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European land use and land cover futures: a global computable general equilibrium assessment with sub-national detail and a climate application

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Theresa Goebel

aus

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Referent: PD Dr. Wolfgang Britz

Korreferent: Prof. Dr. Jan Börner

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Kurzfassung

Land zählt zu den zentralen Grundlagen menschlichen Wohlergehens. Neben der Bereitstellung von Anbauflächen, Lebensräumen sowie Rückzugs- und Erholungsorten spielt es eine entscheidende Rolle für die Erhaltung der Biodiversität und funktionsfähiger Ökosysteme. Zugleich beeinflusst es das Klima maßgeblich. Die Menschheit nutzt heute bereits mehr als 70 % der globalen eisfreien Landoberfläche, wodurch Landnutzung und Landbedeckung zu den wichtigsten anthropogenen Einflussfaktoren auf das Erdsystem zählen.

Während die Menschheit in der Vergangenheit erheblich von Veränderungen der Landnutzung und Landbedeckung profitiert hat, gehen diese heute häufig mit Umweltproblemen einher, darunter Bodendegradation, Nährstoffauswaschung, Biodiversitätsverlust und die Freisetzung von Treibhausgasemissionen. Vor dem Hintergrund einer steigenden Landnachfrage und zunehmend globalisierter Lieferketten besteht eine zentrale gesellschaftliche Herausforderung darin, Landnutzung so zu gestalten, dass soziale, wirtschaftliche und ökologische Ziele gleichermaßen berücksichtigt werden.

Um Unsicherheiten in der zukünftigen Entwicklung von Landnutzung und Landbedeckung zu adressieren, untersucht die Land- und Klimaforschung verschiedene sozio-ökonomische Entwicklungsszenarien. In diesen werden zentrale Treiber des Landnutzungs- und Landbedeckungswandels in Anlehnung an konsistente, vordefinierte Narrative quantifiziert. Dies ermöglicht eine systematische Analyse potenzieller Entwicklungen sowie ihrer sozio-ökonomischen und ökologischen Auswirkungen.

Der Hauptbeitrag dieser Dissertation liegt in der Entwicklung eines neuen methodischen Ansatzes zur Erstellung von Landnutzungs- und Landbedeckungsszenarien. Dieser basiert auf der allgemeinen Gleichgewichtsmodellierungsplattform CGEBox und quantifiziert die fünf sogenannten gemeinsamen sozio-ökonomischen Entwicklungspfade bis zum Jahr 2050. Im Vergleich zu bestehenden Ansätzen verbessert dieser Ansatz sowohl die Transparenz als auch die Flexibilität der Entwicklung von Szenarien. Darüber hinaus verbinden die neuen Quantifizierungen globale Konsistenz mit hoher regionaler und sektoraler Detailgenauigkeit und verbessern die Abbildung sozio-ökonomischer Prozesse.

Im Rahmen dieser Arbeit werden die neuen Landnutzungs- und Landbedeckungsprojektionen zudem in einer Klimasimulation eingesetzt, um Rückkopplungen zwischen Landoberfläche und Atmosphäre bei Landbedeckungsveränderungen zu untersuchen. Durch die Integration sozio-ökonomischer Modellierung, räumlich genauer Herunterskalierung und physikalisch konsistenter Klimasimulationen ermöglicht ein neuer konzeptioneller Ansatz eine kohärente Analyse dieser Effekte über verschiedene Skalen hinweg.

Insgesamt trägt diese Dissertation zu einem vertieften Verständnis der Auswirkungen sozio-ökonomischer Unsicherheiten auf regionale Landnutzungs- und Landbedeckungsdynamiken sowie deren Klimaeffekte bei. Sie unterstützt ökonomisch fundierte Flächenplanung und die Ausgestaltung landbasierter Klimaschutzmaßnahmen und politischer Entscheidungsprozesse.

Abstract

Land constitutes a fundamental foundation for human life and well-being. Beyond providing agricultural land, habitats, and spaces for retreat and recreation, it plays a crucial role in sustaining biodiversity and functioning ecosystems, and it is a key component of the climate system. Today, humanity already uses more than 70% of the global ice-free land surface, making land use and land cover one of the most significant anthropogenic influences on the Earth system.

While humanity has long benefited from changes in land use and land cover, these are now increasingly associated with significant environmental pressures, including land degradation, nutrient run-off, biodiversity loss, and the release of greenhouse gas emissions. In the context of growing land demand and increasingly globalised supply chains, a key challenge for society is therefore to manage land in a way that simultaneously meets social, economic, and environmental objectives.

To address uncertainties in future land use and land cover developments, land and climate research examines various socio-economic development scenarios. Within these scenarios, key drivers of land use and land cover change are quantified based on consistent, predefined narratives. This enables a systematic analysis of potential future developments and their socio-economic and environmental impacts.

