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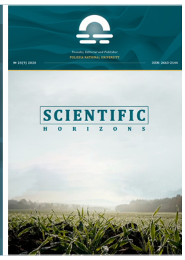

Climate predictors of crop yields in the Polissia and Forest-Steppe regions of Ukraine

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Abstract. The purpose of the study was to identify the key climatic predictors that shaped the variability of winter wheat and maize yields under the agroclimatic conditions of the Polissia and Forest-Steppe regions. The methodology was based on the use of long-term meteorological data combined with statistical and machine-learning modelling algorithms, among which multiple linear regression and the Random Forest method were applied for a comparative assessment of predictive performance. A variable importance mechanism was also implemented in order to determine the most informative climatic indicators. The study analysed the influence of temperature extremes, total atmospheric precipitation patterns, and hydrothermal indices during the key phenological stages of crop development. It was established that April-June conditions played a dominant role for winter wheat, whereas July-August thermal and moisture-related parameters were most influential for maize. It was identified that integral indicators, particularly the hydrothermal coefficient, provided considerably higher predictive power compared to individual temperature- or precipitation-based metrics. The presence of threshold crop responses to extreme climatic factors was confirmed, which resulted in regional differences in sensitivity to heatwaves and droughts. The analysis demonstrated that the Random Forest algorithm delivered the highest predictive accuracy, explaining up to 81% of maize yield variability in the Forest-Steppe region and up to 74% for winter wheat. The practical value of the study lay in the potential use of the obtained results by analytical institutions, agrometeorological services, and agricultural producers for planning sowing areas, assessing seasonal yield risks, and shaping adaptation strategies under climate-change conditions

Keywords: agroclimatic indices; temperature extremes; hydrothermal regime; productivity variability; machine modelling; Random Forest; climatic risks; phenological stressors

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INTRODUCTION

The stability of food systems was determined by the capacity of the agricultural sector to adapt to climatic shifts that caused changes in temperature regimes, a redistribution of precipitation, and an increase in the frequency of extreme weather events. The response of agroecosystems to these shifts became a key factor shaping the yields of cereal crops, which were fundamental for national food security. Regions with significant agricultural potential, particularly the Polissia and Forest-Steppe of Ukraine, demonstrated increasing sensitivity to hydrothermal stress, which necessitated an in-depth analysis of climatic predictors of crop productivity. Consideration of shifts in the intensity and structure of climatic factors made it possible to identify risks in a timely manner and to improve adaptation strategies in agricultural management.

Numerous studies highlighted the significance of climatic influence on the productivity of agroecosystems. According to the findings of K. Abbass *et al.* (2022), global climate change caused an intensification of temperature extremes that disrupted the physiological processes of major field crops and shortened the period of optimal development. Similar conclusions were presented by V.S. Bihun (2024), who emphasised that an increase in the duration of heatwaves created risks for crops sensitive to disturbances in water balance. An analysis of long-term data sequences conducted by I.E. Hansen *et al.* (2023) demonstrated the cumulative effect of global warming, which shaped inertial shifts in the hydrothermal regime, particularly in regions with unstable moisture availability.

At the regional level, researchers focused on assessing spatially differentiated climatic impacts. The study by M.O. Baranovskyi and O.V. Baranovska (2023) showed that grain yields in the northern regions of Ukraine responded significantly to temperature variations and precipitation deficits during active growth phases, which indicated increasing climatic vulnerability in traditionally humid territories. O. Kryvokhyzha *et al.* (2024) established that changes in the hydrothermal state during key developmental phases of crops became the main factor of interannual yield variability and influenced deviations from historical trends. The works of L. Moldavan *et al.* (2023) emphasised that changes in precipitation structure, as well as the increasing frequency of summer drought periods, had already been forming a new configuration of agroclimatic risks in Ukraine.

Another important aspect of contemporary research was the use of reanalysis datasets for assessing the climatic characteristics of territories. In the work of H. Hersbach *et al.* (2020), the global ERA5 system was presented, providing a detailed set of meteorological parameters for modelling climatic conditions at the regional level. Its further development, described in the study by J. Muñoz-Sabater *et al.* (2021), enabled the acquisition of more accurate data on soil moisture, temperature extremes, and other indicators, which was critically important for agroclimatic assessments. The tendencies towards aridisation in certain zones of Ukraine were also confirmed in the work of O. Shevchenko (2023), where a transition of regions from stable moisture conditions to categories with increased drought risk was identified, transforming land-use structure and crop productivity. Similarly, the findings of M. Romashchenko *et al.* (2020) indicated a systemic reconfiguration of the water regime and an increase in the deficit of available moisture against the background of rising temperatures, which reduced the efficiency of traditional agricultural technologies and required adaptive solutions.

