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RESEARCH

Impacts of climate change on biodiversity and ecosystems in Bavaria: a sectoral analysis

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Abstract
Climate change is expected to create a range of impacts on biodiversity, land use, and economic activities, but those sector impacts are rarely analysed together. Here, we assess how climate change and socioeconomic narratives will affect land use and biodiversity in the state of Bavaria, Germany. We apply a multi-sectoral modelling approach with two climate projections (RCP 2.6 and 8.5) downscaled from three different climate models in combination with three land-use scenarios: biodiversity protection, climate change mitigation, and climate change adaptation. We evaluate changes in different sectors such as forestry and agriculture, considering impacts on carbon storage, terrestrial and aquatic biodiversity, and the adaptation of agricultural practices. In our simulations, biodiversity declined sharply under the higher emission scenario, highlighting climate change as a major threat to biodiversity in Bavaria. Prioritising biodiversity through forest conversion and expanding pasture reduced species decline and enhanced carbon storage more effectively than pure climate-focused mitigation. Climate change intensity had minimal impacts on land-use patterns (e.g. allocation of forest types), but it significantly changed farmers' preferences, increasing their inclination toward more conservative land management practices, i.e. favouring the status quo. We conclude from our findings that policymakers should strategically prioritise biodiversity protection alongside targeted forest-management practices to simultaneously enhance ecosystem health, biodiversity, and carbon storage. Intensified agricultural and land management, on the other hand, should be approached cautiously to avoid biodiversity loss.

Keywords Climate change · Biodiversity · Bavaria

Introduction

Biodiversity is essential for the stability and resilience of ecosystems, supporting critical services such as nutrient cycling, climate regulation, food production, and water cycle management, all vital for human survival and well-being (Pereira et al. 2012). However, habitat destruction and degradation due to land-use changes are major threats to biodiversity, impacting nearly 45% of vertebrate populations identified in the Living Planet Index (WWF 2014). In contrast, climate change poses direct threats to only 7.1% of these populations (Titeux et al. 2016). According to the IUCN Red List of Threatened Species, over 85% of vulnerable or endangered mammals, birds, and amphibians in terrestrial ecosystems are affected by habitat changes, whereas fewer than 20% face threats from climate change (Titeux et al. 2016). Climate change impacts biodiversity by shifting species ranges and increasing disturbance events like fires, droughts, and floods (Titeux et al. 2016). Land-use change affects biodiversity through habitat destruction, resource extraction, and pollution of soil, air, and water (IPBES 2019). While land-use change and habitat destruction pose a more immediate threat, the interaction between climate change and land-use change forms a complex relationship (Cabral et al. 2023), further exacerbating their combined

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Extended author information available on the last page of the article impact on biodiversity and contributing to a global decline in species diversity and population numbers (IPBES 2019; Newbold et al. 2015). Such combined impacts for example occur, through shifting cultivation zones due to increasing aridification. This, in turn, feeds back into climate change by destroying natural carbon storage and increasing greenhouse gas emissions (Dale et al. 2011).

Despite the intricate interconnections between biodiversity, land use, and climate, most biodiversity and ecosystem projections primarily focus on the direct impacts of climate change, keeping land cover and other global drivers constant (but see Anderson et al. 2013; Sarmento Cabral et al. 2013). Even when predictive models consider both climate change and land-use change, they often fail to treat land-use change as a consequence of climate change, frequently ignoring the feedback mechanisms between land and climate (see Cabral et al. 2023). Moreover, hitherto socioeconomic narratives focus solely on climate change (O'Neill et al. 2017), ignoring ongoing increase in invasive species, in species homogenisation, and in the loss of biodiversity and ecosystem services (but see IPBES 2019). Challenges especially arise from the fact that regional models typically overlook spatial and higher-level mechanisms, while global models often focus on economic factors and fail to account for the diverse behaviours of farmers, their decision-making processes, and the varying governance structures across different regions (Arneth et al. 2014; Rounsevell et al. 2014). For instance, many models assume profit maximisation, disregarding the complex socio-ecological systems that support sustainable practices at regional levels (Ceddia et al. 2015; Ostrom 2009). Additionally, risk-averse landowners may diversify their land-use practices to mitigate climate change risks (Eisele et al. 2021; Knoke et al. 2011; Pichon 1997). These mismatching assumptions can lead to less accurate predictions of land conversion rates at regional scales (Bayer et al. 2020), which are crucial for assessing biodiversity change since most species have regional distributions.

The Global Assessment of Biodiversity and Ecosystem Services conducted by the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) found that even the most sustainable scenarios developed by the broader climate community, such as shared socioeconomic pathways (SSPs) and representative concentration pathways (RCPs) like SSP1 and RCP2.6, would fail to prevent biodiversity loss (Pereira et al. 2024). These scenarios would also continue to degrade ecosystem services in many regions globally (Pereira et al. 2024). To adequately evaluate regional biodiversity changes in the face of interacting land-use and climate change, multiple factors and sectors must be considered.

In this study, we move beyond the typical climate-focused narrative by introducing simplified land-use scenarios that explore how Bavarian policy could respond to anticipated climate and biodiversity changes, as well as their impacts on land use. We analyse multiple sectors, including biodiversity, land use, carbon uptake, farmer decision-making, and socio-ecological dynamics. Each scenario includes assumptions regarding forestry and agricultural practices in Bavaria and analyses their potential impacts on carbon storage, terrestrial and aquatic biodiversity, and agricultural adaptation. Recognising that climate change is a global issue, the project makes use of regional climate scenarios driven by global RCPs (2.6 and 8.5), with three proposed narratives focusing on (i) biodiversity protection, (ii) climate change mitigation, and (iii) climate change adaptation, which are briefly described below:

Biodiversity Protection Scenario (BDP): This scenario assumes Bavaria is committed to the Kunming-Montreal COP15's Global Biodiversity Framework (CBD 2022), whose 2030 targets include, for example, halting extinctions by 2030, while achieving climate neutrality by 2040 with a focus on nature-based solutions. Key measures include reducing forest harvest to allow persistence of forest species, transitioning to mixed forests to promote ecosystem diversity, increasing deadwood in forests to enhance saproxylic beetle diversity, and converting 10% of arable land to pastures (5%) or forests (5%) for improvement of biodiversity indicators of both grassland and forest species. Furthermore, farmers aim to minimise fertilisation and pesticide use to lower N_2O emissions, nutrient runoff, and lake turbidity.

Climate Change Mitigation Scenario (CCM): This scenario anticipates significant progress towards global climate neutrality by 2040 through climate mitigation measures. In Bavaria, this means cultivating *Miscanthus* on 10% of arable land for bioenergy, optimising field portfolios to enhance soil carbon content and reduce greenhouse gases, and utilising a larger fraction of the forest harvest for products and energy generation. The focus remains on coniferous forests, suited for producing long-life wood products that store carbon and substitute carbon-intensive materials.

Climate Change Adaptation Scenario (CCA): Given global challenges and insufficient climate mitigation progress, this scenario involves proactive adaptation to anticipated climate effects. Bavaria plans a gradual conversion of all coniferous to mixed forests while preserving broadleaf forests and maintaining a constant level of harvest residues. In arable farming, irrigation techniques and increased nitrogen fertilisation ensure adequate moisture and nutrients for crop growth, preparing for the impacts of climate change.

The above outlined scenarios take Bavaria's existing and planned policy framework as starting point, in a simplified manner, especially regarding fertiliser use and biodiversity-focused land restructuring. Here, the CCA scenario, which advocates increased fertiliser application, is a departure from current Bavarian regulations. Recent amendments to the Fertiliser Ordinance, initiated by the EU, impose stricter limits to protect water quality through field-specific upper limits for organic fertilisers in nitrate-polluted areas (StMELF 2024a). These regulations, however, align closely with the BDP scenario, which promotes minimised fertilisation. Nevertheless, the BDP scenario's proposed reduction in timber extraction and targeted land-use restructuring contradict current Bavarian policies, as these do not foresee reduced forestry yields or systematic land-use changes beyond established forest conversion initiatives (Pohle et al. 2022).

