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ARTIFICIAL NEURAL NETWORKS FOR PREDICTING THE NUMBER OF FIELD CROP PESTS

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Abstract. *Every year, farms face the problem of ensuring the necessary development and growth of field crops due to the high probability of field crops being affected by certain types of pests. Pests can significantly impair the development of crops if their population is not controlled. This will reduce the harvest. To ensure a certain level of field crop production, it is necessary to take a series of measures to reduce the risk of harvest losses and optimize the costs of protecting plant growth. A key element of effective farmland management is the reliable prediction of the number of pests using artificial neural networks and their appropriate configuration. This approach will reduce harvest losses and preserve the ecosystem of a particular region. Reliable forecasting of pest numbers is guaranteed to create conditions for minimizing the cost of growing crops.*

However, machine learning can only be implemented if there are relevant results of monitoring the number of pests and the factors that influence changes. These factors include solar activity, temperature, and humidity. Such studies were conducted and samples were formed. Neural networks of different structures were used for forecasting, such as the radial basis function and the multilayer perceptron. The results of the forecasting show a sufficiently high accuracy, which will significantly improve production efficiency.

Keywords: *neural networks, machine learning, forecasting, field crops, agriculture*

Introduction. With modern technologies of field crops cultivation, a reasonable prediction of the timing of occurrence, prevalence and development of a complex of pests by phases of their dynamics, new reproduction cycles, number and levels of harmfulness is becoming increasingly important

(Wang, R., *et al.* 2024, Hongguo Zhang, *et al.* 2023, Rahman, S.M. & Ravi, G., 2022). This allows to optimize plant protection products both in the country as a whole and in individual soil and climatic zones. Of particular importance is the long-term forecast, which is based on solar-terrestrial connections and periodic changes in weather and climate that affect the dynamics of the number, reproduction and spread of pests, with an assessment of their harmfulness. The spread and harmfulness of grain crop phytophages within the long-term indicators depends on both the processes of controlling the phytosanitary state of agrocenoses and the influence of solar insolation, as well as the hydrothermal coefficient (HTC) as the ratio of the amount of precipitation with average daily air temperatures above +10˚C, as the basis for the definition, reproduction and spread of pests, as a constant value that differs in the Steppe and the Forest Steppe. At the same time, the sum of effective temperatures is important for predicting pest reproduction, as it is constant for different geographical populations and ensures the intensity of development, reproduction and number of pest species (Nitta, A. et al. 2024, Rakhonde, G.Y. et al. 2024, Wang Xianfeng, et al. 2018). [1-2; 5;7;9].

Materials and methods. The primary importance is the generalization of numerical values of solar activity, in particular, the number of spots on the disk (Wolf number) with the dependence on them of the number of pests in the years of minimum and maximum of these indicators, which should be used in models for predicting the emergence and development of both soil-dwelling and migratory pests (T. Boopathi, A. L. Rathna Kumar, & M. Sujatha, 2022). The combination of these factors, as the basis for the interaction of pests in space and functional asymmetries, determines the stability of self-regulation mechanisms and the predicted levels of reproduction of species and populations in the process of their formation (Wang Xianfeng, *et al.* 2023, Zhang, Hongguo *et al.* 2023).

An integral part of the assessment of the phytosanitary state of the agrocenosis as a whole is agrotechnical information, as well as the phenology of pests and its coincidence with the phenology of the phases of crop development as components of models of formation and certain mechanisms of stability of the dynamics of pest reproduction in the Steppe and Forest Steppe of Ukraine.

Results and Discussion. Long-term observation (1996-2023) of certain patterns in the Steppe and Forest Steppe characterizes the conditions for analyzing the relationship between the number of pests and these factors (Everitt, B. S., & Howell, D. C., 2021, Biecek, P., & Burzykowski, T., 2021), in particular, hydrothermal coefficient (HTC) and solar activity (Figs. 1-4). HTC (Fig. 1, Fig. 2), which allow generalizing the processes of entomocomplex formation and modeling and predicting the number of dominant phytophagous species in the Steppe with a determination coefficient of $R^2 = 0.73$, and $R^2 = 0.43$ for the Forest Steppe zone (Electronic resource, 2024).

