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Neuron network prediction of damage of *E. integriceps* bug on winter wheat in Ukraine

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Abstract. Protecting wheat from pests directly affects the country's food security. Therefore, the purpose of this study was to create predictive models for estimating the harmfulness of *E. integriceps* by years. The harmfulness of *E. integriceps* was considered depending on the following indicators: pest abundance, environmental index (Wolf number) and hydrothermal moisture coefficient (HTC).

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The study proved the existence of mathematical uncertainty of information flows in relation to the specified pest, and therefore the mathematics of artificial neural networks with the structure of "multilayer perceptron" was used for forecasting. The results of the study of the harmfulness of *E. integriceps* to winter wheat in Ukraine were presented, including a forecast of the phytosanitary state of agrocenoses of Ukraine and recommendations for assessing the distribution of harmfulness of *E. integriceps* by years of observation (1996-2023) for the Odesa Oblast. It was noted that this distribution corresponds to a normal law with a mathematical expectation of 25%, which is confirmed by the results of observations for other regions of the Steppe zone. The relationship between the number of *E. integriceps*, Wolf number, and the accumulated integrated temperature and humidity characteristics of the environment was analysed. It was found that the harmfulness of *E. integriceps* is characterised by a fading periodic component with a period of 10-12 years. This result suggests the impact of the current year's *E. integriceps* damage on the next year in 10-12 years. According to the forecasting results, the dependence of the harmfulness of *E.integriceps* on its number and the Wolf number was presented. Therewith, the accumulated integrated temperature and humidity characteristics of the environment were considered. The obtained findings are recommended for consideration in the organisation of planned technological operations for the protection of cereal grain crops

Keywords: plant protection; artificial neural networks; multilayer perceptron; Wolf number; mathematical expectation

Introduction

With modern crop production technologies, the imperfect forecasting and control of harmful bugs spread substantially contributes to annual significant grain losses due to pests. During pest outbreaks, these losses can be severe, often leading to a marked deterioration in grain quality and, in extreme cases, to complete harvest failure. Improving forecasting accuracy and implementing effective control measures are essential to mitigate these risks and ensure sustainable agricultural production.

Therefore, in the study by I. Rogovskii *et al.* (2024), without a substantiated forecast of phytophage reproduction and protection measures, even with a high agronomic background, the yield of low-quality winter wheat grain is formed within 2-4 t/ha, and with prompt and adequate protection – within 9-10 t/ha. At the same time, according to I.L. Rogovskii (2021), every third and sometimes second hectare of arable land should be accompanied by a comprehensive assessment and modelling of the patterns of development, reproduction, and spread of economically dominant types of pests. B. Motie *et al.* (2023) believe that the rapid identification of pest concentration points and assessment of infestation levels in fields can be useful for production management and reducing the use of chemical sprays. At the same time, the study proposed the use of software computing and image processing approaches to identify areas infested with sunn pests based on the use of aerial photographs in the near-infrared and visible ranges. However, the study did not predict the number of pests to synthesise a crop management strategy.

M. Mehrabadi *et al.* (2012) presented *Eurygaster integriceps Put.* (*Hemiptera*: *Scutelleridae*), which was a major pest of wheat in the Middle East and some other regions, causing serious qualitative and quantitative damage. However, this study also did not offer an opportunity to predict the harmfulness of this pest in crop production. S. Gürsoy *et al.* (2012) proposed to plant different plant varieties in the specified area to reduce the number of pests. P.A. Edde (2021) also presented integrated approaches to pest management in crop production, however, for the accuracy of the forecast of each individual method, it is necessary to use the principles of mathematical modelling.

V. Sakhnenko & D. Sakhnenko (2018) presented long-term data on the dynamics of the number of harmful bugs (*Eurygaster integriceps Put.*) in the Mykolaiv Oblast. The influence of winter wheat predecessors and sowing dates on the number of pests in the Southern Steppe of Ukraine was presented. The researchers presented their findings on the effectiveness of modern insecticides against pests on winter wheat crops. P. Lykhovyd (2023) presented the results of a mathematical study of the 40-year dynamics of the number of *E. integriceps* in the south of Ukraine, as well as statistics on the number of bugs that can be used to predict the development of the specified pest.