However, several substantial overlaps align our scenarios closely with Bavarian objectives. The CCM scenario's emphasis on energy crops, especially *Miscanthus*, aligns with Bavaria's climate strategy, the Bavarian Act on Sustainable Development of Agriculture (BayAgrarWiG), and the Renewable Energy Sources Act. The targeted expansion of agricultural irrigation corresponds under the CCA scenario is directly supported by BayAgrarWiG. Forestry policies match the CCA scenario's restructuring of coniferous into mixed forests, supported by the Bavarian Forest Act (Bay-WaldG) and the Forest Restructuring Campaign 2030 (StMELF 2025; StMUV 2022), which also significantly increases forest conversion, aligning with the BDP scenario. Additionally, the promotion of wood as a climate-neutral, CO_2-binding building material through the Bavarian wood construction initiative "Holzbauinitiative Bayern" (StMELF 2024b) aligns with the CCM scenario.

Ultimately, Bavaria's integrated strategy for achieving climate neutrality by 2040 simultaneously addresses biodiversity conservation, climate adaptation, and mitigation, aligning with the core elements of our proposed narratives of the future, but with different degrees of overlap.

With these narratives, we sought to answer the following questions:

1. What are the sector-specific consequences of climate change and our future narratives for Bavaria?
2. What are the impacts of higher emission scenarios on the different sectors in Bavaria?

For the sector-specific analyses, we concentrate on the impacts on carbon storage, land use, and biodiversity (Fig. 1). Finally, we discuss which political measures Bavaria should consider to maintain high biodiversity.

Methods

Study region

Bavaria is a state in south-eastern Germany with an area of 70,550 km^2. The region has a varied elevation profile, including the Calcareous Alps (Mt. Zugspitze, 2962 m a.s.l.), the Bavarian Forest (Mt. Arber, 1455 m a.s.l.), the Franconian Jura Hills (600–700 m a.s.l.), and the lowlands (100–500 m a.s.l.). The climate ranges from sub-oceanic in the north-west, to sub-continental in the plains and basins, and to montane climate in the Alps. The soil composition varies, with granite and gneiss predominant in the Bavarian Forest and limestone in the Alps and Franconian Jura. Forests cover an area of about 25,600 km^2 and are dominated by coniferous species (68.4%) and broadleaf species (31.6%) (LWF 2005). Agriculture covers an area of about 30,950 km^2, of which 65.4% is arable land, predominantly used for grain production, and the remaining 34.2% is continuous grassland (Bayerisches Landesamt für Statistik 2022). Water bodies in Bavaria cover an area of about 1220 km^2 (Bayerisches Landesamt für Statistik 2022).

Climate projections

To derive future climate scenarios for Bavaria, we used an ensemble of climate projections for the period 1951–2100, provided by the Bavarian Environment Agency (Bayerisches Landesamt für Umwelt). These projections were bias-corrected for the period 1971–2000 using quantile mapping and statistically downscaled from the original spatial resolution of 12.5 × 12.5 km to 5 × 5 km (Bayerisches Landesamt für Umwelt 2020). The original projections were obtained from regional climate model simulations conducted as part of the EURO-CORDEX and ReKliEs-De projects (Bayerisches Landesamt für Umwelt 2020).

To assess the impacts of varying intensities of future climate change, we examined two Representative Concentration Pathways (RCPs). RCP8.5, a high-emission scenario, assumes a continuous increase in radiative forcing throughout the twenty-first century, reaching approximately 8.5 W/m^2 (Calvin et al. 2023; Taylor et al. 2012). In contrast, RCP2.6, a low-emission scenario, projects that radiative forcing will peak mid-century before declining to 2.6 W/m^2 (Calvin et al. 2023; Taylor et al. 2012). For both RCPs, we selected three combinations of global and regional climate model projections to capture a range of potential future climates under different radiative forcing conditions (Table 1).

We used modelled projections of lake surface water temperatures under both RCP scenarios. For RCP2.6, lake temperatures during summer are expected to rise by + 1.5 °C compared to the 1971–2000 baseline, or by + 0.5 °C relative to the 2010–2020 period, by the end of the century (Grant et al. 2021). Under RCP8.5, the average maximum lake temperature is projected to increase by + 4 °C from the 1971–2000 baseline, or by + 3 °C from the 2010–2020 period, by 2100 (Grant et al. 2021).

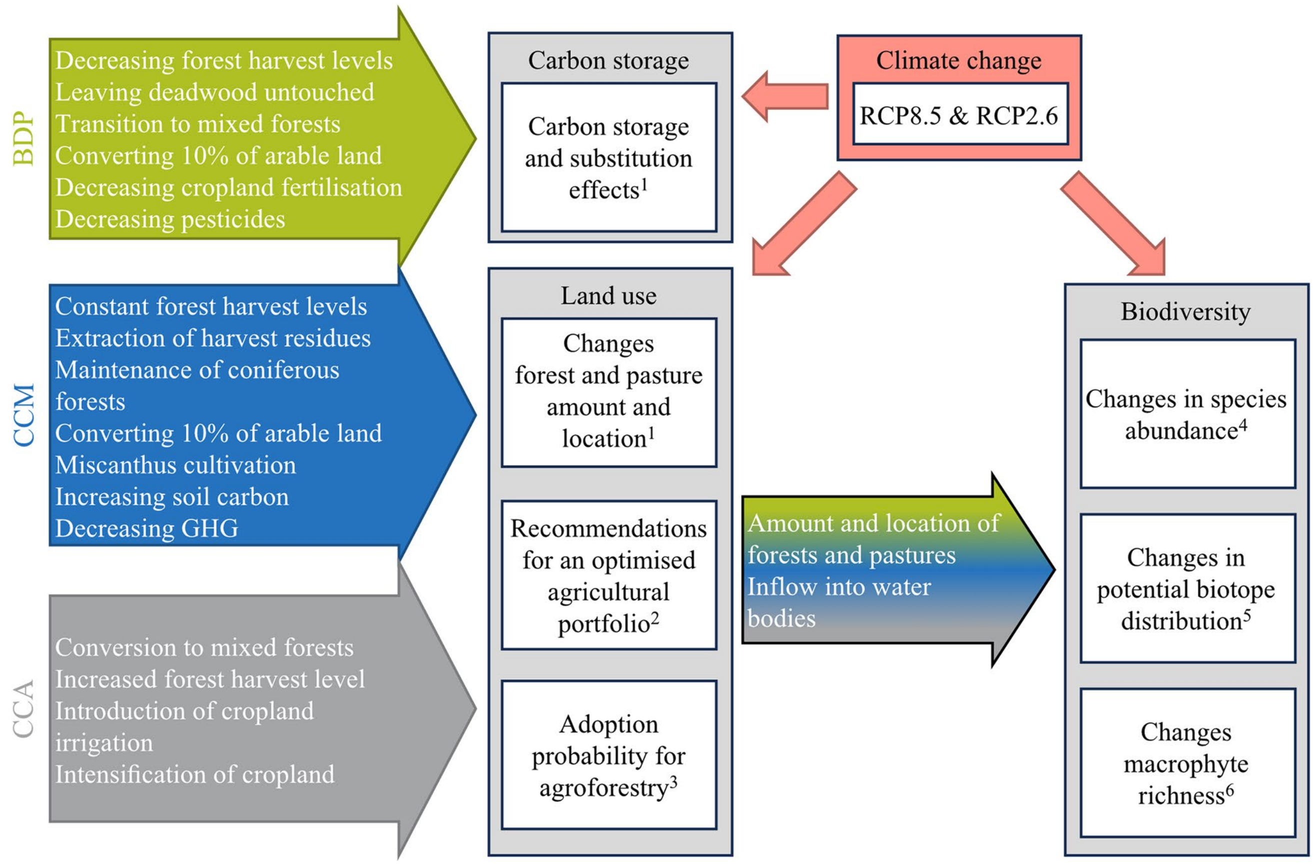

Fig. 1 Conceptual illustration of our approach: Climate change was considered in all scenarios. In the arrows on the left, key assumptions of each scenario are summarised that were implemented in the models estimating changes in land use (uppercase numbers in the figures indicate the different models that were applied: [1]LPJ-GUESS, [2]Robust Optimisation Model, [3]Acceptance Model) and carbon storage ([1]LPJ-GUESS). The projected changes in land use, based on the postulated scenario, were then incorporated into models estimating changes in biodiversity ([4]Species Abundance Distribution Model, [5]Biotope Distribution Models, [6]Macrophytes Abundance Model)