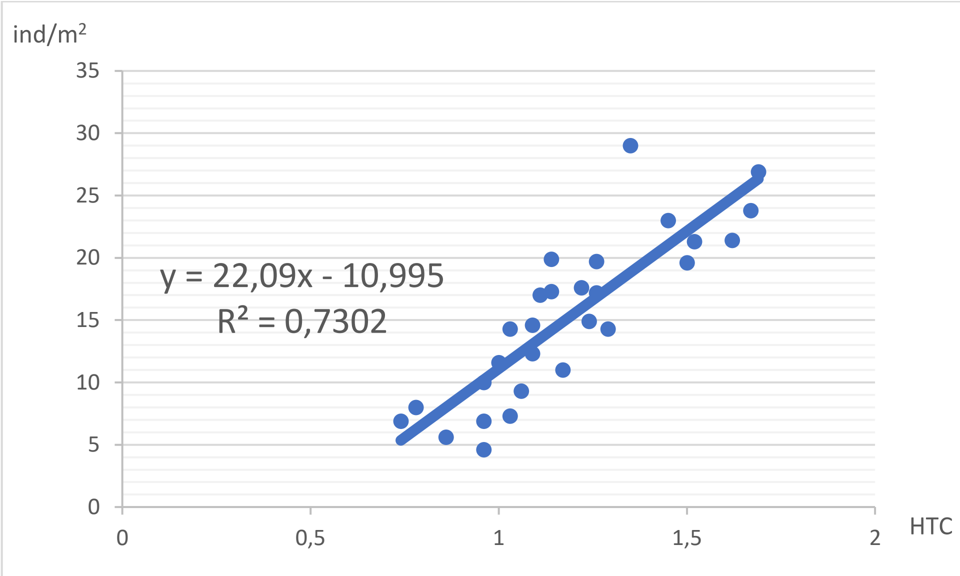

Figure 1. Dependence of the number of pests on the HTC (Steppe)

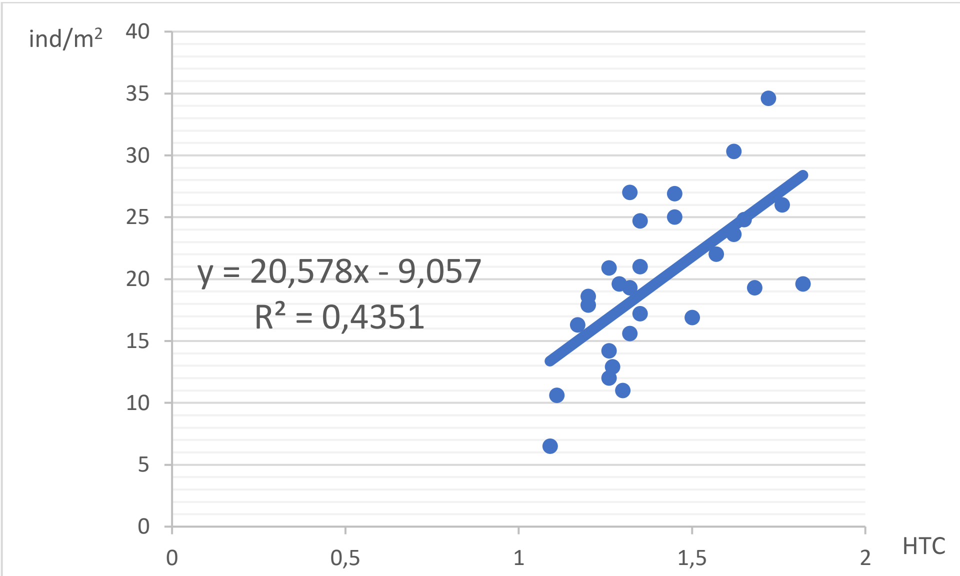

Figure 2. Dependence of the number of pests on the GTC (Forest Steppe)

