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Integrating climate change into pattern-based modelling of agricultural and forest land dynamics in Romania

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Abstract. Climate change is increasingly reshaping land-use/land-cover dynamics worldwide, yet the magnitude and spatial distribution of these changes remain insufficiently understood at the regional scale. This study assesses the potential impact of near-future climatic conditions on agricultural and forest lands in Romania, by integrating three climate projections, namely *SSP1–2.6*, *SSP3–7.0*, and *SSP5–8.5*, into a spatially explicit land-use pattern-based modelling framework, i.e., *CLUE-s* model (*the Conversion of Land Use and its Effects at Small regional extent*). To isolate the climatic signal, non-climatic drivers were held constant across scenarios, while changes in temperature and precipitation were introduced as the only dynamic inputs. The results indicate a generally high persistence of agricultural and forest classes, suggesting limited overall spatial reorganization up to 2050. However, several agricultural and forest classes exhibit localized shifts and transition hotspots, particularly in mountain regions, indicating increased sensitivity to changing climatic conditions. Across scenarios, temperature appears to exert a more consistent influence than precipitation on the projected spatial redistribution of these land systems. These findings highlight the need for regionally adaptive land-management strategies to support climate-resilient agricultural and forestry sectors.

Keywords: Climate signal; Spatially explicit land-use modelling; Agricultural and forest land transitions; Climate change scenarios (SSPs); Romania

1. Introduction

Changes in land-use/land-cover (LULC) patterns have become central to the current environmental agenda given their role in climate change mitigation and adaptation (Winckler et al., 2021), and their importance for land management decisions for sustainable development (Alijani et al., 2020). Climate change is reshaping LULC dynamics worldwide. However, the magnitude and distribution of these transformations remain poorly understood. As previous studies have shown (e.g., Dunford et al., 2015; Fronzek et al., 2019; Raad and White, 2025), LULC is a dynamic and complex phenomenon caused by the interactions of different natural and socioeconomic factors. Although there is a clear interconnection between climate change and LULC (IPCC, 2019), their effects across time and space are not yet fully understood (Barati et al., 2023); therefore, it becomes essential to understand future LULC trends in connection with climate change. Climate change directly influences LULC patterns by altering agricultural productivity (Ahmad et al., 2026), water availability (Mbewu et al., 2024), vegetation distribution (Rosenfield et al., 2025), forest health (Camarero and Gazol, 2022), or land degradation (IPCC, 2019; 2022). Moreover, climate change has profound implications for the configuration of regional landscapes (Arnell et al., 2019; Yang et al., 2024). This evolution can lead to declines in the

delivery of essential ecosystem services (Weiskopf et al., 2020), biodiversity loss (Tefera et al., 2025), and food security (Mirzabaev et al., 2023), all of which are linked to LULC change pathways (Gurgel et al., 2025). Thus, identifying climate-resilient landscape sites across various spatial scales to sustain biodiversity becomes very important (Rosenfield et al., 2025). Several studies have identified a strong correlation between climate drivers and LULC patterns (e.g., Münch et al., 2019; Zewdu et al., 2025), which mainly affects agriculture and forestry (e.g., Beach et al., 2015; Arora et al., 2020).

A critical, yet often overlooked, dimension of LULC dynamics is the intensifying competition for land (Hunsberger et al., 2017), especially between the agricultural and forestry sectors, as the demand for both timber and food is projected to rise (Bousfield et al., 2024). This is likely to generate spatial trade-offs and pressure for land conversion from forestry to agricultural land use (Murray and Diochon, 2026), among others. These sectors are recognized as playing an essential role in carbon sequestration, biodiversity conservation, and nature restoration within recent European policy frameworks, including the European Green Deal (commission.europa.eu/strategy-and-policy/priorities-2019-2024/european-green-deal_en). Moreover, specific climate and biodiversity targets covering agricultural and forest land have been established for 2030 or 2050 in the EU Forest Strategy for 2030, the Nature Restoration Law, the Common Agricultural Policy, and the Biodiversity Strategy, all requiring further studies at regional and local levels to better understand the implications of these policy directions for future landscapes. In this respect, understanding the future dynamics of agriculture and forestry under climate change scenarios at different scales is highly necessary to properly design sustainable land management strategies (Foley et al., 2005; Verburg et al., 2011).

Numerous modelling approaches have been developed to simulate agricultural and forest land dynamics across different spatial and temporal scales, ranging from statistical to pattern- and agent-based models, as widely reported in review studies (e.g., Noszczyk, 2019; Bhatt and Bisht, 2026). Several studies have addressed spatially explicit LULC modeling in Romania for different purposes, focusing primarily on socio-economic and environmental drivers (e.g., Malek et al., 2015; Kucsicsa et al., 2019; Kucsicsa et al., 2022). However, they do not incorporate climate change scenarios, which limits their ability to account for the potential influence of future climate on LULC patterns. Therefore, this study aims to fill this gap by providing a spatially explicit framework for identifying areas potentially exposed to future climatic pressures and changes in land suitability, with a focus on agricultural and forest systems, while holding non-climatic drivers constant. Among these, topography, soil properties, socio-economic conditions, distance factors, and protective measures are the ones taken into consideration in the analysis. Such an approach can help clarify the relative contribution of climate to future agricultural and forest land dynamics (Wang et al., 2017), while also supporting evidence-based policymaking through the early identification of vulnerable agricultural and forest systems and areas suitable for ecosystem restoration (Verburg et al., 2002; Rounsevell et al., 2012), guiding informed land management decisions (Gomes et al., 2020; Gurgel et al., 2025). To achieve this aim, the current study uses three climate change-related scenarios (2019–2050), which are compared with a baseline scenario representing current climatic conditions, modeled through a spatially explicit modelling framework, namely the *CLUE-s* model (*the Conversion of Land Use and its Effects at Small regional extent*).

Subsequently, several indicators are used to quantify the spatial reorganization of LULC patterns under changing climatic conditions. The findings may contribute to a growing understanding of how climate–land use and land cover interactions could shape future agricultural and forest landscapes, and may provide a methodological framework for integrating climate scenarios into spatial planning and

sustainable land management.

2. Methods

2.1. Study Area

The study was conducted in Romania, a South-Eastern European country covering around 238,400 Km², which presents a highly diverse landscape that includes 42% of the Carpathian Mountains (Fig. 1a). The area is characterized by a continental climate (Bogdan et al., 2016) with diverse climatic conditions due to its wide elevational range and relief morphology. The multiannual average temperature ranges from -2.5 °C to 11.5 °C, while annual precipitation ranges from 350 mm to 1600 mm. The agricultural land covers a considerable part of the country (12,689,000 ha, approximately 53% of the country's total area), including arable land, permanent grasslands, permanent crops, and kitchen gardens, ranking Romania 5th in the EU (8.1% of total) (Eurostat, 2024; <https://ec.europa.eu/eurostat/databrowser/view/tag00025/default/table?lang=en>). At the same time, forests cover 6,957,000 ha (approximately 29% of the country's total area), including broadleaved, coniferous and mixed woodland, ranking Romania 10th among EU Member States (3.5% of total) (Eurostat, 2025; https://ec.europa.eu/eurostat/databrowser/view/for_area/default/table?lang=en&category=for.for_sf).

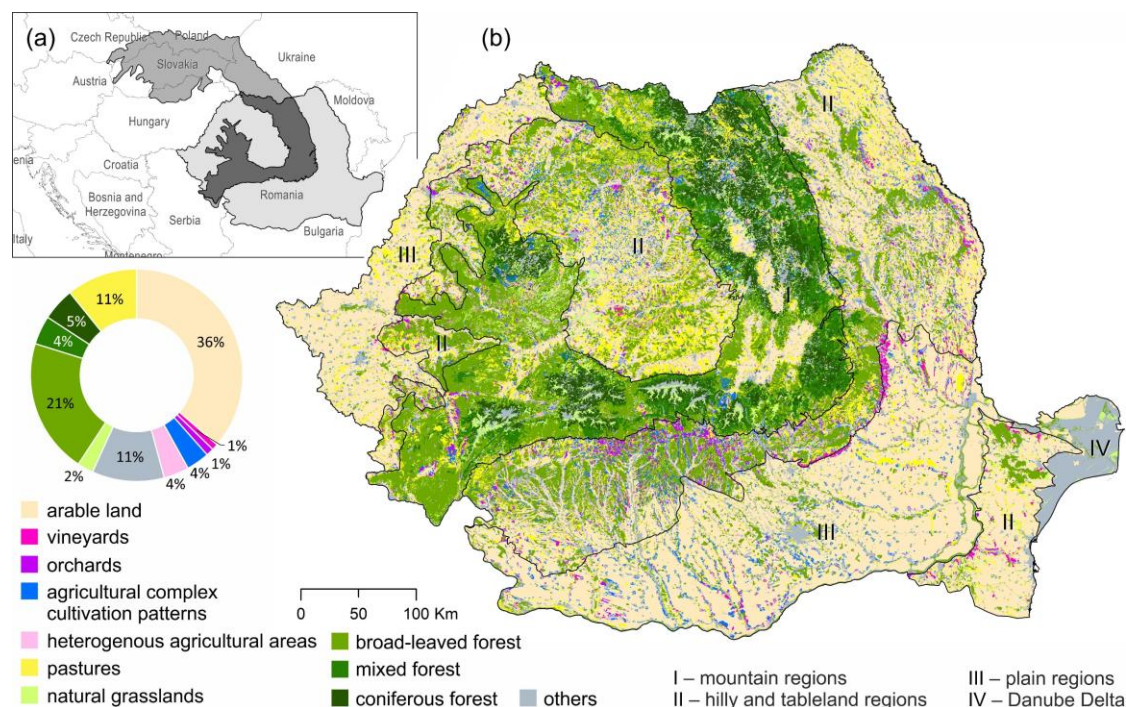


Figure 1. Position of Romania (a) and the current distribution of agricultural and forest classes (b) (CLC, 2018). Maps created using QGIS 3.16 (<https://www.qgis.org/project/visual-changelogs/visualchangelog316/>); graph produced using Microsoft Excel 2021 (<https://www.microsoft.com>)

Agricultural and forest lands exhibit strong regional variability, particularly in relation to the major relief

units (Fig. 1b). According to the latest Corine Land Cover (CLC) inventory (EEA, 2018), agricultural lands and forest vegetation are distributed in Romania as follows: *the mountainous region* (the Carpathians) is dominated by forests (60% of the total forested area), with a low share of agricultural land (13% of the total agricultural area); *the hilly and tableland regions* are mainly covered by agricultural land (48% of the total), but also contain a significant share of forests (35% of the total); *the plain region* is likewise dominated by agricultural land (39% of the total), while forests account for a small share only (5% of the total). As expected, the smallest areas of agricultural land and forest vegetation are found *in the Danube Delta* (0.3% and 0.6%, respectively).

