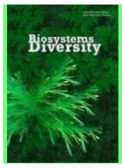


Biosystems
Diversity

ISSN 2519-8513 (Print)
ISSN 2520-2529 (Online)
Biosyst. Divers.

Bioclimatic and soil determinants of buckwheat cultivation prospects under global warming: A case study of the Ukrainian Polissya and Forest-Steppe

Y. Nykytiuk*, O. Kravchenko*, **, O. Komorna*

Polissia National University, Zhytomyr, Ukraine
Institute of Animals Breeding and Genetics nd. a. M. V. Zubets National Academy of Agrarian Sciences of Ukraine,
Kyiv Region, Ukraine

Article info

Received 12.04.2025
Received in revised form 19.05.2025
Accepted 17.06.2025

Polissia National University, Staryi Boulevard, 7, Zhytomyr, 10008, Ukraine. Tel.: +380-67-448-38-48. E-mail: andreyniks2@gmail.com, kravchenko.irgt@gmail.com

Institute of Animals Breeding and Genetics nd. a. M. V. Zubets National Academy of Agrarian Sciences of Ukraine, Pogrebnyaka st., 1, Chubynske, Kyiv Region, 08321,Ukraine.

Nykytiuk, Y., Kravchenko, O., & Komorna, O. (2025). Bioclimatic and soil determinants of buckwheat cultivation prospects under global warming: A case study of the Ukrainian Polissya and Forest-Steppe. Biosystems Diversity, 33(3), e2537. doi:10.15421/012537

The spatial restructuring of agricultural production under climate change necessitates a detailed understanding of crop-specific responses to both climatic and edaphic conditions. Buckwheat (*Fagopyrum esculentum* Moench), known for its short growing season, low input requirements, and high nutritional value, is a promising candidate for climate-resilient agriculture in Eastern Europe. The present study undertakes an evaluation of the present and future suitability of land for buckwheat cultivation across two primary agroecological zones in Ukraine: Polissya and the Forest-Steppe. This evaluation is conducted utilising integrated spatial modelling techniques. Historical yield data from the CROPGRIDS v1.08 dataset, 19 bioclimatic predictors from WorldClim, and nine soil parameters from SoilGrids were harmonized at 2.5 arc-minute resolution. To reduce multicollinearity among predictors, a combined approach of principal component analysis and hierarchical clustering was applied, followed by multiple linear regression using Box–Cox transformation to normalize skewed distributions. The model explained 65% of the variance in harvested area and revealed that buckwheat yield was positively associated with mean diurnal temperature range (BIO2), mean temperature of the wettest quarter (BIO8), and soil bulk density (bdod), and negatively associated with annual precipitation (BIO12), low winter temperatures (BIO11), and high soil nitrogen content. These results underscore buckwheat's preference for temperate, moderately dry climates and well-structured, moderately fertile soils. Projections made under four Shared Socioeconomic Pathways (SSPs), ranging from SSP1-2.6, a sustainability-focused pathway, to SSP5-8.5, a high-emission scenario, have consistently shown a northward shift in suitability between 2021 and 2080. However, the total suitable area is projected to decline, particularly under pessimistic scenarios, with the steepest reductions observed under SSP3–7.0 and SSP5–8.5. Despite improved thermal conditions in Polissya, soil limitations such as acidity and low humus content restrict the expansion of buckwheat cultivation. Analysis of variance showed that SSP scenario choice accounted for 13% of the variation in predicted suitability, time period for 6%, and their interaction for 2%, while the majority (79%) was attributed to local spatial heterogeneity. These findings confirm that while global climate pathways shape the overall trajectory of change, local soil and landscape factors remain dominant in determining actual suitability. The observed reduction in spatial variability and increasing homogeneity of negative changes indicate rising vulnerability of buckwheat agroecosystems. The study highlights the need for anticipatory adaptation strategies, including the spatial reallocation of buckwheat crops, soil improvement in emerging zones, diversification of crop portfolios, and expansion of agro-insurance mechanisms. It demonstrates the value of geospatial modelling as a decision-support tool for regional planning and agricultural resilience. Without targeted interventions, the cumulative effects of climate change and edaphic constraints may significantly reduce buckwheat's role in future food systems, despite its ecological and nutritional advantages. Spatially explicit adaptation pathways should therefore integrate climate projections, soil data, and socioeconomic considerations to ensure sustainable development of buckwheat production under global change.

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

Introduction

Yield forecasting is a crucial tool in modern agricultural planning, enabling efficient production management, ensuring food security, and promoting adaptation to climate change (Zymaroieva et al., 2019). Timely assessments of expected crop yields empower farmers to make informed decisions regarding crop selection, planting areas, resource allocation, and the timing of interventions (Mahesh & Soundrapandiyan, 2024). Research has demonstrated that this approach can assist in the mitigation of risks associated with adverse weather conditions, pests and diseases. This is of particular importance for the effectiveness of agro-insurance systems (Zeng et al., 2025). From a public policy and market perspective, yield forecasting provides an analytical foundation for regulating supply, logistics, and price stability (Tchonkouang et al., 2024). It is essential to recognize the importance of long-term forecasts in evaluating the impacts of climate change and developing adaptive strategies within the agricultural sector. The preceding discourse thus demonstrates how, when considered collectively, the aforementioned advantages underscore the pivotal role of yield forecasting as an instrument for achieving sustainable development in agriculture (Jabed & Azmi Murad, 2024). Modern technologies have been shown to play a crucial role in crop yield prediction by enabling the integration of large data sets, achieving high model accuracy, and automating processes (Mushtaq et al., 2024). The utilisation of remote sensing technologies, such as satellite imagery, geographic information systems (GIS) (Fedonyuk et al., 2020), the Internet of Things (IoT), sensor networks, and machine learning, facilitates continuous monitoring of agroclimatic conditions, plant physiological status, soil moisture, and other critical parameters (Eze et al., 2025). This facilitates real-time evaluation of crop conditions and supports the development of predictive models that account for dynamic environmental changes. The application of artificial intelligence further refines forecasting parameters adaptively, allowing for adjustments based on new data inputs. These technological advancements have been shown to enhance agricultural efficiency, optimise decision-making processes, and reduce the risks associated with climatic uncertainty (Bharadiya et al., 2023). The field of yield forecasting offers a wide range of practical applications, encompassing both strategic planning and operational management of agricultural systems (Schauberger et al., 2020). The utilisation of contemporary predictive models enables farmers to make timely and well-informed decisions regarding optimal crop placement, sowing schedules, variety selection, fertilization regimes, and responses to stress factors (Kumar et al., 2024). The ability to predict future yields is predicated on the ability to forecast potential risks associated with adverse weather conditions, diseases, or soil degradation. The ability to anticipate future developments in the field enables the early adaptation of technologies, with a view to minimising losses (Broekhuizen et al., 2023). At the national level, such forecasts provide a foundation for the development of food security policies. They serve to justify government support programmes for farmers, as well as to determine appropriate volumes for imports and exports. On a global scale, the capacity to predict yields is of critical importance in the monitoring of food availability, the prevention of crises, and the shaping of long-term development scenarios for the agricultural sector in the face of climate change (Filippi et al., 2025).

The impact of global climate change on agricultural systems worldwide is becoming increasingly significant, manifesting primarily through shifts in temperature regimes, changes in precipitation patterns, intensification of extreme weather events, and disruptions in seasonality (Prajapati et al., 2024). In this context, yield forecasting assumes a pivotal role, as it facilitates the adaptation of agricultural production to the dynamic conditions that are in a state of constant flux. Modern yield models have been developed to incorporate both climatic and agroecological factors, thereby providing valuable insights for risk assessment, the optimisation of sowing times, variety selection, and the development of adaptive farming strategies (Jabed & Azmi Murad, 2024). In light of the evidence that vulnerable regions, particularly those most adversely affected by droughts or heatwaves, it is imperative that these areas are subject to systematic monitoring and the implementation of predictive tools. This is in order to mitigate potential losses and enhance food security (Shafiee-Jood & Cai, 2016). The forecasts of crop yield play a pivotal regulatory role in the formulation of climate-oriented agricultural policies, the design of adaptation programs, and the implementation of agricultural insurance schemes. In view of the escalating climate challenges, the function of yield prediction transcends its role as a technological support system for farmers, thereby emerging as a strategic instrument for sustainable development planning in the agricultural sector (Li et al., 2025). Global warming leads to a decline in the yields of most agricultural crops, necessitating the adaptation of agroecosystems to changing climate conditions (Hu et al., 2024). The predominant methodological approaches for evaluating the impact of climate change on crop yield include empirical modelling, process-based agro-physical models, and machine learning techniques. Empirical models are predicated on statistical relationships between climate variables and historical yield data, thereby enabling rapid assessments based on existing information (Lobell & Burke, 2010). Agro-physical models simulate the physiological processes of plant growth in response to meteorological conditions, soil properties, and agronomic practices, thereby providing detailed insights into the effects of climate variability. Machine learning models have been shown to integrate numerous variables and capture complex, non-linear interactions, thus offering high predictive accuracy, especially in multifactorial conditions. Optimal strategies frequently entail the integration of multiple approaches to enhance the precision and robustness of yield forecasts (Feng et al., 2023). The assessment of climate change impacts on crop yields is conducted through the utilisation of several methodological approaches, each of which possesses its own strengths and limitations (Rezaei et al., 2023). One approach involves the conducting of manipulative experiments under controlled conditions, where factors such as temperature, humidity, and CO_2 concentration are varied to study the physiological responses of crops. Another widely used approach is the application of process-based models that simulate the biophysical processes of plant growth and development, enabling yield forecasting under different climate scenarios (Höglind et al., 2016). Concurrently, empirical statistical models are utilised, drawing upon historical data and correlations between weather conditions and yield, enabling expeditious assessments across extensive regions. In recent years, machine learning models have gained significant traction due to their high accuracy and capacity to capture complex, nonlinear relationships. In order to enhance the reliability of predictions, ensemble approaches are also employed, combining outputs from different types of models to reduce uncertainty. The integration of these methods is a fundamental strategy for developing adaptive agricultural responses in the face of climate change (Hayman et al., 2024).