The purpose of this study was to develop predictive models for assessing the harmfulness of the *E. integriceps* on winter wheat.

Materials and Methods

Data Sources and Variables:

The primary data sources included long-term forecasts of the phytosanitary state of agrocenoses in Ukraine, along with recommendations for plant protection (Map of solar insolation of Ukraine, n.d.; Phytosanitary status of agricultural plants, 2024). The study focused on Odesa Oblast from 1996 to 2023, using electronic resources to obtain the most recent data (Map of solar insolation of Ukraine, n.d.; Phytosanitary status of agricultural plants, 2024).

Key variables influencing the harmfulness of the *E. integriceps* were identified as follows:

1. Population Size (K): The number of *E. integriceps* bugs present in the region, which directly affected the extent of crop damage.
2. Solar Radiation Intensity: This was quantified using the Wolf number (W), a numerical indicator of solar activity correlated with the number of sunspots observed. Solar radiation affected various biological processes and environmental conditions.
3. Temperature-Humidity Characteristics (HTC): Integrated temperature and humidity measurementsthat accounted for cumulative environmental conditions influencing the life cycle and behaviour of the *E. integriceps* bug.

Methodological Approach:

- Analysis of historical data. Historical data on the distribution of harmfulness of the *E. integriceps* bug was analysed to identify trends and patterns. This involved examining records of harmfulness and correlating them with environmental and biological factors (Suárez-Varela *et al.*, 2022; Tam *et al.*, 2022).
- Statistical analysis. The harmfulness of the *E. integriceps* bug (S) was assessed using statistical methods to determine its distribution.
- Predictive modelling. Based on the identified factors (K, W, and HTC), predictive models were created to estimate future harmfulness levels. These models incorporated historical patterns and current environmental data to forecast potential outbreaks and assess the impact on wheat crops.
- Graphical representation. The findings were visually represented through graphs and charts to illustrate the distribution patterns and forecast models. This visual representation offered insight into the trends and helped to make data-driven decisions for pest management and crop protection.
- Correlation analysis. Methods of correlation analysis, including constructing autocorrelation functions, were used to assess the impact of each variable on the dynamics of pest numbers for subsequent years. This approach helped in understanding the temporal relationships and dependencies between different factors.
- Mathematical model selection. The normal law of harmfulness distribution by years provided a basis for analysing the possibilities of using mathematical models of different content and choosing the best option (Suárez-Varela *et al.*, 2022; Tam *et al.*, 2022). Specifically, the following formula was used:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}, \tag{1}$$

where σ is the standard deviation; μ is the mathematical expectation.

J Neural network tools. Neural network tools were employed to assess the forecast of pest harmfulness, considering long-term statistics. These advanced techniques enabled the modelling of complex, non-linear relationships between variables, and improved the accuracy of harmfulness predictions.

The research methodology ensured a comprehensive understanding of the factors affecting the harmfulness of the *E. integriceps* bug and provided a robust framework for predicting and mitigating its impact on wheat production.

Results and Discussion

The results of the analysis on the distribution of the number of pests are presented in the form of a normal distribution in Figure 1. The distribution presented in Figure 1 suggests that it corresponds to the normal law with a mathematical expectation of 25%, which is confirmed by the results of observations for other regions of the Steppe zone.