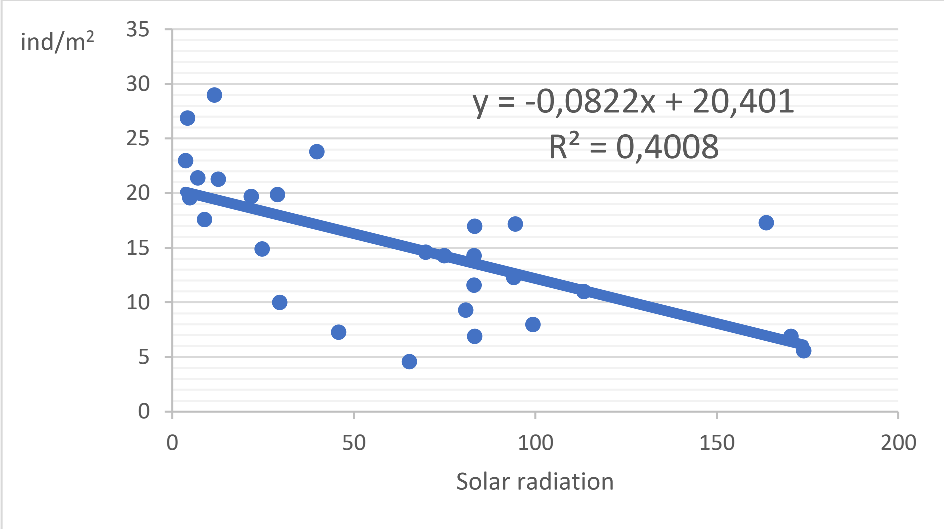

Figure 3. Dependence of the number of pests on solar radiation (Steppe)

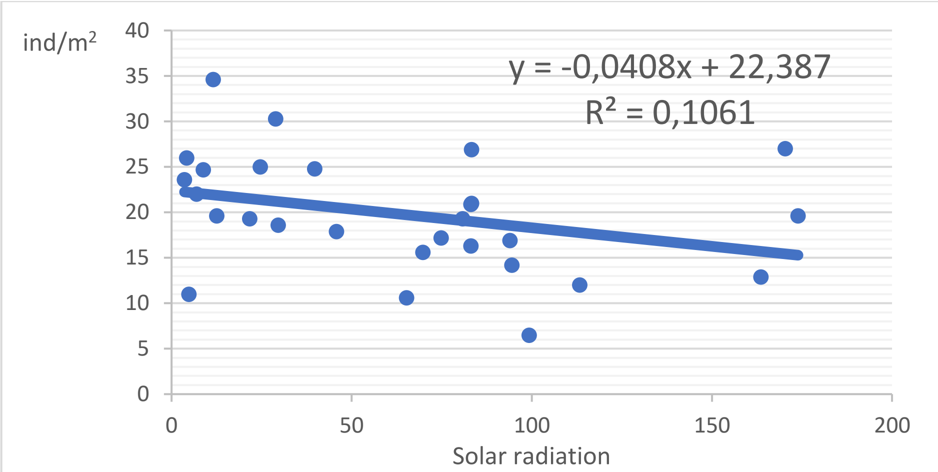

Figure 4. Dependence of the number of harmful organisms on solar radiation (Forest Steppe)

In the case of linear correlations with a low level of adequacy (the coefficient of determination does not exceed 0.7302 and 0.4351, respectively, for the Steppe and Forest Steppe zones), the determined numerical values can be used for forecasting using regression equations. At the same time, it can be argued that there are certain conditions of uncertainty that characterize the peculiarities of the biology and ecology of entomocomplexes in general.

Thus, solar activity (Fig. 3 and Fig. 4), using a linear correlation, affects the number of pests under conditions of uncertainty, as evidenced by the small values of the linear correlation coefficients (- 0.0802 and - 0.0408, respectively) and determination coefficients (0.408 and 0.1061). This means that in this case, it is not recommended to use the regression equation for forecasting.

Thus, the presence of uncertainty conditions leads to the use of a neural network to predict the occurrence of pests, the number of which depends mainly on the dynamics of the HTC level and solar activity with functional connections in the neural network. The principle of forecasting and forming a control decision can be implemented using machine learning for control systems, which is an example given in Essien, A., & Giannetti, C. (2020), Saleem, M. H. *et al.* (2021), Kurumatani, K. (2020).

Since the number of pests depends on the SST and solar activity (Fig. 1-4), an important component of their forecasting is the development of a model for predicting the SST and solar activity by years (Electronic resource, 2024). As already noted, long-term observations of changes in HTC and solar activity over the past almost 30 years have made it possible to obtain systemic links between the studied factors and the complex of harmful insect phytophagous species, which should be considered in new forms of crop production using the forecast of their number and harmfulness (Fig. 5-7).