Buckwheat (*Fagopyrum esculentum*) is an important pseudo-cereal crop distinguished by its high nutritional value, adaptability to poor soils, and short growing season (Verma et al., 2020). In the context of climate change and the need for diversification of agroecosystems, particularly where traditional cereal crops are less productive or carry higher cultivation risks, the relevance of the subject is increasing. Buckwheat is a rich source of proteins, antioxidants, dietary fibre, and is naturally gluten-free, characteristics which contribute to its high value as a foodstuff. It contributes to the conservation of biodiversity, is well-suited for organic farming, and improves soil structure. Buckwheat is thus a promising crop for sustainable agriculture and for strengthening food security (Verza et al., 2025). Buckwheat is characterized by a high content of essential nutrients, including indispensable amino acids, micronutrients, and antioxidants, which highlights its importance for healthy nutrition. Due to its resilience to adverse climatic conditions, short growing season, and ability to thrive on low-fertility soils, buckwheat is considered a promising crop in the context of climate change and the need for diversification of agricultural production. Its ecological plasticity and relative independence from mineral fertilizers make it an attractive option for organic farming and the sustainable development of agroecosystems (Virili et al., 2024). Buckwheat plays a significant role in global agricultural production; however, its utilization remains comparatively limited when compared to major cereals. The value of buckwheat lies in its unique nutritional properties, particularly its high protein content, which features a well-balanced amino acid profile, as well as its presence of antioxidants, dietary fiber, and the absence of gluten, making it suitable for individuals with celiac disease. Globally, buckwheat is utilized not only as a food crop but also as an ingredient in functional foods, a forage crop, and a green manure (Zamaratskaia et al., 2024). It demonstrates a high degree of adaptability to diverse climatic conditions and can be cultivated in low-input farming systems, especially in regions with less fertile soils. Consequently, buckwheat is regarded as a promising crop for future agroecosystems that require enhanced ecological resilience and diversity. In the context of climate change, it is anticipated that its role will increase, particularly concerning adaptation strategies and the assurance of food security (Popović et al., 2014).

The analysis of available literature highlights the growing importance of buckwheat as both a food crop and an agroecologically valuable species in the global context. Its popularity is driven by its high nutritional value, adaptability to diverse growing conditions, and contribution to sustainable agroecosystems. However, despite its significance, research focused on spatial forecasting of areas suitable for buckwheat cultivation under global climate change remains limited. Therefore, the aim of this study is to assess, based on historical data, the role of bioclimatic and soil factors in shaping favorable conditions for buckwheat cultivation, to develop a spatial model of these influencing factors, and to project changes in the extent of suitable cultivation areas under different climate change scenarios.

Materials and methods

The present study focuses on two major agroclimatic zones of Ukraine, namely Polissia and the Forest-Steppe, which differ significantly in their climatic and soil conditions (Nykytiuk et al., 2025). Polissia is distinguished by a cooler and more humid climate, exhibiting a moderately continental regime, characterised by high precipitation levels and limited thermal resources. These factors impose constraints on the cultivation of heat-demanding crops (Nykytiuk & Kravchenko, 2024). The soils in this region are predominantly sod-podzolic and peat-bog types, which are typically characterised by low nutrient content and acidic reaction. Conversely, the Forest-Steppe zone is distinguished by its more favourable agroclimatic conditions, characterised by higher average annual temperatures, superior thermal supply, and sufficient moisture. The predominant soil types in this region are various subtypes of chernozems, which are distinguished by their high natural fertility and elevated humus content. This environmental contrast facilitates the analysis of the spatial variability of conditions conducive to buckwheat cultivation and supports the assessment of agricultural adaptation prospects under changing climatic conditions within some of Ukraine's most representative agro-landscapes.

Historical data on harvested area of buckwheat (*Fagopyrum esculentum* Moench) were obtained from the global dataset CROPGRIDS v1.08 (Tang et al., 2024), which provides a spatially harmonized map of the harvested area and yield for 173 crops as of the year 2020, at a resolution of 0.05°. This dataset was developed through the hybridization of previous Multi-Resolution Fusion (MRF) modelling approaches (Monfreda et al., 2008), the integration of up-to-date satellite and statistical sources (including FAOSTAT), followed by quality-based ranking for each country and crop, was used to enhance the dataset. To account for climatic conditions in yield modelling, 19 bioclimatic variables (BIO1–BIO19) from the WorldClim v2.1 dataset were used, with a spatial resolution of 2.5 arc-minutes (~5 km). These variables are derived from monthly temperature and precipitation values and represent annual trends, seasonality, and ecologically relevant extremes that influence crop development. After downloading, the bioclimatic rasters were clipped to the study area boundary and masked according to the extent of agricultural lands. They were then reprojected to match the coordinate reference system (CRS) of the harvested area layer using bilinear interpolation and resampled to ensure consistent spatial resolution. To characterize soil conditions influencing crop productivity, nine soil predictors were obtained from the global SoilGrids database (via the soil_world function) for the 5–15 cm depth layer. These included: bulk density (bdod), coarse fragments (cfvo), clay content (clay), total nitrogen (nitrogen), predicted organic carbon (ocd), soil pH (phh2o), as well as sand, silt, and soil organic carbon content (soc). Each variable was clipped to the study area, masked, reprojected to the CRS of the harvested area layer using bilinear interpolation, and resampled to a common resolution. The variable “ocs” (organic carbon stock) was excluded to avoid excessive collinearity with other organic matter indicators. All historical variables used as input predictors for yield modelling were compiled into a single raster stack. This stack included: the buckwheat harvested area mask, 19 bioclimatic variables (BIO1–BIO19), and the nine soil variables described above. Prior to stacking, the compatibility of all layers was verified in terms of coordinate projection, spatial extent, and resolution to ensure accuracy of further analysis. This alignment ensured pixel-perfect spatial consistency across all predictor variables. To address the issue of multicollinearity among the numerous bioclimatic variables and to reduce the dimensionality of the climatic space, a principal component analysis (PCA) was performed using standardized values of the BIO1–BIO19 variables. The analysis included only those pixels that had finite values for all variables and excluded any variables with zero variance. For further modeling, four principal components with eigenvalues (λ) greater than 1 were selected based on Kaiser’s criterion. From each component, the variable with the highest loading was identified and used as an independent climatic predictor (referred to as primary_vars). To eliminate collinearity between the remaining bioclimatic variables and these key predictors, regression residuals (residuals) of each non-primary variable against the primary_vars were calculated. These residual variables (denoted with the suffix_resid) retained unique, non-collinear information and were included in the model as orthogonalized climatic predictors.

Following the orthogonalization of climatic variables, a subset of pixels with complete data availability (denoted as idx) was identified. For these pixels, corresponding values of soil variables were extracted from the soil_hist layer. To prepare the final predictor matrix for yield modeling, these soil data were combined with harvested area values (harvarea) as the response variable, selected primary climatic predictors, regression residuals of the remaining bioclimatic variables (orthogonalized variables), and the full set of soil variables. This resulted in the predictor_df table, where each row corresponds to a single pixel in the study area, and each column represents a predictor used in statistical modeling. Since the distribution of the response variable (harvested area) was positively skewed and contained zero values, a Box–Cox transformation was applied to stabilize variance and approximate normality. A small positive constant ε (equal to half the minimum positive value of harvarea) was added to all values to enable proper log transformation when the Box–Cox λ parameter approached zero. The optimal λ value was determined by maximizing the log-likelihood within the interval [−2, 2]. Depending on the value of λ, either a power or logarithmic transformation was applied. Using the transformed response variable (harv_bc) and the predictor matrix (including primary climatic variables, orthogonalized climatic residuals, and soil indicators), a multiple linear regression model was fitted. Model evaluation enabled the identification of significant relationships between environmental conditions and the spatial distribution of buckwheat productivity during the baseline period.

