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BIOCLIMATIC CONSTRAINTS AND EDAPHIC PREFERENCES OF WHEAT: IMPLICATIONS FOR ENVIRONMENTAL SUITABILITY FORECASTING UNDER CLIMATE CHANGE

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Background. Understanding how environmental factors influence the spatial suitability of wheat is critical for sustaining productivity under climate change. In regions like Ukrainian Polissia and the Forest-Steppe, where climatic and soil gradients are strong, changes in agroecological conditions may substantially affect cultivation potential. While global studies exist, regional assessments that integrate both climate and soil data remain limited. Identifying key environmental drivers and their response patterns supports targeted adaptation and land use planning, helping ensure food security in a changing climate.

Materials and Methods. The spatial suitability of wheat cultivation in the Polissia and Forest-Steppe regions of Ukraine was assessed using agroecological modelling. We compiled a dataset of observed wheat cover from official agricultural statistics. The environmental predictors included 19 bioclimatic variables (WorldClim), soil properties (texture, pH, and organic matter content), and topographic factors. Multicollinearity was reduced via principal component analysis and correlation filtering. Four modelling approaches: ordinary least squares (OLS), ridge regression, generalised additive models (GAM), and random forest (RF), were applied to identify key predictors and response patterns.

Results and Discussion. Among the tested models, random forest provided the highest accuracy, followed by GAM and ridge regression, while OLS lagged behind. Key predictors of wheat suitability included warm-quarter temperature (bio10), growing seasonal precipitation, and soil factors, such as pH, clay content, and bulk density. Wheat showed clear sensitivity to high summer temperatures, with response curves revealing nonlinear, bell-shaped patterns indicative of ecological optima. Climate projections suggest a northward shift and fragmentation of suitable areas, especially under SSP3-7.0 and SSP5-8.5 scenarios. While marginal gains are possible short-term, long-term suitability is likely to decline in the southern and central zones. These findings underscore the need to integrate climatic and soil data in regional planning and to support adaptation through targeted crop relocation and variety selection.

Conclusion. This study demonstrates that the spatial suitability of wheat in Ukraine's Polissia and Forest-Steppe regions is strongly influenced by both bioclimatic and edaphic factors. Random forest modelling proved the most effective for capturing complex environmental responses. Climate change projections indicate a northward shift and reduction of suitable areas, emphasising the need for adaptive land-use strategies. Integrating climate and soil data into agroecological assessments is critical for anticipating risks, guiding crop management decisions, and ensuring long-term food security in vulnerable agricultural landscapes.

***Keywords**:* crop suitability modelling, edaphic limitations, temperature–precipitation interactions, spatial regression, agroecological zoning, Shared Socioeconomic Pathways, Eastern European agriculture, land-use adaptation

INTRODUCTION

The utilisation of predictive models to anticipate the repercussions of climate change on agricultural productivity is progressively recognised as a strategic instrument for safeguarding food security at both regional and global scales (Sable et al., 2025). There is a pressing need for timely analysis and adaptation of agricultural systems to new environmental conditions, given the increasing climate risks, which include rising temperatures, irregular precipitation patterns, more frequent droughts, and extreme weather events (Datta *et al.*, 2022). Spatio-temporal forecasting facilitates the identification of regions where both a decrease and a potential increase in crop productivity are possible (Marino, 2023; Mykhailyuk *et al.*, 2023b). This is particularly pertinent to wheat, one of the key crops for achieving food self-sufficiency (Kettlewell *et al.*, 2023; Stefanovska *et al.*, 2024). Climate modelling provides a toolkit for assessing the favourability of crop cultivation in different future scenarios that consider greenhouse gas emissions, socio-economic development, and adaptive potential (Semenov & Porter, 1995). Such forecasts identify threats and opportunities for expanding agricultural production in regions that were not previously considered optimal (Tamasiga *et al.*, 2023; Kunakh *et al.*, 2024). This provides a foundation for building regionally specific adaptation strategies, encompassing the modification of crop structure, the introduction of new varieties, the optimisation of agricultural techniques, the enhancement of irrigation systems, and the integration of agroforestry practices (Sanjaya *et al.*, 2024; Panchenko *et al.*, 2024).

The effectiveness of a forecast largely depends on the accuracy of the input data and the models' ability to adequately capture the complex relationships between abiotic factors and agricultural productivity (Lisovets *et al.*, 2024; Collins *et al.*, 2024). The non-linear nature of crop response to climate and soil factors requires flexible approaches such as generalised additive models, random forests, and other machine learning algorithms (Ruane *et al.*, 2024). These methods allow for taking into account threshold effects, saturation of the impact, and compensatory mechanisms, such as the ability of crops to adapt to new conditions through plasticity or targeted selection (Yin *et al.*, 1995). Forecasting makes it possible to assess how the area of cultivation of a particular crop will change and identify high-risk areas where preventive measures are needed (Ganesan *et al.*, 2021; Molozhon *et al.*, 2023). Identifying areas of degradation or loss of agroclimatic potential is a prerequisite for formulating public policy. Such a policy must prioritise investment in irrigation systems, support for small farmers, and land management reform (Stefanovska *et al.*, 2025). The necessary preconditions have been established to expand production, enhance export potential, and stabilise market prices in regions where favourable conditions are expected to increase. Climate forecasting is becoming a scientific tool for formulating national food security strategies (Westerveld *et al.*, 2021). It facilitates a transition from reactive to proactive agricultural management, where decisions are made not in hindsight, but based on scenario analyses of potential changes (Klemm & McPherson, 2017). A flexible and spatially sensitive forecasting system is essential for timely responses and the long-term sustainability of the agricultural sector in the face of climate uncertainty (An-Vo *et al.*, 2021).