This marked relief-related differentiation makes Romania a relevant case study for examining the spatial response of agricultural and forest systems to changing climatic conditions. The strong contrast between lowland agricultural areas and mountain forest landscapes provides a suitable framework for analysing potential shifts in land suitability and spatial reorganisation under future climate scenarios.

2.2. Methodology

To analyze agricultural and forest land dynamics under projected climate conditions for 2019–2050, a spatially explicit simulation framework of LULC patterns was implemented, integrating environmental and socioeconomic driving factors. Furthermore, several procedures were applied to explore the potential contribution of climate change to LULC spatial shifts, the magnitude of change, and transition trajectories. The methodological workflow is presented in Figure 2, illustrating the general structure of the approach adopted in this study.

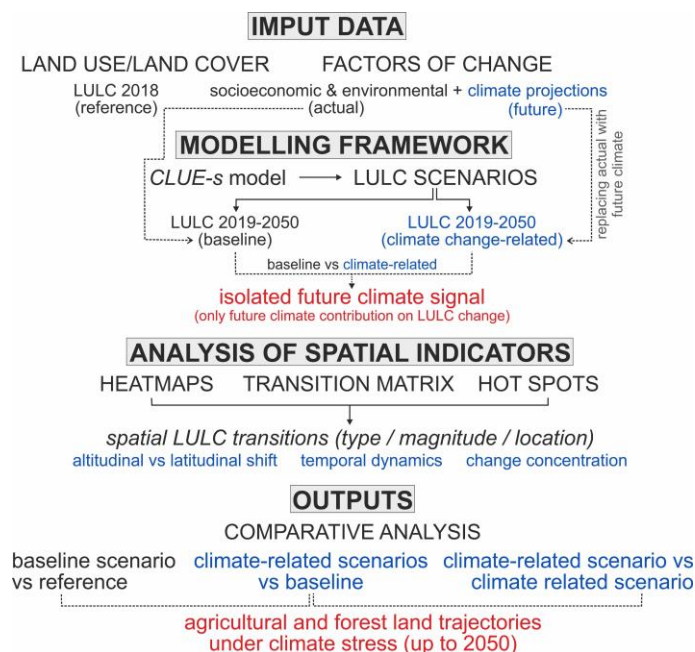


Figure 2. Schematic representation of the methodological workflow. Color coding: black = core workflow and reference/baseline components; blue = climate change-related components; red = climate signal and resulting land-use trajectories

Land use/land cover datasets

To project LULC pattern dynamics, two datasets were derived from the CLC database, versions 2006 and 2018 (EEA, 2006; 2018). These inventories provide a highly relevant and detailed classification of land use types across Europe (García Álvarez and Camacho Olmedo, 2023). For modeling purposes, the LULC datasets were classified into 13 categories (see Table 1 in the Supplementary Materials), which aggregate 27 subclasses according to Level 3 of the CORINE nomenclature. The datasets were used to analyze two temporal reference points: first, historical LULC changes (2006–2018) used to support scenario construction; and second, the 2018 LULC dataset, used as the initial condition (“year 0”) for model simulation and as a reference for comparative analysis of the projected LULC patterns. Given their characteristics, certain LULC categories, namely water bodies, wetlands, mineral and dump sites, and rocks, were not included in the simulation process. As a result, the simulations covered a total surface area of 23,057,800 ha (97% of the country’s total area).

CLUE-s modelling framework

LULC pattern scenarios were modelled using a spatially explicit *CLUE-s* model, which has proven effective for predicting LULC dynamics by considering both spatial and temporal dependencies (Verburg et al., 2002, 2005; Verburg, 2010), and combines statistical analyses and decision rules that determine the sequence of LULC types (Schaldach and Priess, 2008). It is widely used for simulating qualitatively and quantitatively LULC change under alternative scenarios at relatively fine spatial resolution, providing accurate data support for developing regional future ecosystem trajectories (Feng et al., 2023). The model requires several key parameters, briefly described below, with detailed descriptions provided in the Supplementary Materials (Key parameters required by the *CLUE-s* model):

- i) The *LULC demand*, defining the scenario-specific requirements for each LULC class over the simulation period, which in this study were estimated from observed historical dynamics and extrapolated to the simulation horizon based on the linear trends identified for 2006–2018;
- ii) The *LULC location characteristics*, describing the relationship between the LULC pattern and its determining factors using a binomial logit model, which defines the spatial preference of each LULC class;
- iii) The *LULC-specific conversion*, which determines the temporal dynamics of the simulations by setting conversion elasticity and *LULC* transition sequences;
- iv) *Spatial policies and restrictions*, indicating areas where LULC changes are not allowed for specific transitions due to land management constraints.

Based on these requirements, the model simulates spatial changes in LULC pattern in response to predefined land demand and location-specific suitability. At each time step, the most likely changes were calculated for each grid cell based on location suitability and competition among LULC types, determined by demand, conversion settings, and spatial constraints. In the present study, the model was used as a controlled scenario framework, with the modelling workflow structured to isolate the potential effects of climate change on LULC patterns. Specifically, the climatic inputs, namely mean temperature and precipitation during the growing season, were varied across the baseline scenario, which used recent observed climate conditions as the reference, and the climate-change scenarios, which incorporated projected changes, while all other environmental and socioeconomic driving factors were kept constant. This approach enables the simulated changes in agricultural and forest lands to be interpreted as potential climate-induced responses rather than comprehensive projections of future LULC change.

Understanding the climate contribution to agricultural and forest lands

To quantify the relative importance and directional contribution of climate to LULC patterns, SHAP (*SHapley Additive Explanations*; Lundberg & Lee, 2017) and SHAP dependence plots were applied. This framework provides a unified approach for interpreting variable effects in complex models, enabling direct comparison of specific drivers with all other factors in terms of their contribution to model predictions. In this study, SHAP and SHAP dependence plots were used to examine the relative contribution of temperature- and precipitation-related predictors within the broader set of environmental and socioeconomic variables included in the suitability modelling process. The SHAP values and SHAP dependence plots were computed for each binomial logistic regression model using a linear explainer.

Deriving land use scenarios in the climate change context

To explore the potential effects of climate change on agriculture and forest patterns, four scenarios were developed and modelled. The first is a baseline scenario (S_b), modelled in accordance with current socioeconomic and environmental conditions, including observed recent climate used as a static reference input, and three future climate-change scenarios constructed under the same environmental and socioeconomic assumptions, except for the climatic variables, which were replaced by the three climate projections used as dynamic inputs. The three future scenarios incorporated contrasting climate projections aligned with the Shared Socioeconomic Pathways (SSPs) presented in the IPCC AR6 (IPCC, 2023): i) *SSP1–2.6*, a low-emission scenario that assumes strong climate policies and rapid technological advancements in mitigation (Ferreiro-Lera et al., 2026); ii) *SSP3–7.0*, a high-emission scenario representing a "middle of the road" pathway with moderate climate policies (Shiogama et al., 2023); and iii) *SSP5–8.5*, a high-emission scenario with little to no mitigation efforts, leading to significant warming and climate instability (Riahi et al., 2017). The projections used in this study span the period from 2019 to 2050. The selected variables include mean seasonal temperature and precipitation, considered key indicators of climate variability affecting the LULC system. Their changes are expected to influence water availability, with impacts on crop yields (Birsan et al., 2026), evapotranspiration rates (Sonny et al., 2026), and forest productivity and species distribution (Prăvălie et al., 2023). Accordingly, our working hypothesis assumes that changes in thermal and pluvial regimes will lead to shifts in the spatial distribution of agricultural and forest lands, while non-climatic drivers remain constant throughout the modelling period. In this respect, changes in agricultural and forest lands are quantified exclusively as potential responses to the modelled climatic variation. Therefore, the resulting LULC patterns should be interpreted as potential climate-induced responses, assuming that other environmental and socioeconomic conditions remain constant, rather than as comprehensive forecasts of future LULC change driven by multiple interacting driving forces.