To reduce the impact of multicollinearity among predictors, a hierarchical clustering method based on the correlation structure of the variables was applied (Kayode Ayinde & Nwosu, 2021). At the first stage, all predictors were standardized using the formula z = (x – mean(x)) / sd(x), thereby transforming them into a dimensionless scale with a mean of 0 and a standard deviation of 1. A matrix of pairwise correlations between all variables (excluding the response variable) was then constructed using Pearson's correlation coefficient. A symmetric distance matrix was derived from these correlations as 1 – |r|, where r is the absolute correlation value. This distance matrix was used to perform hierarchical clustering of variables using the average linkage method. The number of clusters (e.g., k = 12) was chosen empirically based on the dendrogram structure. From each cluster, one variable was selected — the one with the lowest average correlation to other variables within the same cluster. This resulted in a set of representative predictors included in the final linear regression model. This approach helped to minimize informational redundancy among variables and reduce the risk of unstable coefficient estimates typically associated with excessive multicollinearity.

To assess spatial changes in buckwheat suitability for the future period of 2061–2080, climate projections from CMIP6 (CNRM-CM6-1 model) were used under four Shared Socioeconomic Pathways (SSP1–2.6, SSP2–4.5, SSP3–7.0, SSP5–8.5) (Table 1). Climate variables (bioclimatic predictors BIO1–BIO19) were retrieved from the global CMIP6 database at a spatial resolution of 2.5 arc-minutes and were subsequently reprojected, resampled, and spatially aligned to the extent and resolution of the historical agricultural land-use mask using the project() and resample() functions with bilinear interpolation. Soil parameters were assumed to remain constant over time; thus, values from historical data were incorporated into the predictive raster stack. To reduce multicollinearity among bioclimatic predictors, residual components were calculated by regressing additional climate variables against the primary predictors. These residuals, along with the main bioclimatic and soil predictors, were compiled into the matrix. For each SSP × time interval combination (2021–2040, 2041–2060, 2061–2080), yield projections were generated using the previously trained linear regression model that employed Box–Cox transformation. The inverse transformation was applied based on the estimated λ parameter. Any negative yield values, potentially arising from numerical error, were replaced with zero. Based on the predicted values, spatial raster maps of projected buckwheat yield and delta maps showing changes relative to the historical baseline were produced. For visualizing spatial yield changes, a diverging blue–white–red color scale was applied, centred at zero. The projected yield values and their differences were also appended to the final dataframe, which contains the geographic coordinates of all pixels, enabling further analysis and the creation of cartographic outputs.

Results

A linear regression model was constructed using 12 predictors selected through cluster-based multicollinearity grouping (Table 2). The model demonstrated good explanatory power (adjusted $R^2 = 0.65$), with most coefficients being highly significant ($P < 0.001$). The most substantial positive contributions to the predicted buckwheat yield were made by the mean temperature of the wettest quarter (bio8), the mean diurnal temperature range (bio2), the minimum temperature of the coldest month (bio6), and soil bulk density (bdod). Conversely, the mean temperature of the coldest month (bio11), annual precipitation (bio12), and total nitrogen content in the soil (nitrogen) were found to be negatively associated with yield. The precipitation of the wettest quarter (bio18) and the mean temperature of the driest month (bio9) were statistically non-significant ($P > 0.05$).

Table 1
Characteristics of SSP climate scenarios (Riahi et al., 2017)

Scenario	Radiative forcing by 2100, W/m²	Full name	Description of societal development	Climate and land use implications
SSP1–2.6	2.6	Sustainability	Focus on environmental balance, inclusive development, high levels of education and healthcare, and reduced inequality. Active global cooperation and rapid transition to renewable energy.	Low greenhouse gas emissions, limited cropland expansion, reduced anthropogenic pressure on ecosystems. High probability of keeping temperature rise < 2 °C.
SSP2–4.5	4.5	Moderate Scenario ("Middle of the Road")	Continuation of current development trends with political and economic inertia. Moderate climate policies. Inequality persists but does not worsen.	Moderate emissions growth. Partial implementation of climate strategies. Limited agricultural modernization, high ecosystem vulnerability.
SSP3–7.0	7.0	Regional Rivalry ("Fortress World")	A fragmented world with low international cooperation. National interests dominate; limited access to education and technology. Rapid population growth in developing countries.	High emissions, aggressive cropland expansion at the expense of natural areas. Weak climate adaptation and poor biodiversity outcomes.
SSP5–8.5	8.5	Fossil-Fueled Development	Global focus on economic growth and technological progress based on fossil fuels. High urbanization and resource consumption. Economic priorities prevail over environmental concerns.	Maximum greenhouse gas emissions. Large-scale land transformation for infrastructure and agriculture. Temperature increase exceeds +4 °C by century's end without decisive climate action.

Table 2
Results of the linear regression of the dependent variable (Box–Cox transformed yield) on selected predictors after grouped multicollinearity reduction (N = 11,803; $R_{adj}^2 = 0.65$). Standardized regression coefficients (β) and standard errors (SE) are presented in the format β ± SE

Predictor	*β* ± SE	*t*	*P*-value
(Intercept)	1.67 ± 0.01	255.96	< 0.001
Precipitation of the wettest quarter (bio18)	–0.01 ± 0.01	–0.83	0.404
Mean temperature of the coldest month (bio11)	–0.54 ± 0.01	–63.39	< 0.001
Mean diurnal temperature range (bio2)	0.22 ± 0.01	27.40	< 0.001
Temperature of the wettest quarter (bio8)	0.11 ± 0.01	13.80	< 0.001
Minimum temperature of the coldest month (bio6)	0.18 ± 0.01	25.03	< 0.001
Temperature of the driest quarter (bio9)	0.00 ± 0.01	–0.01	0.993
Annual precipitation (bio12)	–0.35 ± 0.01	–32.69	< 0.001
Precipitation of the wettest month (bio13)	0.10 ± 0.01	14.71	< 0.001
Precipitation of the driest month (bio14)	0.06 ± 0.01	6.34	< 0.001
Precipitation of the wettest quarter (bio16)	0.09 ± 0.01	11.50	< 0.001
Soil bulk density (bdod)	0.55 ± 0.01	51.31	< 0.001
Total nitrogen content in soil (nitrogen)	–0.29 ± 0.01	–33.54	< 0.001

The analysis of spatial variability in the projected share of agricultural land allocated for buckwheat cultivation under 12 scenario combinations (4 SSPs × 3 time intervals) reveals a consistent and coherent pattern across most regions (Fig. 1). In all scenarios, the spatial distribution of projected cultivation areas is predominantly concentrated in the western, southwestern, and central parts of the study area. The highest values are forecasted for the early period (2021–2040) under nearly all SSPs, with maxima exceeding 3.9%, particularly in SSP1–2.6 (3.90), SSP2–4.5 (3.93), and SSP3–7.0 (4.26). At the same time, some pixels show values dropping to zero, indicating potential buckwheat disappearance from specific regions. As the time horizon shifts toward mid-term (2041–2060) and long-term (2061–2080) periods, a downward trend in maximum values is observed regardless of the SSP scenario. For instance, under SSP5–8.5, the maximum decreases from 3.62 (2021–2040) to 2.84 (2061–2080), while in SSP2–4.5 it declines from 3.93 to 2.81. This trend indicates a general reduction in buckwheat cultivation area due to the influence of future climate change. Despite this decline, the spatial structure remains relatively stable, with areas of highest yield potential remaining largely within the same agroclimatic zones. The spatial models not only depict absolute projections of buckwheat yield but also illustrate the dynamics of spatial reorganization in response to different socioeconomic development pathways and climate change scenarios. This enables the identification of both climate-resilient regions and vulnerable zones that may require targeted adaptation strategies in agriculture.

The projected spatiotemporal variation in agricultural land area allocated to buckwheat cultivation reveals a pronounced trend toward reduction across most regions (Fig. 3). The smallest changes are observed under the SSP1–2.6 scenario, where certain areas in the western part of the study region retain or even increase their share of buckwheat cultivation. While the SSP2–4.5 scenario also shows some localized positive deviations, the overall trend is predominantly negative. Under SSP3–7.0 and especially SSP5–8.5, negative changes extend across much of the region, including both northern and central-eastern areas, with the most severe decline projected for the final period (2061–2080). Spatial patterns of buckwheat persistence are concentrated primarily in the west, while eastern and northern parts experience substantial contraction regardless of the scenario. A decline in spatial variability over time is also evident, indicating a progressive homogenization (in a uniformly negative direction) of agroecosystem responses to changing climatic conditions.