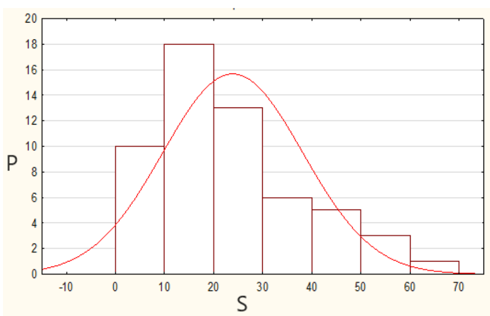

***Figure 1.** Normal distribution of the harmfulness of the E. integriceps bug*

Note: *abscissa axis – harmfulness (S), %; ordinate axis – probability (P), %*

Source: developed by the authors of this study based on Map of solar insolation of Ukraine (n.d.), Phytosanitary status of agricultural plants (2024)

To choose a mathematical modelling method, it is necessary to analyse the relationship between harmfulness and the factors mentioned above. The study showed a relationship between harmfulness and K number, where the result is presented in Figure 2a. Figure 2b shows the relationship between virulence and Wolf number W, while Figure 2c shows the relationship between virulence and HTC. According to M. Mehrabadi *et al.* (2014) and J. Motie *et al.* (2023), results from the analysis suggested the presence of significant uncertainty, as the linear correlations are low, and the coefficient of determination suggests that the linear mathematical model is inadequate. This was partially confirmed by other researchers – B.R. Critchley *et al.* (1998), H. Dizlek & M.S. Özer (2024). B.R. Critchley *et al.* (1998) revealed the statistics of pest outbreaks and noted the absence of a clear strategy for controlling pest populations. H. Dizlek & M.S. Özer (2024) showed the consequences of damage to the wheat kernel caused by the pest, which affects the yield.

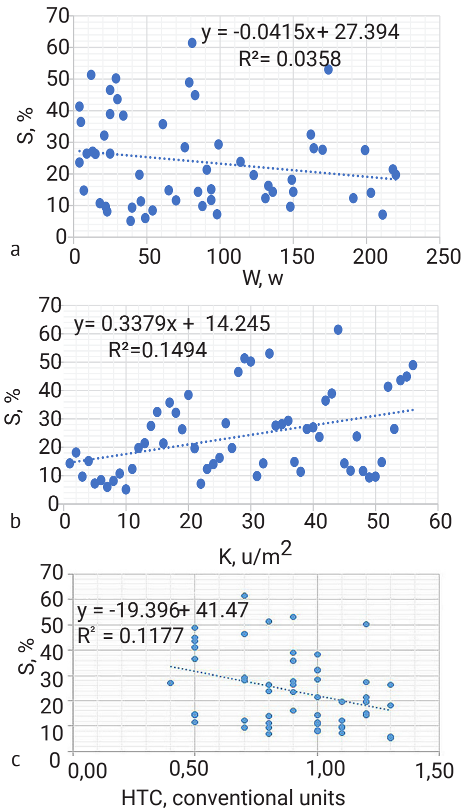

***Figure 2.** Dependence of the harmfulness of the bug-harmful shell on key variables*

Note: a – Wolf number, b – Population Size, c – HTC

Source: developed by the authors of this study based on Map of solar insolation of Ukraine (n.d.), Phytosanitary status of agricultural plants (2024)

Interesting conclusions can be drawn by constructing the autocorrelation function of the harmfulness of the *E. integriceps* bug (shift of the ordinate by years with a discreteness increasing from 0 by 1 year – Fig. 3).

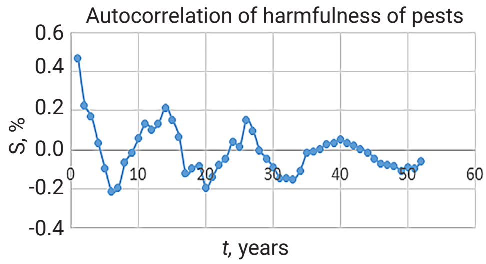

Figure 3. *The autocorrelation function of the harmfulness of the E. integriceps bug (shift of the ordinate by years)*
Source: developed by the authors of this study based on Map of solar insolation of Ukraine (n.d.), Phytosanitary status of agricultural plants (2024)

The autocorrelation function was constructed from sample data as follows (Tam *et al.*, 2022):

$$R_{xx}(\tau) = \frac{1}{N-\tau-1}\sum_{i=1}^{N-\tau}(x_i - M_x)(x_{i+\tau} - M_x), (2)$$

where *N* is the data sample; τ is the shift between ordinates; M_x is the mathematical expectation of harmfulness as a random variable x.