In the Polissia and Forest-Steppe zone of Ukraine, the productive potential of crops is shaped by both environmental and agronomic factors (Zymaroieva *et al.*, 2019). Spatial variability in yields is primarily driven by climatic and soil conditions, while long-term trends depend on the level of agricultural technology and management (Romashchenko *et al.*, 2023). Environmental factors account for up to 60 per cent of yield variability, emphasising the need to consider them in adaptive land management (Kunah *et al.*, 2018; Zymaroieva *et al.*, 2019). On this territory, there are zones with specific types of temporal dynamics of crop yields, which are homogeneous within each zone but differ significantly from each other (Zymaroieva *et al.*, 2019). Changes in the hydrological regime, in particular the lowering of the groundwater level and reduction of spring flooding, disrupt the seasonal dynamics of biocenoses and reduce the water-regulating capacity of landscapes (Mykhailyuk *et al.*, 2023). Peatland drainage caused by land reclamation further increases the region's vulnerability (Trifanova *et al.*, 2023; Tutova *et al.*, 2025).

The study aims to identify the most suitable regression model for assessing spatial patterns of favourable environmental conditions for wheat cultivation in the Forest-Steppe and Polissia regions of Ukraine, to identify key ecological predictors, build models of favourability response in the gradient of soil and bioclimatic factors, and to model the spatial distribution of wheat suitability for specific future time intervals under different climate change strategies.

MATERIALS AND METHODS

The study area encompasses a substantial part of Ukraine, exhibiting significant spatial heterogeneity in natural conditions. It comprises northern Polissia, central and southern regions of the Forest-Steppe zone, as well as transitional zones (Nykytiuk *et al.*, 2025). To model the spatial distribution of areas under crops, we used the global geospatial dataset CROPGRIDS v1.08 (Tang *et al.*, 2024)at a resolution of 0.05° (about 5.6 km at the equator, which contains maps of the regions under 173 crops with a spatial resolution of 0.05° (~5.5 km) in the WGS-84 coordinate system. Bioclimatic variables from the global WorldClim v2.1 dataset, which contains 19 derived climate indicators (BIO1–BIO19) describing average, extreme and seasonal aspects of temperature and precipitation, were used to characterise climate conditions. To describe soil conditions, we used the global SoilGrids v2.0 array (ISRIC – World Soil Information), which provides digital soil maps with a spatial resolution of 250 m for several physicochemical parameters in standard depth intervals.

To address the problem of multicollinearity in constructing a linear regression model using the least squares method, stepwise filtering of variables based on their mutual correlation was applied (Kayode Ayinde & Nwosu, 2021).

The linear regression in this study was based on the standard ordinary least squares (OLS) model. The model formula was as follows:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_k x_k + \varepsilon,$$

where Y is the transformed response variable (crop area); $\beta_{(0)}$) is the free term; x_1, x_2, ..., $x_{(k)}$ are the selected independent variables; β_1, β_2, ... $\beta_{(k)}$ are the regression coefficients reflecting the effect of each predictor; ε is the random error that covers unmodelled factors. The model was built using the *lm*() function in R, and its parameters were estimated by minimising the sum of squared residuals.

Ridge regression was used in this study to build a stable linear model in the presence of a large number of potentially correlated predictors. Ridge regression minimises the following loss function:

$$\min_\beta \left[\sum_{i=1}^{n} \left(y_i - \beta_0 - \sum_{j=1}^{p} \beta_j x_{ij} \right)^2 + \lambda \sum_{j=1}^{p} \beta_j^2 \right],$$

where y_i is the value of the dependent variable (area under crop after Box-Cox), $x_{(ij)}$) is the value of the j-th predictor in the i-th observation (all standardised), β_j are the model coefficients, and λ is the regularisation parameter controlling the strength of the penalty.

To account for the potentially nonlinear effect of environmental predictors on the transformed value of the crop area, a generalised additive model (GAM) was built using the *mgcv* package in R. In this model, the response variable is modelled as a sum of smooth functions from each of the predictors. Formally, the model has the form:

$$Y = \beta_0 + s_1(x_1) + s_2(x_2) + ... + s_k(x_k) + \varepsilon,$$

where Y is the transformed response variable (crop area); $\beta_{(0)}$) is the free term; $s_{(j)}x_{(j)}$) is a smooth function (spline) of the j-th predictor; ε is the random error covering unmodelled factors.

To model the spatial patterns of crop area distribution, a random forest (RF) model was built, which implements an ensemble regression approach by aggregating many independent tree solutions.

RESULTS

The regression models analysed revealed that the most significant predictor of spatial variability in the proportion of wheat area is the average daily temperature amplitude, which accounts for 28.9 % of the explained variance in both ordinary least squares (OLS) and generalized additive models (GAM), 14.3 % in ridge regression, and 5.9 % in random forest (RF) models (**Table 1**). The second most influential factor in the linear OLS, ridge, and GAM models is soil organic carbon, contributing 16.4 % in OLS, 10.7 % in ridge, and 16.8 % in GAM. In contrast, pH is the second most significant factor in the random forest model, explaining 6.1 % of the variance. In the OLS model, the third most

Table 1. **Contribution of predictors to the explained variability in wheat cultivation area across different regression models (OLS, Ridge, GAM, RF)**