Table 1 Overview of regional climate model projections including consequences for temperature and precipitation in RCP2.6 and RCP8.5 by the year 2100 that were applied in our study

Global model	Regional model	Short name	Temperature	Precipitation
ICHEC-EC-EARTH_r12i1p1	KNMI-RACMO22E	ECEARTH-RACMO	RCP2.6: + 1.21 °C (± 0.08 °C) RCP8.5: + 4.14 °C (± 0.18 °C)	RCP2.6: + 98.79 mm (± 37.37 mm) RCP8.5: + 143.18 mm (± 53.82 mm)
MIROC-MIROC5_r1i1p1	CLMcom-CCLM4-8–17	MIROC-CLM	RCP2.6: + 1.68 °C (± 0.04 °C) RCP8.5: + 4.60 °C (± 0.06 °C)	RCP2.6: – 39.07 mm (± 22.33 mm) RCP8.5: – 17.59 mm (± 19.81 mm)
MPI-M-MPI-ESM-LR_r1i1p1	CEC-WETTREG2018	MPI-WETTREG	RCP2.6: + 1.00 °C (± 0.04 °C) RCP8.5: + 3.49 °C (± 0.13 °C)	RCP2.6: + 11.49 mm (± 25.38 mm) RCP8.5: – 90.50 mm (± 89.95 mm)

Overview over sectoral models applied and modelling protocols

We employed seven sectoral models, all driven by the same climate change projections for cross-sectoral experimental consistency. To implement the land-use assumptions of the three scenarios, we linked some models through their outputs and inputs. Consequently, three models directly incorporated the scenario's land-use assumptions, while the other four models were indirectly influenced by outputs from other models (Fig. 1). Thus, we categorised the models into those that directly implemented the scenario's land-use assumptions and those that indirectly incorporated them. This approach ensured coherent integration of both climate projections and scenario-based land-use assumptions across all models.

Models directly implementing land-use scenario assumptions

The process-based dynamic vegetation model LPJ-GUESS

LPJ-GUESS (Smith 2001; Smith et al. 2014) is a dynamic vegetation model that simulates terrestrial vegetation and soil dynamics on regional or global scales. The model is driven by meteorological data, prescribed land-use patterns, and soil properties. Each grid cell contains patches representing natural vegetation, where plant functional types (PFTs) or species compete for light, water, and nutrients. Processes like photosynthesis and hydrology are modelled on a daily timestep, while growth and mortality are calculated annually. The model includes land-use transitions such as agriculture and forestry (Lindeskog et al. 2013). Disturbance events (e.g. wind storms) are also simulated, allowing for secondary vegetation succession (Hickler et al. 2004). LPJ-GUESS can model various management strategies, from pristine forests to managed systems, and tracks land-use changes while maintaining the soil and vegetation history of the grid cell (Lindeskog et al. 2021).

In this study, LPJ-GUESS was applied to project changes in the amount and distribution of different forest types, croplands, and pastures across Bavaria. Based on the LPJ-GUESS projection, we classified forest types as coniferous or broadleaf when more than 90% of the forest consisted of one functional group, and as mixed forest otherwise, following the forestry concept of a "pure stand". Furthermore, the model was used to quantify the amount of total carbon stored in litter, vegetation, soil, and woody products. Model output also included cumulative carbon mitigation through forests, total carbon stocks, and substitution effects for fuel and materials under various scenarios (Gregor et al. 2024). The model was forced with the six climate model-RCP combinations (Table 1), simulating the timespan 1951–2100 for three land-use scenarios, as explained below. For the analyses, the aggregated simulation values of the variables of interest for 2010–2020 served as the reference, with projections for 2090–2100 as the projected future values.

BDP: Forest harvesting was reduced to 50% compared to present-day values in 2021 to reduce anthropogenic disturbances in forests. The forestry sector was assumed to gradually convert all forests to mixed forests by planting both needleleaf and broadleaf species in presently conifer-dominated forests, thereby offering moderate adaptation to climate change, and promoting greater biodiversity. To support potential enhancement of saproxylic beetle diversity, harvest residues and deadwood were left in forests following harvests, and salvage logging after disturbances was avoided. Additionally, 10% of Bavaria's arable land was gradually converted to pastures (5%) and unmanaged forests (5%) until 2050. On the remaining arable land, fertilisation was reduced gradually until 2050, reaching final levels of 20% less fertilisation in 2050 compared to 2020.

CCM: In this scenario, it was assumed that in the LPJ-GUESS simulations, 10% of arable land was dedicated to the cultivation of the bioenergy plant *Miscanthus*. While forest harvest rates were kept constant, woody residues were increasingly extracted for energy generation, while other harvests were increasingly used for long-lived products, contributing to carbon storage and reducing carbon-intensive material use.

CCA: The main assumption for the LPJ-GUESS runs within this scenario was that coniferous forests were actively converted to mixed forests by planting only broadleaf species post-harvest, while existing broadleaf forests were preserved. Forest harvest levels and residue extraction were kept constant. In arable farming, irrigation techniques were gradually expanded, targeting full crop irrigation by 2050, and nitrogen fertilisation was linearly increased to reach 20% above 2020 levels by 2050, ensuring adequate moisture and nutrients for optimal crop growth.

Robust optimisation model for agricultural portfolios

This model used a robust optimisation framework with a multi-objective approach, designed as a Min–Max problem to minimise the regret across various objectives and uncertainty scenarios (Jarisch et al. 2022; Knoke et al. 2020, 2025). This means that the difference between the outcomes of the optimal decisions (which cannot be foreseen under uncertainty) and the actual decision made is as small as possible. The model uses predefined land-use types as decision alternatives to which area shares can be allocated by the simulated decision-maker, ensuring that the total allocated area sums to 100%. This configuration allows for the optimisation of land-use or landscape compositions based on the preferences and uncertainty tolerance of the decision-maker, striving for the optimal compromise (Gosling et al. 2021). Our robust optimisation of land-use allocations on farm landscape level includes both farmers' private and social interests (Gosling et al. 2021; Reith et al. 2020). As objectives we included ecosystem service indicators representing socio-economic and ecological interests, namely the annuity as long-term profitability measure, carbon input as indicator for soil quality and water retention, nitrogen fertiliser as indicator for emissions and groundwater quality, greenhouse gas emissions, and a plant protection index measuring the amount and intensity of applied pesticides (Rössert et al. 2022; Stetter & Sauer 2022). The land-use types considered in this study include cultivation of barley, grain maize, potatoes, rapeseed, silage maize, short rotation coppice, sugar beet, and wheat. To estimate the indicator values, the model applied specific settings for each scenario (Rössert et al. 2022).

The model baseline from 2020 was used as the reference value, with projections for 2100 serving as the projected future values.

BDP: Efforts focused on minimising fertilisation, thereby reducing N_2O emissions, and limiting pesticide application on croplands to support more sustainable agricultural practices. The annuity as the third indicator represents interest in long-term economic returns.
CCM: The goal was to enhance soil carbon content and reduce greenhouse gas emissions, aligning with strategies to improve carbon sequestration and mitigate climate impacts while also considering profitability.
CCA: The model aimed to maximise agricultural profitability.

Macrophyte growth model

The Macrophytes Growth Model (MGM) is an eco-physiological, process-based model for submerged macrophytes (Lewerentz et al. 2023; Van Nes et al. 2003). The MGM simulates the life-cycle and daily growth of a macrophyte species in different depths of a lake, depicting the development of its daily biomass, height, and number of individuals, using the super-individual approach (Scheffer et al. 1995). The model uses as inputs geographic factors (daylength, water depth) and environmental conditions (surface irradiance, nutrients, temperature, and turbidity). Growth is driven by photosynthesis and respiration, with additional influences from self-thinning, mortality, and self-shading. The model simulates a potential biomass growth, as it does not consider competition, herbivory, and dispersal.