In the context of agrometeorological modelling, the study of yield forecasting methods remained relevant. In the work of V.H. Hnatiienko *et al.* (2024), it was shown that the use of multifactor analysis and intelligent models, particularly neural networks, enhanced forecast accuracy owing to their capacity to account for nonlinear and threshold dependencies between climatic indices and yields. The results of T. van Klompenburg *et al.* (2020) demonstrated the advantage of machine-learning methods over classical statistical models in cases of complex data structures typical of agroclimatic systems. The study by B. Yang *et al.* (2022) confirmed that spatiotemporal models made it possible to consider the heterogeneity of climatic impacts, which was especially important for territories with contrasting agroclimatic conditions, such as the Polissia and Forest-Steppe regions.

Therefore, contemporary scientific sources indicated the necessity of a comprehensive analysis of agroclimatic predictors, oriented towards the specific phenological phases of crops and variables characterising extreme events rather than averaged meteorological parameters. In the light of the identified tendencies, the purpose of this study was to ensure a comprehensive identification and quantitative assessment of the influence of a set of phenologically specific climatic predictors on the interannual variability of winter wheat and maize yields in the contrasting agroclimatic conditions of the Polissia and Forest-Steppe regions of Ukraine.

MATERIALS AND METHODS

The study encompassed two agroclimatic zones of Ukraine, which differed significantly in moisture availability, soil conditions, and the nature of climatic risks. The Polissia zone included the Volyn, Rivne, Zhytomyr, and Chernihiv regions, characterised by sod-podzolic soils and comparatively higher moisture levels, which had become unstable over recent decades. The Forest-Steppe zone comprised the Khmelnytskyi, Vinnytsia, Cherkasy, Poltava, and Kyiv regions, representing territories with chernozem soils and an increasing frequency of summer droughts. This spatial selection ensured the possibility of comparing agroecosystem responses to climatic changes under contrasting conditions.

The study objects were two major cereal crops. Winter wheat (*Triticum aestivum* L.) was sensitive to overwintering conditions and moisture availability during the period of spring vegetation recovery. Maize for grain (*Zea mays* L.) depended on the temperature-moisture regime of July-August, when flowering, pollination, and grain filling occurred. The database was constructed from two types of information for the period 1991-2023. Data on actual yields of winter wheat and maize were obtained from the State Statistics Service of Ukraine (2024), which provided annual mean yield values at the level of administrative regions. Climatic parameters were obtained from the ERA5-Land reanalysis, which contained daily values of the main meteorological indicators with a spatial resolution of approximately 9 km (Muñoz-Sabater *et al.*, 2021). Data on mean, minimum, and maximum air temperature, soil temperature at a depth of 7 cm, daily precipitation totals, solar radiation, and wind speed were used. To ensure consistency of spatial scales, daily gridded data were averaged within each region.

The actual time series of yields contained two components: a technological trend (Y_tech), driven by the introduction of new varieties, technologies, and agronomic practices, and climatic variability (Y_clim), determined by the weather conditions of a given year (Evans, 1993). To correctly isolate the climatic component, detrending was performed. For each crop and each region, the technological trend was approximated using a second-degree polynomial model as a function of the year. The climatic component Y_clim was calculated as the relative deviation of actual yield from the estimated trend and expressed as a percentage:

$$Y\_clim\ (\%) = (Y\_observed - Y\_tech)/Y\_tech \times 100. \quad (1)$$

Based on the daily ERA5-Land data, more than 40 agroclimatic indices were calculated, defined separately for the biologically significant developmental phases of the crops. The calculations were performed not for entire seasons but for clearly delineated phenological intervals. For winter wheat, the April–June period was considered, corresponding to the phases of spring vegetation recovery and grain formation. For maize, the July-August period was analysed, during which flowering, pollination, and grain filling occurred. The range of calculated indices included:

1. Temperature indicators – sums of active temperatures (>5°C), sums of effective temperatures (>10°C), the number of days with Tmax > 30°C and Tmax >32°C in the corresponding months;

2. Moisture indicators – precipitation totals for key phases and the 3-month Standardised Precipitation Index (SPI);

3. Combined indicators – the hydrothermal coefficient (HTC), calculated as the ratio of total precipitation to the sum of temperatures above 10°C multiplied by a coefficient of 0.1. HTC was determined separately for May-June (wheat) and July-August (maize).