Variables	Contribution of variables by regression models (%)			
	Linear model (OLS)	Ridge regression	GAM	Random forest
Water index of soil reaction (pH)	1.2	4.7	4.5	6.1
Average daily temperature amplitude	28.9	14.3	28.9	5.9
Organic carbon content in the soil	16.4	10.7	16.8	4.8
Residual component of the maximum temperature of the warmest month	–	0.8	1.6	4.6
Annual precipitation	–	2.2	0.3	4.5
Average temperature of the coldest quarter	4.9	4.8	0.5	4.4
Share of sand in the soil	1.5	3.4	3.6	4.1
Residual component of the average temperature of the wettest quarter	1.4	1.5	2.1	4.0
Residual isothermal component	–	2.3	5.4	3.7
Residual component of the average temperature of the warmest quarter	6.5	3.1	0.6	3.7
Share of silt in the soil	–	0.9	1.2	3.6
Residual component of the minimum temperature of the coldest month	–	1.2	1.3	3.6
Residual component of the annual temperature range	–	5.0	2.0	3.5
Residual component of precipitation in the wettest quarter	–	3.5	0.8	3.5
Residual component of precipitation in the coldest quarter	–	0.5	1.1	3.4
Residual component of temperature seasonality	–	5.3	2.2	3.3
Average temperature of the driest quarter	5.6	0.1	2.5	3.2
Soil bulk density	–	1.2	2.7	3.0
Volume fraction of coarse impurities in the soil	–	6.2	3.0	3.0
Residual component of precipitation in the driest quarter	–	1.6	2.3	3.0
Residual component of precipitation in the wettest month	–	1.7	0.9	2.9
Share of clay in the soil	5.5	1.8	3.0	2.9
Residual component of precipitation in the driest month	–	4.6	4.8	2.8
Density of organic carbon in the soil	7.2	3.8	2.4	2.7
Residual component of mean annual temperature	11.4	6.3	0.5	2.7
Total nitrogen content in the soil	–	3.9	0.7	2.5
Residual component of precipitation in the warmest quarter	9.7	2.7	1.1	2.4
Residual component of precipitation seasonality	–	1.9	3.5	2.2

crucial variable is the residual component of annual mean temperature, accounting for 11.4 %. In ridge regression, the residual component of temperature seasonality is the third most significant factor at 5.3 %. In GAM, the residual component of isothermality contributes 5.4 %, while in RF, the residual component of the maximum temperature of the warmest month accounts for 4.6 %. The contribution of pH in OLS is relatively low, explaining only 1.2 % of the variance, while it accounts for 4.7 % in ridge, 4.5 % in GAM, and 6.1 % in RF. Other soil properties, such as sand content (1.5–4.1 %), clay content (1.8–2.9 %), and bulk density (1.2–3.0 %), along with residual climate components (0.1–5.6 %), have smaller individual contributions. Overall, the findings suggest that the spatial distribution of wheat is primarily influenced by the integration of daily temperature fluctuations and fundamental soil properties, with detailed climate adjustments playing a lesser role.

The application of different regression models revealed significant differences in their ability to reproduce the spatial variation in the share of wheat area. The most straightforward approach was the ordinary linear model (OLS), which demonstrated limited accuracy. Although the proportion of variance explained was 73 %, the model made significant prediction errors, including a root mean square error (RMSE) of over 1200 (**Table 2**). The use of ridge regression significantly improved the accuracy. Both the coefficient of determination and the errors increased, indicating a specific reduction in overfitting due to the inclusion of multicollinearity. An even more pronounced increase in accuracy was demonstrated by the generalised additive model (GAM), which, due to the inclusion of nonlinear relationships, reduced errors by almost half compared to OLS. The most reliable approach was the random forest approach, which almost entirely reproduced the observed variance (R^2 = 0.99) and provided minimal error values, indicating this model's exceptional efficiency for this type of spatial data. Visualisation of the correspondence between the observed and predicted values reinforces these conclusions.

Table 2. **Comparison of the efficiency of regression models in terms of explained variation (R^2), RMSE and MAE**

Regression models	Explained variation (R^2)	Root mean square error (RMSE)	Mean absolute error (MAE)
Linear model (OLS)	0.73	1270.75	898.70
Ridge regression	0.83	43.69	33.74
GAM	0.90	33.04	24.64
Random forest	0.99	10.28	7.25

The favourability of wheat cultivation depends on the physical and chemical properties of the soil, and the nature of these dependencies is predominantly non-linear (**Fig. 1**). An increase in the bulk density of the fine earth fraction to a value of approximately 1.3 kg/dm³ is accompanied by a marked improvement in conditions, indicating an optimal combination of aeration and water-holding capacity. Further compaction above 1.4 kg/dm³ no longer brings additional benefits, and the favourability levels off or even decreases. A gradual increase in the volume fraction of coarse impurities (particles larger than 2 mm) leads to a steady decline in the area suitable for cultivation, likely due to mechanical limitations on the development of the root system. A similar adverse