The autocorrelation function is characterised by a decreasing periodic component with a period of 10-12 years. This suggests the influence of the harmfulness of the current year's sunn pest on the next one in 10-12 years. This circumstance should be considered when planning measures to protect grain crops, paying attention to the factors of influence and their periodicity in nature (Wolf number, abundance, HTC).

A special place among the factors affecting the harmfulness of the sunn pest is its number. In this case, it is necessary to build and analyse the autocorrelation function of the number of *E. integriceps* bugs with a shift along the ordinate axis by year, increasing from zero with a discreteness of 1 year (Fig. 4). The complex form of the autocorrelation function indicates a significant influence of the first current year on the next 10-12 years later, and then the influence "fades". Perhaps the reason is also inaccuracy in measurements based on the results of observations.

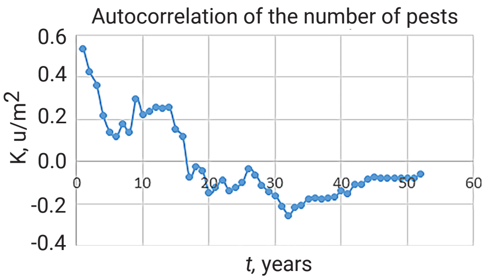

Figure 4. *Autocorrelation function of the number of sunn pest bugs (with a shift of ordinates by years with a discreteness of 1 year)*
Source: developed by the authors of this study based on Map of solar insolation of Ukraine (n.d.), Phytosanitary status of agricultural plants (2024)

As already mentioned, predicting the harmfulness of the *E. integriceps* bug is the main goal of this study. Since uncertainty is involved, it is advisable to achieve this goal by using artificial neural networks. The experience of using an artificial neural network with the structure of a "multilayer perceptron" (Lysenko *et al.*, 2022) allows recommending it to achieve this goal (Fig. 5).

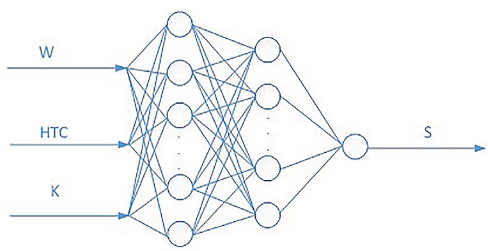

Figure 5. *Structure of the artificial neural network "multilayer perceptron"*
Source: developed by the authors of this study

For multilayer networks, the output of the previous layer is the input of the next one (Zaiets *et al.*, 2019):

$$y^{m+1} = f^{m+1}(w^{m+1} y^m + b^{m+1}), m = 0,1,\ldots,M-1, (3)$$

where M is the number of network layers; y is the input vector, w is the weight matrix, b is the shift vector, f is the activation function; m is the layer number.

For this type of neural networks, the fastest descent algorithm for calculating the root mean square error with the learning rate α has the following form (Tregub *et al*., 2020, Tam *et al*., 2022):

$$w_{ij}^{m}(k+1) = w_{ij}^{m}(k) - \alpha \frac{\partial \overline{F}}{\partial w_{ij}^{m}};$$

$$b_{i}^{m}(k+1) = b_{i}^{m}(k) - \alpha \frac{\partial \overline{F}}{\partial b_{i}^{m}}, \qquad (4)$$

where *i, j* are the elements of the matrix of input values; x_{ik} and x_{jk} are the k^{th} elements of the vectors x_i and x_j, respectively; F is the sensitivity value of the network function. The results of predicting the harmfulness of the *E. integriceps* bug are presented in Figures 6, 7. The analysis of the results of observations and analytical materials in Figure 8 points to a complex form of influence of the Wolf number on harmfulness. This is especially pronounced when this factor is within 120-220 and 20-100. The minimum harmfulness is achieved at a Wolf number of 140 and 60. It is advisable to use this information to minimise the use of insecticides used in modern crop protection technologies.