The main contribution of this dissertation lies in the development of a new methodological approach for generating land use and land cover scenarios. This approach is based on the computable general equilibrium modelling platform CGEBox and quantifies the five so-called Shared Socio-Economic Pathways up to 2050. Compared to existing approaches, it improves both the transparency and the flexibility of scenario development. Furthermore, the new quantifications combine global economic consistency with a high level of regional and sectoral detail and enhance the representation of socio-economic processes.

As part of this work, the new land use and land cover projections are further used in a climate application to analyse land-atmosphere feedbacks resulting from land cover changes. By integrating socio-economic modelling, spatial downscaling, and physically consistent regional climate simulations, a new conceptual framework enables a coherent analysis of these effects across different scales.

Overall, this dissertation contributes to an improved understanding of how socio-economic uncertainties translate into regional land use and land cover dynamics and associated climate impacts. These insights support economically grounded land use and land cover planning, as well as the design and assessment of land-based adaptation and mitigation measures, and policy-relevant decision-making.

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Abbreviations

Acronym	Definition
AEZ	Agro-Ecological Zone
BAU	Business As Usual
CCI	Climate Change Initiative
CES	Constant Elasticity of Substitution
CET	Constant Elasticity of Transformation
CGE	Computable General Equilibrium
CLM	Community Land Model
COSMO	Consortium for Small-scale Modeling
EAA	Economic Accounts for Agriculture
EFTA	European Free Trade Association
ESA	European Space Agency
EU	European Union
FAO	Food and Agricultural Organization of the United Nations
FFD	Fossil-Fueled Development
FSS	Farm Structure Survey
GAMS	General Algebraic Modeling System
GDP	Gross Domestic Product
GDX	GAMS Data Exchange
GHG	Greenhouse Gas
G-RDEM	GTAP-based Recursive-Dynamic Economic Model
GTAP	Global Trade Analysis Project
GVA	Gross Value Added
HIC	High-Income Country
HPD	Highest Posterior Density
IAM	Integrated Assessment Model

LC	Land Cover
LIC	Low-Income Country
LU	Land Use
LUH2	Land Use Harmonization 2
LULC	Land Use and Land Cover
MAIDADS	Modified Implicit Directly Additive Demand System
MIC	Middle-Income Country
NLC	Natural Land Cover
NLP	Non-Linear Programming
NUTS	Nomenclature des Unités Territoriales Statistiques
PE	Partial Equilibrium
PFT	Plant Functional Type
RCM	Regional Climate Model
RCP	Representative Concentration Pathway
SEALS	Spatial Economic Allocation Landscape Simulator
SSP	Shared Socio-Economic Pathway
SSS	Stratified Societies
TFP	Total Factor Productivity
TSMP	Terrestrial Systems Modeling Platform
TSS	Towards Sustainability

Chapter 1
Introduction

Land, the physical surface of the Earth, constitutes a fundamental foundation for human life and well-being. It provides habitats and freshwater resources and enables the production of food, feed, and fibre. Beyond these direct benefits, land delivers a wide range of less visible contributions, including aesthetic and recreational values, and plays a crucial role in sustaining ecosystem services and biodiversity (FAO, 2021; IPBES, 2018; IPCC, 2019). In addition, land is a key component of the climate system. It contributes to greenhouse gas (GHG) emissions through land management and changes in carbon stocks, and influences climate through alterations of biophysical processes such as surface albedo, evapotranspiration, and energy fluxes. Consequently, land-based adaptation and mitigation strategies are widely regarded as essential elements of climate policy (IPCC, 2019; Pielke et al., 2016).

Land use and land cover (LULC) – defined as the human use of land (e.g., cultivation of specific crops) and its biophysical surface coverage (e.g., cropland) – is one of the most significant anthropogenic influences on the Earth system (IPBES, 2018; IPCC, 2019). Currently, more than 70% of the Earth's ice-free land is already used by humans (IPCC, 2019), largely driven by infrastructure development and the expansion and intensification of agriculture, which have brought significant benefits to society (Li et al., 2025; Ramankutty et al., 2018; Zhang et al., 2023). However, land is increasingly subject to multiple and competing demands, including food and feed production, bioenergy generation, urban expansion, and biodiversity conservation. This growing competition drives both the conversion of natural ecosystems and the intensification of land management. As a result, LULC change is frequently associated with substantial environmental pressures, including soil degradation, nutrient run-off, habitat loss, and the disruption of ecosystem functioning (IPBES, 2018; IPCC, 2019; Popp et al., 2017).

Looking ahead, pressures on land resources are expected to intensify further. Global population projections indicate continued growth until at least 2050, while rising incomes and changing consumption patterns are likely to increase demand for agricultural and other land-based products (Dellink et al., 2017; KC and Lutz, 2017; Popp et al., 2017). At the same time, increasingly globalised supply chains link LULC dynamics across regions, so that demand and land use decisions in one region can drive land system change elsewhere (Meyfroidt et al., 2013, 2020; Ramírez-Mejía et al., 2025). LULC developments are further shaped by a wide range of interacting socio-economic drivers, including consumer preferences, societal values, environmental awareness, governance structures, international cooperation, and technological progress (Alexander et al., 2015; Stehfest et al., 2019; van Vliet et al., 2015). A key challenge for society is therefore to manage land in a way that simultaneously meets social, economic, and environmental objectives, while navigating inherent trade-offs and potential synergies between competing land uses (IPBES, 2018; IPCC, 2019).