Predictive power of the model

Due to the lack of comparable spatially explicit LULC datasets, model validation was conducted only using a statistical approach. Specifically, the predictive performance of the suitability models was evaluated using the AUC-ROC (*Area Under the Receiver Operating Characteristic Curve*) method. This method assesses the goodness of fit of logistic regression models, similar to the R^2 statistics in ordinary least-squares regression (Verburg et al., 2005), and is commonly applied in the validation of raster-based

spatial modelling (Pontius et al., 2001, Mas et al., 2013). It is particularly appropriate for the *CLUE-s* framework, which operates with continuous probability values (Verburg et al., 2005). Although this procedure does not provide a full spatial validation of simulated future patterns, it offers an evaluation of the explanatory capacity of the suitability modelling component used within the *CLUE-s* framework.

Additional procedures

To estimate spatial trends in air temperature and precipitation, the non-parametric *Mann–Kendall test* (Kendall, 1975) was applied, while trend magnitude was quantified using *Sen’s slope estimator* (Sen, 1968). To account for serial autocorrelation, the *trend-free pre-whitening Mann–Kendall method* (TFPW-MK) proposed by Yue and Wang (2004) was implemented. This procedure removes the estimated trend, applies pre-whitening to eliminate first-order autocorrelation, and then restores the trend before performing the Mann–Kendall test, thereby reducing the influence of serial dependence in the trend analysis.

To further explore the spatial response of LULC patterns to changes in climatic variables, *bidimensional heatmaps* were used to characterize the distribution of LULC classes along altitudinal and latitudinal gradients. For this purpose, the average proportion of each LULC class was calculated across both gradients for each scenario. We also used a *LULC transition matrix* to capture the structural dynamics of pattern change. By considering persistence and the number, magnitude, and diversity of transitions among LULC classes, this approach allows a comparative assessment of changes in landscape structure across scenarios.

Furthermore, to identify *areas of concentrated LULC change* under climate change scenarios, we analysed the number and magnitude of transitions within 1 km² grid cells. Cells exceeding the 90th percentile were selected as *hotspots*, highlighting areas with the most pronounced and ecologically significant LULC transformations (Kuemmerle et al., 2016).

3. Results

3.1. Climatic influence on agricultural and forest dynamics

The SHAP analysis (Fig. 3) revealed that biophysical (X_1 – X_6) and distance-related variables (X_{13} – X_{15} , X_{20}) are the main factors shaping agricultural and forest land-use patterns. Climatic factors exert a moderate but class-specific contribution, while generally showing a greater influence than other environmental (X_5 and X_6) and socio-economic variables (X_7 – X_{12}). Overall, temperature shows a more consistent contribution across the analysed LULC classes, whereas precipitation remains particularly relevant for arable land, permanent crops, and broad-leaved forest. For individual agricultural and forest classes, the SHAP dependence plots, provided in the Supplementary Materials (Fig. 4), illustrate how the SHAP contributions of temperature and precipitation change across their observed value ranges. However, these patterns should be interpreted in light of covariation between climatic and other predictors included in the modelling.

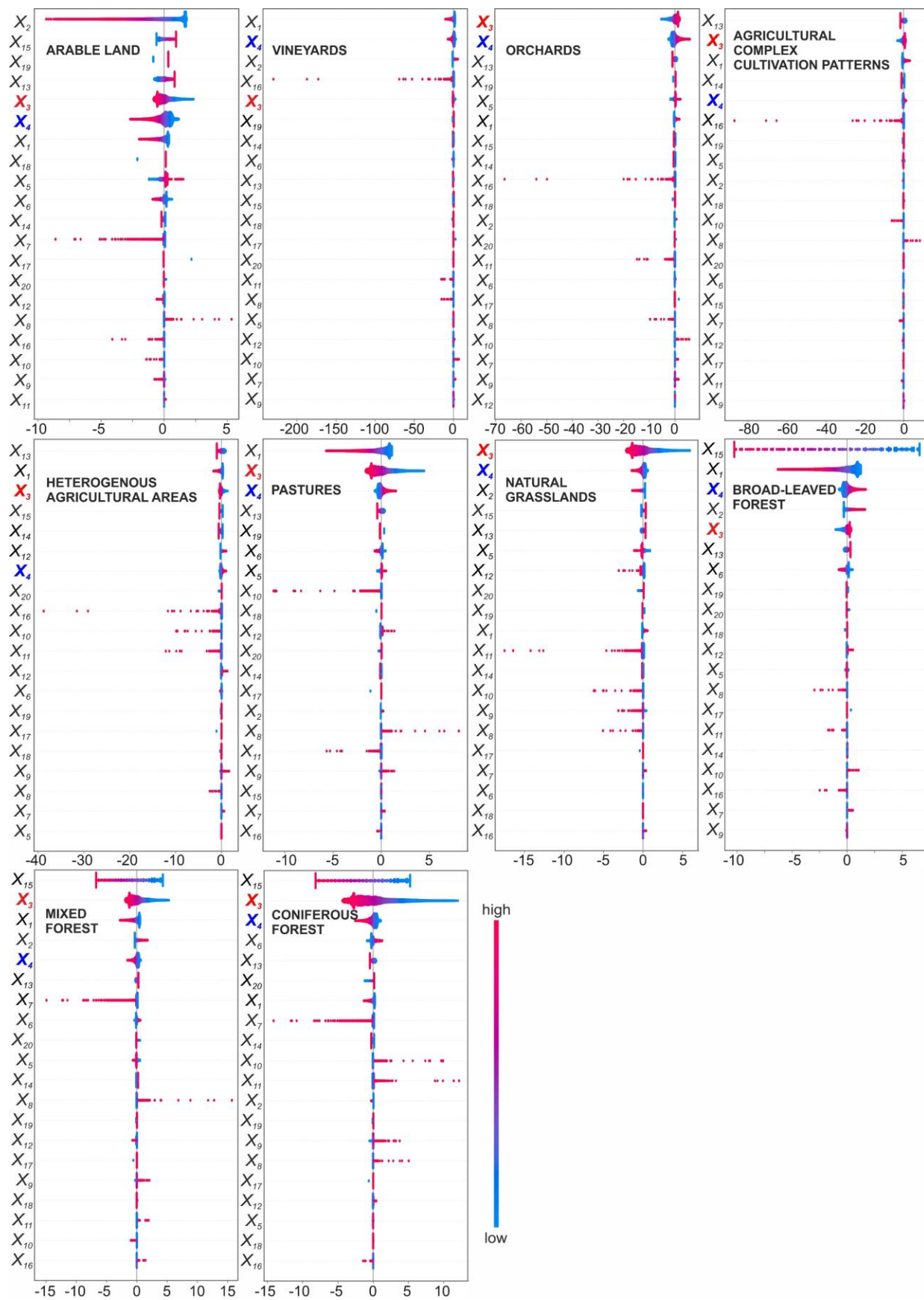


Figure 3. SHAP summary plots for the logistic regression models. Predictors are ranked from top to bottom according to the magnitude of their predictive contribution (mean absolute SHAP value). The predictors X_3 (Average temperature in the growing season) and X_4 (Average precipitation in the growing season) are highlighted in red and blue, respectively. X_1 – X_{20} designate the following drivers: X_1 – Altitude; X_2 – Slope; X_3 – Average temperature in the growing season; X_4 – Average precipitation in the growing season; X_5 – Available Water Capacities; X_6 – Organic content in top soil; X_7 – Population density; X_8 – Population 65+; X_9 – Permanent migration; X_{10} – Economically active population; X_{11} – Large livestock units; X_{12} – GDP ratio; X_{13} – Distance to Settlements; X_{14} – Distance to roads; X_{15} – Distance to afforested area; X_{16} – Average farm size; X_{17} – Major protected areas (National Parks); X_{18} – Major protected areas (Natural parks); X_{19} – Major protected areas (all); X_{20} – Distance to main cities. SHAP analysis and visualization were performed using Python 3.11.9 (<https://www.python.org>) and the SHAP package 0.48.0 (<https://shap.readthedocs.io/>)

3.2. The projected evolution of climate indicators

Table 1 provides a comparative analysis between observed mean climate patterns (1990–2018) and the projected values (2019–2050). The differences indicate spatially differentiated but overall moderate changes. Mountain and hilly regions, and the Danube Delta generally show slight increases, while plain regions exhibit minor decreases. When comparing deviations from the reference climatological mean, the calculations ($\Delta = T/PP_{2050} - T/PP_{1990-2018}$) indicate increases in temperature for all projections, with averages rising from 1.6 to 2.5°C, particularly in plain and mountain regions. Precipitation shows slight decreases across plain regions and the Danube Delta, while mixed trends are observed in mountain, hilly, and tableland regions. The projected differences in temperature and precipitation presented here were not statistically tested and should therefore be interpreted as projected changes rather than statistically significant differences.

Table 1. Comparison of historical (1990–2018) and projected (2019–2050) growing-season mean temperature and precipitation

	Major relief units	Period	MEAN			DEVIATION		
		1990-2018	SSP1–2.6	SSP3–7.0	SSP5–8.5	SSP1–2.6	SSP3–7.0	SSP5–8.5
Temperature (°C)	Mountain regions	13.5	14.8	14.8	15.0	1.5	2.0	2.4
	Hilly & tableland regions	17.4	18.8	18.7	19.0	1.5	1.9	2.4
	Plain regions	19.5	21.0	20.8	21.1	1.7	2.1	2.6
	Danube Delta	19.3	20.7	20.5	20.8	1.6	1.9	2.4
	AVERAGE	16.9	18.3	18.2	18.5	1.6	2.0	2.5
Precipitation (mm)	Mountain regions	588	606	599	607	19	-8	-9
	Hilly & tableland regions	415	428	426	429	13	-3	-7
	Plain regions	346	343	344	345	-7	-17	-21
	Danube Delta	199	202	204	200	-2	-3	-11

The spatial trend over 2019–2050 (Fig. 5) indicates an overall temperature increase of 0.28°C under the *SSP1–2.6* scenario, 1.48°C under the *SSP3–7.0* scenario, and 1.92°C under the *SSP5–8.5* scenario, as well as an overall precipitation decrease of 1.4 mm under the *SSP1–2.6* scenario, 34.6 mm under the *SSP3–7.0* scenario, and 49.5 mm under the *SSP5–8.5* scenario. All pixel-based trends were statistically significant ($p < 0.001$).