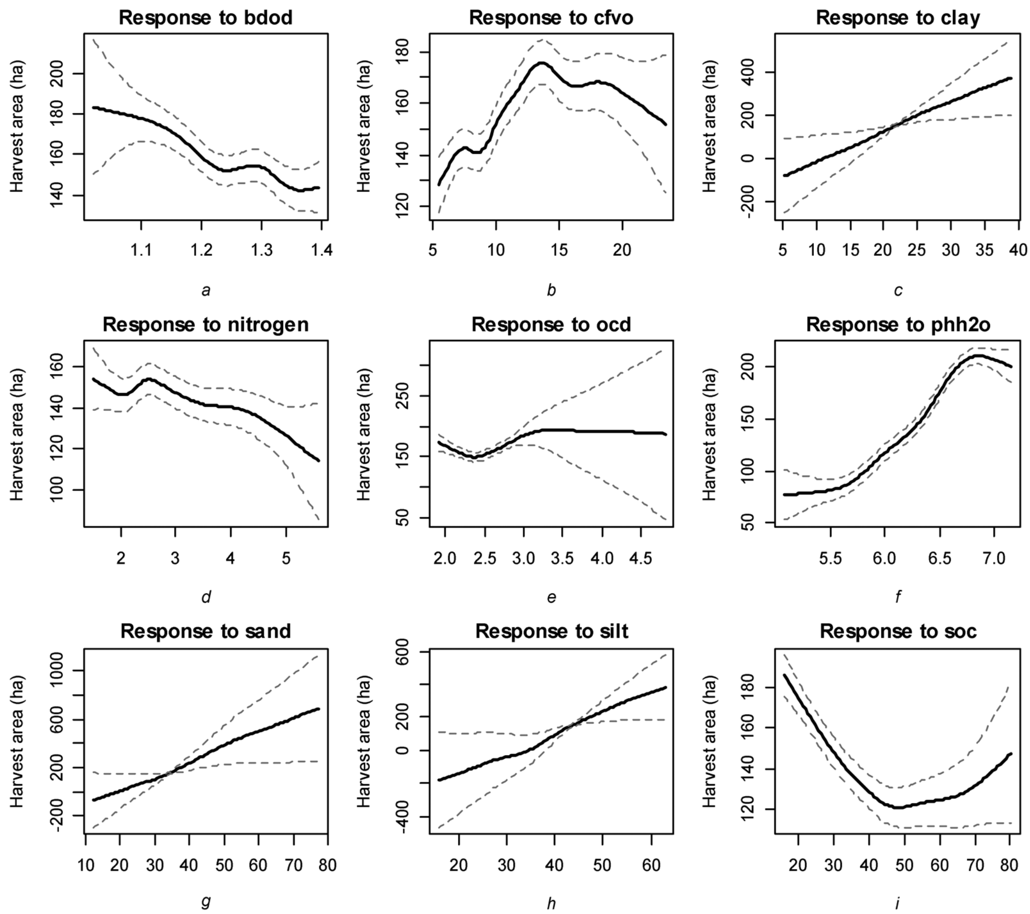

Fig. 1. Partial dependence plots of the GAM model showing the response of wheat cultivation area to soil factors: ***a*** (bdod) is the bulk density of the fine soil fraction (kg dm^{-3}); ***b*** (cfvo) is the volume fraction of coarse debris (> 2 mm) in the fine soil fraction (%); ***c*** (clay) is the fraction of clay (< 0.002 mm) in the fine soil fraction (%); ***d*** nitrogen is the total nitrogen content (g/kg); ***e*** (ocd) is the density of organic carbon (kg/m^3); ***f*** (phh2o) is the pH of the soil in the water extract; ***g*** (sand) is the proportion of sand (> 0.05 mm) in the fine soil fraction (%); ***h*** (silt) is the proportion of dust (0.002–0.05 mm) in the fine soil fraction (%); ***i*** (soc) is the organic carbon content in the fine soil fraction (g/kg)

effect is observed with an excess of clay particles: although the proportion of clay within 15–30 % is optimal for the water-air regime, exceeding this level, especially above 40 %, significantly worsens conditions due to reduced drainage and aeration. In contrast, the total nitrogen content in the fine soil fraction shows a positive linear relationship. With the growth of this factor, agronomic properties improve, which underlines the importance of nitrogen nutrition. The density of organic carbon in the soil shows a pronounced saturation curve. The favourability increases up to a value of about 30–35 kg/m^3, after which a plateau is reached. This dynamic is consistent with improving structure and water retention up to a certain threshold level of organic content. The acid-base reaction of the soil also plays a significant role. The most favourable is the pH range of 6.0–7.5. An acidic environment (below 5.5) sharply worsens the suitability due to toxicity to plants and reduced availability of nutrients, while an alkaline environment (above 8.0) is likely to reduce the bioavailability of trace elements. Among the textural characteristics, the best conditions are provided by a sandy particle content of 30–40 %, which supports good drainage and aeration. Still, excessive lightness of the soil impairs the ability to retain moisture. Dusty particles in the range of 25–35 % ensure a balanced water-air regime, while excessive and insufficient amounts reduce productivity. An increase in the organic carbon content in the fine-earth fraction to 30 g/kg improves conditions, after which the effect stabilises, consistent with the agronomic saturation of the soil with organic matter.

Moderate deviations from the average annual temperature, in either direction, create favourable conditions for wheat cultivation. However, a significant increase in temperature reduces suitability (**Fig. 2*a***). A daily range of approximately 7–10 °C was