The projected area allocated to buckwheat cultivation shows considerable variation driven by both socioeconomic scenarios (SSPs) and time periods. According to the results of analysis of variance (ANOVA), the scenario (SSP) is the primary factor explaining 13% of the total variance, while the forecast period accounts for 6% (Table 2). Additionally, the interaction between scenario and period contributes another 2%. The remaining 79% of the variance is attributed to residual spatial heterogeneity within the region.

Table 3
Results of the analysis of variance (ANOVA) assessing the effects of socioeconomic development scenarios (SSPs), time periods, and their interaction on the predicted proportion of agricultural land allocated for buckwheat cultivation. Degrees of freedom, sum of squares, mean squares, F-statistic, P-values, and the proportion of variance explained (η²) by each source of variation are provided

Source of Variation	Degrees of Freedom	Sum of Squares	Mean Square	*F*-statistic	*P*-value	η² (Variance Explained)
SSP	4	13639	3410	4916.1	< 0.001	0.13
Period	2	6730	3365	4851.8	< 0.001	0.06
SSP × Period	6	1745	291	419.4	< 0.001	0.02
Residuals	125925	87341	0.69	–	–	0.79
Total	125937	109455	–	–	–	1.00

This is supported by the results of the graphical analysis: the predicted cultivation area decreases along the gradient from SSP1–2.6 to SSP5–8.5, as well as over time, from 2021–2040 to 2061–2080 (Fig. 3). Visual differences between scenarios are reinforced by letter-based coding of statistically significant groupings (a–d), indicating a consistent decline in buckwheat-suitable area under high-emission scenarios. Thus, although the forecast is influenced by global development pathways and temporal horizons, spatial factors remain the dominant source of variation, highlighting the importance of localized modelling for accurately assessing projected changes.

Discussion

From a historical standpoint, the favourable conditions for buckwheat cultivation have been shaped by a combination of climatic factors. These factors have had statistically significant and biologically plausible effects on the crop's performance. The most substantial positive contributions to the spatial variation in harvested area were observed for the temperature of the wettest quarter (bio8), the mean diurnal temperature range (bio2), and the minimum temperature of the coldest month (bio6). The findings indicate that buckwheat performs better in temperate climates with pronounced seasonality, where minimum temperatures do not drop excessively low and daily temperature contrasts support biomass accumulation.

Conversely, the mean temperature of the coldest month (bio11) and total annual precipitation (bio12) exhibited a negative correlation with harvested area, underscoring the crop's susceptibility to excessive moisture and protracted cold periods.

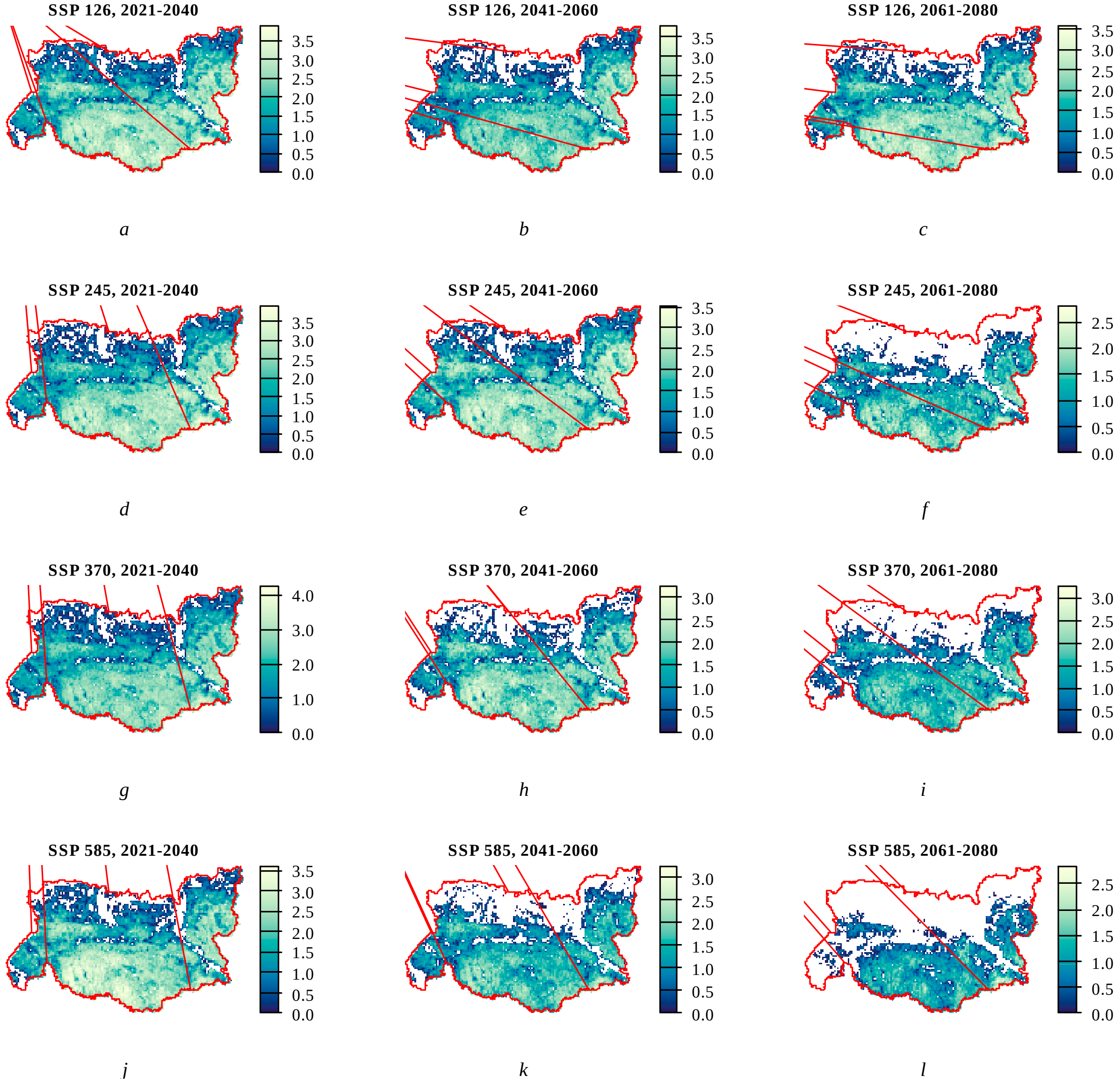
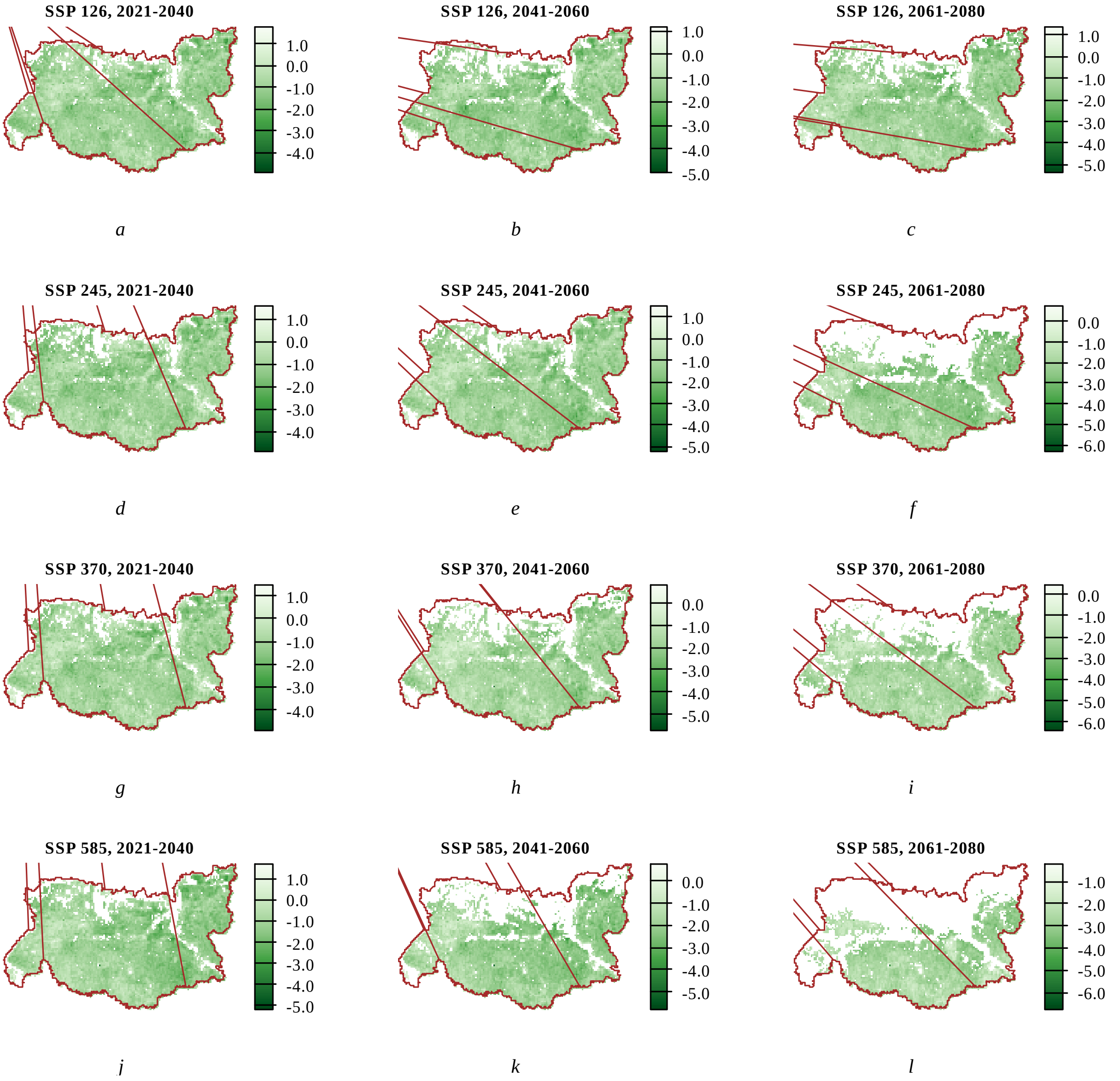