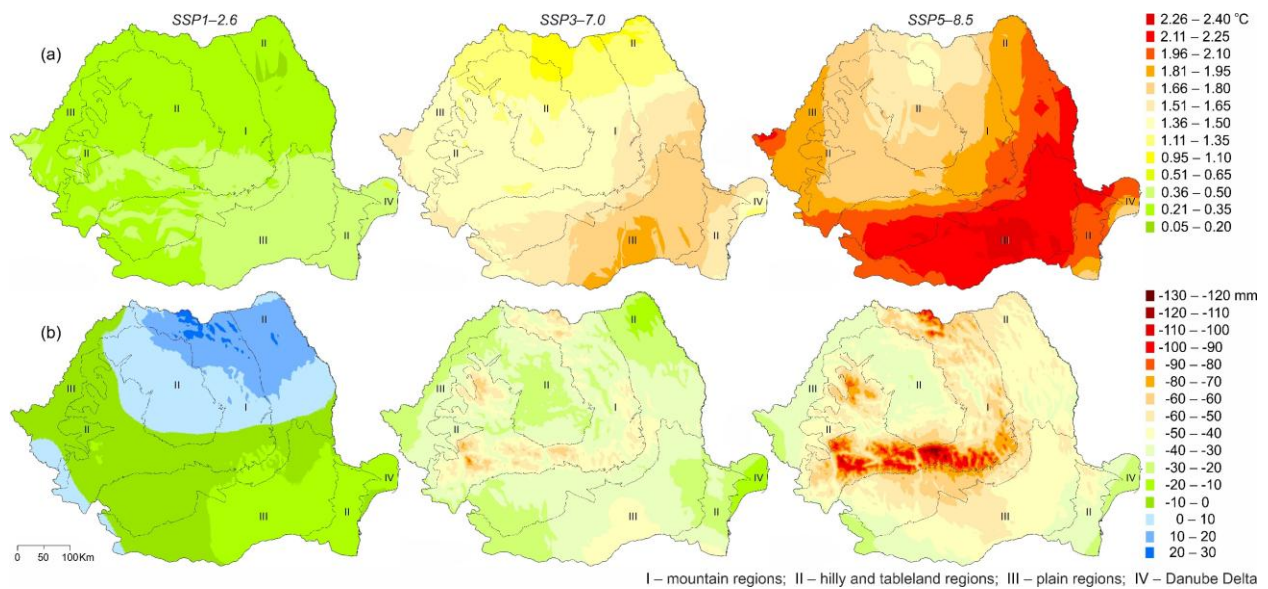


Figure 5. The spatial trends of temperature and precipitation during the growing season under the analysed climatic scenarios (2019-2050). Maps created using QGIS 3.16 (<https://www.qgis.org/project/visual-changelogs/visualchangelog316/>)

3.3. Agricultural and forestry dynamics

In general, except for arable land and natural grasslands under *SSP3–7.0*, all projected scenarios indicate a decrease in agricultural land compared with the reference year (2018) (Fig. 6a). At the same time, except for the mixed forest category under *SSP5–8.5*, forest land is projected to increase under all scenarios. Compared with the S_b scenario, the magnitude of changes associated with the climate change scenarios varies considerably (Fig. 6b). The *SSP1–2.6* and *SSP3–7.0* scenarios exhibit the largest negative deviations, whereas *SSP5–8.5* results in more moderate changes.

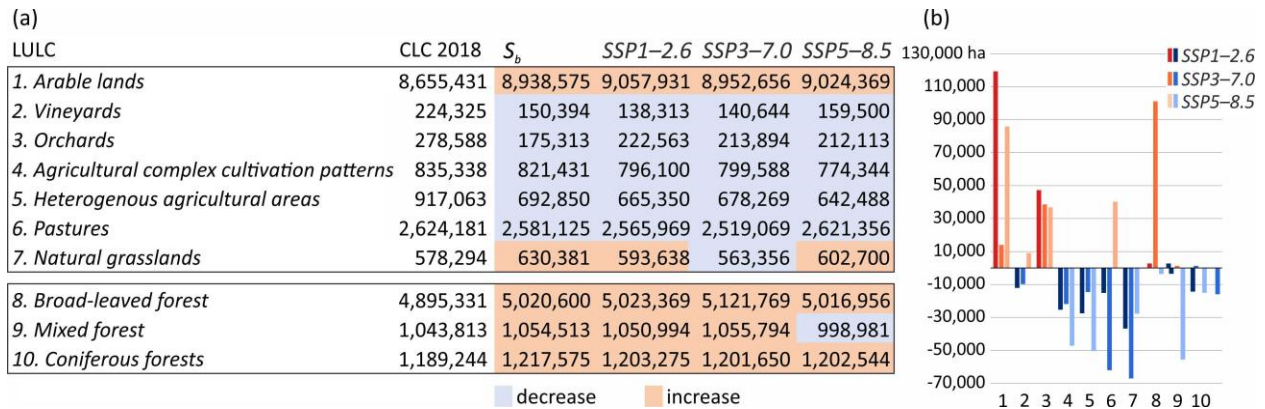


Figure 6. The estimated changes in agricultural and forest classes under different scenarios. Graphs produced using Microsoft Excel 2021 (<https://www.microsoft.com>)

The transition matrices shown in Figure 7 indicate that major gains are projected for arable land and complex cultivation patterns at the expense of pastures, while pastures are expected to expand over arable land, particularly in *SSP3–7.0* and *SSP5–8.5* relative to the S_b . Gains in broad-leaved forests are primarily indicated at the expense of pastures and arable land. Mixed forests are projected to expand mainly over pastures, whereas coniferous forests are projected to expand over natural grasslands. Compared with the S_b , in *SSP1–2.6*, 19,343,970 ha are projected to persist (64.1% agricultural land; 35.9% forests), while 1,599,484 ha are affected by internal and external transitions. In *SSP3–7.0*, persistence reaches 19,645,312 ha (64.3% agricultural land; 35.7% forests), with 1,696,100 ha undergoing transitions. Similarly, in *SSP5–8.5*, 19,499,168 ha (65.1% agricultural land; 34.9% forests) remain persistent, while 1,783,580 ha are projected to change. A slight net variation in the number of transition types (–1 for *SSP1–2.6*; +7 for *SSP3–7.0*; +8 for *SSP5–8.5*) was calculated compared with the baseline scenario (101), with more pronounced changes occurring in agricultural lands, particularly in heterogeneous agricultural areas, arable land, and natural grasslands.