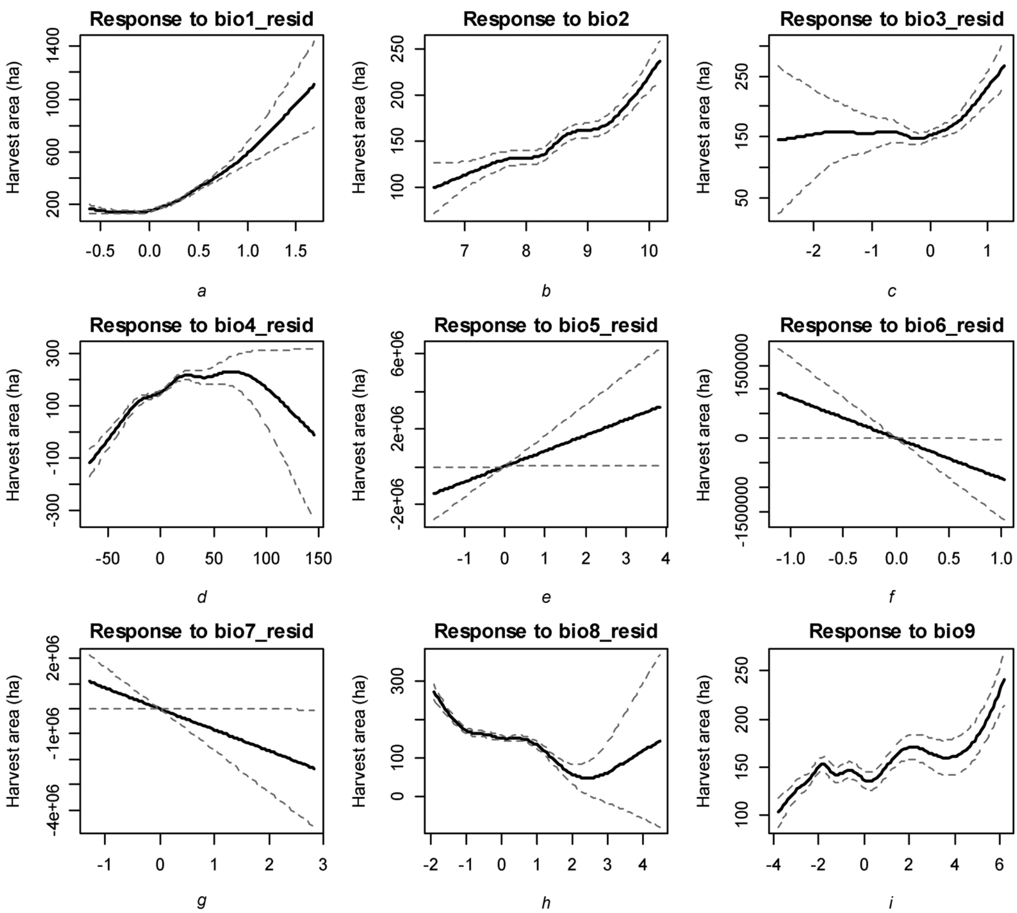

Fig. 2. Partial dependence plots of the GAM model showing the response of wheat cultivation area to soil factors: ***a*** (bio1_resid) is the residual of the mean annual temperature from the linear trend (°C); ***b*** (bio2_resid) is the residual of the mean daily temperature range from the trend (°C); ***c*** (bio3_resid) is the residual of the isothermicity (ratio of daily to annual temperature range × 100) from the trend; ***d*** (bio4_resid) is the seasonality of temperature (standard deviation × 100) (-); ***e*** (bio5_resid) is the residual of the maximum temperature of the warmest month from the trend (°C); ***f*** (bio6_resid) is the residual of the minimum temperature of the coldest month from the trend (°C); ***g*** (bio7_resid) is the annual amplitude range of temperatures (°C); ***h*** (bio8) is the average temperature of the wettest quarter (°C); ***i*** (bio9) is the average temperature of the driest quarter (°C)

found to be optimal: at lower temperatures, the crop does not receive enough heat for photosynthesis, while at higher temperatures, it loses excessive moisture and experiences heat stress (**Fig. 2*b***). The best results are observed with an average ratio of daily and annual temperature fluctuations: both too uniform and too contrasting temperature conditions lead to a drop in yield (**Fig. 2*c***). The pronounced seasonality, with a clear difference between winter and summer conditions, positively correlates with crop yields due to the combination of cold hardening and thermal growth acceleration (**Fig. 2*d***).

All four SSP climate scenarios (SSP1-2.6, SSP2-4.5, SSP3-7.0 and SSP5-8.5) show a similar overall pattern of spatial and temporal shifts in wheat cultivation favourability compared to the historical background (**Fig. 3**). The local maximums of the area