As the ecophysiological parameters of most submerged macrophyte species are unknown, we used as species 900 random parameter combinations from the parameter space for oligotraphenic, mesotraphenic, and eutraphenic functional types as described in Lewerentz et al. (2023). Each combination of parameters represents a hypothetical, virtual species. Virtual species which do not die during the burn-in phase of 10 years (the period necessary to reach quasi-stationary equilibrium) within the modelled environment build the potential species richness.

This model was used to simulate the potential species richness of macrophytes in 31 Bavarian deep lakes. To estimate the number of species, the model applied the following settings for each scenario. The settings depend on the RCP, as we take into consideration the interactive effects of water temperature increase and nutrient levels like internal fertilisation and turbidity (algae blooms) in lakes (Adrian et al. 2009). The reference period is 2010–2020 and the projections for 2100 were considered as projected future values.

BDP: Due to the focus on biodiversity and ecology, it is assumed that measures such as riparian buffer stripes or limited fertiliser use are widespread, and that soil erosion will not increase (Rippel & Stumpf 2008). We consequently assume a reduction of nutrients and turbidity by 25% for RCP2.6 and a constant level of nutrients and turbidity (+ 0%) for RCP8.5 due to the interactive effects of water temperature increase and nutrients and turbidity.
CCM: Due to the focus of agriculture on energy and forage crops, without an increase in fertilisation and soil erosion, we expect a constant level of turbidity and nutrients for RCP2.6 (+ 0%) and for RCP8.5 an increase of + 25% due to the increased temperature.
CCA: Under the adaptation scenario, we expect an increase in turbidity and nutrients of + 25% (RCP2.6) or + 50% (RCP8.5), respectively, due to increased land use combined with warmer water temperatures leading to significant increases in nutrients from fertilisation, soil erosion (Rippel & Stumpf 2008), release of humic substances (DOC), longer and more intense algal blooms, and calcite precipitation within the lakes.

Models indirectly implementing land-use scenario assumptions

Acceptance model

A discrete choice experiment (DCE) was conducted to examine farmers' preferences for various land-use options in Bavaria (Stetter & Sauer 2024) according to our three scenarios. The DCE included three labelled payments for ecosystem services, and qualification as ecological priority areas (Langenberg & Theuvsen 2018; Menapace et al. 2013; Musshoff 2012). The ranges of the attribute values presented to the farmers were determined based on official data, previous studies, and expert consultations (LfL 2018; StMELF, 2018).

The experiment used 36 choice cards, divided into three blocks of twelve, following Viney et al. (2005) to reduce cognitive burden on participants. The collected survey data, along with weather information, were analysed using a random parameter logit model to estimate farmers' preferences and simulate their adaptive responses to extreme weather events (Hensher & Greene 2003). Detailed information on the experimental setup can be found in Stetter and Sauer (2024).

The model baseline served as the reference value, while climate projections for the year 2100 were used as the projected future values under the assumption of 2020 land use preferences. The land-use scenario assumptions were implemented by fixing the attribute values of the land-use types according to the corresponding scenario in the post-estimation simulation (Stetter & Sauer 2024).

BDP: Economic returns and subsidies ranked alley-cropping > short-rotation coppice > status quo crop farming, with alley-cropping and short-rotation coppice having shorter minimum useful lifetimes and lower variability.
CCM: Economic returns and subsidies ranked short-rotation coppice > alley-cropping > status quo crop farming, again with alley-cropping and short-rotation coppice having shorter minimum useful lifetimes and lower variability.
CCA: Returns ranked short-rotation coppice = alley-cropping < status quo crop farming, with no subsidies offered and short-rotation coppice and alley-cropping maintaining relatively high lifetimes and variability.

Insect species abundance distribution model

We applied a mechanistic range modelling approach using the metaRange R package to simulate population dynamics of interacting animal species (Fallert et al. 2025). The climate projections and land-use cover emerging from the models directly applying the narratives (see below) were used as environmental input raster data. Metapopulation dynamics of virtual species were modelled based on mechanistically relevant traits such as dispersal ability and reproductive capacity as well as on emergent state variables, such as local abundances. Species interactions with the environment were captured through processes like reproduction, dispersal, and metabolic scaling following the metabolic theory of ecology (Brown et al. 2004).

Population dynamics were modelled using the Ricker equation (Ricker 1954), incorporating factors like carrying capacity and Allee effects (Cabral & Schurr 2010). The carrying capacity is modulated by the habitat suitability, which is calculated by matching the species' environmental preferences with the local environmental conditions from the environmental input raster data. Dispersal was simulated using a kernel approach, with habitat suitability weights guiding dispersal towards more favourable conditions (Savary et al. 2024). This method captures key ecological processes, enabling the simulation of species dynamics under various environmental scenarios.

We used this model to simulate 400 theoretical insect species with their preferred niches covering the environmental diversity of Bavaria. From these species, 100 species were set to be specialised in only one of the Bavaria's land-use types. The abundance of insect species in 2020 was set as the reference value, with the projected future value based on projections for 2100.

Scenarios: Besides the respective climate change input, the model takes as input the forecasted changes in forest types and pasture distributions from the LPJ-GUESS model emerging from each of the three scenarios.

Plant species abundance distribution model

We applied a mechanistic range modelling approach using the MetaRange.jl Julia package to simulate population dynamics of plant species (Blechschmidt & Cabral 2025). The MetaRange.jl Julia package is based on the first version of the metaRange model (Faller 2021), adapted to simulate plant species distributions by integrating overlapping generations via Beverton-Holt equation for the reproduction submodel. As previous model, species interactions with the environment were captured through processes like reproduction, dispersal, and metabolic scaling following the metabolic theory of ecology (Brown et al. 2004). Habitat suitability is calculated using species-specific minimum, maximum, and optimum niche values (Yin et al. 1995). Population dynamics are updated using the Beverton-Holt model, with reproduction and mortality rates as well as carrying capacity determined by habitat suitability. The original Ricker equation (Ricker 1954) is also available for annual species. Seed dispersal follows a negative exponential kernel, with species-specific mean dispersal distances, ensuring realistic movement across grid cells. Recruitment can be modelled deterministically or stochastically via a Poisson distribution, incorporating demographic stochasticity.

We employed the model to simulate 400 theoretical plant species, with 100 species assigned to each suitable land-use type, with their preferred niches capturing the environmental diversity of Bavaria. The abundance of plant species in 2020 was set as the reference value, with the projected future value based on projections for 2100.

Scenarios: Besides the respective climate change input, the model takes as input the forecasted changes in forest types and pasture distributions from the LPJ-GUESS model emerging from each of the three scenarios.

Biotope distribution model

Using the Maximum Entropy Algorithm (Maxent), this model assesses the suitability of a raster cell for a specific biotope based on existing environmental conditions. Together with the climate projections, the model predicts the future suitability of each raster cell for its respective biotope (Rubanschi et al. 2023). We applied 14 different biotope distribution models, covering both grassland and forest biotopes, to project their potential distributions under the climate projections. The current biotope distribution served as the reference, while projections for the year 2100 provided the projected future values.

Scenarios: To align these models with scenario assumptions, a raster cell was only considered suitable for a certain biotope if the necessary amount of a specific land-use type (such as pasture or forest type) was projected by LPJ-GUESS in that cell.

Analysed output variables across sectors

To offer a detailed overview of the outcomes of the postulated scenarios across the different climate projections, we categorised our analysis into three sectors: land-use sector, carbon storage sector, and biodiversity sector (Fig. 1).

The **land-use sector** encompasses model outcomes related to changes in land use, including changes in the amount and location of forests and pastures (LPJ-GUESS), optimal agricultural portfolios (Robust Optimisation Model), and the likelihood of agroforestry adaptation (Acceptance Model). The **carbon storage sector** addresses all changes related to carbon storage, including the geographical distribution of total carbon storage and the total carbon storage in soil, vegetation, and products (LPJ-GUESS). Additionally, it encompasses the cumulative total carbon mitigation through forests, carbon stocks, and substitution effects for fuel and material (LPJ-GUESS). The **biodiversity sector** encompasses all changes in biodiversity resulting from the different land-use scenarios and climate change. It employs geographical projections evaluating the biotope suitability (Biotope Distribution Models), the abundance of insect and vascular plant species (Species Abundance Distribution Models), and the abundance of macrophytes in Bavarian lakes (Macrophyte Growth Model). Each of the models was evaluated for its performance in separate, already published studies, and we provide a summary of the model performances in the results section.