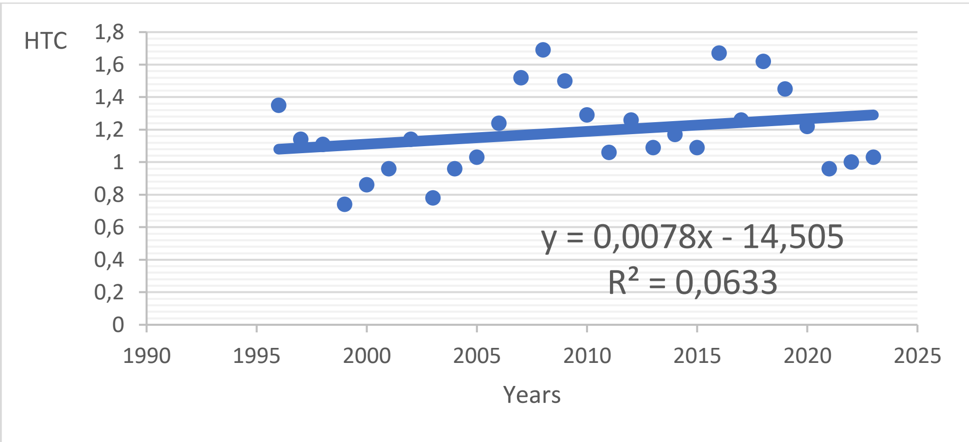

Figure 5. HTC values by years of observation 1996-2023 (Steppe)

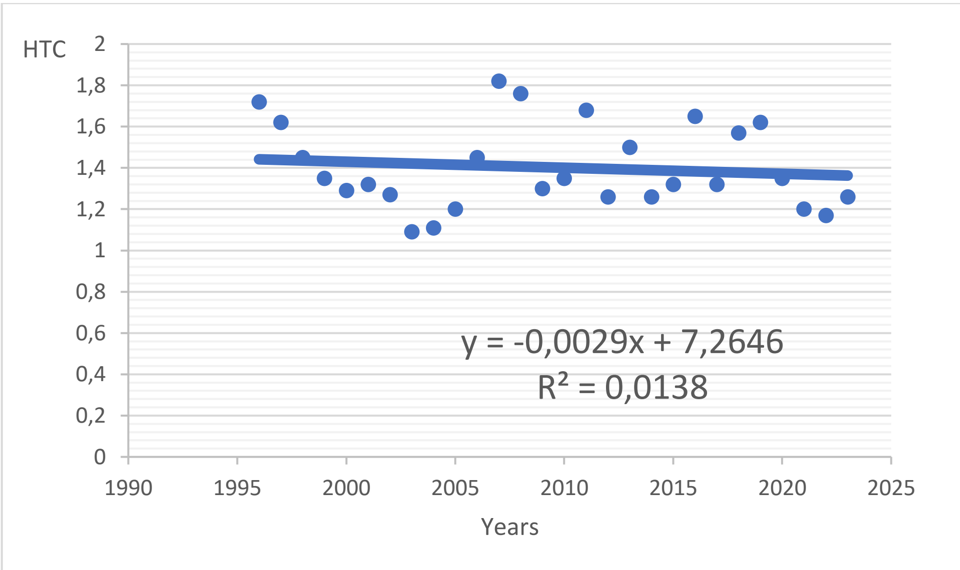

Figure 6. HTC values by years of observation 1996-2023 (Forest Steppe)