In response to this challenge, major international policy frameworks such as the Sustainable Development Goals, the Kunming-Montreal Global Biodiversity Framework, or the European Green Deal, aim to steer LULC towards more sustainable trajectories (EU, 2021; UN, 2015, 2022). However, the complexity, path dependency, and uncertainty of land system dynamics make it difficult to anticipate future developments and assess the implications of alternative policy pathways. To this end, the climate and land research communities increasingly rely on scenario-based approaches. These approaches explore contrasting futures by varying key socio-economic drivers according to predefined, internally consistent narratives. This enables the systematic analysis of potential LULC trajectories and their environmental and socio-economic implications (Moss et al., 2010; O'Neill et al., 2014; Popp et al., 2017).

1.1 Motivation and research gap

The most recent set of such predefined, internally consistent socio-economic narratives is embodied in the five Shared Socio-Economic Pathways (SSPs; O'Neill et al., 2014; Riahi et al., 2017). These narratives – summarised in Figure 1.1 – describe developments across a wide range of dimensions, including demographic, educational, and lifestyle-related factors, economic and political aspects, institutional and governance structures, environmental conditions, and technological progress. Together, these developments result in different challenges for climate change adaptation and mitigation (O'Neill et al., 2017). The SSP narratives are further complemented by quantitative, country-specific projections of demographic trends (Jiang and O'Neill, 2017; KC and Lutz, 2017) and gross domestic product growth (Crespo Cuaresma, 2017; Dellink et al., 2017; Leimbach et al., 2017) throughout the 21st century.

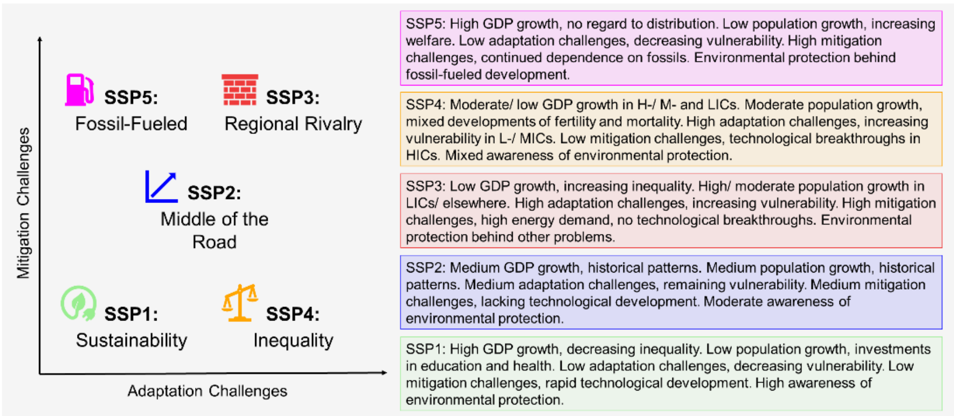

Figure 1.1 Overview of the shared socio-economic pathways.

Source: Goebel and Britz (2025). Remark: L-/ M-/ HIC stands for low-/ middle-/ high-income country.

LULC developments across the five SSPs have been quantified with Integrated Assessment Models (IAMs) and are subject to ongoing refinement (Doelman et al., 2018; Popp et al., 2017; Zeng et al., 2022). IAMs are loosely coupled modelling frameworks that integrate multiple disciplines. They typically include economic components to project sectoral demands for energy, land, and agriculture, which then feed into sector-specific modules. In this way, IAMs capture interactions between human behaviour and Earth system dynamics by linking socio-economic and biophysical processes and explicitly representing mechanisms such as carbon sequestration, vegetation dynamics, and climate responses to GHG emissions. This integrative capacity constitutes a key strength of IAMs (Hare et al., 2018; IPCC, 2022).

Despite their strengths, coupling diverse components and computing large scenario ensembles often require simplifying certain aspects of the modelling framework. As a result, IAMs frequently operate at coarse regional and sectoral resolution and represent only a subset of the drivers of structural and LULC change. While IAM-based LULC projections are well suited for many applications, these characteristics can limit their usefulness for detailed and economically grounded regional analyses (Gambhir et al., 2022; Johnson et al., 2023, 2025; Popp et al., 2017). Furthermore, LULC modelling is subject to inherent uncertainties, and there is broad agreement that ensemble approaches – building on different models and methodologies – enhance the robustness and credibility of LULC projections (Alexander et al., 2017; Popp et al., 2017; Prestele et al., 2016). Consequently, there remains a need for complementary approaches that provide higher regional and sectoral resolution and incorporate a broader range of socio-economic drivers to better capture regionally differentiated LULC dynamics and their implications for the Earth system.