Evaluation of sectoral changes

Since all models incorporated different aspects of the scenarios, operated on different geographical scales, and considered different assumptions for both reference and projected future values, we developed metrics to make the different model outputs comparable. We evaluate changes for sectors per raster cell, as well as total changes in Bavaria for individual projections within each sector.

Calculation of metrics for evaluating the total change

For the models that provide spatial projections, we summed up per model the values from all raster cells (Eq. 1 n_{cell}) to obtain a total value for the reference (Eq. 1 sum of V_{ref} over all raster cells) and projection (Eq. 1 sum V_{fut} over all raster cells) for Bavaria. For the models which provided total values, we used the projections directly. We then determined the greater value between the reference and the projected future value, using this as the maximum potential value (Eq. 1 V_{max}). Changes within each projection (Eq. 1 $\Delta V_{\mathrm{total}}$) were calculated by subtracting the reference value from the projected future value (Eq. 1 V_{fut}) and normalising this difference by the maximum potential value (Eq. 1 V_{max}), yielding a scale ranging from − 1 to 1. Negative values indicate a decrease, meaning the reference value is higher than the projected future value. Positive values indicate an increase, where the projected future value is greater than the reference value. A value of 1 indicates establishment, as the reference value was initially zero.

$$\Delta V_{\mathrm{total}} = \frac{\sum_{i=1}^{n_{\mathrm{cell}}} V_{\mathrm{fut}} - \sum_{i=1}^{n_{\mathrm{cell}}} V_{\mathrm{ref}}}{\sum_{i=1}^{n_{\mathrm{cell}}} V_{\mathrm{max}}} \tag{1}$$

For the Acceptance Model and the Robust Optimisation Model for agricultural portfolios, which provide direct percentage outputs, we directly subtracted the reference value from the projected future value.

Given the use of three distinct climate models in most cases, we averaged the results across these climate projections. For the macrophyte model, we calculated an average value across the Bavarian lakes.

Calculation of metrics for the evaluation of regional changes within Bavaria

To illustrate regional changes, we analysed in each raster cell changes in the amount of forests and pastures, we also evaluated the changes in total carbon storage, and we examined the changes in the number of suitable biotopes along with the abundance of insects and vascular plants. To quantify changes in the projections (Eq. 2 ΔV_{cell}), we identified the highest value of either the reference (Eq. 2 $V_{\mathrm{cell,ref}}$) or projected future value (Eq. 2 $V_{\mathrm{cell,fut}}$) for each raster cell and used this as the cell's maximum potential value (Eq. 2 $V_{\mathrm{cell,max}}$). Changes in each raster cell were subsequently calculated by subtracting the reference value from the projected future value and normalising this difference by the maximum potential value, creating a scale from − 1 to 1. Negative values indicate a decrease (where the reference value exceeds the projected future value), and positive values indicate an increase (where the projected future value was greater), with a value of 1 demonstrating the establishment since the reference value was zero. Given that we used three different climate models, we averaged the calculated changes to account for the range of climate projections.

$$\Delta V_{\text{cell}} = \frac{V_{\text{cell,fut}} - V_{\text{cell,ref}}}{V_{\text{cell,max}}} \tag{2}$$

We averaged all projections within the biodiversity sector. In the land-use sector, transitions between different forest types were sometimes simulated, resulting in an increase in one forest type and a corresponding decrease in another. This could lead to a misleading representation of no change when aggregating these transitions within a raster cell. To accurately reflect these changes, we summed the absolute changes from the projections and divided this total by the number of land-use types experiencing changes. This approach provides a clearer and more accurate depiction of sectoral changes.

To identify which of the sectors caused the largest changes in each raster cell, we performed a ternary composition analysis. This involved dividing the absolute value of each sector's change by the total absolute changes from all sectors, calculating a percentage for each sector that summed to 100%, thereby indicating its relative contribution to the overall change within the raster cell.

Results

Model evaluation: comparison with observational data for the Bavarian case study

Before using the models to project future outcomes under various scenario assumptions and climate change projections, we first evaluated their performance in reproducing current conditions in Bavaria. We report here for all models already published model evaluations and results from our own work (Tab. S1).

LPJ-GUESS has been thoroughly evaluated (e.g. Gregor et al. 2024; Smith et al. 2014) and effectively simulated essential vegetation structure variables in Bavaria. Total forest vegetation carbon was estimated at 308–319 MtC, aligning closely with literature values of 305–325 MtC for 2002 (Klein & Schulz 2012). Carbon stored in wood products was simulated at 61–63 MtC, also consistent with literature estimates of 58 MtC for 2008 (Klein & Schulz 2012). Additionally, forest carbon fluxes in Bavaria were accurately modelled, with gross and net primary productivity estimated at 1527–1671 and 624–710 gC/m^2/year, respectively, matching satellite data from GOSIF (Li & Xiao 2019) and MODIS (Running & Zhao 2021) (1444 and 687 gC/m^2/year for 2000–2015).

The results of the robust multi-objective portfolio optimisation were evaluated with selected crops representing a coverage of 75% of the Bavarian cropland (Rössert et al. 2022) and compared the suggested economically oriented agricultural landscape composition (shares of land allocated to different crops) with the current coverage of the crops. This comparison showed good agreement with the share of wheat and silage maize in 2020, but the model overestimated the shares of sugar beet and potatoes. We still considered the model results as realistic and a good basis to investigate changes under different preferences and climate scenarios.

Rubanschi et al. (2023) demonstrated that the biotope distribution models used in this study showed high accuracy, with a mean AUC of 0.946 ± 0.097.

The Acceptance Model, being based on actual farmers' preferences, accurately reflects the current preferences, which is then extrapolated into future scenarios (Stetter & Sauer 2024).

The abundance models used in this study, such as the Plant & Species Abundance Distribution Model and the Macrophyte Growth Model, simulated functional species types. As a result, these models cannot be directly validated against present-day distributions of real species in Bavaria. Nevertheless, they were calibrated with parameter values reflecting the species groups they intended to simulate for insects and terrestrial herbs they can be found in the supplementary (Tables S2 & S3), and for the aquatic plants in Lewerentz et al. (2023).

Simulated changes in the land-use sector

In the land-use sector, forest transformations were carried out according to the scenarios. In the BDP scenario, mixed forests were established (increase of 0.09 in each RCP, Fig. 2). Coniferous forests were largely maintained in the CCM scenario (decrease of − 0.08 under RCP2.6 and − 0.12 under RCP8.5, Fig. 2), but were fully converted to mixed forests in the CCA scenario (Fig. 2 & Fig. S1). Despite the preference for coniferous forests in the CCM scenario, climate change made their cultivation unsustainable in some areas, particularly under RCP8.5, leading to reduced coverage (Fig. 2). Furthermore, in the CCM scenario, coniferous trees within mixed forests could not withstand the effects of climate change, leading to an expansion of broadleaf forests (0.39 under RCP2.6 and 0.56 under RCP8.5). However, new mixed forests were established in northern Bavaria, maintaining overall mixed forest coverage at a stable level (Fig. 2 & Fig. S1). Similarly, in the CCA scenario, these regions could not support coniferous trees within mixed forests, leading to their reclassification as broadleaf forests (Fig. 2 & Fig. S1).