Fig. 1. Projected changes in buckwheat yield (*Fagopyrum esculentum* Moench) under alternative societal development scenarios used for climate change modelling with varying greenhouse gas forcing levels (SSP), 2021–2080: the maps illustrate the spatial variability of projected buckwheat yield (in hectares per pixel) across the study region in Ukraine for three future time periods (2021–2040, 2041–2060, 2061–2080) under four shared socioeconomic pathways (SSP1–2.6, SSP2–4.5, SSP3–7.0, SSP5–8.5); these SSP scenarios represent distinct trajectories of societal development combined with differing levels of greenhouse gas emissions, reflecting potential outcomes of climate change impacts on crop production: *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

Temperature conditions during critical phases of plant development and precipitation during the growing season are identified as key climatic factors that shape the ecological niche of buckwheat and drive the spatial heterogeneity of its cultivation potential across the region (Weymann et al., 2015). At the scale of the study area, the most significant soil properties determining the suitability of conditions for buckwheat cultivation were found to be the physical and chemical characteristics reflecting water retention capacity, bulk density, and soil fertility (Zhukov et al., 2018). The findings of the study demonstrated a positive effect in relation to higher soil bulk density, which is likely to be attributable to enhanced moisture retention in heavier soils. This is of particular relevance under summer water deficit conditions. Conversely, elevated total nitrogen levels were found to be associated with diminished suitability for buckwheat cultivation. This may be indicative of indirect factors, such as the prevalence of intensively fertilized soils in areas dedicated to specialized agriculture, where buckwheat is cultivated less frequently. It may also be posited that buckwheat is better adapted to soils with moderate fertility and lower nitrogen availability, where competition from other crops is reduced. It is evident that the influence of soil factors indicates that buckwheat exhibits a predilection for conditions characterised by adequate moisture and moderate nutrient availability, while eschewing excessive nitrogen inputs. The increase in buckwheat cultivation area on plots with higher bulk density is likely linked to the crop's prevalence on less fertile sandy substrates. Sandy soils characteristically display higher density, diminished water-holding capacity, and constrained nutrient reserves. Nevertheless, buckwheat has exhibited resilience and demonstrated capacity for growth under such conditions. This observation underscores the relatively modest fertility requirements of the crop in comparison to other agricultural practices, thereby conferring a competitive advantage in the cultivation of marginal lands (Yakovenko & Zhukov, 2021). In a significant number of agricultural establishments, these lands are deliberately designated for buckwheat cultivation, as alternative crops have been found to be either less productive or unfeasible (Zymaroieva et al., 2021). Consequently, the observed positive correlation between soil density and the cultivation area of buckwheat can be attributed to the species' specific ecological plasticity and an adaptive agricultural strategy under suboptimal soil conditions (Zymaroieva et al., 2019).



a *b* *c*

d *e* *f*

g *h* *i*

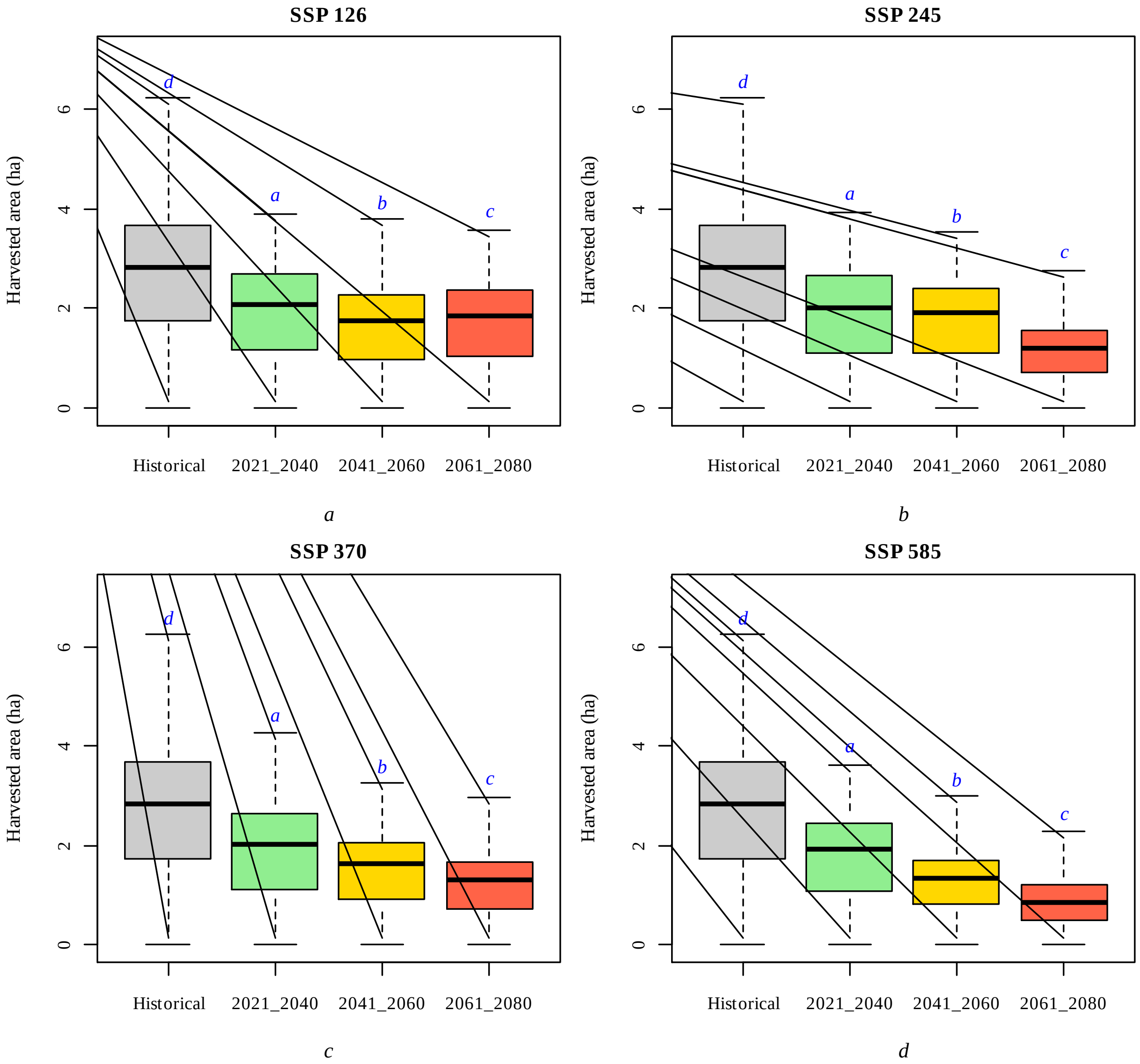
j *k* *l*

Fig. 2. Projected changes in buckwheat (*Fagopyrum esculentum* Moench) 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

The SSP1–2.6 scenario is associated with the least negative changes in buckwheat cultivation prospects, as it is based on assumptions of global sustainable development, active climate policy, and widespread implementation of low-emission technologies. This finding suggests that, among all the pathways considered, this scenario would result in the least intense climate change. In such conditions, the rate of temperature increase remains relatively moderate, and changes in precipitation patterns – both in terms of quantity and seasonality – are less drastic. This approach serves to mitigate the risk of both excessive drought and heat stress, which have been identified as critical limiting factors for buckwheat. The maintenance of climatic conditions that approximate the historical baseline is conducive to the agroclimatic stability of the region for this crop. Consequently, the favourable conditions for buckwheat cultivation are largely maintained due to the moderate nature of climate shifts under SSP1–2.6.