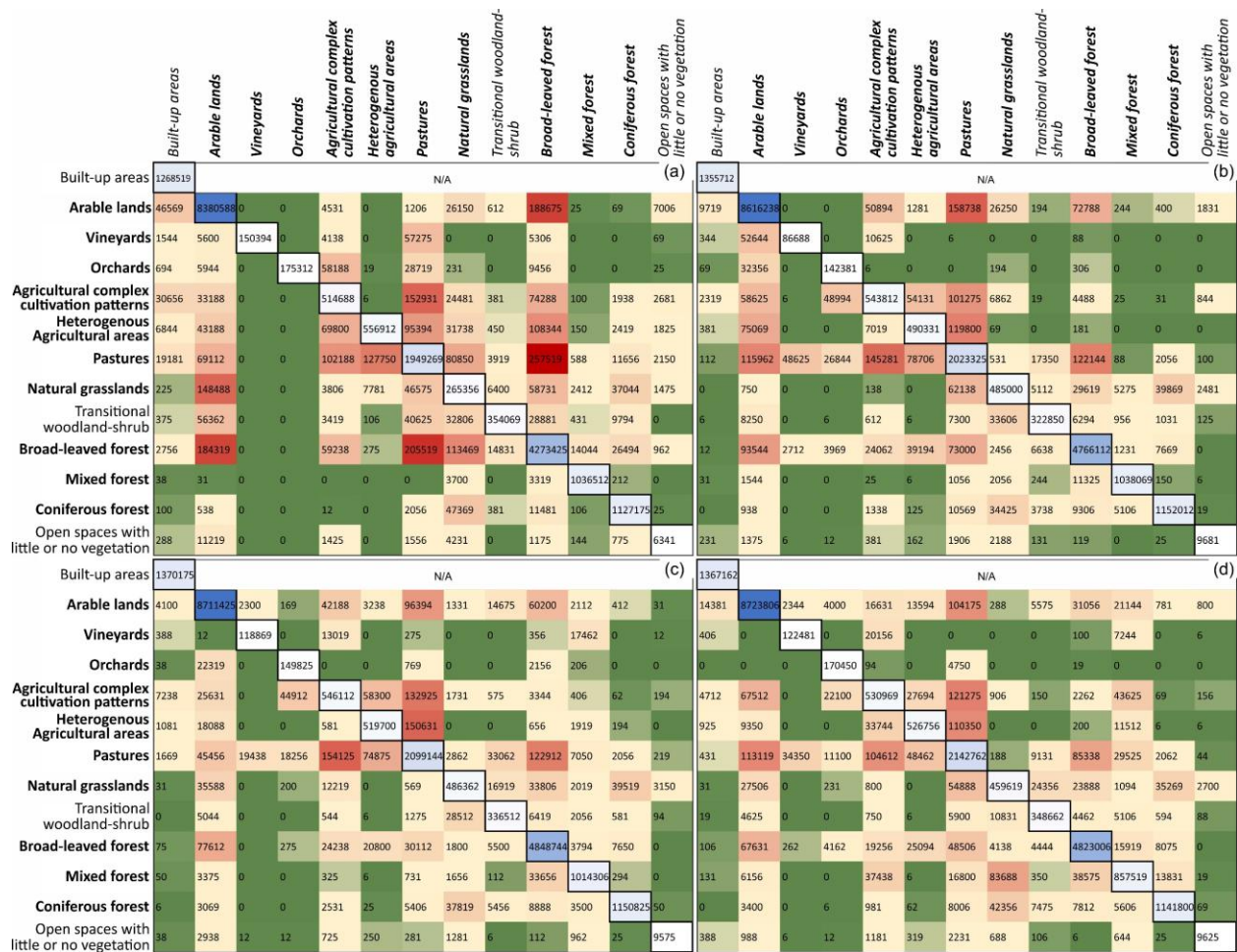


Figure 7. Land use/land cover transition matrices showing internal and external changes in agricultural and forest lands: baseline scenario (S_0) relative to the reference year 2018 (a); $SSP1-2.6$ scenario relative to the baseline scenario (b); $SSP3-7.0$ scenario relative to the baseline scenario (c); and $SSP5-8.5$ scenario relative to the baseline scenario (d). Note: N/A indicates not applicable transitions, due to the defined conversion constraints in the modelling procedure. Graphs produced using Microsoft Excel 2021 (<https://www.microsoft.com>)

Spatially, the modelled changes (Fig. 8a, b) exhibit heterogeneous patterns of climate-related response, with more pronounced differences among the major relief units. Figure 8c illustrates that class persistence remains dominant across all scenarios, with its extent increasing for agricultural lands and decreasing for forest lands as the severity of climate change intensifies. In terms of changes, internal agricultural transitions (i.e., increases and decreases in land-use intensity) dominate across all scenarios, with the highest magnitudes observed in $SSP1-2.6$. For forest classes, the most pronounced changes occur in mountain regions, where dominant transitions indicate forest expansion over agricultural lands, especially in $SSP3-7.0$ and $SSP5-8.5$, but also forest losses to agricultural uses, mainly in $SSP5-8.5$.

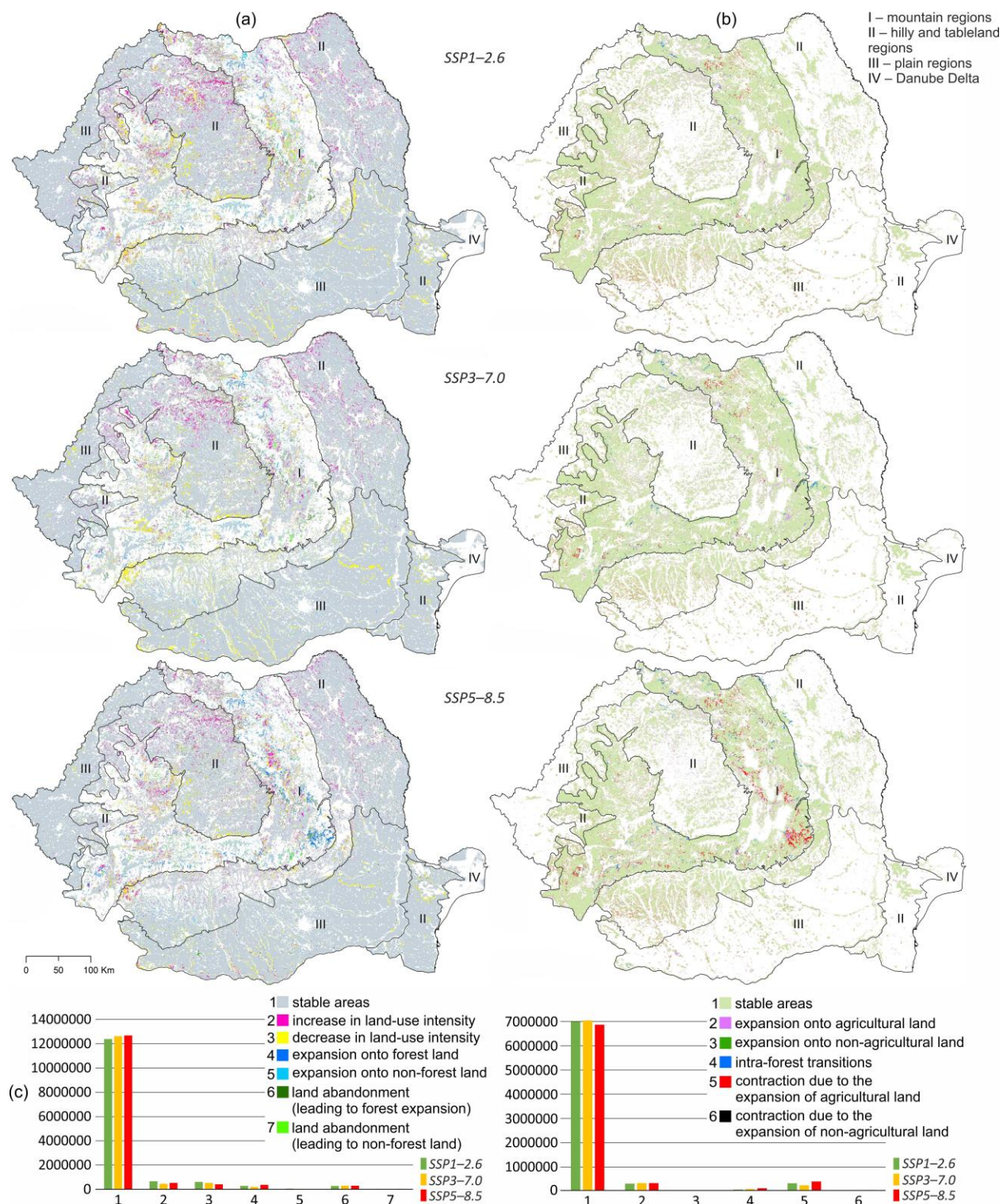


Figure 8. Spatial transitions induced by climate change in agricultural (a) and forest (b) lands, and their magnitude (c, in ha), under different climate change scenarios. Maps created using QGIS 3.16 (<https://www.qgis.org/project/visual-changelogs/visualchangelog316/>); graph produced using Microsoft Excel 2021 (<https://www.microsoft.com>)

Spatial shift analysis

The heat maps presented in Fig. 9 highlight the shifts among the analysed LULC classes across all scenarios, as derived from potential changes in their elevation and latitude. When focusing on the mean spatial distribution (centroid location), arable land and forest categories appear relatively stable, while other agricultural classes exhibit mixed patterns. A clearer signal emerges at the distribution margins, where arable land, complex cultivation patterns, and pastures generally show an expansion of their altitudinal range, whereas vineyards and heterogeneous agricultural areas exhibit a downward shift in altitude accompanied by an upward shift in latitude, particularly under *SSP3–7.0* and *SSP5–8.5*. Among forest classes, broad-leaved forests display a consistent upward shift across all climate scenarios, particularly above 46° latitude. Mixed forests maintain a relatively stable altitudinal range under *SSP1–2.6* but show a marked downward shift of the lower limit under *SSP3–7.0* and a downward shift of both upper and lower limits under *SSP5–8.5*. Coniferous forests exhibit simultaneous decreases in both upper and lower altitudinal limits across all scenarios, particularly above 46° latitude.