1.2 Research objective and structure of the thesis

In response to the limitations of existing IAM-based approaches, this dissertation aims to develop complementary LULC projections for the five SSPs that combine global economic consistency with a high level of regional and sectoral detail and extend the representation of socio-economic processes. The resulting projections are intended to improve the understanding of how socio-economic uncertainties translate into regional LULC dynamics and associated climate impacts, and to support economically grounded LULC, adaptation, and mitigation planning.

To this end, this dissertation presents a new methodological approach to generate SSP-based LULC projections through 2050. This approach uses the open-source computable general equilibrium modelling platform CGEBox, which is well suited for this application for two reasons. First, its global economic structure – including international trade – enables the analysis of interconnected socio-economic drivers and their direct and spillover effects on LULC dynamics, while maintaining a high level of regional and sectoral detail. Second, its modular design allows for the flexible integration of application-specific components (Britz, 2022; Britz and van der Mensbrugghe, 2018). The SSP-based LULC projections are implemented as recursive-dynamic baseline scenarios, using the GTAP-based recursive-dynamic economic model (G-RDEM), which incorporates key economic and demographic adjustment processes and updates drivers of structural change over time (Britz and Roson, 2019; Roson and Britz, 2021). Additional CGEBox modules enhance the representation of LULC, energy use, climate-relevant emissions, and sub-national production functions, thereby enabling the generation of highly detailed LULC projections.

To structure the analysis, this dissertation addresses three research questions corresponding to the core chapters. The first research question is:

How can SSP-aligned LULC projections be developed that are economically grounded, globally consistent, and detailed at regional and sectoral scales?

Chapter 2 provides a comprehensive description of the new methodological approach, including data preparation, model set-up, and SSP implementation. By relying on a computationally efficient, stand-alone, and open-source economic model that explicitly integrates structural change drivers and key integrated assessment features, this approach improves transparency and adaptability of SSP-based LULC projections. It further enables the incorporation of sub-national detail and a high level of LULC differentiation. Presenting global-scale results, this chapter benchmarks CGEBox's LULC projections against established IAM-based outputs and situates the new approach within the existing literature. Overall, CGEBox produces plausible LULC outcomes and offers new insights into complex interactions between socio-economic drivers and land system dynamics. These features position CGEBox as a valuable complement to IAMs, particularly for supporting economically grounded assessments of LULC change and its implications.

The second research question is:

How can regional and sectoral detail be integrated into global SSP-aligned LULC projections, and how can these projections support applied analyses?

Chapter 3 complements the methodological framework introduced in Chapter 2 by providing additional insights into the integration of regional and sectoral detail within the global CGEBox simulation, with a particular focus on Europe. The resulting SSP-based LULC projections are publicly available and include European data at national and sub-national (NUTS2) levels, while regions outside Europe are represented at national or aggregated scales. The dataset distinguishes eight land cover (LC) types (e.g., cropland, pastureland, shrubland) and 65 corresponding land use categories (e.g., individual crops), covers all five SSPs, and is available at two- and five-year intervals from 2020 to 2050. These high-resolution European LULC projections enable a wide range of applications, including their use as input for climate or biodiversity studies, economically grounded assessments of long-term LULC change in Europe, and ensemble-based analysis of LULC futures under uncertainty.

The third research question is:

How do socio-economically driven LC changes influence regional climate through biophysical land-atmosphere interactions?

Chapter 4 applies the new SSP-based LULC projections to analyse land-atmosphere feedbacks of LC change. To examine how socio-economic development pathways propagate from global economic dynamics to local climate effects, this chapter introduces a conceptual modelling framework loosely coupling LC projections with regional climate simulations. CGEBox NUTS2 level LC projections are downscaled to a 300 m × 300 m grid using a high-resolution LC downscaling model. The resulting spatially explicit LC projections are applied to a 450 km x 450 km test region in Northern and Central Germany and serve as input for a regional climate model that explicitly represents land-atmosphere interactions. By combining socio-economic modelling, spatial downscaling, and physically consistent climate simulations, this approach enables a coherent analysis of land-atmosphere feedbacks of LC change across scales. The analysis demonstrates that even moderate LC changes can produce significant regional climate feedbacks. This is particularly relevant under sustainable, low-emission scenarios, where LC interventions can contribute significantly to regional climate outcomes. These findings highlight the importance of integrating socio-economic and biophysical modelling for robust adaptation and mitigation planning.

Finally, Chapter 5 summarises the major contributions of the dissertation, discusses the applied methodologies and their limitations, highlights implications for future research and policy, and concludes.