Conversely, the SSP2–4.5 scenario, which assumes moderate socio-economic development and only partial implementation of climate policy, demonstrates a gradual decline in areas suitable for buckwheat cultivation, exhibiting pronounced spatial variability. In the short term (2021–2040), the changes are relatively minor, indicating the persistence of some historically favourable locations, particularly in the northern and western parts of the region. However, in the mid- and long-term periods (2041–2060 and 2061–2080), a more significant reduction in area is observed, associated with deteriorating climatic conditions, especially increasing drought risk, heat stress, and shifts in the growing season. The most significant losses are concentrated in the southern and eastern districts, which are more vulnerable to rising temperatures and declining water availability. The trend within SSP2–4.5 reflects a gradual contraction of the buckwheat cultivation range, particularly in the long term, as agroclimatic stability in the region declines.

The SSP3–7.0 scenario is characterized by highly unfavourable conditions for buckwheat cultivation due to elevated greenhouse gas emissions, weak international cooperation, and limited investment in climate change adaptation. Spatially, a distinct northward shift of suitable cultivation areas is observed: traditional agroecosystems in the southern part of the region gradually lose functionality as aridification intensifies, soils degrade, and water scarcity becomes more pronounced. Signs of area reduction are already evident in the 2021–2040 period, while in the long term (especially after 2060), most areas that historically had high potential become unsuitable for buckwheat. At the same time, northern regions exhibit relative stability or even slight improvement in conditions; however, this is insufficient to compensate for the overall decline. In SSP3–7.0, the area suitable for buckwheat cultivation shrinks the fastest and most severely, highlighting the crop's critical sensitivity to cumulative climate stressors in the absence of effective climate policy.



a *b* *c* *d*

Fig. 3. Boxplots of harvested area (ha) under four SSP scenarios (SSP126, SSP245, SSP370, SSP585) across different time periods: historical baseline, 2021–2040, 2041–2060, and 2061–2080; different letters above the boxes indicate statistically significant differences between periods within each SSP according to Dunn's test (with Bonferroni correction, $P < 0.05$); the central line indicates the median; the box represents the interquartile range; whiskers extend to 1.5 times the interquartile range: *a* is the SSP1–2.6; *b* is the SSP2–4.5; *c* is the SSP3–7.0; *d* is the SSP5–8.5

The SSP5–8.5 scenario presents the most severe negative changes in the spatial distribution of areas suitable for buckwheat cultivation, particularly in the second half of the 21st century. This scenario is based on intensive economic growth driven by fossil fuels, leading to rapid global warming, extreme temperature increases, and substantial shifts in seasonal regimes. In the study region, these changes manifest as a progressive reduction of suitable areas, especially in the south, where moisture deficits intensify and agroclimatic potential declines. Over time, this degradation extends to central regions as well. Only a few northern districts retain relatively stable conditions, but their extent is insufficient to offset the losses. The high concentration of heat and water stress under this scenario exceeds buckwheat's tolerance thresholds, rendering its cultivation increasingly risky and less viable. SSP5–8.5 therefore predicts the worst prospects for maintaining or expanding buckwheat cultivation due to critically intensified climatic constraints.

The dominant contribution of SSP scenarios to the explained spatial variability in projected areas suitable for buckwheat cultivation is due to the fact that these scenarios define the overall trajectory of climate change at both global and regional scales. Each SSP represents a distinct socio-economic development pathway that shapes the magnitude and nature of future greenhouse gas emissions, the pace of global warming, shifts in precipitation patterns, and the frequency of extreme weather events. These factors, in turn, directly affect key climatic variables that determine agroclimatic suitability – such as temperature, precipitation during critical growth stages, and seasonal climate structure. Thus, SSP scenarios set the boundaries of potential climatic conditions under which projections are made, while the temporal factor (Period) simply refines the gradual changes within a given scenario. This explains why variation among scenarios is the most significant source of differences in spatial projections of buckwheat-suitable areas. The smaller contribution of the Period factor to the explained variance indicates that the projected area suitable for buckwheat changes gradually over time within each SSP, but the primary differences are driven by the type of development trajectory (i.e., SSP). In other words, whether the projection refers to the near future (2021–2040) or the more distant future (2061–2080), the nature and magnitude of changes within a single SSP remain relatively consistent in spatial pattern. This reflects a relative stability in the trajectory of climate impacts within each scenario, whereas transitioning between SSPs implies a qualitatively different level of climatic change. Therefore, the temporal factor refines the extent of impacts but does not determine their direction, which accounts for its lower contribution to the overall explained variance. The observed interaction between Period and SSP suggests that the temporal effect on buckwheat-suitable area is not uniform across scenarios. In other words, the nature and pace of changes over time depend on the chosen socio-economic development pathway and its associated climate impacts. For instance, in less favourable scenarios such as SSP3–7.0 or SSP5–8.5, substantial reductions in potential buckwheat cultivation areas are observed as early as the first half of the 21st century. In contrast, under more optimistic scenarios (e.g., SSP1–2.6), even long-term changes are relatively minor. This interaction points to the anticipatory nature of negative changes under extreme scenarios, underscoring the critical importance of global development pathways and the pace of transformation for the adaptive capacity of agroecosystems. The overall conclusion from the obtained results is that under all considered climate scenarios, favourable conditions for buckwheat cultivation demonstrate a clear trend of shifting northward, toward the Polissia region. However, despite the observed improvement in climatic conditions, the soil quality of this region continues to represent a significant constraint on agricultural productivity. This is particularly evident in the case of acidic soils, which are characterised by poor nutrient content and challenging accessibility for mechanised farming practices. This leads to the fact that the potential expansion of the cultivation area does not compensate for the losses in the more favorable southern regions (Tutova et al., 2025). As a result, a general decrease in the area suitable for buckwheat is observed, along with significant spatial restructuring of agroecological zones. This situation highlights the need to consider not only climatic but also soil factors in the planning of adaptation measures.

The practical results of the study indicate the importance of integrating climatic and soil factors in planning agricultural production under climate change conditions. Based on the modelling, the following recommendations can be formulated: adaptation of buckwheat crop placement, consideration of soil constraints, risk management and diversification, application of spatial modelling in agro-planning, and targeted support for farmers.

It is imperative to adapt the placement of buckwheat crops in response to changes in agroclimatic conditions. This is due to the fact that regions with historically high productivity may experience a decline in agroclimatic attractiveness, while new suitable zones are emerging in more northerly regions (Mykhailyuk et al., 2023). In order to address these challenges, it is imperative to adapt agricultural policy to the prevailing circumstances, with a particular emphasis on the reallocation of crop areas (Zymaroieva et al., 2019). As demonstrated by the modelling, in the context of climate change, traditional areas of buckwheat growth in Ukraine – specifically those in the central and southern regions – are progressively experiencing a decline in favourable agro-climatic conditions for the cultivation of this crop. Rising temperatures, precipitation instability, and the intensification of extreme weather events are leading to a reduction in areas suitable for stable buckwheat cultivation in the southern steppe (Zymaroieva et al., 2021). The modelling indicates the formation of new potentially favourable zones in northern regions, including the northern part of the Forest-Steppe and Polissia. This suggests the possibility of a gradual geographic shift in the primary areas of buckwheat cultivation towards more northerly regions. The adaptation of agricultural production to these changes involves technological readiness for crop relocation and appropriate updates to regional agricultural strategies, infrastructure, and logistics. This necessitates investment in processing facilities, storage infrastructure, transportation networks, and the adaptation of agricultural insurance systems in new production regions. In considering such a shift, it is imperative to take into account the social implications, with particular attention to the role of local farmers in adopting new production processes and acquiring the necessary agrotechnologies. It is imperative that spatial adaptation strategies become an integral component of national climate adaptation policies, with the objective of ensuring food security in the face of increasing climatic instability.

It is essential to consider the limitations imposed by the soil, especially in light of the notable improvements in climatic conditions observed in the northern regions. However, these enhancements have not sufficiently mitigated the challenges posed by the infertile, acidic, or excessively moist soils of Polissia, which adversely affect the viability of stable buckwheat cultivation. This situation necessitates the implementation of targeted agronomic measures, such as liming, fertility enhancement, drainage, or the introduction of more tolerant crop varieties. In northern Ukraine, particularly within the Polissia region, the predominant soil types are characterized by their acidic, sandy, or waterlogged nature, coupled with a lack of nutrients and an unfavourable structure. These characteristics render them unsuitable for buckwheat cultivation. As a result, yield reductions may occur, and in some cases, the soils may become entirely unfit for this specific crop. The suitability of territories should be assessed by considering not only climatic factors but also soil parameters. These parameters include, but are not limited to, the following: organic matter content, granulometric composition (particularly the proportions of clay and silt fractions), soil acidity, and bulk density. In certain cases, agronomic interventions may be implemented to mitigate soil limitations, such as liming, organic amendments, and land reclamation; however, these interventions require resources, technical expertise, and economic justification. It is essential to consider soil constraints when developing strategies for the successful relocation of crops, particularly within the context of comprehensive agricultural planning. The integration of climatic models with detailed soil data is crucial for the scientific identification of zones suitable for expanding or relocating buckwheat cultivation in response to climate change.