For the optimised agricultural landscape portfolios, the BDP scenario under RCP2.6 favoured short rotation

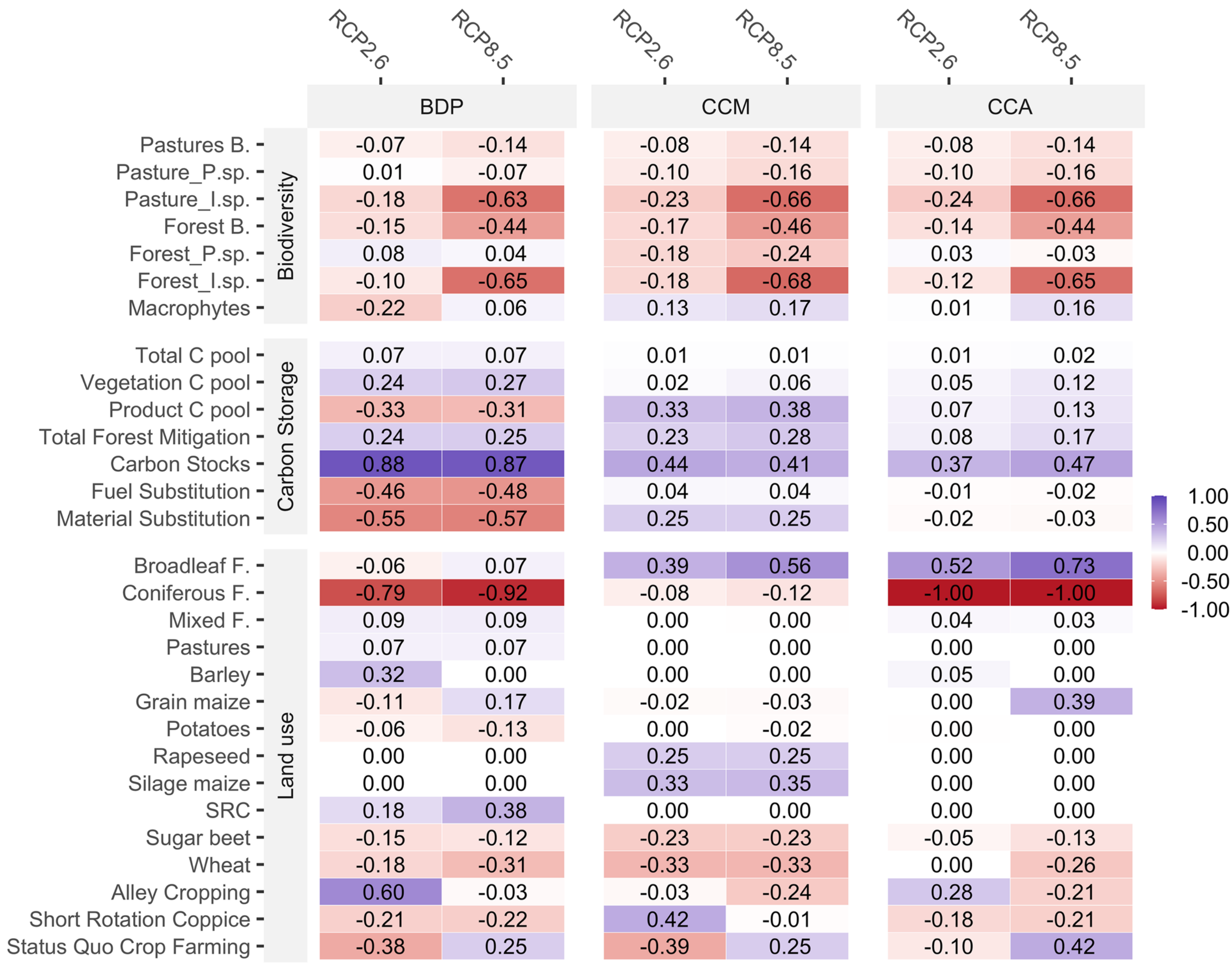

Fig. 2 Percentual changes in the model projections group by sector (first rows biodiversity sector, middle rows carbon storage sector, last rows land-use sector) and scenario (left BDP scenario, middle CCM scenario, right CCA scenario) which are distinguished by the climate change projections (first column per scenario RCP2.6 and second column per scenario RCP8.5)

coppicing and barley as the most viable crops, replacing sugar beet and wheat. Under RCP8.5, short rotation coppicing and grain maize replaced wheat and potatoes. In the CCM scenario, rapeseed and silage maize were more advantageous under both RCPs, reducing sugar beet and wheat cultivation. The CCA scenario showed minimal changes, except under RCP8.5, where grain maize became more attractive than sugar beet and wheat (Fig. 2).

Farmer acceptance of agroforestry techniques also varied by scenario. In the BDP scenario, alley cropping was more accepted under RCP2.6 but declined under RCP8.5, favouring the status quo. In the CCM scenario, short rotation coppicing was initially accepted under RCP2.6 but decreased under RCP8.5, with a preference for the status quo. Similarly, in the CCA scenario, alley cropping acceptance increased under RCP2.6 but declined under RCP8.5 in favour of maintaining existing practices (Fig. 2).

Spatially, land-use changes primarily occurred outside the Alpine regions, with the most notable changes in the BDP scenario, followed by the CCA scenario, and the least in the CCM scenario (Fig. 3C). In the BDP scenario, widespread changes occurred due to the conversion of arable fields into pastures and the establishment of mixed forest (Fig. 3C & S1). In the CCA scenario, changes were concentrated in the mid-eastern and northern forest regions, mainly involving the transition of coniferous to mixed or broadleaf forests (Fig. 3C & S1). In the CCM scenario, changes were focused in the Franconian wine lands, where mixed forests were converted to broadleaf forests (Fig. 3C & S1).

The BDP scenario had the most pronounced land-use changes, notably affecting many raster cells compared to other scenarios. This influence was reduced in the CCA scenario and almost negligible in the CCM scenario (Fig. 3D).

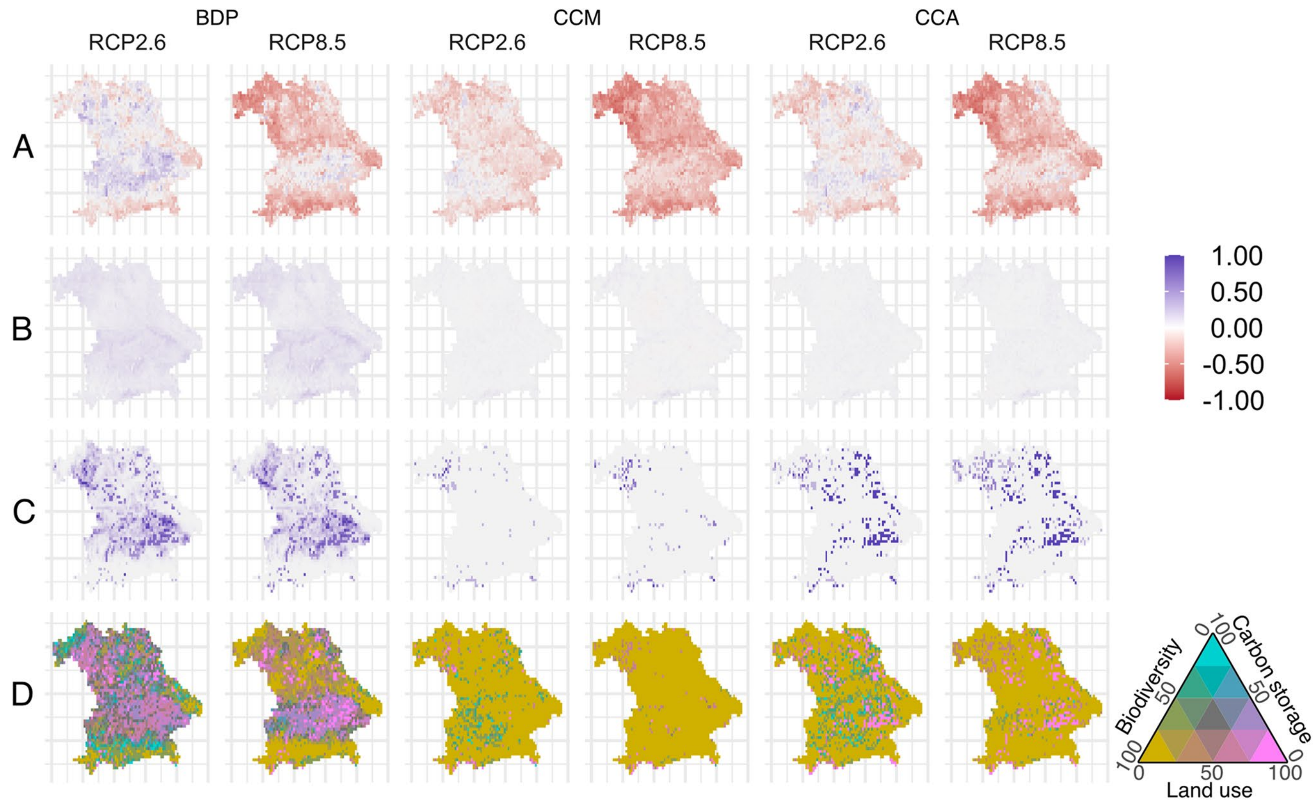

Fig. 3 Maps of Bavaria illustrating changes across the individual sectors: **A** biodiversity, **B** carbon storage, **C** land use, and **D** the sector with the most pronounced changes, highlighting change hotspots. Columns display results for the BDP, CCM, and CCA scenarios under the two different climate projections: RCP2.6 (low-emission scenario) and RCP8.5 (high-emission scenario)