HTC has a relatively uniform effect on the harmfulness of *E. integriceps* bug compared to the Wolf number in Figure 8. Therefore, it is the number of pests that should be considered, which largely determines the final damage.

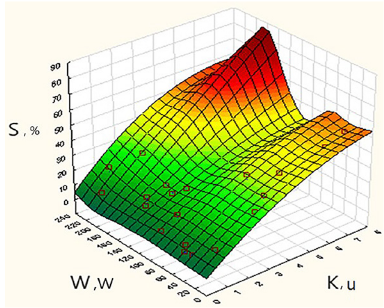

Figure 6. *Dependence of E. integriceps bug damage on its number and Wolf number*

Note: K is the number of *E. integriceps* bugs, W is the Wolf number, S is the damage, %

Source: developed by the authors of this study

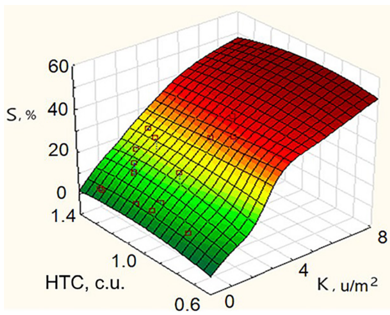

Figure 7. *Dependence of E. integriceps bug damage on its number and HTC*

Source: developed by the authors of this study

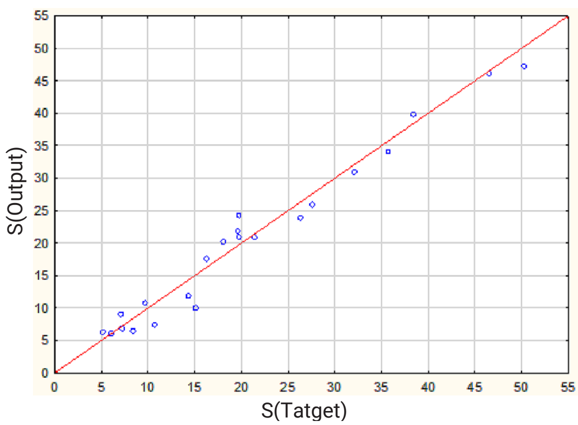

Figure 8. *Comparison of the result of the neural network (Output) with observation data (Target)*

Source: developed by the authors of this study

It is important to decide on the results of forecasting harmfulness by comparing them with observational data, as presented in Figure 10. The analysis of the materials in this figure suggests that the accuracy is sufficiently high: only for certain years, the error does not exceed 20%. According to practicing agronomists, this result creates all the conditions for high-quality preparatory work on planning the control of the *E. integriceps* in the year following the current one.

K. Sabanci *et al.* (2022) presented findings on detection of pest-damaged wheat grains using deep learning. Using the created image acquisition mechanism, healthy and uniform wheat grains were displayed. Scientists performed image pre-processing applied to the raw images, and then performed data augmentation. The augmented image data was provided as input for two different deep learning architectures. Therewith, a comparison was made according to the accuracy of the operation of these two architectures.

However, the cited studies do not indicate the possibility of using modern tools regarding the possibility of forecasting the harmfulness of pests. It is proposed to use the neural network tool to implement harmfulness prediction. For the application of the mentioned approach, a clear multi-year sample is necessary, which will allow achieving a high accuracy of the forecast. S. Khaki & L. Wang (2019) showed yield prediction using deep neural networks. In this study, the results also illustrated that environmental factors had a significant effect on yield. However, the scientists performed neural network prediction based on defined training data, which included three sets: crop genotype, yield indicators, and environment (weather and soil). The impact of pests on plant development was not fully demonstrated. In the study, the scientists implemented a neural network with sufficient accuracy. Machine learning techniques were used to predict yield, including multivariate regression, decision trees, association rule analysis, and artificial neural networks. G. Aubakirova *et al.* (2022) presented the application of an artificial neural network for forecasting the yield of wheat. In the study, scientists considered a series of factors affecting the development of wheat and its harvest in the territory of Kazakhstan. However, the researchers used a sample of data only for 2008-2022. The influence of pests as one of the factors on productivity was presented, and therefore the question of determining the forecasting of the number of pests arises.