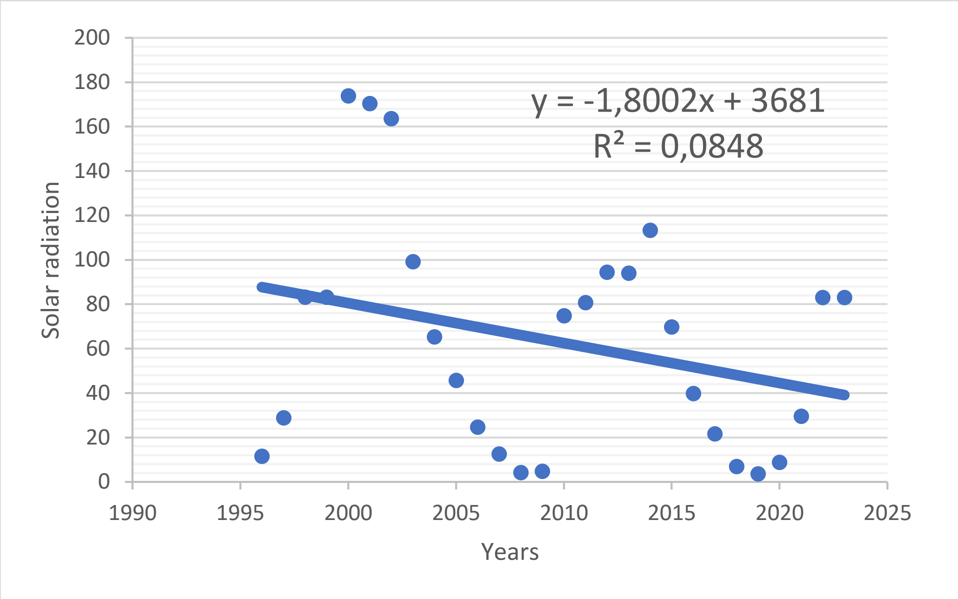

Figure 7. Solar radiation by years of observation 1996-2023

The analysis of the materials presented in Figs. 5-7 allows us to draw conclusions about the feasibility of using neural network theory to forecast HTC and solar radiation by year.

The experience of using a neural network with a radial basis function structure for other tasks (prediction of ambient temperature in Lysenko V. *et al.*, 2022) has given grounds to recommend its use for predicting the impact of technological factors on the formation and spread of pests. The principle of using neural networks to control technological processes is also highlighted in the works of Viswanatha, V. *et al.* (2023), Lovesum, J., & Prince, B. (2023), the results of such researches are presented in Fig. 8.

a)

Case name	ГТК (С) Target	ГТК (С) - Output 3.RBF 1-5-1
1	1,350000	
5	0,860000	1,042454
6	0,960000	0,808866
7	1,140000	1,206651
9	0,960000	0,964901
10	1,030000	0,997721
11	1,240000	1,296603
12	1,520000	1,489711
13	1,690000	1,542991
14	1,500000	1,550101

b)

Case name	ГТК (Л) Target	ГТК (Л) - Output 1.RBF 1-5-1
1	1,720000	
5	1,290000	1,338079
6	1,320000	1,289728
7	1,270000	1,225910
9	1,110000	1,131096
10	1,200000	1,189415
11	1,450000	1,499582
12	1,820000	1,830811
13	1,760000	1,685841
14	1,300000	1,376167

c)

Case name	Сон.рад. Target	Сон.рад. - Output 1.RBF 1-5-1
1	11,6000	
5	173,9000	170,7123
6	170,4000	178,4903
7	163,6000	156,0176
9	65,3000	71,8201
10	45,8000	41,1690
11	24,7000	23,6501
12	12,6000	13,6798
13	4,2000	6,8885
14	4,8000	2,6712

Figure 8. Results of using the radial basis function neural network for predicting HTC for the Steppe and Forest Steppe (a, b, respectively) and solar radiation (c)

Since SST and solar radiation affect the number of pests, the numerical values of previous years and their impact on the structures of entomocomplexes and the number of dominant species in subsequent periods are reasonable predictors of the forecast. This is confirmed by the autocorrelation functions of the number of pests, HTC and solar radiation by years of observation (Fig. 8-9). In the quantitative version, the characteristics of the Forest-Steppe and Steppe zones are somewhat different, but their qualitative appearance is similar. These dependencies are characterized by a periodic component that dampens with a period of 10 years. This circumstance should be taken into account when growing crops.