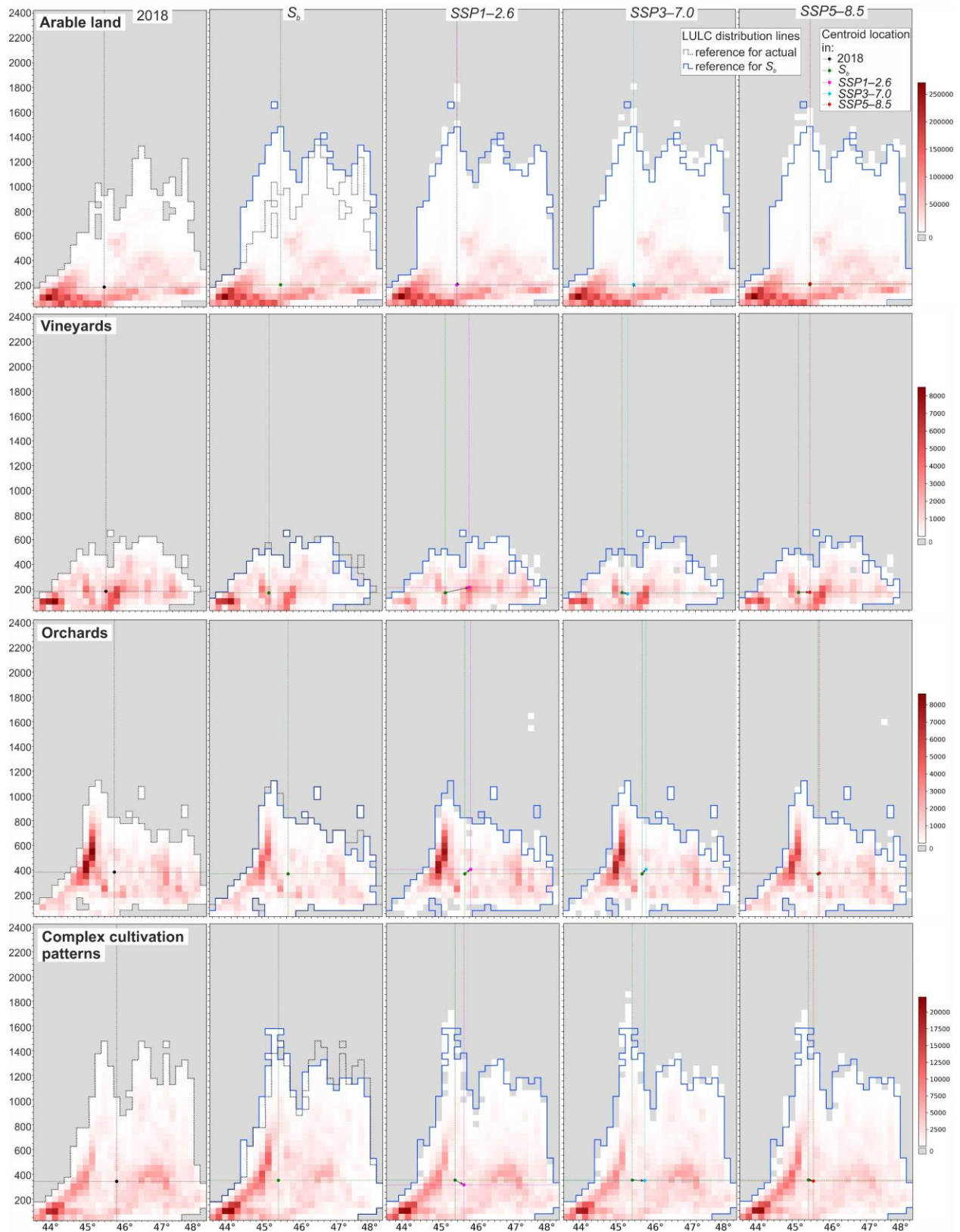


Figure 9. Heatmaps showing projected altitudinal (in m) and latitudinal shifts of agricultural and forest lands under climate change scenarios (SSP1-2.6, SSP3-7.0, SSP5-8.5) relative to the baseline scenario (S_b), and the baseline

scenario (S_b) relative to the reference year (2018). The heatmaps and their graphical representation were generated using Python 3.11.9 (<https://www.python.org>)

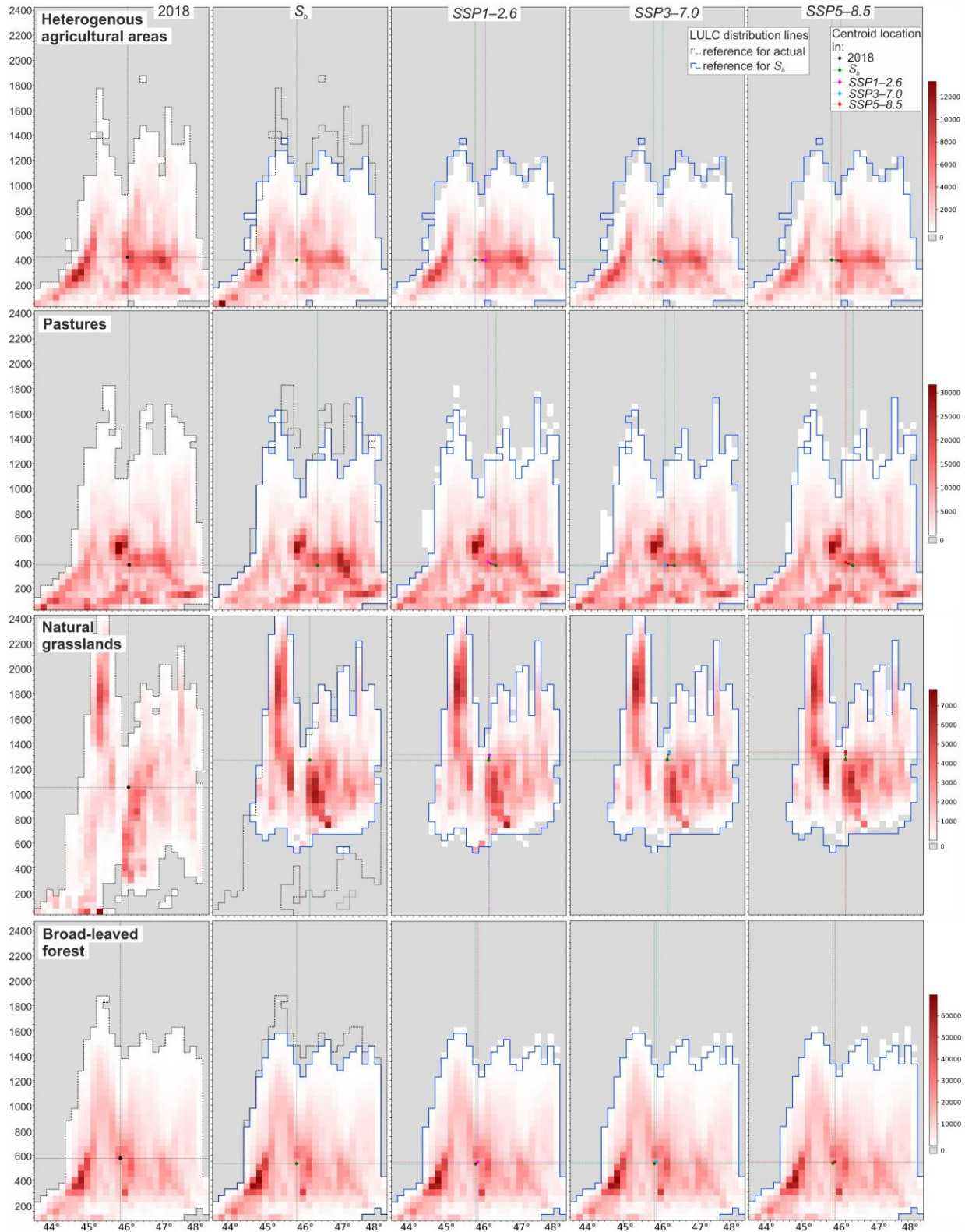


Figure 9. Continuation (a)

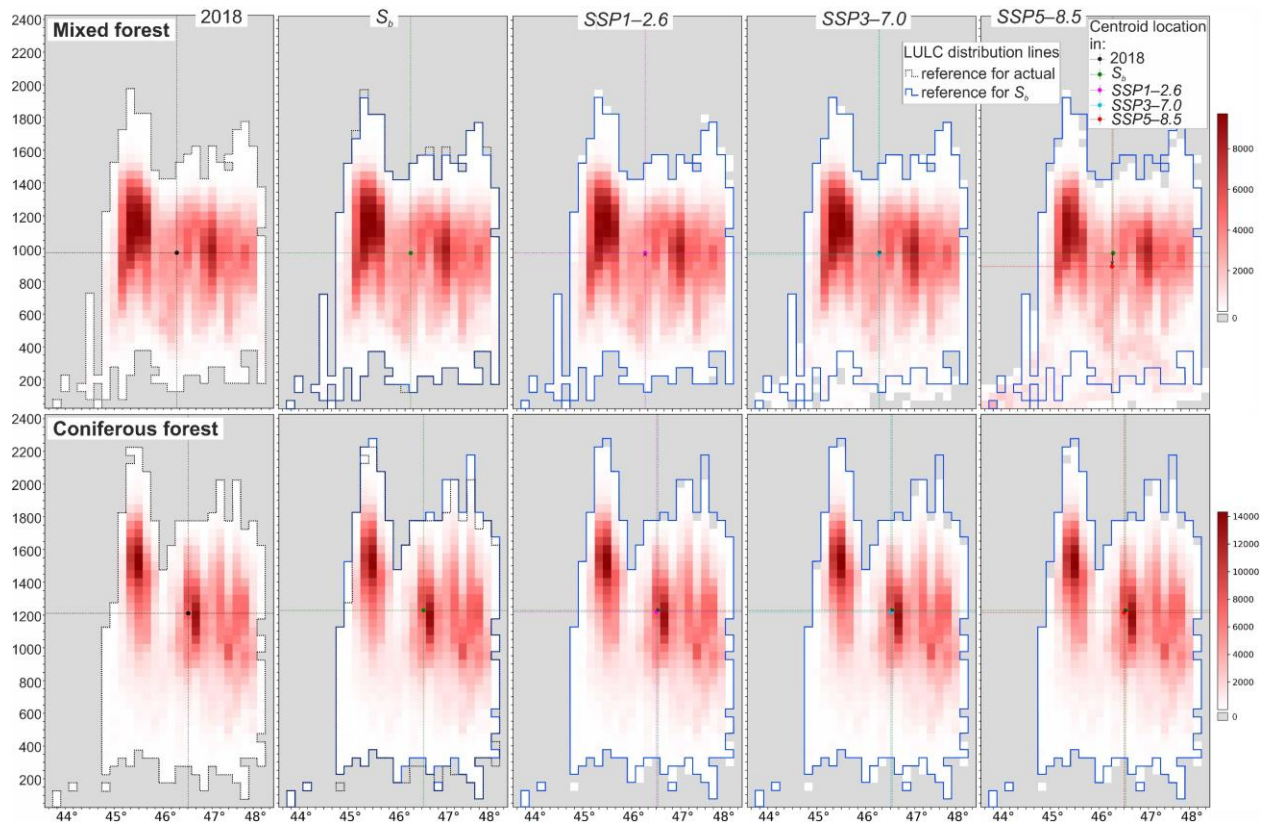


Figure 9. Continuation (b)

Regional hotspots

The analysis of hotspots (Fig. 10) reveals a significant concentration of analysed LULC changes across the study area. Early hotspots (*SSP1–2.6* relative to S_b) correspond to systems responding to mild climatic shifts, while those emerging under more severe scenarios (*SSP3–7.0* relative to S_b and *SSP5–8.5* relative to S_b , respectively) reflect delayed responses. Under *SSP1–2.6*, hotspots mainly involve agricultural internal dynamics, resulting in a relatively balanced pattern of increasing land-use intensity (transitions from lower- to higher-intensity uses) and decreasing intensity (transitions from higher- to lower-intensity uses), as well as internal forest transitions and gains linked to agricultural lands. Under *SSP3–7.0*, hotspots involve even more pronounced internal and external agricultural transitions, predominantly associated with decreasing land-use intensity and forest gains, while forest land is still mainly characterised by internal transitions, but to a greater extent than under *SSP1–2.6*. Under *SSP5–8.5*, hotspots are even more strongly dominated by external agricultural transitions linked to decreasing land-use intensity, whereas forest land increasingly exhibits external transitions associated with agricultural land use gains.