Before modelling, all predictors were tested for multicollinearity. Variables with a correlation coefficient above 0.85 were removed or aggregated, ensuring the correct performance of the multiple linear regression (MLR) model. Indices of solar radiation, wind speed, and SPI were included in the initial set of variables but were excluded from the final model due to low variability and the absence of a substantial contribution to yield prediction. Two methods were applied to model the "climate-yield" relationship. Multiple linear regression (MLR) served as the baseline model for assessing linear dependencies. The Random Forest (RF) algorithm was used as the main method for capturing nonlinear, threshold, and synergistic relationships between predictors and yields. RF parameters were selected using random search. The model consisted of 500 trees, the *mtry* parameter ranged between 3 and 8 depending on the crop, and the minimum number of observations per terminal node was 5.

To avoid overfitting, the data were divided into a training set (75%) and a test set (25%). The performance of the models was evaluated using the coefficient of determination (R^2) and the root mean square error (RMSE). Since the target variable represented relative anomalies of Y_clim (%), RMSE was expressed as a percentage, ensuring correct comparability of results between crops and zones. All computations were performed in the R programming environment using the *randomForest* package (Breiman, 2001). The concentration of atmospheric CO_2 was not included as a separate predictor, which was a standard approach for regional models of climate-yield relationships and did not affect the accuracy of the climatic index analysis.

RESULTS AND DISCUSSION

The application of polynomial detrending to the time series of winter wheat and maize yields for the period 1991-2023 made it possible to isolate the climate-driven component Y_clim and to assess the degree of interannual variability for the two agroclimatic zones. The resulting anomaly series revealed substantial fluctuations in yields, which confirmed the significant influence of weather conditions on crop productivity. The highest variability was characteristic of maize in the Forest-Steppe zone, where the standard deviation amounted to 18.5% of the technological trend. For winter wheat in the Polissia zone, the corresponding value reached 14.2%, indicating lower sensitivity of this crop to short-term climatic stressors, particularly in regions with comparatively higher moisture availability. This difference between the crops was consistent with their biological characteristics: the critical developmental phases of maize occurred during periods of peak summer temperatures and moisture deficit, whereas winter wheat passed most of its defining phases before the onset of the hottest months. Based on the obtained time series, a set of phenologically specific agroclimatic indices was generated, calculated for key developmental periods of the crops in accordance with the methodology. This enabled the assessment of which indices determined the largest share of yield variability. For this purpose, the Random Forest algorithm was applied, within which the predictors were ranked according to the decrease in model accuracy (Mean Decrease in Accuracy).

For winter wheat in both agroclimatic zones, the top predictors included indicators describing the thermal and moisture conditions of early summer and spring: the number of days with temperatures above 30°C in June, precipitation totals for May and April, the hydrothermal coefficient for May-June, and the minimum soil temperature in winter. For maize, the decisive role belonged to the conditions of the second half of summer during flowering and grain filling: the hydrothermal indices for July and August, the number of days with Tmax above 35°C in July, precipitation totals for July, and the mean July temperature. The obtained results were fully consistent with the biological nature of the crops: for winter wheat, spring vegetation conditions were critical, whereas for maize, the temperature-moisture balance during the formation of generative organs was decisive. The evaluation of model performance was conducted on an independent test sample (25% of the data), using the coefficient of determination (R^2) and the root mean square error (RMSE), as required by the methodology. The indicators are presented in Table 1.