Simulated changes in the biodiversity sector

Nearly all model projections in the biodiversity sector indicated a decline of species richness and biotopes across Bavaria particularly under RCP8.5 (Fig. 2). Notable exceptions included the abundance of forest vascular plants, which showed a modest increase in the BDP scenario (0.08 under RCP2.6 and 0.04 under RCP8.5, Fig. 2), and macrophytes, which exhibited higher richness in both the CCA (0.01 under RCP2.6 and 0.16 under RCP8.5, Fig. 2) and CCM scenarios (0.13 under RCP2.6 and 0.17 under RCP8.5, Fig. 2). Insect abundance, however, consistently declined by over − 0.6 across all scenarios under RCP8.5.

Regionally, the RCP8.5 predicted a substantial biodiversity decline across Bavaria for all scenarios (Fig. 3A). Insect abundance, in particular, is expected to be severely impacted by high warming, as are forest biotopes, which will also experience significant declines. Conversely, plant species abundance appear less affected by the higher emission scenarios.

Under RCP2.6, biodiversity declines were concentrated in specific regions, including the Alpine area, the Bavarian Forest, the Spessart, and the Rhön. In contrast, biodiversity increased between the Danube and Isar rivers and in the Franconian Forest, driven by the expansion of pasture biotopes and the abundance of forest insects and plants (Fig. S2). These increases were most pronounced in the BDP scenario, followed by the CCA and CCM scenarios. The BDP scenario, in particular, showed scattered regions benefiting from positive biodiversity impacts.

The negative biodiversity trends observed in the biodiversity sector were the strongest compared to the other sectors within a raster cell, particularly in the Alpine region and the Bavarian Forest (Fig. 3D). This effect intensified under RCP8.5 and extended into both CCA and CCM scenarios. In the CCM scenario under RCP8.5, nearly all raster cells showed negative biodiversity changes (Fig. 3D).

Simulated changes in the carbon storage sector

In the BDP scenario, the vegetation carbon pool increases under both RCPs (0.24 under RCP2.6 and 0.27 under RCP8.5, Fig. 2) and contributes substantially to the total carbon pool (increase of 0.07 under both RCPs, Fig. 2). This relatively high carbon storage is not observed in the other scenarios. However, the BDP scenario shows notable decreases in carbon storage related to products (− 0.33 under RCP2.6 and − 0.31 under RCP8.5, Fig. 2), which are reflected in decreasing substitution effects (Fig. 2). In contrast, the largest increases in products occurred in the CCM scenario (0.33 under RCP2.6 and 0.38 under RCP8.5, Fig. 2). Cumulatively, the total carbon stocks and forest mitigation are highest in the BDP scenario, with carbon storage levels almost twice as high as in the other scenarios (Fig. 2).

Geographically, the carbon storage sector shows only minor variations, with no region indicating notable increases or decreases (Fig. 3B). Notable increases across Bavaria are only observed in the BDP scenario, irrespective of the RCP. The other two scenarios show almost no changes in carbon storage.

The carbon storage sector has the less pronounced effect in Fig. 3D.

Discussion

In this study, we selected RCP2.6 and RCP8.5 to frame the sensitivity of biodiversity, land use, and carbon storage to different levels of climate change. Our intention was not to present RCP8.5 as the most likely future trajectory, but rather to use it as a high-end stress-test scenario to evaluate the upper bound of potential climate impacts. While scenarios such as RCP4.5 may represent more moderate and potentially more likely pathways, they lie within the range bounded by our selected scenarios and would therefore not substantially extend the interpretation of sectoral responses. In this context, RCP8.5 serves as an upper-bound risk scenario and RCP2.6 as a lower-bound mitigation benchmark.

Sector-specific impacts of the scenario

Our scenarios consisted of assumptions about how Bavaria's land use could evolve in the future, depicting different priorities such as preserving forests and expanding natural areas in the BDP scenario, mitigating climate change in the CCM scenario, and actively adapting to climate change impacts in the CCA scenario. Changes in land use, specifically the increase in the spatial extent of pasture areas under the BDP scenario, resulted in an overall reduced decline in pasture plant and insect species abundance (Fig. 2). Still, while the overall trend showed a decline, we identified areas where the increase in pasture areas led to higher abundance of pasture plants and insects, unlike in the other scenarios (Fig. 3 & S1 & S2). This finding aligns with other studies showing that abandoning agricultural areas can mitigate biodiversity loss by providing new habitats (Jones et al. 2023; Reidsma et al. 2006). However, these studies assumed that abandoned arable areas result from the intensification of more productive agricultural lands (Jones et al. 2023), which differs from our BDP scenario that aims to minimise fertilisation and pesticide use. The effect of the land-use change scenarios on the potential distribution of biotopes was similar between the scenarios (Fig. 2 & S2), likely because the raster cells already had sufficient land-use type coverage (Rubanschi et al. 2023).

Furthermore, the conversion of coniferous forests into mixed or broadleaf forests, along with the expansion of forest areas under the BDP scenario, enhanced habitat availability for plants and insects (Fig. 2 & Fig. S2). A similar positive effect of forest conversion was observed in the CCA scenario, though it was less pronounced, as no new forest areas were established.

We showed that carbon storage outcomes differed across the various scenarios due to expanding forest areas and changing specific forest management practices, such as reducing harvest rates and transitioning to mixed forests. While additional forest areas naturally increased carbon uptake (Jones et al. 2023), the BDP scenario also aimed to enhance carbon in the existing forests by reducing harvest, leading to higher carbon storage in vegetation (Fig. 2). This is also reflected in the geographical distribution of carbon storage in the biodiversity scenario (Fig. 3 & S1). Carbon storage increased not only in all reforested areas but also in regions where cropland was converted to pasture. This differs from the CCM scenarios, which led to higher carbon storage in products. However, overall carbon storage was lower compared to the BDP scenario. The CCA scenario maintained forest harvest intensity and focused on adapting forest composition without incorporating bioenergy crops. This led to similar carbon uptake levels as the BDP scenario, primarily due to consistent forest management practices and stable harvest rates.

The increased carbon uptake in the BDP scenario is further supported by the results from the optimised agricultural portfolio (Fig. 2), which identified short rotation coppice as beneficial, although it was not favoured from an economic perspective. However, the application of short rotation coppicing should be approached with caution, as it may negatively impact biodiversity by replacing naturally open areas (Meller et al. 2015). In contrast, the optimised agricultural portfolios in other scenarios did not consider short rotation coppices, despite farmers preferring it in the CCM scenario. This discrepancy highlights the model's sensitivity to farmer and other preferences where trade-offs between purely economic agricultural portfolios and the broader public preferences may exist. Farmers may prefer certain practices due to immediate economic benefits, lower risk, or practicality in terms of labour and resource requirements, which are important to be considered in land-use allocation models. The robust multiple objective approach represents a development into this direction.

For macrophytes, the BDP scenario was the only one showing a decrease or stability in species richness. While this signals a decline in biodiversity, healthy lakes often support a specific species composition with low biodiversity but rare, highly valuable species (Lewerentz et al. 2023; Lewerentz & Cabral 2022). Thus, the increase in macrophyte numbers under the other scenarios may indicate rather a decline in lake health.

The findings across the biodiversity sector suggest that land-use changes do not necessarily harm biodiversity if they create new habitats where species and biotopes can thrive. Regarding carbon uptake, we demonstrated that focusing solely on climate change mitigation could negatively affect biodiversity. Furthermore, we showed that with appropriate land use, carbon uptake can be higher in the BDP scenario than in the CCM scenario. The CCA scenario has a less dramatic impact on biodiversity compared to the CCM scenario, but it fails to meet biodiversity or climate targets. However, to maintain biodiversity and provide carbon storage, conservation efforts are needed to implement the scenario assumptions; otherwise, the desired outcomes cannot be achieved, as shown in other regions (Hill & Olson 2013).