In light of the spatial restructuring and the overall reduction of suitable land area, it is recommended that crop diversification strategies and risk insurance be implemented, particularly in regions experiencing a decline in favourable conditions. The anticipated spatiotemporal instability of climatic conditions, which affects the suitability of land for buckwheat cultivation, necessitates the implementation of risk management strategies. Among these, crop diversification plays a pivotal role, involving the rotation of buckwheat with other crops that are more tolerant to extreme weather fluctuations or specific soil conditions. This approach has been shown to reduce farmers' dependence on a single crop and lower the likelihood of total crop failure under adverse conditions. Effective risk management demands consideration of not only biophysical factors but also economic trends, access to agro-technologies, logistics, and agricultural infrastructure. The development of adaptive models of cropping systems that are capable of responding to projected climate changes at both the regional level and within individual farms is of high relevance. This encompasses the strategic scheduling of sowing dates, the utilisation of varieties exhibiting diverse growth durations, and the anticipation of economic risks associated with market volatility. Diversification of the crop portfolio, in conjunction with the territorial redistribution of buckwheat plantings, contributes to increasing the resilience of agroecosystems to climate challenges and forms the foundation for a more sustainable agricultural strategy.

The proposed methodology for forecasting changes in land suitability can be integrated into national and regional land-use planning systems, enabling timely responses to long-term changes. Spatial modeling is a vital tool for informed decision-making in agriculture under climate change conditions. It allows the identification of areas with the highest potential for buckwheat cultivation by accounting for a combination of climatic and soil factors, as well as forecasting temporal changes in their suitability. This enables agricultural planning to focus not only on current productivity but also on long-term stability. In the context of climate change adaptation, spatial models help assess prospective shifts in agricultural production, identify risk zones with potential loss of suitability, and formulate response scenarios. Such models are particularly valuable for developing zonal agropolicies, supporting decision-making at community and regional levels, and prioritizing investments in infrastructure or land improvement measures. Spatial modeling and geographic information systems (GIS) are integral to the digital transformation of agricultural planning, where crop potential maps, risk assessments, and adaptive scenario development become available in a visualized and practically applicable format.

Amid increasing climate risks and spatial shifts in the suitability of agricultural lands, the implementation of targeted support mechanisms for farmers becomes particularly important. Modeling results indicate that certain regions may experience a significant decline in their potential for buckwheat cultivation, while opportunities may increase in other areas. In such a context, farmers require not only information but also practical support to adapt to new agroclimatic conditions. Targeted support should be differentiated according to regional change scenarios. In areas losing suitability, it may include compensation mechanisms, retraining programs, or support for transitioning to alternative crops. In promising regions, support should focus on investments in infrastructure, logistics, seed production, irrigation, or mechanization, as well as facilitating market access. Strengthening the advisory system is essential: farmers need regionally adapted recommendations, forecasts, and services based on spatial analysis that integrates climatic and soil conditions. The proposed approach will help mitigate the negative socio-economic impacts of climate change and ensure the sustainable production of buckwheat as an important food crop.

The obtained results open up several avenues for further research aimed at deepening the understanding of climatic and soil determinants influencing the spatial distribution of buckwheat cultivation under climate change conditions. A particularly promising direction involves the inclusion of additional agroclimatic factors, such as the probability of spring frosts, drought occurrence during critical growth phases, vegetation duration, and thermal resources. Integrating these parameters will enhance the accuracy of forecasts and adaptive scenarios. Special attention should also be given to a more detailed consideration of soil properties, including texture, drainage, water-holding capacity, and acidity, as well as their interactions with management practices (e.g., application of organic matter, gypsum, or lime). This will contribute to the development of comprehensive agroecological suitability maps. Another important direction is the integration of spatial modeling with economic assessments to evaluate the feasibility of adaptation scenarios in terms of costs, profitability, and risk resilience. It is also advisable to compare buckwheat with other crops in order to identify potential resource competition in regions where the agroclimatic niche for buckwheat is shifting. Furthermore, it is crucial to investigate the social and institutional barriers to implementing adaptation measures, which will help ensure the effective application of spatial analysis results in agricultural policy and practice. Such an interdisciplinary approach will not only improve forecasting accuracy but also ensure the practical relevance and impact of decision-making tools.

Conclusion

The spatial variability of areas suitable for buckwheat cultivation within the Polissia and Forest-Steppe zones of Ukraine is driven by the interaction of climatic and soil factors, though the dominant determinants differ between these two natural-climatic regions. In Polissia, a region distinguished by its abundant precipitation and temperate climate, soil conditions are the primary limiting factor. Specifically, the combination of low humus content, high acidity, and poor permeability, in conjunction with the risk of waterlogging, results in a land that is not optimally suited for buckwheat cultivation. This is due to the fact that buckwheat is sensitive to excess moisture and exhibits limited tolerance for acidic soils. Despite the theoretical possibility of rising temperatures in northern regions, resulting in enhanced conditions for plant growth, soil limitations ultimately prevail, overshadowing the potential benefits of climate shifts. In the forest-steppe, where soils tend to exhibit superior agrophysical characteristics, climatic factors predominate in determining the viability of the terrain for buckwheat cultivation. It is evident that temperature regimes, with particular reference to the average temperature experienced during the growing season, precipitation levels, and moisture indices, have been identified as significant predictors. It is evident that alterations in the parameters under consideration, in the context of specific climate scenarios, exert a direct influence on both the productivity and the expansion or contraction of potentially suitable areas within the designated zone. While soil control is the most salient feature in Polissia, climatic control is more prominent in the Forest-Steppe. This regional differentiation elucidates the spatial patterns of the projected changes in areas suitable for buckwheat cultivation. The areas most conducive to buckwheat cultivation in Ukraine exhibit a high degree of sensitivity to climate change, with projections indicating substantial variations in response to different future development scenarios. The incorporation of both climatic and soil factors into a spatial modelling framework enabled the identification of regions exhibiting increasing or decreasing potential for buckwheat cultivation. Across all SSP scenarios, there is a general northward shift of favourable conditions. However, due to the unfavorable soil characteristics of Polissia, the total area suitable for this crop is expected to decrease substantially. The scenario SSP1–2.6 is predicted to result in the least negative consequences, whereas SSP3–7.0 and SSP5–8.5 indicate early and significant losses of suitable areas, respectively. A statistical assessment confirmed that the socio-economic development scenarios (SSPs) have a decisive influence on the forecasted areas for buckwheat cultivation, surpassing both in their contribution to overall variance and the significance of their interaction with the temporal factor. This underscores the imperative for integrating socio-economic preconditions with climatic characteristics in long-term agricultural planning. The practical recommendations of this study emphasise the need for adapting the spatial allocation of crops, accounting for soil constraints, diversifying agricultural production, applying geospatial models, and delivering targeted support to farmers. The findings are of great importance for developing adaptation strategies in agriculture and can serve as a foundation for future research focused on other crops, broader time horizons, or greater regional detail.

References

Bharadiya, J. P., Tzenios, N. T., & Reddy, M. (2023). Predicting crop yield using deep learning and remote sensing. Journal of Engineering Research and Reports, 24(12), 29–44.

Broekhuizen, T., Dekker, H., de Faria, P., Firk, S., Nguyen, D. K., & Sofka, W. (2023). AI for managing open innovation: Opportunities, challenges, and a research agenda. Journal of Business Research, 167, 114196.

Eze, V. H. U., Eze, E. C., Alaneme, G. U., Bubu, P. E., Nnadi, E. O. E., & Okon, M. B. (2025). Integrating IoT sensors and machine learning for sustainable precision agroecology: Enhancing crop resilience and resource efficiency through data-driven strategies, challenges, and future prospects. Discover Agriculture, 3(1), 83.

Fedonyuk, T. P., Galushchenko, O. M., Melnichuk, T. V., Zhukov, O. V., Vishnevskiy, D. O., Zymaroieva, A. A., & Hurelia, V. V. (2020). Prospects and main aspects of the GIS-technologies application for monitoring of biodiversity (on the example of the Chornobyl Radiation-Ecological Biosphere Reserve). Kosmična Nauka ì Tehnologìâ, 26(6), 75–93.

Feng, X., Tian, H., Cong, J., & Zhao, C. (2023). A method review of the climate change impact on crop yield. Frontiers in Forests and Global Change, 6, 1198186.