***Table 1**. Performance indicators of MLR and RF models on the test sample*

Model	Crop	Crop	R^2 (test)	RMSE (%, test)
MLR	Winter wheat	Polissia	0.52	12.5
RF	Winter wheat	Polissia	0.71	8.9
MLR	Winter wheat	Forest-Steppe	0.55	14.1
RF	Winter wheat	Forest-Steppe	0.74	10.2
MLR	Maize	Polissia	0.49	15.0
RF	Maize	Polissia	0.68	11.5
MLR	Maize	Forest-Steppe	0.60	16.2
RF	Maize	Forest-Steppe	0.81	9.8

***Source:** developed by the authors*

The analysis of the presented indicators demonstrated a consistent advantage of the Random Forest models over the linear models. For all crops and zones, the R^2 values of the RF models exceeded the corresponding MLR values by 0.16-0.21, while the RMSE was lower by 20-35%. The highest predictive accuracy ($R^2 = 0.81$) was provided by the models for maize in the Forest-Steppe zone, where the variability of yield was almost entirely determined by the climatic conditions of July-August. The superiority of the RF approach was methodologically expected: most agroclimatic indices had a nonlinear nature of influence, complex interactions and numerous threshold values (for example, sharp changes in productivity after exceeding temperature thresholds of 30-35°C), which could not be correctly represented by linear regression.

The obtained results confirmed that the decisive contribution to yield formation was made by the conditions during the reproductive phases of the crops. The presence of hydrothermal balance indices, extreme temperature indicators and cumulative precipitation values among the top predictors reflected the synergistic character of plant responses to the combination of thermal and moisture-related stresses. It was the ability of the RF algorithm to account for these interactions that ensured the high accuracy of the modelling.

The identified limitations of this study logically followed from the methodological choices applied. The spatial aggregation of ERA5-Land data to the regional level smoothed local microclimatic differences, and the use of a polynomial trend might not have captured abrupt changes in agricultural technologies in specific years. Furthermore, the models did not incorporate short-term adaptive actions by farmers or the potential effect of increasing atmospheric CO_2 concentration on the photosynthetic activity of the crops.

The identified patterns were consistent with global tendencies regarding the impact of climate change on agricultural crops, as outlined in the IPCC reports. In the document Climate Change and Land (2019), it was emphasised that the increasing frequency of heatwaves, the alteration of moisture regimes and the rise in the amplitude of climatic variability constituted key threats to agricultural systems. A similar dependence was confirmed by the obtained results: indices that characterised the combination of heat and moisture possessed the highest predictive weight, whereas extreme temperatures during critical developmental phases caused sharp productivity losses. The high sensitivity of yields to temperature thresholds aligned with the findings of R. Guntukula (2020), where it was demonstrated that major field crops in India responded more strongly to short-term thermal anomalies than to average seasonal changes in temperature. A comparable pattern in the present results was exhibited by temperatures of 30-35°C, which caused the most pronounced deviations from trend-based values. The differences concerned the structure of climatic influence: in India, the decisive factor was the seasonal dynamics of monsoons, whereas in Polissia and the Forest-Steppe, short but intense episodes of heatwaves were the determining elements.

The sensitivity of maize to the hydrothermal regime of July and August was consistent with the findings of H. Gurkan *et al.* (2020), where it was established that similar periods of heat and precipitation deficit substantially reduced sunflower yield in Turkey. The common element was the phase-specific nature of crop responses: the most prominent influence occurred during the generative phases of development. At the same time, in Turkish conditions, the dominant factor was soil moisture deficit, while the influence of temperature was mitigated by the different climatic structure, which represented a key distinction from the situation in the Ukrainian Forest-Steppe. The patterns established for winter wheat corresponded with the findings of K. Heil *et al.* (2020). The authors noted that rising summer temperatures combined with alterations in the water balance led to significant yield fluctuations on loess soils in Central Europe. In their long-term experiment, the prominence of the soil factor was higher; however, atmospheric conditions remained the principal drivers of productivity, which fully corresponded to the directions of change identified in the present analysis.

The advantage of the Random Forest models confirmed the patterns described by V. Konduri *et al.* (2020), where machine learning models were shown to capture complex nonlinear and threshold relationships between climatic variables and crop yields with considerably higher accuracy. The high accuracy of the models for the Forest-Steppe reflected precisely the nonlinear structure of interactions characteristic of maize during periods of thermal stress. The use of phenologically specific indices was consistent with the approaches outlined by N. Kussul *et al.* (2020), who emphasised the need for high-temporal monitoring of vegetation states based on satellite imagery. The correlation with the conclusions of M. Yemelyanov *et al.* (2022) was also evident: the authors demonstrated that shifts in climatic regimes directly affected the spatial structure of crop distribution in Ukraine.