Climate change impacts on the different sectors

While the intensity of climate change had minimal impact on simulated changes in the land-use sector, carbon storage, and the optimised agricultural portfolio (Figs. 2, 3 & S1), it had a significant effect on farmers' preferences, with an increasing tendency to favour the status quo. This suggests that as climate change intensifies, farmers become more uncertain about production conditions and risks and more likely to adopt a conservative approach to land management (e.g. Rössert et al. 2022).

Despite farmers' preferences, the intensity of climate change had profound implications for biodiversity (Figs. 2, 3 & S2). Biotopes and insect abundance experienced severe declines under high climate change projections, regardless of the scenario (Fig. S2). While other studies suggest that land-use change is the strongest driver negatively impacting current and future biodiversity (Maxwell et al. 2016), our results showed that the impact of land-use change on biodiversity was limited, making climate change the next major threat. This finding was also observed by Pereira et al. (2010) and Dullinger et al. (2020). Similar to our results, these studies showed that land-use change had a profound effect on biodiversity. However, the future range of suitable environmental conditions was more affected by changes in climate (Dullinger et al. 2020; Pereira et al. 2010). Macrophytes showed an increase in species richness under higher climate change projections, which can be an indicative of deteriorating water quality across Bavaria (Lewerentz et al. 2023; Lewerentz & Cabral 2022). This increase is likely due to eutrophication and mainly affects shallow water, while species numbers in medium and deeper waters decrease (Lewerentz et al. 2023), ultimately leading to a decline in overall lake ecosystem quality. While this was consistent across all land-use scenarios, land-use change remained a strong driver.

While it seems that the climate change effect is stronger on the distribution of biotopes and insect abundance, vascular plants appear to be more resilient to changes in climate, a trend also observed by Vermaat et al. (2017). This may be due to the ability of certain species to persist for long periods in secondary habitats (Pereira et al. 2010).

Based on these results, we have to acknowledge that climate change had minimal effects on carbon storage and mild effects on the land-use sector, but much greater impacts on biodiversity. It is here noteworthy to mention that these impacts are most likely underestimated, as the simulated species pool did not include warm-adapted and ruderal species coming from outside Bavaria that may replace resident biodiversity and lead to larger biodiversity changes. The dependence of biodiversity on specific climatic conditions presents a critical issue that cannot be resolved solely through conservation or restoration efforts. While conservation and restoration can help stabilise local habitats, they do not address the broader, systemic impacts of rising temperatures, altered precipitation patterns, and extreme weather events driven by climate change. For example, species that require specific temperature ranges or moisture conditions may not survive even in restored or conserved habitats if those climatic conditions are no longer present (Hof 2021). While these efforts can protect landscapes from land-use changes, they cannot shield them from the fundamental shifts in climate and related biodiversity shifts.

Limitations and perspectives

We combined several models designed to represent particular sectors, such as land-use change, carbon uptake, or species distribution at a regional scale. This differs from previous multi-sector studies, which mostly focused on global analyses (Jantz et al. 2015; Reidsma et al. 2006) and often employed species distribution models to assess changes in biodiversity (Dullinger et al. 2020; Hof et al. 2018). Our approach used mechanistic models to assess shifts in species, providing a detailed understanding of species distribution and survival by considering factors such as dispersal and persistence within secondary habitats. Mechanistic models further offer advantages over species distribution models by incorporating biological processes and environmental interactions, resulting in more robust predictions under novel conditions (Higgins et al. 2020). Nevertheless, previous studies showed comparable findings to ours, indicating that land-use change has a significant effect on biodiversity, along with changes in climate. However, the impact of land use was often greater in the low emission scenario (RCP2.6), which included more ambitious mitigation actions, such as large-scale bioenergy production that exceeds the assumptions of our scenario. In these scenarios, achieving climate mitigation through bioenergy required significant landscape conversion, leading to habitat destruction (Hof et al. 2018; Jantz et al. 2015). With that, the SSP and RCP scenarios making land-use changes the strongest driver of biodiversity changes, which is acknowledged by the IPBES (Durán et al. 2023; Kim et al. 2023; but see Pereira et al. 2024). To address this, new scenarios are being developed that place a higher value on nature (Durán et al. 2023; Kim et al. 2023). Although we could not fully implement all these assumptions in our scenarios, we aimed to minimise biodiversity loss by avoiding the conversion of natural or semi-natural areas into other land-use types. Furthermore, these areas are mainly protected under federal and state nature conservation acts in Bavaria (§ 30 and 39 of the BNatSchG/Federal Nature Conservation Act, articles 16 and 23 of the BayNatSchG/Bavarian Nature Conservation Act). Therefore, we assumed a conversion from some cropland into bioenergy croplands in the mitigation scenario, as cropland is already used for agricultural purposes and is less ecologically sensitive compared to natural areas.

Besides the general assumptions of our scenarios and the models used, the projections until 2100 may introduce uncertainties (Albert et al. 2020; Meller et al. 2015). The long-time horizon used in these scenarios poses a challenge, as political changes and unforeseen factors may alter the outcomes. Furthermore, feedback loops from policies reacting to changes in climate, land-use, and biodiversity would significantly affect our results. Therefore, our results should be seen as a policy screening tool (Kim et al. 2023). Models predicting the consequences of different policy interventions, particularly direct drivers, reflecting different perspectives on biodiversity, carbon storage, and land-use under climate change.

Implications for policymakers

Our study highlights how political decisions on future land-use development shape land-use outcomes, affecting both carbon storage and biodiversity. Additionally, we demonstrated the impact of global climate change on these sectors.

The CCM scenario led to the highest carbon storage through products and energy production but had the most negative impact on biodiversity, largely because land use did not change substantially. Interestingly, the CCA scenario, which aimed to intensify land use, proved more beneficial for biodiversity in some areas compared to the CCM scenario. In contrast, the BDP scenario enhanced carbon uptake—primarily through vegetation—while involving substantial land-use changes, resulting in the highest biodiversity preservation, ultimately achieving its purpose. However, to achieve the goals and targets of the Kunming-Montreal Global Biodiversity Framework (COP15, 2022), a narrative focused on biodiversity conservation need to be even more ambitious, which includes the current debate on the so-called Nature Futures Framework (NFF) to improve shared socioeconomic pathways by including biodiversity dimensions (Alexander et al. 2023; D'Alessio et al. 2025; Durán et al. 2023). Although not legally binding, the Kunming-Montreal Global Biodiversity Framework has already prompted novel national legislations, such as the UK's Biodiversity Net Gain Initiative (GOV.UK 2025), which requires improvements in biodiversity indicators for any planned development project. Our findings demonstrate that such improvements are possible across different biodiversity components, from aquatic to terrestrial realms, from grassland to forest species. Encouragingly, these efforts can be reconciled with climate mitigation through increased carbon uptake.

This information allows policymakers to adopt a more holistic approach, combining narrative elements from different sectors (i.e. climate and biodiversity) to maximise positive outcomes. They could encourage even more sustainable land-use changes, as demonstrated in the BDP scenario, to increase carbon uptake in vegetation while incorporating targeted extraction of coniferous forests, as seen in the mitigation scenario, to enhance carbon storage. However, effective conservation and restoration efforts are crucial to ensure that species can access these areas and that proper management and monitoring is implemented.

Beyond the effects of land-use change, our study also emphasises that climate change poses a substantial threat to biodiversity, an issue that cannot be mitigated by policymakers in Bavaria alone. As a global problem, it demands worldwide action. Nevertheless, our study provides valuable insights into the regional impacts of climate change, raising awareness among local policymakers about the urgent need to address this growing threat and convey it to higher institutions.

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Data availability Data is provided within the manuscript and in the supplementary information files.

Declarations

Declaration of generative AI and AI-assisted technologies in the writing process During the preparation of this work, the authors used ChatGPT, Grammarly, and DeepL to improve readability and language. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the final version of the publication.

Competing interest The authors declare no competing interests.

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