, poorly accessible to plants and a considerable decrease in the content of macronutrients in the upper layer of soil. A relatively stable situation and a slight decrease in soil fertility are forecasted in the central (southern black soils) and northern (common black soils) parts of the region.

The above approaches, methods and results on space-time modelling make it possible to thoroughly examine the issue of steppe soil fertility, their agro-chemical state and effectiveness of the current agricultural practices for further development and implementation of scientifically based solutions in order to increase effectiveness of agricultural land management in the Steppe zone. The obtained result affects territorial priorities of the regional policies and allows applying differentiated effectiveness of the soil-protecting block of agricultural systems, and the suggested methods and results have sufficient genericity to be used in other regions.

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