Additional confirmation was identified in the results of O. Zhygailo *et al.* (2021), where a decline in sunflower productivity under elevated temperatures in the Northern Steppe of Ukraine was described. Similar mechanisms of heat stress were evident in the established patterns for maize, which may have indicated a gradual shift of climatic zones. The synthesis of results demonstrated their clear consistency with contemporary scientific principles presented in the study by V. Pepeliaev *et al.* (2023). In that work, the authors modelled the responses of various crops to changes in mean annual temperatures and established that even minor deviations from optimal thermal regimes were capable of causing abrupt changes in productivity. A comparable threshold-type influence of temperature was also detected in the present analysis: yield indicators decreased sharply after exceeding critical limits during the phase of active biomass accumulation. The distinction lay in the climatic context: in the modelling conducted by V. Pepeliaev *et al.*, the dominant factor was long-term warming, whereas in the regions examined in Ukraine, short and intensive heatwaves were more decisive.

Significant attention was drawn to the findings reported by T. Telo da Gama (2023), where the systemic significance of soil characteristics in either amplifying or mitigating climatic stressors was highlighted. The author substantiated that soil degradation, reductions in organic matter and deterioration of soil structure intensified the negative impact of thermal and moisture anomalies on crop productivity. A comparison of the established results with these principles indicated that within Polissia, soil properties partially compensated for moisture deficits, whereas in the Forest-Steppe they amplified the effect of heat stress. The common feature in both cases was the decisive role of the hydrothermal balance as a fundamental regulator of crop performance.

The study by N. Brannigan *et al.* (2022) focused on modelling erosion processes under future climate change and showed that the instability of temperature and precipitation was capable of transforming not only yield levels but also the structure of agro-landscapes. It was particularly emphasised that the increasing intensity of rainfall combined with summer heatwaves produced a spatially uneven distribution of productivity. A similar pattern of heterogeneity was identified in the analysis of Ukrainian regions, where intensifying climatic variability led to increased spatial contrasts in crop yields. At the same time, the mechanism of these disparities differed: in the work of N. Brannigan *et al.*, water erosion played the dominant role, whereas in Polissia and the Forest-Steppe, thermal and moisture deviations during the generative development of crops were the prevailing drivers.

Overall, the synthesis of findings indicated that the obtained patterns were fully aligned with the contemporary scientific consensus: the productivity of cereal crops was determined by the combination of temperature extremes, water regime and their synergy, while machine learning methods provided the most relevant tools for forecasting these complex interactions.

CONCLUSIONS

A comprehensive analysis of the climatic predictors of winter wheat and maize yields under the conditions of Polissia and the Forest-Steppe made it possible to identify the patterns that determined crop responses to key weather factors. The application of statistical and machine-learning modelling methods demonstrated that the yields of both crops were formed mainly under the influence of integrated thermal and moisture indicators and extreme temperature regimes characteristic of critical phenological phases. The greatest contribution to the variability of winter wheat yields was provided by the number of days with temperatures above 30°C in June, the amount of precipitation in April-May and the hydrothermal coefficient in May-June. For maize, the decisive factors were the hydrothermal indicators of July-August, the frequency of temperature extremes above 35°C and the precipitation regime during the period of intensive grain filling.

The comparative evaluation of models demonstrated a substantial advantage of the Random Forest algorithm over multiple linear regression. Models constructed using Random Forest explained between 68-81% of yield variability, which confirmed the nonlinear nature of the relationships within the "climate-yield" system and the presence of critical sensitivity thresholds. The high predictive accuracy for maize in the Forest-Steppe indicated that yields in this region were largely determined by weather conditions in the second half of summer. At the same time, the increasing importance of drought indices for Polissia served as evidence of climatic shifts that brought the conditions of the region closer to those of more southern climatic zones.

The obtained results emphasised the importance of using combined and extreme indices rather than mean seasonal meteorological parameters for yield forecasting. The applied methodology confirmed the effectiveness of machine-learning approaches in identifying key climatic dependencies and detecting nonlinear responses of agricultural crops. Prospects for further research lay in the transition from regional to pixel-level yield models, the integration of satellite data, the analysis of soil characteristics, the study of agronomic adaptation measures and the development of early-season risk-forecasting systems for agricultural production.