The hotspots are associated with increasing temperatures, with a mean rise of about 0.3 °C (in *SSP1–2.6*) and 1.35 °C (in *SSP3–7.0*) to around 1.8–2.0 °C (in *SSP5–8.5*), as well as a decrease in precipitation of about –5 mm (in *SSP1–2.6*) and –35...–40 mm (in *SSP3–7.0*) to approximately –55...–60 mm (in *SSP5–8.5*). The extent of LULC change does not increase proportionally with the scenario severity. For agricultural lands, it evolves from a mean value of 40% (under *SSP1–2.6*) to 36% (under *SSP3–7.0*) and further to 37% (under *SSP5–8.5*). In contrast, for forest lands, it increases from a mean value of 16%

(under *SSP1–2.6*) to 17% (under *SSP3–7.0*), reaching 24% (under *SSP5–8.5*).

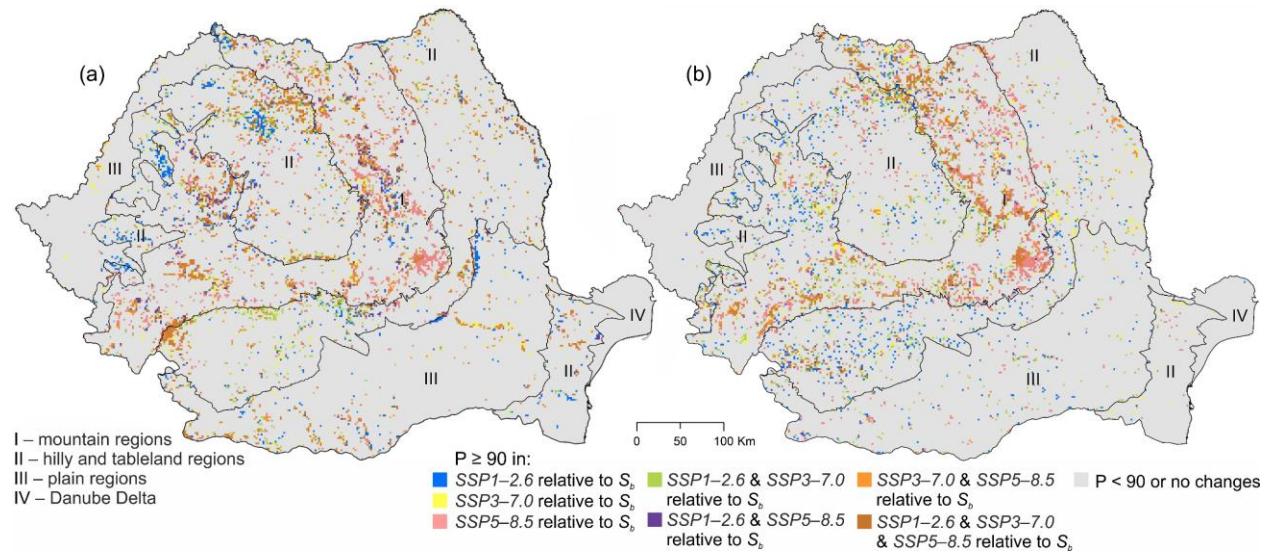


Figure 10. Hotspots of LULC changes across agricultural (a) and forest (b) lands under climate change scenarios relative to the baseline scenario. Hotspots were identified using Python 3.11.9 (<https://www.python.org>) and mapped using QGIS 3.16 (<https://www.qgis.org/project/visual-changelogs/visualchangelogs316/>)

Predictive power of the model

Statistical validation based on the AUC-ROC approach indicated satisfactory predictive performance of the probability outputs. The AUC values (see Table 4 in the Supplementary Materials) indicate a good agreement between the estimated suitability patterns and the observed distribution of LULC classes. With the exception of heterogeneous agricultural areas and pastures, the AUC values indicate a high explanatory capacity of the selected driving factors. These results support the adequacy of the suitability modelling component used in the *CLUE-s* framework, although they should not be interpreted as a full spatial validation of the projected LULC scenarios.

4. Discussion

Romania's climate clearly experiences warming trends and changes in precipitation patterns (Micu et al., 2021; Starea Climei – România, 2024; Birsan et al., 2025). These changes already increased LULC sensitivity, with particular vulnerability observed in agricultural (Sima et al., 2015; Alexandru et al., 2019; Gitea et al., 2019; Popescu et al., 2023) and forest (Prăvălie et al., 2014; García-Duro et al., 2021; Mihai et al., 2022) sectors. Hence, understanding how LULC systems will respond to climate change in the future becomes a central concern, as increasing climatic stress can alter both their spatial distribution and structural stability (Berger et al., 2019; Winkler et al., 2021; Xiu et al., 2026), and consequently influence LULC decisions and adaptation strategies (Lucash et al., 2017; Peng and Li, 2018; Asamoah et al., 2021; Effiong et al., 2024).

In this context, our results provide evidence of these processes: heatmaps reveal potential spatial shifts along altitudinal and latitudinal gradients, transition matrices highlight the magnitude and diversity of transformations, and hot-spot maps show the most significant changes by aggregating shift

characteristics. Overall, the observed high persistence may suggest a general stability of agricultural and forestry systems up to 2050. However, this reflects a reduction in the extent of land undergoing transitions, rather than a general stability of the systems. Moreover, several LULC classes exhibit transitions of varying magnitude. These dynamics suggest a redistribution of suitable climatic conditions, creating opportunities for expansion and relocation, as well as contractions where increasing climatic stress exceeds adaptive capacity. These processes become more pronounced under *SSP3–7.0* and especially *SSP5–8.5*, where shifts increase compared to the *SSP1–2.6*.

Our outcomes are broadly consistent with findings reported in similar studies. For example, research focusing on agricultural land-use dynamics under climate change indicates that shifts in temperature and precipitation regimes lead to both spatial expansion and reallocation of agricultural land (e.g., Anderson et al., 2020; Fan et al., 2020). These changes vary by region and by class of agricultural land, resulting in an expansion of suitability for cropland, particularly in the northern latitudes (Zabel et al., 2014). However, in the most sensitive regions, climatic stressors constrain productivity, leading to a decrease in agricultural land-use intensity (Anderson et al., 2020). Furthermore, studies emphasize that agricultural land-use transitions, including abandonment, represent a dominant component of LULC transformations (Winkler et al., 2021). Moreover, the expansion of agricultural area across five SSPs at the global level was found to be mainly associated with the reduction of forest and conversely, increasing forest land is linked to the reduction of agricultural area (Goebel and Britz, 2025). These findings support our results, which reveal comparable trends in agricultural land systems, including a general latitudinal increase in land-use intensity, particularly in the northern part of the country, reflecting a shift in climatic suitability toward higher latitudes. Concurrently, the localized decrease in land-use intensity and land abandonment in the southern regions indicates diminishing climate suitability and associated constraints. Moreover, although less pronounced, these patterns are further reinforced by a general positive altitudinal shift, suggesting that suitable climatic conditions for agricultural lands are also extending to higher elevations. Nevertheless, the differences in the magnitude of transitions between scenarios reflect distinct responses, potentially leading to restructuring and adaptation, depending on regional and local climate change specifics. The complexity of land-climate interaction and the increasing role of local conditions have been emphasized in studies before, with agricultural land abandonment and subsequent revegetation leading to a cooling effect in western and central Europe, but rather to a warming effect in eastern Europe (Huang et al., 2020), pointing to the importance of regional-specific approaches in land management strategies (Gvein et al., 2023).

Within the forest sector, changes in climate conditions also lead to patterned responses, especially in mountain environments, where climate change impacts occur more rapidly (Cudlin et al., 2017; Liu et al., 2018), thus accelerating altitudinal redistribution of forest species. At the same time, some species are expected to experience a contraction or restriction of their altitudinal range (La Sorte et al., 2010; Noce et al., 2023) due to changes in climatic suitability. Besides, landscape patterns can influence these climate-driven responses. For example, increased fragmentation in forest-cropland landscapes may alter forest sensitivity to climate stressors, leading to an overall temperature increase (Ferro et al., 2026), with forest transition being mentioned with the greatest impact on topsoil temperature (Ferro et al., 2025). Our results are aligned with this dynamic, although with limited magnitude, showing a positive altitudinal shift for broad-leaved forests, an expansion to lower altitudes for mixed forests, and relative stability or a slight negative trend for coniferous forests. The observed shifts indicate not only a structural reorganization of forest systems within their ecotone areas but also constraints on upslope expansion at the upper forest

limits, as reported in other studies (e.g., Engler et al., 2011; Noce et al., 2023). Similar to previous studies (e.g., Zolkos et al., 2015; Lenoir et al., 2020), our results also identified a northward latitudinal shift for both deciduous and coniferous forests, suggesting a gradual adjustment in response to changing climatic conditions.