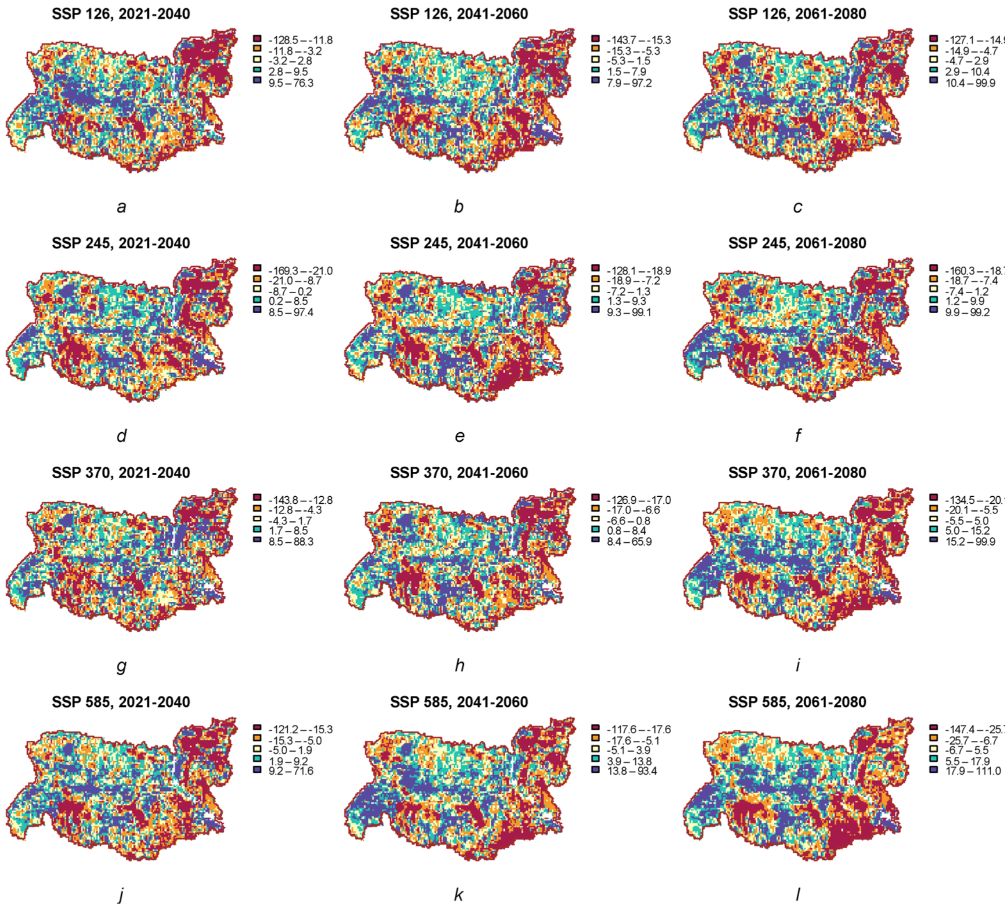

Fig. 3. Projected changes in wheat cultivation area relative to the historical baseline (delta), under different SSP scenarios for the period 2021–2080. Values represent the difference between projected and baseline cultivation areas. Positive values (lighter shades) indicate an expansion of buckwheat cultivation, while negative values (darker shades) reflect a reduction. The boundaries of the study region are marked in red: ***a*** is the SSP1-2.6 scenario for 2021–2040; ***b*** is the SSP1-2.6 scenario for 2041–2060; ***c*** is the SSP1-2.6 scenario for 2061–2080; ***d*** is the SSP2-4.5 scenario for 2021–2040; ***e*** is the SSP2-4.5 scenario for 2041–2060; ***f*** is the SSP2-4.5 scenario for 2061–2080; ***g*** is the SSP3-7.0 scenario for 2021–2040; ***h*** is the SSP3-7.0 scenario for 2041–2060; ***i*** is the SSP3-7.0 scenario for 2061–2080; ***j*** is the SSP5-8.5 scenario for 2021–2040; ***k*** is the SSP5-8.5 scenario for 2041–2060; ***l*** is the SSP5-8.5 scenario for 2061–2080

under the crop remain stable or slightly increase in most scenarios (to about 100–111 conventional units of growth), while the main changes concern the minimum values that reflect the greatest losses. The deepest decline is recorded under the SSP2-4.5 scenario in 2021–2040 (-169), while for other scenarios, the initial losses range from -121 to -144 conventional units. In the medium term (2041–2060), all scenarios except SSP2-4.5 show some mitigation of extreme losses, but in the long term (2061–2080), most scenarios show a new exacerbation of negative changes or fluctuations with a predominance of the loss zone (minimum values reach -135...-148 conventional units). Spatially, the largest negative deviations are consistently concentrated in the central and southern parts of the study area, while the north and northeast retain relatively stable or even positive delta values. The maximum values gradually increase by the end of the 21st century in all scenarios, indicating the presence of compensatory potential in certain locations. Such a spatial and temporal structure of changes may indicate both climate fluctuations that compensate for local extremes and the prospects for adapting agricultural practices in the future.

Climate modelling in all four SSP scenarios predicts an overall increase in the average area under wheat compared to the historical background. In the SSP1-2.6 and SSP2-4.5 scenarios, an increase is clearly visible already in 2021–2040, after which the figures remain at a consistently high level in the next two time intervals. In the SSP3-7.0 scenario, the growth rate is somewhat lower in the short term, but the average area peaks in 2041–2060, followed by a partial decline in 2061–2080, which does not fall to historical levels. The SSP5-8.5 scenario also shows a marked expansion of the area under crops in the first interval, followed by a further increase until the middle of the century, and a slight decrease in the last period. Despite these differences, in all cases, the average area in the future remains statistically higher than historical values, indicating a potential expansion of wheat area under climate change.

DISCUSSION

Our study demonstrates that climate–soil interactions govern wheat suitability in Ukraine. Under future climate scenarios, optimal cultivation zones are projected to shift. These changes pose both challenges and opportunities for regional food security. Integrating these insights into land use planning is essential for adaptive management. Several regression approaches have been used to model the spatial variability of favourable conditions for wheat production, including linear regression (OLS), ridge regression, generalised additive model (GAM) and random forest model (RF). Each of them has its advantages depending on the nature of the input data and the complexity of the system under study. Linear regression (OLS) provides a simple and transparent interpretation of the results, allowing for a direct assessment of the direction and strength of the relationship between bioclimatic or soil variables and wheat production areas (Roustaei, 2024). At the same time, it has a limited capacity to capture non-linear or interactive effects that are frequently observed in environmental data. Ridge regression as a regularised form of OLS demonstrates better robustness to multicollinearity, which is especially important when modelling based on a large number of interdependent bioclimatic predictors (Pavlou *et al.*, 2016). This avoids over-calculation of coefficients and stabilises estimates in conditions of high correlation between variables.

The generalised additive model (GAM) significantly expands the modelling capabilities by flexibly accounting for the nonlinear nature of the relationships (Lai *et al.*, 2024). It allows the identification of non-parametric dependencies, which is particularly important when describing crop responses to abiotic factors with optimal or threshold levels. The random forest (RF) model proved to be the most powerful in terms of prediction accuracy (Breiman, 2001; Ponomarenko *et al.*, 2024). This approach enables the incorporation of complex interactions and nonlinearities without the necessity of making preliminary assumptions regarding the functional form. RF enables the assessment of the relative importance of variables, which is instrumental in the interpretation of the role of individual environmental factors. Nevertheless, the limitations of this approach pertain to the less transparent interpretation of the model structure and the difficulty of reproducing the analytical formula. The selection of the model is contingent upon the objectives that have been delineated. OLS or GAM should be preferred for describing mechanisms, while for spatial forecasting and assessing the role of factors, the random forest model demonstrates the best results. The models were selected based primarily on forecasting accuracy and the ability to detect non-linear relationships between wheat growing conditions and environmental factors. The random forest model (RF) was chosen as the main tool for forecasting because it provided the highest forecasting accuracy and allowed adequate accounting of complex and nonlinear interactions of factors. In contrast, the generalised additive model (GAM) was used as an additional tool for interpreting the responses of culture to individual variables, thanks to the possibility of constructing partial dependence curves. This approach strikes a balance between the reliability of the forecast and the ecological interpretability of the results.