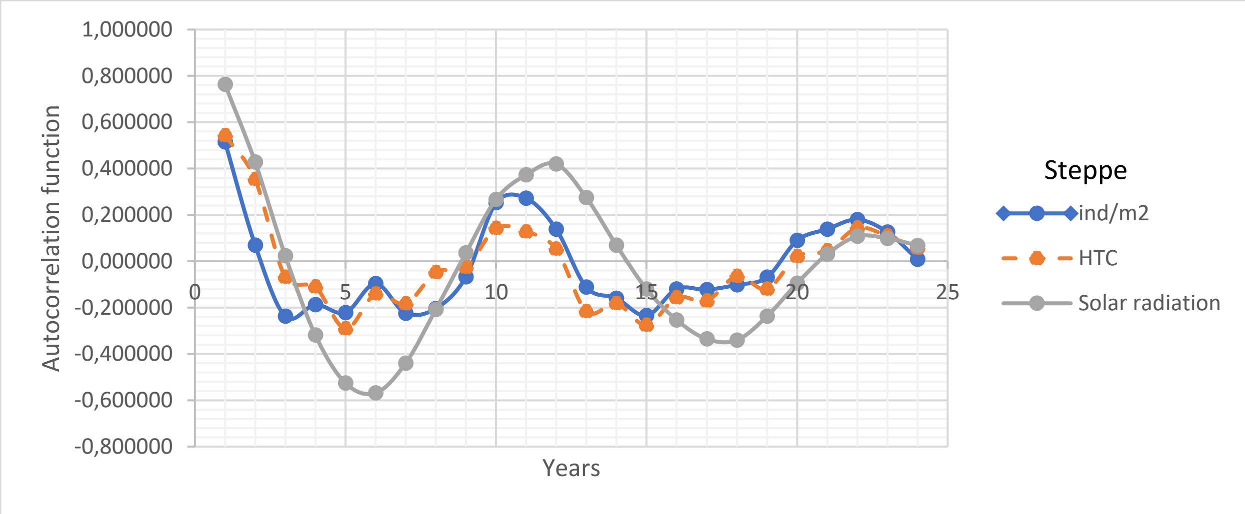

Figure 9. Correlation function between the number of pests in the HTC and solar radiation by years of observation (Steppe)

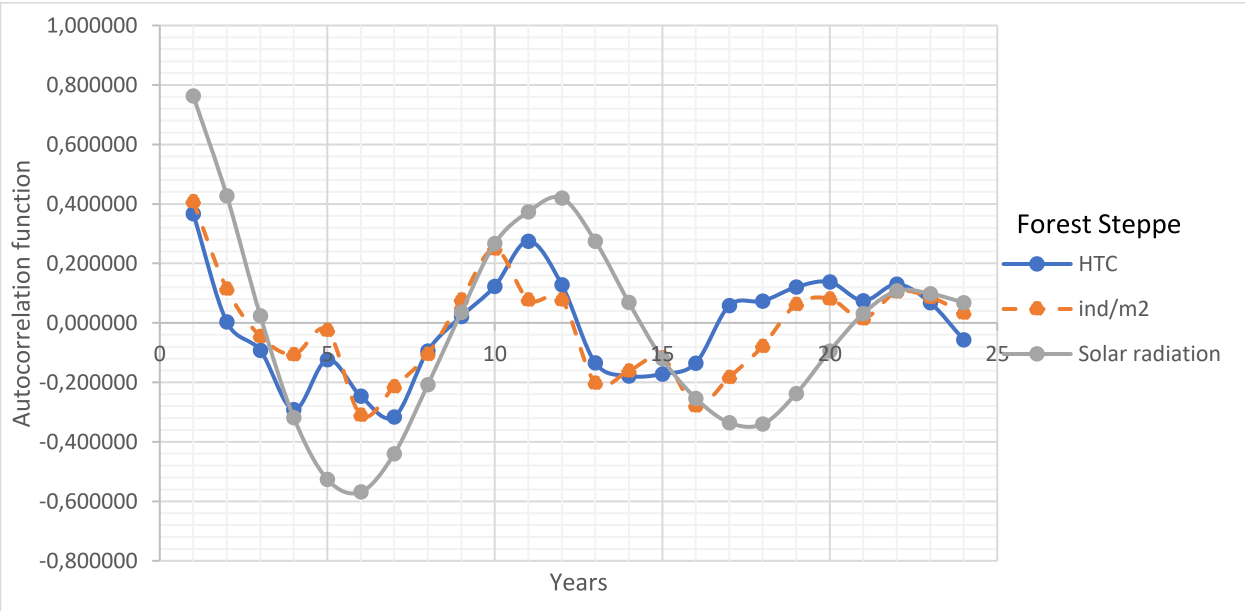

Figure 10. Correlation function of the number of pests, HTC and solar radiation by years of observation (Forest Steppe)

Based on personal experience, a neural network with a multilayer perceptron structure was used to predict the number of pests depending on the HTC and solar activity (Lysenko V. *et al.*, 2022). The researchers' experience has shown a satisfactory result of the neural networks with the "multilayer perceptron" structure (N. A. Pasichnyk et al. 2023, N. Kiktev *et al.*, 2023). The forecast depth was 1 year, and the results are shown in Fig. 11.

Case name	К (С) Target	К (С) - Output 5. MLP 2-7-1
1	14,30000	14,49711
2	9,30000	10,05788
3	17,20000	17,23457
5	11,00000	11,17699
6	14,60000	14,66895
7	23,80000	23,67396
8	19,70000	19,75783

Figure 11. Results of predicting the number of pests based on the use of the "multilayer perceptron" neural network

The block diagram of machine learning for predicting the number of pests is shown in Fig. 12.