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[1] Abbass, K., Qasim, M.Z., Song, H., Murshed, M., Mahmood, H., & Younis, I. (2022). A review of the global climate change impacts, adaptation, and sustainable mitigation measures. *Environmental Science and Pollution Research*, 29, 42539-42559. doi: 10.1007/s11356-022-18847-3.

[2] Baranovskyi, M.O., & Baranovska, O.V. (2023). Features of assessing the impact of climatic factors on agricultural crop yields: Case of Chernihiv region. *Ukrainian Journal of Natural Sciences*, 6, 34-43. doi: 10.32782/naturaljournal.6.2023.4.

[3] Bihun, V.S. (2024). The impact of climate change on agriculture: Adaptive strategies for increasing crop resilience. *Dumka Molodoho Vchenoho*, 35, 179-188. doi: 10.37128/2707-5826-2024-4-15.

[4] Brannigan, N., Mullan, D., Vandaele, K., Graham, C., McKinley, J., & Meneely, J. (2022). Modelling soil erosion by water under future climate change: Addressing methodological gaps. *Catena*, 216(B), article number 106403. doi: 10.1016/j.catena.2022.106403.

[5] Breiman, L. (2001). Random forests. *Machine Learning,* 45(1), 5-32. doi: 10.1023/A:1010933404324.

[6] Climate Change and Land. (n.d.). Retrieved from https://www.ipcc.ch/srccl/.

[7] Evans, L.T. (1993). *Crop evolution, adaptation and yield*. Cambridge University Press.

[8] Guntukula, R. (2020). Assessing the impact of climate change on Indian agriculture: Evidence from major crop yields. *Journal of Public Affairs*, 20(1), article number e2040. doi: 10.1002/pa.2040.

[9] Gurkan, H., Ozgen, Y., Bayraktar, N., Bulut, H., & Yildiz, M. (2020). Possible impacts of climate change on sunflower yield in Turkey. *IntechOpen*. doi: 10.5772/intechopen.91062.

[10] Hansen, J.E., *et al.* (2023). Global warming in the pipeline. *Oxford Open Climate Change*, 3(1), article number kgad008. doi: 10.1093/oxfclm/kgad008.

[11] Heil, K., Lehner, A., & Schmidhalter, U. (2020). Influence of climate conditions on the temporal development of wheat yields in a long-term experiment in an area with pleistocene loess. *Climate*, 8(9), article number 100. doi: 10.3390/cli8090100.

[12] Hersbach, H., *et al.* (2020). The ERA5 global reanalysis. *Quarterly Journal of the Royal Meteorological Society*, 146(730), 1999-2049. doi: 10.1002/qj.3803.

[13] Hnatiienko, V.H., Hnatiienko, H.M., Zozulia, O.L., & Snytyuk, V.Y. (2024). Method of forecasting yield of agricultural crops using multifactor analysis and neural networks. *Scientific Bulletin of Uzhhorod University. Series of Mathematics and Informatics*, 44(1), 93-105. doi: 10.24144/2616-7700.2024.44(1).93-105.

[14] Konduri, V.S., Vandal, T.J., Ganguly, S., & Ganguly, A.R. (2020). Data science for weather impacts on crop yield. *Frontiers in Sustainable Food Systems*, 4, article number 52. doi: 10.3389/fsufs.2020.00052.