We found distinct responses of the agricultural and forest sectors to changing climatic conditions. On one hand, the absence of a proportional increase in changes across scenarios suggests that the systems respond in a threshold-driven manner rather than following a linear pattern. On the other hand, agricultural land exhibits a greater spatial extent of change compared to forest systems, reflecting lower ecological inertia. In contrast, the lower responsiveness of forests may result from two combined effects. First, ecologically, forests are characterized by long life cycles and slow successional dynamics (Bugmann and Seidl, 2022), and their ability to track their optimal climate is generally lower than the rate of climate change (Lenoir et al., 2020). Second, model settings impose temporal constraints on forest transitions. Both are reflected in our observed internal transitions and forest expansion.

We show that the analysed LULC classes are largely persistent over the simulated period. However, the spatial pattern of changes exhibits pronounced heterogeneity. Mountain regions are particularly sensitive to climate change, with hotspots reflecting a shift from early responses to sustained sensitivity. Here, the growing dominance of agricultural land transitions from higher-intensity use to lower-intensity use points to a gradual decrease in agricultural land-use intensity, which may lead to agricultural land abandonment, especially in marginal areas, allowing the natural establishment of woody vegetation. In the forest sector, the observed dynamics reflect both internal restructuring and increasing exchanges with adjacent LULC classes, with these processes intensifying under more severe scenarios.

Within the present modelling approach, climate-only perturbations produced smaller changes than the baseline scenario, which is consistent with previous studies (e.g., Rounsevell et al., 2006; Dunford et al., 2015; Fronzek et al., 2019). Specifically, the exhibited heatmaps show that LULC changes simulated under S_b often exceed those simulated under climate-related scenarios, particularly for agricultural classes. These findings suggest that anthropogenic pressures may play a more significant role in shaping LULC dynamics than projected changes in mean temperature and precipitation during the growing season. In agricultural systems, this can be explained by the stronger influence of land management practices, policy frameworks, market dynamics, or declining interest in agricultural activities, which can rapidly drive land-use decisions and transitions compared to the more gradual effects of climate change. These findings are consistent with previous studies that outlined the complex interactions of the land use systems with socio-economic drivers, which may further lead to high regional differences and increased uncertainties (Goebel and Britz, 2025). Forest areas exhibit even more limited changes under all climate-related scenarios, suggesting lower sensitivity to climate change pressures, at least in the short term. As mentioned earlier, this relative stability may be explained by the long-life cycles and high ecological inertia of forest ecosystems, which buffer forests against climatic variability.

Limitations of the study

While the study provides valuable insights into the potential impacts of climate change on agricultural and forest lands in Romania, several limitations must be acknowledged that may influence the interpretation of the results. First, the LULC projections were based on the *CLUE-s* model, which, despite its effectiveness, depends heavily on the accuracy of input data and assumptions about transition probabilities. The extrapolation of future land demand is inherently uncertain, as it relies on historical LULC trends that may

not adequately reflect future changes in the factors driving LULC dynamics. Model parameterization and transition rules introduce additional uncertainty because they are based on assumptions regarding the suitability and likelihood of specific LULC conversions. In particular, the use of historical linear trends for land demand across all scenarios may not fully account for future changes in political, social, economic, or land-use management conditions. Nevertheless, limiting temperature and precipitation to the sole dynamic drivers allowed us to better isolate the climatic signal in the future projections. At the same time, temperature and precipitation alone may not fully capture the complexity of LULC responses to climate change, particularly for agricultural and forest classes, which may also be influenced by other climate-related factors, such as drought frequency and intensity or the occurrence of extreme weather events. Furthermore, due to the complexity and size of the datasets used, as well as the limitations of the *CLUE-s* model, the spatial resolution of the simulation does not fully capture local changes and therefore limits its ability to provide insights into land management practices at a finer spatial scale.

In addition, the CHELSA dataset is subject to several sources of uncertainty, primarily related to the underlying CMIP6 model outputs, statistical downscaling, and bias adjustment under the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP3b) protocol (Berio Fortini et al., 2023; Karger et al., 2023). Spatial interpolation artifacts may persist in the final product, while uncertainty varies across climate variables and terrain types. Overall, the reliability of bias correction also depends on the density and quality of the underlying observational station network (Otto et al., 2016; Littell et al., 2011; Fierke et al., 2024). In addition, the considered SSP emission scenarios represent a broad range of possible future conditions and are associated with inter-model uncertainty and differences in climate sensitivity (Li et al., 2021). These uncertainties may influence projected LULC patterns, potentially affecting the magnitude and spatial distribution of projected changes in agricultural and forest lands across different climate scenarios.

Another limitation of the model is the lack of spatial validation. Although the reported AUC-ROC statistics demonstrate the performance of the logistic suitability models, they do not directly assess the spatial allocation accuracy of the *CLUE-s* simulations. Hence, the use of spatial validation metrics, such as the Figure of Merit (Pontius et al., 2008) or $K_{Simulation}$ (van Vliet et al., 2011), could provide a more direct assessment of the agreement between simulated and observed spatial LULC patterns. However, their application was not possible in the present study because of the lack of an observed LULC dataset in the simulation period. Therefore, the absence of spatial validation may affect confidence in the simulated spatial distribution and magnitude of LULC changes, limiting the assessment of how accurately the model represents the spatial processes underlying LULC transitions (García-Álvarez et al., 2022). Nevertheless, previous studies conducted for Romania using the same framework and validated spatially using the *Kappa index* (Cohen, 1960), with an overall accuracy of 85.8% (Kucsicsa et al., 2019), and $K_{Simulation}$ (van Vliet et al., 2011), with an overall value of 0.84 (0.97 for $K_{Transition}$ and 0.86 for $K_{TransLoc}$) (Kucsicsa et al., 2022), indicate that the *CLUE-s* model can reasonably project future potential LULC changes, at least over short- to medium-term horizons.

Study relevance

Given that agriculture and forestry are foundational to Romania's economy and environmental sustainability, the findings from this research are important for informing policy decisions related to land use and climate adaptation in Romania, and understanding the future impact of climate change on these sectors, being essential for formulating long-term national and regional strategies (Foley et al., 2005;

Verburg et al., 2011).

By integrating three climate change scenarios with a spatially explicit modelling framework, the study provides a methodological framework for assessing potential climatic pressures and changes in LULC suitability. The findings indicate that increasing climate forcing may lead to spatial reorganization over significant areas, with potential implications for agricultural land-use and forest ecosystem functioning. The observed gradient of sensitivity, particularly among intensively used agricultural lands and coniferous forests, underscores the need for policies that guide land-use transitions to prevent a decrease in land-use intensity and abandonment while maintaining their reversibility. In relatively stable agricultural lands, where spatial reorganization is limited, climate resilience depends primarily on enhancing the capacity of existing systems to cope with climatic stress. Moreover, strengthening protective measures and facilitating forest expansion into climatically suitable areas may increase forest resilience under changing conditions.

Beyond their direct policy relevance, this study also provides valuable insights into the broader scientific knowledge base, enabling extrapolation to different regions, more detailed analyses, and applications in related fields such as biodiversity conservation, spatial planning, or management of natural hazards (Hussain et al., 2022; Bojer et al., 2025).

5. Conclusions

To our knowledge, this study is the first at the national level in Romania that quantifies the potential impact of future climate change on the agricultural and forest sectors by integrating climate projections within a hybrid spatially explicit land-use model. By keeping other environmental and socioeconomic driving factors constant, the modelling framework specifically isolates the potential contribution of climate change to LULC pattern changes, providing a controlled assessment of potential climate-induced responses in agricultural and forest lands. The outcomes highlight diverse responses, with distinct regional patterns emerging across the climate scenarios. Five core findings can be derived:

- i) the SHAP analysis indicates that temperature has a more consistent influence across all analysed LULC classes, while precipitation is particularly important for certain agricultural classes, with both effects varying spatially;
- ii) the transition matrices show an overall high persistence of analysed LULC classes, suggesting a general stability of agricultural and forestry systems up to 2050 under climate change, but:
 - large areas could be affected by various internal and external transitions, reflecting gradual changes shaped by LULC competition under climate change;
 - significant altitudinal and latitudinal shifts could occur, showing possible climate-induced expansion, displacement, or contraction for certain LULC classes;
- iii) the spatial pattern of changes exhibits pronounced heterogeneity, with mountain regions particularly sensitive to climate change;
- iv) agricultural and forest systems exhibit contrasting responses in terms of the magnitude of changes, suggesting possible differences in their ecological inertia;
- v) within the present modelling approach, climate-only perturbations produced smaller changes than the baseline scenario, suggesting that anthropogenic pressures may play a more significant role in shaping LULC dynamics than projected changes in mean temperature and precipitation.

Even though our results do not indicate a dominant influence of changes in mean air temperature and precipitation during the growing season, their effects should still be considered in land-use planning, as

they contribute to long-term uncertainties affecting agricultural and forest systems. They also underscore the need to integrate LULC scenarios into broader climate adaptation frameworks to ensure the sustainability of agriculture and forest systems, with key benefits for economic and biodiversity sectors. Overall, embedding these insights into national and regional policies can support proactive, rather than reactive, land-use decisions that enhance long-term resilience and sustainability.

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Data availability statements

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

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