Filippi, P., Han, S. Y., & Bishop, T. F. A. (2025). On crop yield modelling, predicting, and forecasting and addressing the common issues in published studies. Precision Agriculture, 26(1), 8.

Hayman, G., Redhead, J. W., Brown, M., Pinnington, E., Gerard, F., Brown, M., Fincham, W., Robinson, E. L., Huntingford, C., & Pywell, R. F. (2024). A framework for improved predictions of the climate impacts on potential yields of UK winter wheat and its applicability to other UK crops. Climate Services, 34, 100479.

Höglind, M., Van Oijen, M., Cameron, D., & Persson, T. (2016). Process-based simulation of growth and overwintering of grassland using the BASGRA model. Ecological Modelling, 335, 1–15.

Hu, T., Zhang, X., Khanal, S., Wilson, R., Leng, G., Toman, E. M., Wang, X., Li, Y., & Zhao, K. (2024). Climate change impacts on crop yields: A review of empirical findings, statistical crop models, and machine learning methods. Environmental Modelling and Software, 179, 106119.

Jabed, M. A., & Azmi Murad, M. A. (2024). Crop yield prediction in agriculture: A comprehensive review of machine learning and deep learning approaches, with insights for future research and sustainability. Heliyon, 10(24), e40836.

Kayode Ayinde, O. O. A., & Nwosu, U. I. (2021). Solving multicollinearity problem in linear regression model: The review suggests new idea of partitioning and extraction of the explanatory variables. Journal of Mathematics and Statistics Studies, 2(1), 12–20.

Kumar, V., Sharma, K. V., Kedam, N., Patel, A., Kate, T. R., & Rathnayake, U. (2024). A comprehensive review on smart and sustainable agriculture using IoT technologies. Smart Agricultural Technology, 8, 100487.

Li, C., Camac, J., Robinson, A., & Kompas, T. (2025). Predicting changes in agricultural yields under climate change scenarios and their implications for global food security. Scientific Reports, 15(1), 2858.

Lobell, D. B., & Burke, M. B. (2010). On the use of statistical models to predict crop yield responses to climate change. Agricultural and Forest Meteorology, 150(11), 1443–1452.

Mahesh, P., & Soundrapandiyan, R. (2024). Yield prediction for crops by gradient-based algorithms. PLoS One, 19(8), e0291928.

Monfreda, C., Ramankutty, N., & Foley, J. A. (2008). Farming the planet: 2. Geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000. Global Biogeochemical Cycles, 22(1), GB1022.

Mushtaq, M. A., Ahmed, H. G. M.-D., & Zeng, Y. (2024). Applications of artificial intelligence in wheat breeding for sustainable food security. Sustainability, 16(13), 5688.

Mykhailyuk, T., Lisovets, O., & Tutova, H. (2023). Steppe vegetation islands in the gully landscape system: Hemeroby, naturalness and phytoindication of ecological regimes. Regulatory Mechanisms in Biosystems, 14(4), 581–594.

Nykytiuk, Y., & Kravchenko, O. (2024). Regulatory mechanisms in agroecosystems: A retrospective and forecast of spatial and temporal dynamics of precipitation as a factor of crop yield. Regulatory Mechanisms in Biosystems, 15(4), 688–695.

Nykytiuk, Y., Kravchenko, O., Pitsil, A., Bambura, V., & Seredniak, D. (2025). Global climate change may reduce the anti-erosion regulatory capacity of vegetation cover in Ukraine's Polissya and Forest-Steppe regions. Regulatory Mechanisms in Biosystems, 33(1), e25004.

Popović, V., Sikora, V., Berenji, J., Filipović, V., Dolijanović, Ž., Ikanović, J., & Dončić, D. (2014). Analysis of buckwheat production in the world and Serbia. Ekonomika Poljoprivrede, 61(1), 53–62.

Prajapati, H. A., Yadav, K., Hanamasagar, Y., Kumar, M. B., Khan, T., Belagalla, N., Thomas, V., Jabeen, A., Gomadhi, G., & Malathi, G. (2024). Impact of climate change on global agriculture: Challenges and adaptation. International Journal of Environment and Climate Change, 14(4), 372–379.

Rezaei, E. E., Webber, H., Asseng, S., Boote, K., Durand, J. L., Ewert, F., Martre, P., & MacCarthy, D. S. (2023). Climate change impacts on crop yields. Nature Reviews Earth and Environment, 4(12), 831–846.

Riahi, K., van Vuuren, D. P., Kriegler, E., Edmonds, J., O'Neill, B. C., Fujimori, S., Bauer, N., Calvin, K., Dellink, R., Fricko, O., Lutz, W., Popp, A., Cuaresma, J. C., Kc, S., Leimbach, M., Jiang, L., Kram, T., Rao, S., Emmerling, J., Tavoni, M. (2017). The shared socioeconomic pathways and their energy, land use, and greenhouse gas emissions implications: An overview. Global Environmental Change, 42, 153–168.

Schauberger, B., Jägermeyr, J., & Gornott, C. (2020). A systematic review of local to regional yield forecasting approaches and frequently used data resources. European Journal of Agronomy, 120, 126153.

Shafiee-Jood, M., & Cai, X. (2016). Reducing food loss and waste to enhance food security and environmental sustainability. Environmental Science and Technology, 50(16), 8432–8443.

Tchonkouang, R. D., Onyeaka, H., & Nkoutchou, H. (2024). Assessing the vulnerability of food supply chains to climate change-induced disruptions. Science of the Total Environment, 920, 171047.

Tutova, H., Ruchiy, V., Khrystov, O., Lisovets, O., Kunakh, O., & Zhukov, O. (2025). Influence of morphology and functional properties of floodplain water bodies on species diversity of macrophyte communities. Regulatory Mechanisms in Biosystems, 33(1), e25012.

Verma, K. C., Rana, A. S., Joshi, N., & Bhatt, D. (2020). Review on common buckwheat (*Fagopyrum esculentum* Moench): A potent Himalayan crop. Annals of Phytomedicine, 9(2), 125–133.

Verza, M., Camanzi, L., Mulazzani, L., Giampaolo, A., Rodriguez, S., Malorgio, G., & Mattas, K. (2025). Underutilized crops for diversified agri-food systems: Spatial modeling and farmer adoption of buckwheat in Italy. Frontiers in Sustainable Food Systems, 9, 1534246.

Virili, A., Marusig, D., Vedove, G. D., & Marraccini, E. (2024). Buckwheat (*Fagopyrum esculentum* Moench.) as an emerging companion crop in annual cropping systems: A systematic review. Italian Journal of Agronomy, 19(1), 100006.

Weymann, W., Böttcher, U., Sieling, K., & Kage, H. (2015). Effects of weather conditions during different growth phases on yield formation of winter oilseed rape. Field Crops Research, 173, 41–48.

Yakovenko, V., & Zhukov, O. (2021). Zoogenic structure aggregation in steppe and forest soils. In: Dmytruk, Y., & Dent, D. (Eds.). Soils under stress. Springer International Publishing, Cham. Pp. 111–127.

Zamaratskaia, G., Gerhardt, K., Knicky, M., & Wendin, K. (2024). Buckwheat: An underutilized crop with attractive sensory qualities and health benefits. Critical Reviews in Food Science and Nutrition, 64(33), 12303–12318.

Zeng, X., Lu, H., Qi, H., & Ji, L. (2025). Does extreme weather affect the resilience of agricultural economies? Analysis based on agricultural insurance. Frontiers in Environmental Science, 13, 1551030.

Zhukov, O., Kunah, O., Dubinina, Y., & Novikova, V. (2018). The role of edaphic, vegetational and spatial factors in structuring soil animal communities in a floodplain forest of the Dnipro river. Folia Oecologica, 45, 8–23.

Zymaroieva, A., Zhukov, O., Fedoniuk, T., Pinkina, T., & Hurelia, V. (2021). The relationship between landscape diversity and crops productivity: Landscape scale study. Journal of Landscape Ecology, 14(1), 39–58.

Zymaroieva, A., Zhukov, O., Fedoniuk, T., Pinkina, T., & Vlasiuk, V. (2021). Edaphoclimatic factors determining sunflower yields spatiotemporal dynamics in Northern Ukraine. OCL, 28, 26.

Zymaroieva, A., Zhukov, O., Fedonyuk, T., & Pinkin, A. (2019). Application of geographically weighted principal components analysis based on soybean yield spatial variation for agro-ecological zoning of the territory. Agronomy Research, 17(6), 2460–2473.

Zymaroieva, A., Zhukov, O., Romanchuck, L., & Pinkin, A. (2019). Spatio-temporal dynamics of cereals grains and grain legumes yield in Ukraine. Bulgarian Journal of Agricultural Science, 25(6), 1107–1113.