[15] Kryvokhyzha, Ye.M., Matviishyn, A.I., & Bryn, V.T. (2024). The impact of climate change on the yield of the main agricultural crops in Ukraine. *Podilian Bulletin: Agriculture, Engineering, Economics*, 44, 3-5. doi: 10.37406/2706-9052-2024-3.5.
[16] Kussul, N., Shelestov, A., Yailymov, B., Yailymova, H., Lavreniuk, M., & Shumilo, L. (2020). Crop monitoring technology based on time series of satellite imagery. In *Proceedings of the 2020 IEEE 11th International conference on dependable systems, services and technologies (DESSERT)* (pp. 346-350). IEEE. doi: 10.1109/DESSERT50317.2020.9125008.
[17] Moldavan, L., Pimenowa, O., Wasilewski, M., & Wasilewska, N. (2023). Sustainable development of agriculture of Ukraine in the context of climate change. *Sustainability*, 15(13), article number 10517. doi: 10.3390/su151310517.
[18] Muñoz-Sabater, J., *et al.* (2021). ERA5-Land: A state-of-the-art global reanalysis dataset for land applications. *Earth System Science Data*, 13(9), 4349-4383. doi: 10.5194/essd-13-4349-2021.
[19] Pepeliaev, V.A., Golodnikov, O.M., & Golodnikova, N.O. (2023). Modeling the impact of climate change on the productivity of agricultural crops. *Cybernetics & Systems Analysis*, 59(6), 96-104.
[20] Romashchenko, M., Husyev, Y., Shatkovskyi, A., Saidak, R., Yatsyuk, M., Shevchenko, A., & Matiash, T. (2020). Impact of climate change on water resources and agricultural production. *Land Reclamation and Water Management*, 1, 5-22. doi: 10.31073/mivg202001-235.
[21] Shevchenko, O. (2023). The impact of climate change on agricultural land use in Ukraine. *Agricultural Sciences*, 4, 108-114. doi: 10.33730/2310-4678.4.2023.292725.
[22] State Statistics Service of Ukraine. (2024). *Methodological provisions of the state statistical observation "Areas, gross output and yield of agricultural crops"*. Kyiv: State Statistics Service of Ukraine.
[23] Telo da Gama, J. (2023). The role of soils in sustainability, climate change, and ecosystem services: Challenges and opportunities. *Ecologies*, 4(3), 552-567. doi: 10.3390/ecologies4030036.
[24] van Klompenburg, T., Kassahun, A., & Catal, C. (2020). Crop yield prediction using machine learning: A systematic literature review. *Computers and Electronics in Agriculture*, 177, article number 105709. doi: 10.1016/j.compag.2020.105709.
[25] Yang, B., Wu, S., & Yan, Z. (2022). Effects of climate change on corn yields: Spatiotemporal evidence from geographically and temporally weighted regression model. *ISPRS International Journal of Geo-Information*, 11(8), article number 433. doi: 10.3390/ijgi11080433.
[26] Yemelyanov, M.O., Shelestov, A.Yu., Yailymova, H.O., & Shumilo, L.L. (2022). Impact of climate change on the area of major crops. *Space Science & Technology*, 28(2), 30-38. doi: 10.15407/knit2022.02.030.
[27] Zhygailo, O.L., Volvach, O.V., Tolmachova, A.V., & Kostiukievych, T.K. (2021). The influence of climate change on sunflower yield in the Northern Steppe of Ukraine: Analysis and forecast. *Scientific Progress & Innovations*, 1, 180-186. doi: 10.31210/visnyk2021.01.22.

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Анотація. Метою роботи було визначення ключових кліматичних предикторів, які формують варіабельність урожайності озимої пшениці та кукурудзи в агрокліматичних умовах Полісся й Лісостепу. Методологія ґрунтувалася на використанні багаторічних метеорологічних даних у поєднанні зі статистичними та машинними алгоритмами моделювання, серед яких застосовувалися множинна лінійна регресія та Random Forest для порівняльної оцінки прогнозної ефективності. Також було реалізовано механізм визначення важливості змінних із метою встановлення найбільш інформативних кліматичних індикаторів. У ході дослідження було проаналізовано вплив температурних екстремумів, сумарного режиму атмосферних опадів та гідротермічних індексів у ключові фазові періоди розвитку культур. Було встановлено, що для озимої пшениці домінуючу роль відігравали умови квітня-червня, тоді як для кукурудзи найбільше значення мали теплово-вологісні параметри липня-серпня. Було виявлено, що інтегральні показники, зокрема гідротермічний коефіцієнт, забезпечують значно вищу прогностичну вагу порівняно з окремими температурними чи опадовими метриками. Було підтверджено наявність порогових реакцій культур на екстремальні кліматичні фактори, що зумовлювало відмінності між регіонами за рівнем чутливості до теплових хвиль і посух. Було узагальнено, що алгоритм Random Forest забезпечив найбільшу точність прогнозування, пояснюючи до 81 % варіабельності врожайності кукурудзи в Лісостепу та до 74 % – озимої пшениці. Практична цінність роботи полягає у можливості використання отриманих результатів аналітичними центрами, агрометеорологічними службами та агровиробниками для планування посівних площ, оцінювання ризиків сезонної урожайності та формування адаптаційних стратегій в умовах кліматичних змін

Ключові слова: агрокліматичні індекси; температурні екстремуми; гідротермічний режим; варіабельність продуктивності; машинне моделювання; Random Forest; кліматичні ризики; фазові стресори