Based on regression approaches, it was found that both climatic and soil factors have the most significant impact on the favourable conditions for wheat cultivation. Among the bioclimatic variables, annual precipitation plays the key role, determining the level of water supply to crops throughout the growing season (Thapa *et al.*, 2019). Another important factor is the seasonality of temperature, which reflects the contrast between warm and cold seasons and affects the synchronisation of crop growth phases. The temperature of the coldest quarter and the minimum temperature of the coldest month are particularly critical for winter wheat overwintering, while precipitation in the driest month and quarter indicates the likelihood of stressful conditions during the growing season. Soil characteristics enhance this understanding. In particular, organic matter content is a crucial factor in nutrient availability and water stabilization. Textural properties, such as the proportions of loam and sand, influence water retention and aeration, while soil acidity (pH) regulates nutrient availability and microbial activity (Yakovenko & Zhukov, 2021). These factors are consistently recognized as significant across all models, although their relative importance varies depending on the methodology employed. In random forest models, climate variables play a predominant role, whereas in the generalized additive model (GAM), soil indicators exhibit distinct nonlinear effects, facilitating a more nuanced interpretation of their contributions to conditions favourable for wheat growth.

The results show an almost monotonous deterioration in wheat growing conditions with increasing soil density. This pattern has a clear agrophysiological basis (Liu *et al.*, 2024). As soil bulk density increases, its porosity decreases, especially macroporosity, which leads to a deterioration in the aeration regime and reduces infiltration capacity (Fu *et al.*, 2019). The compacted soil is less permeable to water, which, on the one hand, makes it difficult for it to reach the root zone, and on the other hand, causes moisture stagnation, especially in the lower layers (van Verseveld & Gebert, 2020). High soil density creates mechanical resistance to root growth, limiting their development in both vertical and lateral directions (Veen & Boone, 1990). This diminishes the efficiency of water and nutrient uptake, particularly during the intensive growth phases of wheat. Consequently, plants undergo physiological stress, leading to slowed growth rates, reduced leaf area, suppressed photosynthesis, and, as a result, decreased biomass accumulation and impaired formation of reproductive organs (Chawla & Balasaheb, 2023). The combination of these factors leads to a steady decline in crop productivity. The observed deterioration of conditions with the increasing density is the result of a complex effect of negative factors, among which the main ones are deterioration of the water-air regime, restriction of root system development and disturbance of metabolic balance in plants. Such dynamics is consistent with previous studies that set critical soil density limits for wheat at 1.3–1.5 g/cm^3, above which yields are significantly reduced.

A non-linear relationship was found between the area harvested with wheat and the level of nitrogen supply. At low levels of nitrogen content, there is a certain increase in the area under crops, which is likely due to the transition from a limiting deficit to a minimum sufficient level of supply that allows maintaining productivity at an acceptable level. Within the average nitrogen supply, the area stabilises, which may reflect the achievement of the agro-economic optimum, when fertilisation provides maximum returns without stimulating further expansion of crops. At high nitrogen levels, there is a gradual decline in the area under wheat. These results are consistent with findings indicating that excessive nitrogen may have a negative impact on the total area under the crop, despite increasing yield per unit area (Wang *et al.*, 2024). Nitrogen over-saturation can have a negative impact on crop growth and quality, especially in conditions of disturbed water regime or soil degradation. Higher fertiliser doses are more commonly used in specialised intensive systems, which involve a reduction in area while increasing investment per unit area. The resulting pattern may reflect the physiological response of the crop to nitrogen levels and the specifics of agronomic strategies and economic decisions regarding the spatial structure of crop rotations.

The positive correlation between average annual temperature and the area harvested for wheat suggests that, when other agro-environmental factors (such as moisture supply, soil fertility, and acidity) are maintained at satisfactory levels, increases in temperature alone have a beneficial effect on wheat production. This pattern suggests that wheat, unlike some other crops, can adapt to climate change by maintaining or even expanding its cultivation area under warming scenarios. This explains the relatively stable or even positive projected productivity situation for wheat in the medium and long term, even under conditions of significant climate stress. The negative correlation between the temperature of the warmest quarter and the area under wheat cultivation indicates a high crop sensitivity to heat stress during the active growing season. Increasing temperatures at this time, especially under moisture deficit conditions, can disrupt reproductive processes and reduce yields. This response explains the projected reduction in favourable wheat-growing areas in regions where climate scenarios predict intense summer warming. This underscores the need for adaptation strategies to reduce the impact of high temperatures during key phases of crop development. These findings are consistent with results confirming that temperature variables, particularly the temperature of the warmest quarter, significantly influence the spatial distribution of species. The negative correlation between the temperature of the warmest quarter and the area under wheat cultivation indicates the crop's high sensitivity to heat stress during the active growing season, corroborating the idea that climatic extremes constrain agricultural distribution (Zelenova *et al.*, 2024; Chetvertak *et al.*, 2025).

Although the total area under wheat cultivation in Polissia and the Forest-Steppe zone remains generally stable regardless of the climate change scenario, the spatial distribution of this crop is undergoing significant transformations. Forecast maps of the deltas show a significant restructuring of the spatial organisation of wheat production: there is a redistribution of suitable areas within the regions, which changes the configuration and location of the main wheat growing zones. There has been a gradual shift in areas of high suitability towards the northern Forest-Steppe and the southern Polissia. This indicates the expansion of the wheat area to territories that were previously considered to be marginal in terms of thermal conditions. The warming provides an increase in heat availability in these areas without a critical moisture deficit, which creates favourable conditions for wheat. In the southern part of the Forest-Steppe and border areas with an increased probability of summer droughts, a decrease in suitable areas is forecast, which manifests itself in the reduction or fragmentation of former continuous cultivation areas. Another significant trend is the emergence of spatial micromosaicism; even within individual administrative districts, there is a variation of areas exhibiting both improved and deteriorated predicted suitability. This is due to the interaction of local soil and climatic factors, which react differently to changes in temperature, precipitation, and seasonal dynamics.

It can be concluded that the results obtained provide a robust and practical framework for the planning of agriculture that is spatial in nature. The framework is capable of providing guidance on adjustments to crop rotation, optimisation of fertilisation and irrigation; the aforementioned can be directly integrated into the strategies employed at both regional and national levels for climate adaptation. It is recommended that future research efforts concentrate on the refinement of these projections in the context of evolving farming practices. This refinement should incorporate socio-economic drivers of adaptation, and extend the modelling approach to include additional crops and regions across Ukraine.