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Chapter 2
Global land use and land cover projections under the shared socio-economic pathways: An integrated computable general equilibrium analysis with sub-national resolution for Europe[1]

Abstract

Anticipating uncertain land use and land cover trajectories, central to global sustainability and climate action, requires scenario-based projections grounded in socio-economic narratives. This study presents a new modelling framework for generating globally consistent land use and land cover projections, applied to the five Shared Socio-Economic Pathways through 2050. Compared to existing work, this approach offers four key advancements: (1) avoiding multi-model coupling and increasing transparency through the use of an open-source, stand-alone economic model with integrated assessment features; (2) integrating key structural

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change drivers in a recursive-dynamic set-up; (3) achieving high regional resolution, including NUTS2 level disaggregation for European economic dynamics; and (4) representing land using production activities and products with high-resolution. The new projections are generated using CGEBox, an open-source Computable General Equilibrium modelling platform tailored for long-term baseline development, with integrated accounting for land use, land cover, and energy. CGEBox produces complementary projections within the range of results from established Integrated Assessment Models, offering new insights into the complex interactions between socio-economic drivers and land system dynamics. Only the most sustainable scenario – combining strong behavioural change, ambitious policy action, and favourable technological progress – shows a marked increase in natural land cover. The remaining scenarios range from near-stable natural land cover to notable losses in cases lacking environmental protection. The new projections are particularly valuable for economically grounded policy assessments of land use and land cover change and its implications – especially where timely updates, distributional effects, or regional and land use details are essential.

Keywords: Land use, land cover, Shared Socio-economic Pathways (SSPs), scenarios, Computable General Equilibrium (CGE) modelling.

2.1 Introduction

Land use and land cover (LULC) dynamics are critical for the future of our planet, with changes in carbon stocks among the main drivers of climate change. At the same time, LULC-based mitigation options – such as afforestation, enhanced soil carbon sequestration, and biomass substitution for fossil fuels – are considered particularly promising (IPCC, 2019; Rose et al., 2012). Beyond their role in the climate system, land resources provide food, feed, fibre, and numerous other ecosystem services, thereby shaping sustainability outcomes such as food security and biodiversity conservation (Smith et al., 2013). There is broad consensus that future LULC trajectories will be shaped primarily by socio-economic drivers, whose evolution remains highly uncertain. To address this, the climate research community employs a scenario-based approach, exploring contrasting futures through variations in socio-economic trends aligned with predefined narratives (Stehfest et al., 2019). The most recent set of such narratives is embodied in the five Shared Socio-Economic Pathways (SSPs; Riahi et al., 2017; van Vuuren et al., 2014), summarised in Figure 2.1. The SSPs describe developments across demographic, educational, health, economic, lifestyle, political, institutional, technological, and environmental dimensions, resulting in futures with varying challenges to climate change adaptation and mitigation (O'Neill et al., 2017). Building on these narratives, quantitative, country-specific projections of demographic trends (KC and Lutz, 2017; Jiang and O'Neill, 2017) and gross domestic product (GDP) growth (Crespo Cuaresma, 2017; Dellink et al., 2017; Leimbach et al., 2017) have been developed for each pathway throughout the 21st century and shared with the global research community (IIASA, 2024, 2025).

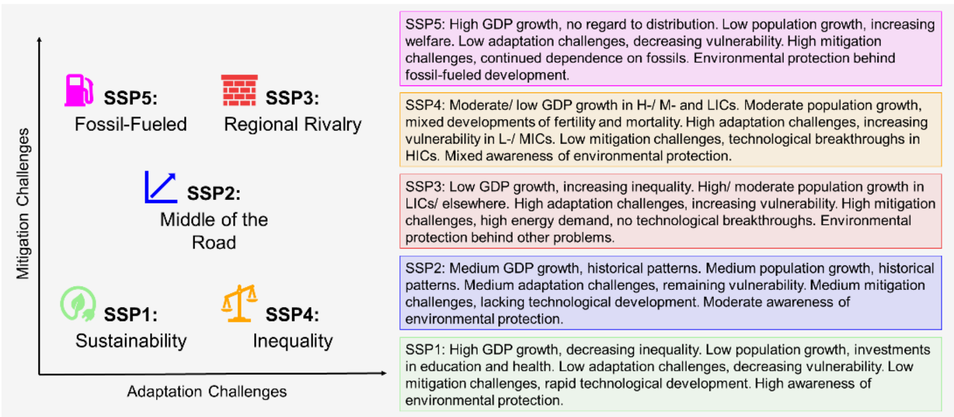

Figure 2.1 Overview of the shared socio-economic pathways.

Source: Own illustration based on O'Neill et al. (2014, 2017). Remark: L-/ M-/ HIC stands for low-/ middle-/ high-income country.