Conclusions

According to the results of observations, it was shown that the principal factors influencing the harmfulness of the *E. integriceps* bug are its quantity, Wolf number, and HTC. Since the declared factors of influence on the harmfulness of the *E. integriceps* bug are characterised by small values of the coefficient of determination, which indicates the inadequacy of the linear model, and small values of linear correlation coefficients, it can be concluded that such dependencies are uncertain. Since the regression equation does not allow for a high-precision forecast under conditions of uncertainty, it is recommended to use artificial neural networks. An artificial neural network with a "multi-layer perceptron" structure creates conditions for predicting the harmfulness of a sunn pest bug with sufficient accuracy for preparatory work.

To save resources planned for controlling the number of *E. integriceps* bugs and their damage, it is advisable to consider not only the projected number of pests, but also factors such as the Wolf number and HTC. The analysis of the results of observations and analytical materials indicates a complex form of influence of the Wolf number on the harmfulness of the *E. integriceps* bug. This is especially pronounced for indicators of the specified factor within 120-220 and 20-100. Therewith, the minimum harmfulness is achieved for the Wolf number of 140 and 60. It is advisable to use the specified information to minimise the use of insecticides. The presented findings of the analysis of long-term observations create the conditions for an early forecast of grain yield assessment, which will enable early planning and organisational preparation for the next stage in grain production.

Acknowledgements

None.

Conflict of Interest

None.

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Нейромережеве прогнозування шкідливості клопа-шкідливої черепашки на пшениці озимій в Україні

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Анотація. Захист пшениці від її шкідників безпосередньо впливає на продовольчу безпеку країни. Тому метою досліджень було створення за роками прогнозних моделей для оцінок шкідливості клопа-шкідливої черепашки. Шкідливість клопа-шкідливої черепашки розглядали в залежності від наступних показників: чисельність шкідника, показник природнього середовища (число Волфа) та гідротермічного коефіцієнту зволоження (ГТК). Доведено, що стосовно зазначеного шкідника існує математична невизначеність інформаційних потоків, а тома для прогнозування використовувалась математика штучних нейронних мереж із структурою «багатошаровий перцептрон». Наведено результати дослідження шкідливості клопа-шкідливої черепашки для пшениці озимої в Україні матеріалів, що включає прогноз фітосанітарного стану агроценозів України та рекомендації з оцінки розподілу шкідливості клопа-шкідливої черепашки за роками спостереження (1996-2023 роки) для Одеської області. Зазначено, що цей розподіл відповідає нормальному закону із математичним очікуванням 25 %, що підтверджується результатами спостережень для інших регіонів Степової Зони. Виконано аналіз зв'язку між чисельністю клопа-шкідливої черепашки, числом Вольфа та накопиченої інтегрованої температурно-вологістної характеристики навколишнього середовища. Визначено, що шкідливість клопа-шкідливої черепашки характеризується затухаючою періодичною складовою із періодом 10-12 років. Наведений результат свідчить про вплив шкідливості клопа-шкідливої черепашки поточного року на наступний через 10-12 років. За результатами прогнозування наведено залежності шкідливості клопа-шкідливості черепашки від її чисельності та числа Вольфа. При цьому враховувалась накопичена інтегрована температурно-вологістна характеристика навколишнього середовища. Отримані результати досліджень рекомендуються до врахування для організації проведення планових технологічних операцій захисту зернових колосових культур

Ключові слова: захист рослин; штучні нейронні мережі; багатошаровий перцептрон; число Вольфа; математичне очікування