CONCLUSION

The key environmental predictors of favourable wheat-growing conditions in the Forest-Steppe and Polissia regions of Ukraine include the temperature of the warmest quarter, precipitation during the growing season, and soil physical properties, particularly density and acidity (pH). Wheat responds positively to a moderate increase in average annual temperatures under satisfactory water conditions; however, it is sensitive to excessive temperature increases during the warmest period of the year, which can significantly reduce productivity in southern areas. Even under favourable climatic conditions, high soil density and low pH also limit agricultural production potential. The results of the study demonstrated a high stability of the total area suitable for wheat cultivation within the Polissia and Forest-Steppe regions of Ukraine under various climate scenarios (SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5). Concurrently, significant transformations in the spatial structure of production have been identified. It is possible to predict the emergence of a new configuration of favourable zones for crop cultivation, with a clear tendency for optimal conditions to shift northward within the Forest-Steppe zone and increase crop diversity. This indicates an adaptive response of agricultural landscapes to climate change and presents new opportunities for rethinking the spatial organization of wheat production. It is important to note that the potential for expanding areas favourable for wheat cultivation, driven by bioclimatic factors, can only be realised if soil quality is adequate and the level of agrotechnical support is sufficient. Without proper land reclamation, compaction reduction, pH optimisation, and the implementation of adaptive technologies, the anticipated climate benefits may not materialise. Ensuring the sustainability of wheat production in the face of climate change necessitates spatially adapted management that considers local soil and climatic conditions, crop sensitivity, and the application of modern precision farming technologies. This approach will help minimise risks associated with global climate change and effectively address the spatial and temporal variability of environmental conditions.

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COMPLIANCE WITH ETHICAL STANDARDS

Conflict of Interest: the authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Human Rights: this article does not contain any studies with human subjects performed by any of the authors.

Animal studies: all international, national, and institutional guidelines for the care, maintenance and use of laboratory animals were followed.

AUTHOR CONTRIBUTIONS

Conceptualization, [Y.N]; methodology, [O.K.; Y.N.]; investigation, [Y.N.; O.K.; D.V.]; data analysis, [Y.N.; A.P.; I.B.]; writing – original draft preparation, [O.K.; Y.N.]; writing – review and editing, [O.K.]; visualization, [Y.N.]; supervision, [O.K; D.V.]; project administration, [O.K; D.V.]; funding acquisition, [–].

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БІОКЛІМАТИЧНІ ЧИННИКИ ТА ҐРУНТОВІ ПРЕФЕРЕНЦІЇ ПШЕНИЦІ: ЗНАЧЕННЯ ДЛЯ ПРОГНОЗУВАННЯ ЕКОЛОГІЧНОЇ ПРИДАТНОСТІ В УМОВАХ ЗМІНИ КЛІМАТУ

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Передумови. В умовах глобальних кліматичних змін розуміння того, як екологічні чинники впливають на просторову придатність сільськогосподарських культур, є надзвичайно важливим для збереження продуктивності сільського господарства. Пшениця, одна з найважливіших зернових культур у світі, є дуже чутливою до змін температури, кількості опадів і властивостей ґрунту. У таких регіонах як Українське Полісся й Лісостеп, де кліматичні та ґрунтові градієнти є вираженими, зміни агроекологічних умов можуть мати значний вплив на потенціал сталого вирощування пшениці.

Матеріали та методи. Просторову придатність вирощування пшениці в Поліссі та лісостепових регіонах України було оцінено за допомогою агроекологічного моделювання. Ми склали базу даних спостережень за посівами пшениці на основі офіційної сільськогосподарської статистики. Екологічні предиктори включали 19 біокліматичних змінних (WorldClim), властивості ґрунту (текстура, pH та вміст органічної речовини) і топографічні фактори. Для виявлення ключових предикторів і моделей реакції було застосовано чотири підходи до моделювання: метод найменших квадратів (OLS), регресію Ріджа, узагальнені адитивні моделі (GAM) та випадковий ліс (RF).

Результати й обговорення. Серед чотирьох протестованих моделей алгоритм Random Forest показав найвищу прогнозну ефективність, за ним ішли GAM і регресія Ріджа, тоді як OLS показав менш точні результати. Найвпливовішими предикторами придатності пшениці були температура найтеплішого кварталу (bio10), кількість опадів протягом вегетаційного періоду (і такі параметри ґрунту як pH, вміст глини та об'ємна щільність). Виявлено сильну негативну залежність між високими літніми температурами та покриттям пшениці, що вказує на вразливість культури до теплового стресу. Криві реакції показали нелінійні, часто дзвоноподібні закономірності, що підкреслює наявність екологічного оптимуму, а не лінійних тенденцій. Прогнози на основі сценаріїв продемонстрували поступове зміщення на північ і фрагментацію придатних територій за майбутніх кліматичних умов, особливо за сценаріями SSP3-7.0 та SSP5-8.5.

Висновок. Високі температури під час вегетаційного періоду та несприятливі ґрунтові умови, такі як низький pH і висока об'ємна щільність, значно знижують потенціал вирощування. Моделювання методом випадкового лісу виявилося найефективнішим для відображення складних реакцій навколишнього середовища. Прогнози зміни клімату вказують на зсув на північ і скорочення придатних територій, що підкреслює необхідність адаптивних стратегій землекористування. Інтеграція даних про клімат і ґрунти в агроекологічні оцінки має вирішальне значення для прогнозування ризиків, прийняття рішень щодо управління культурами та забезпечення довгострокової продовольчої безпеки в уразливих сільськогосподарських ландшафтах.

Ключові слова: моделювання придатності культур, едафічні обмеження, взаємодія температури й опадів, просторова регресія, агроекологічне зонування, спільні соціально-економічні шляхи розвитку, сільське господарство Східної Європи, адаптація землекористування

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