Modelling exercises employing Integrated Assessment Models (IAMs) have quantified LULC trajectories under the SSPs at the level of aggregated world regions (Popp et al., 2017), with these projections undergoing further refinement (Doelman et al., 2018; Zeng et al., 2022). However, the regional and sectoral resolution of these projections is often considered insufficient for more targeted analyses. Moreover, due to inherent uncertainties in LULC modelling, there is broad agreement that an ensemble approach drawing on multiple models and methodologies enhances the robustness and credibility of insights (Alexander et al., 2017; Popp et al., 2017). In light of these considerations, this study presents a new modelling framework for generating globally consistent LULC projections, applied to the five SSPs through 2050. Compared to existing work, this approach offers four key advancements:

(1) **Avoiding multi-model coupling and increasing transparency:** The new SSP-based projections are generated using a global, recursive-dynamic Computable General Equilibrium (CGE) model implemented in the open-source modelling platform CGEBox (Britz and van der Mensbrugghe, 2018), calibrated to the latest Global Trade Analysis Project (GTAP) Database (Version 11; Aguiar et al., 2022). By integrating features such as a dedicated LULC modelling system with Agro-Ecological Zone (AEZ) differentiation, an energy system extension (GTAP-E), emissions accounting, and sub-national detail, CGEBox eliminates the need for complex multi-model coupling. The SSP narratives are operationalised through a comprehensive set of assumptions on LULC drivers, drawing on updated demographic and GDP projections (IIASA, 2024). This set-up facilitates replication and supports further development, such as refining scenario assumptions or adding regional detail outside Europe.

(2) **Integrating key structural change drivers:** The CGE framework builds on the GTAP-based Recursive-Dynamic Economic Model (G-RDEM; Britz and Roson, 2019; Roson and Britz, 2021), which is tailored for constructing and analysing long-term economic baselines.

(3) **Achieving high regional resolution:** Within the study's focus region defined in alignment with the EURO-CORDEX domain (WRCP, 2024), European Union (EU) Member States (including accession candidates), Norway, Switzerland, and the United Kingdom are represented at sub-national level of administrative NUTS2 regions. The remaining countries in the EURO-CORDEX domain are disaggregated into broader AEZs. Outside the focus region, continental aggregates are constructed differentiated by AEZs, consistent with previous SSP quantifications.

(4) **Representing land using production activities and products with high-resolution:** The new SSP-based projections differentiate 30

cropland production activities/ products (each with irrigated and rainfed variants), four pastureland production activities/ products, and managed forest.

The remainder of the paper is structured as follows: Section 2.2 outlines the CGE framework and methodological approach; Section 2.3 presents the global-scale results, establishing a basis for comparison with existing projections; Section 2.4 discusses the findings in the context of previous SSP-based LULC assessments; and Section 2.5 concludes with policy implications and directions for future research.

2.2 Methodology

Economic simulation models are valuable tools for analysing the impact of interrelated socio-economic drivers on LULC dynamics. Changes in consumption and production – shaped by purchasing power, preferences, technology, factor availability, and political interventions – affect land supply and demand through market mechanisms. However, economic models only partially cover integrated assessment features, and a trade-off exists between modelling interactions across the global economy and capturing detailed production and market structures. While CGE models represent the entire economy, including trade, they typically lack regional and sectoral detail compared to partial equilibrium (PE) models. Existing SSP quantifications address these limitations through model linkages (Delzeit et al., 2020; Riahi et al., 2017). In contrast, this study extends relevant production activities and products in a CGE model to PE level resolution, while directly embedding integrated assessment features. The quantification of the SSPs in this analysis is based on two pillars: (1) adoption of SSP-specific exogenous projections, and (2) translation of the SSP narratives into comprehensive assumptions regarding LULC drivers.