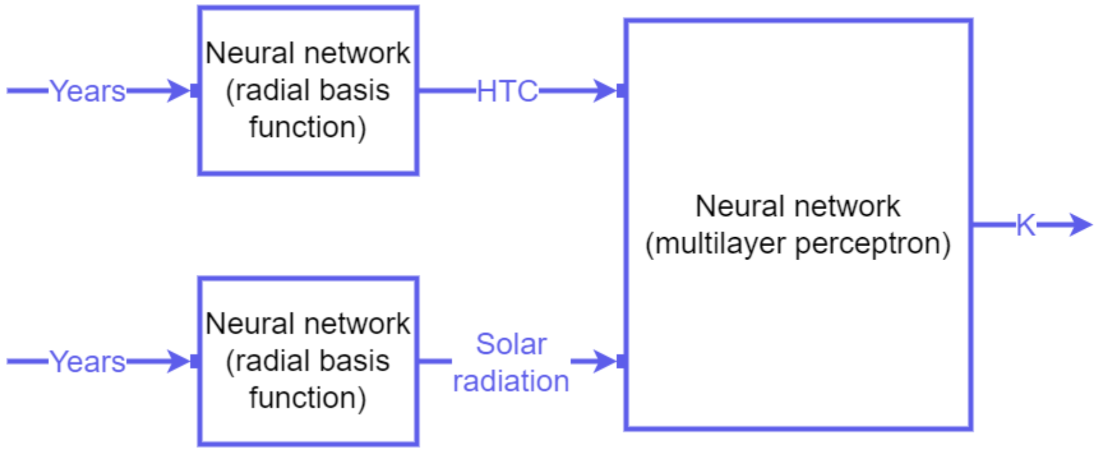

Figure 12. Neural networks for machine learning and pest prediction

The results show a fairly good convergence and can be used for preparatory work on pest control.

Conclusions.

1. The level of long-term population and harmfulness of insect phytophages of agrocenoses depends on changes in weather and climatic conditions and modern technologies of field crops cultivation with the manifestation of systematic resistance and formation of phytosanitary conditions in both the Steppe and Forest Steppe of Ukraine.

2. Based on the results of many years of research, a new tool for modeling the dynamics of phytophage reproduction under the cause-and-effect relationship of pests with environmental factors has been developed, which consists in the use of machine learning, artificial neural networks with the structure of "radial-base function" and "multilayer perceptron".

3. The results of the use of neural models for predicting the number of pests have created conditions for generalizing basic information on the parameters of the dynamics of insect-phytophagous reproduction and determining the levels of its dependence on the HTC and Wolf number in the Steppe and Forest Steppe of Ukraine.

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ШТУЧНІ НЕЙРОМЕРЕЖІ ДЛЯ ПРОГНОЗУВАННЯ ЧИСЕЛЬНОСТІ ШКІДНИКІВ ПОЛЬОВИХ КУЛЬТУР

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Анотація. *Щороку перед господарствами постає проблема забезпечення необхідного розвитку та росту польових культур у зв'язку з високою ймовірністю ураження польових культур окремими видами шкідників. Шкідники можуть значно погіршити розвиток сільськогосподарських культур, якщо не контролювати їх популяцію. Це зменшить урожай. Для забезпечення певного рівня виробництва польових культур необхідно вжити комплекс заходів щодо зниження ризику втрат врожаю та оптимізації витрат на захист росту рослин. Ключовим елементом ефективного управління сільськогосподарськими угіддями є надійне прогнозування чисельності шкідників за допомогою штучних нейронних мереж та їх відповідної конфігурації. Такий підхід дозволить зменшити втрати врожаю та зберегти екосистему окремого регіону. Достовірне прогнозування чисельності шкідників гарантовано створює умови для мінімізації витрат на вирощування сільськогосподарських культур.*

Однак машинне навчання можна реалізувати лише за наявності відповідних результатів моніторингу чисельності шкідників та факторів, що впливають на зміни. Ці фактори включають сонячну активність, температуру та вологість. Такі дослідження були проведені та сформовані вибірки. Для прогнозування використовувалися нейронні мережі різної структури, такі як радіальна базисна функція та багатошаровий персептрон. Результати прогнозування свідчать про достатньо високу точність, що значно підвищить ефективність виробництва.

Ключові слова: *нейронні мережі, машинне навчання, прогнозування, польові культури, сільське господарство*

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