2.2.1 Database and modelling framework

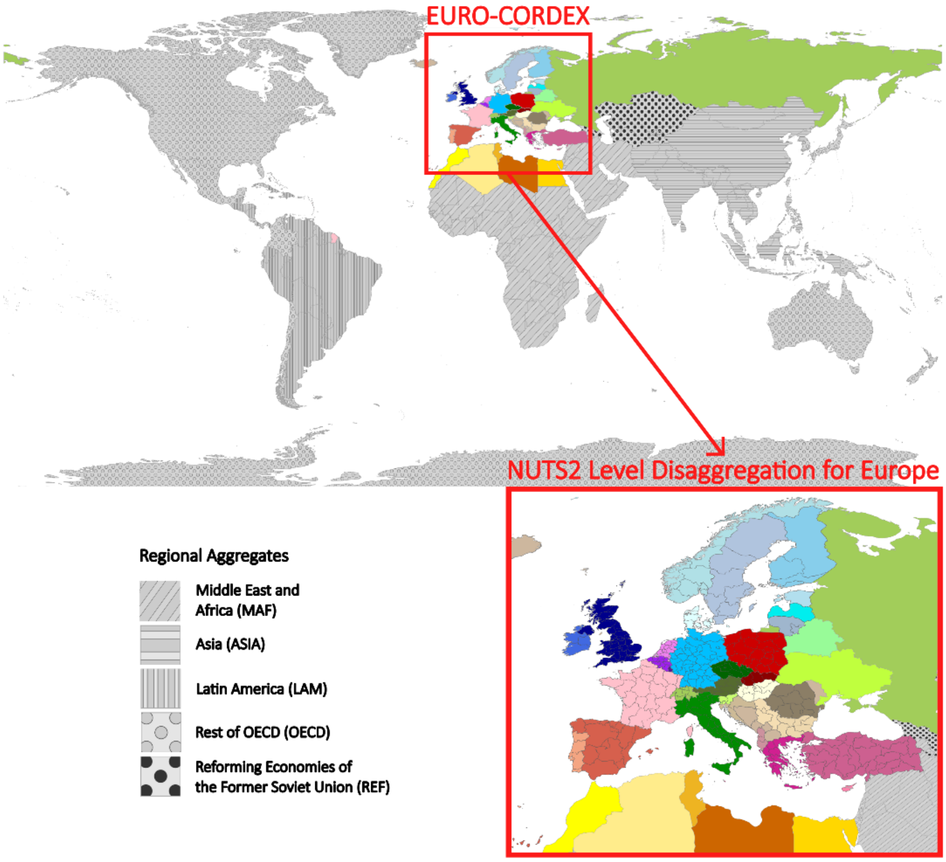

Figure 2.2 Regional resolution in the shared socio-economic pathway quantifications in CGEBox.

Source: Own illustration.

The database used in this study builds on the GTAP v11 Power database[2] (Aguiar et al., 2022; Chepeliev, 2023; GTAP, 2023), which represents the global economy in 2017, including data on power generation, emissions, air pollution, and LULC. To address discrepancies between GTAP-reported land areas and actual regional extents, the input data are adjusted using CIA world factbook statistics (CIA, 2025), global FAOSTAT tree cover statistics (FAO, 2024), and European 2018 CORINE land cover (LC) data (COPERNICUS, 2024) as explained by Goebel and Britz (2025a). The resulting database distinguishes among the GTAP-defined LC categories –

[2] CGEBox is open-source and open-access, but GTAP input data is subject to a paid licence.

cropland, pastureland, forest, savannah, shrubland, built-up land, and other land – and additionally introduces unmanaged forest. To improve computational efficiency, the LC-modified GTAP v11 Power database is partly aggregated: broader regions are defined outside the EURO-CORDEX domain, electricity products are consolidated, and labour types are grouped to skilled and unskilled categories. Conversely, greater detail is introduced where it is considered particularly useful: EU countries (including accession candidates), Norway, Switzerland, and the United Kingdom are disaggregated to NUTS2 level[3]; agricultural and food-related production activities and products are split into 38 and 19 categories, respectively[4]; and irrigation water is introduced as a production factor, allowing differentiation between irrigated and rainfed cropland production activities[5]. Figure 2.2 illustrates the regional resolution of the disaggregated database, Figure 2.3 (upper right) summarises the generation process, and Table 2.1 shows the resulting LULC detail. The final database on which the SSP quantifications build encompasses 47 countries or regions, 317 NUTS2 regions, 143 production activities, 103 products, and six production factors. Appendix A.2.1 provides a detailed mapping between the aggregated or disaggregated elements and the original GTAP entries.

The CGE analysis is implemented in the open-source modelling platform CGEBox (Britz and van der Mensbrugghe, 2018)[6], with G-RDEM (Britz and Roson, 2019; Roson and Britz, 2021) at its core. Building on the GTAP standard model (van der Mensbrugghe, 2018), G-RDEM is tailored for long-term economic baseline generation and analysis. It incorporates four key recursive-dynamic features: (1) exogenous GDP updates via region-specific total factor productivity (TFP) shifts; (2) exogenous demographic and labour supply changes; (3) capital accumulation; and (4) consideration of foreign

[3] NUTS (Nomenclature des Unites territoriales statistiques) is a regional classification administrated by the Statistical Office of the EU. Level 2 covers districts with the same regional policy (EU, 2025). The sub-national disaggregation is described in detail in Goebel and Britz (2025a).
[4] The agri-food disaggregation follows Britz (2022b) but relies on more recent data (FAO, 2025; GTAP, 2025).
[5] Methodology described in Britz (2022a).
[6] For more (technical) information on CGEBox and its features please refer to its documentation (Britz, 2022a), which also includes necessary information to download, install, and use the model. The quantifications presented here build on model revision 6281. Details on how to replicate the model runs can be found in Appendix A.2.2.

savings and related debt dynamics in the balance of payments. In addition, exogenous drivers of structural change such as macro-saving rates, input-output cost shares, government and investment expenditure shares, caloric consumption patterns, and built-up area developments are updated using empirically estimated relationships[7]. Cropland and yield developments are calibrated to projections from the Food and Agricultural Organization of the United Nations (FAO; FAO, 2018). Further model extensions include a rank-three modified implicit directly additive demand system (MAIDADS) with food detail for private consumption (Britz, 2022c), differentiated TFP growth across three broad economic sectors, and multi-layered nested constant elasticity of substitution production functions.

To support integrated assessment capabilities, G-RDEM operates with additional CGEBox modules. The AEZ module, based on the GTAP-AEZ framework (Lee et al., 2009), enhances LULC representation by disaggregating land into 18 AEZs with similar cultivation conditions and by improving substitution among land uses (LUs). Compared to the original GTAP-AEZ model, CGEBox introduces three key improvements: (1) an additive constant elasticity of transformation land supply function to preserve physical area balances (van der Mensbrugghe and Peters, 2016); (2) a six-level land nesting structure distinguishing annual from perennial crops; and (3) statistically estimated cropland conversion patterns from grassland, managed forest, or unmanaged land (Britz, 2022a). Beyond the AEZ module, emission accounting modules[8] enable the tracking and taxation of climate-relevant emissions using GTAP-related data (Chepeliev, 2020, 2022). The energy module, derived from GTAP-E (McDougall and Golub, 2007), supports detailed substitution among energy carriers and between energy and capital and represents energy quantities in million tonnes of oil equivalent. Lastly, the sub-national module disaggregates production functions and factor markets to sub-national levels (Britz, 2022a).

[7] The updates are based on econometrically estimated relations to demographics and GDP. While the estimations for the first four elements originate from the development of G-RDEM, built-up area development has been introduced for this study based on available literature (Chen et al., 2020).

[8] CO2 emission accounting and non-CO2 emission accounting.

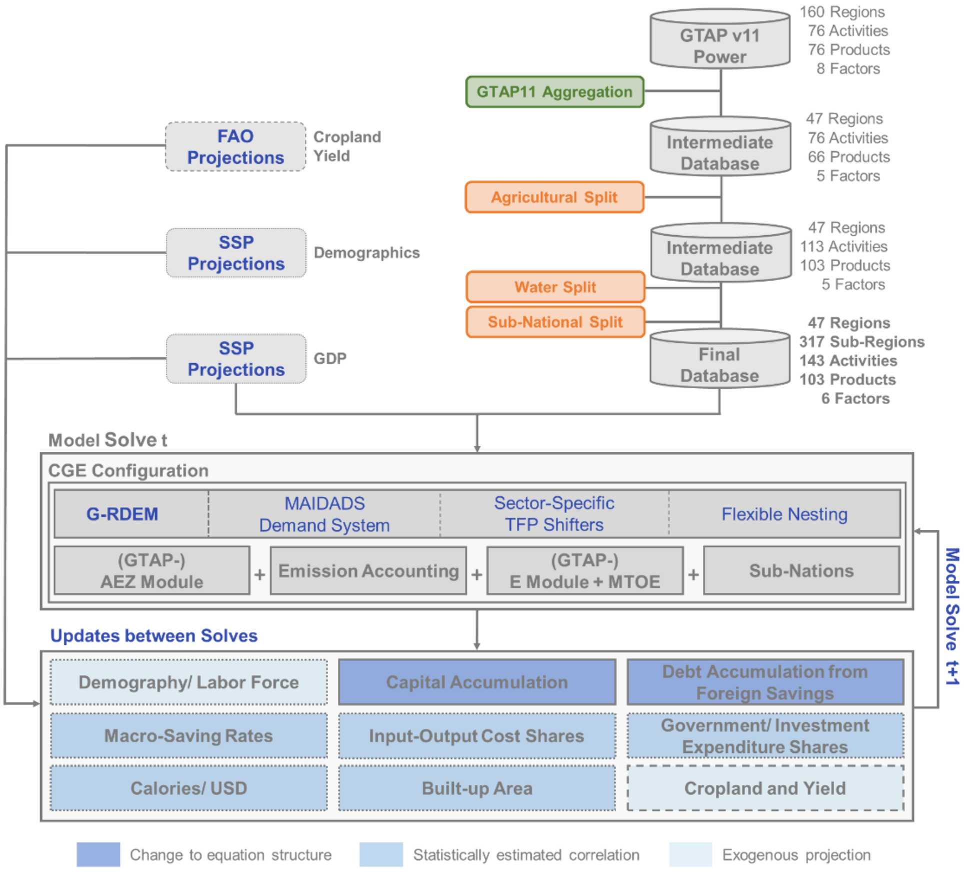

Figure 2.3 Database and modelling framework used in the shared socio-economic pathway quantifications in CGEBox.

Source: Own illustration. Remark: GTAP-based Recursive-Dynamic Economic Model (G-RDEM) features are highlighted in blue.

Table 2.1 Land use and land cover detail in the shared socio-economic pathway quantifications in CGEBox.

Land Cover	Managed	Land Use			
Cropland	Yes	- Apples - Bananas/ plantains - Barley - Citrus fruits - Cocoa beans - Coffee beans - Grapes - Leguminosae - Maize - Nuts	- Oats - Olives - Oth. cereals - Oth. crops - Oth. fruits - Oth. oilseeds - Oth. roots/ tubers - Oth. vegetables - Paddy rice	- Palm oil fruit - Plant-based fibres - Potatoes - Rape seed - Rye - Sorghum - Soy bean - Sugar cane/ beet	- Teas - Tomato - Wheat All as irrigated and rainfed variants.
Pastureland	Yes	- Cattle for meat	- Oth. ruminant for meat	- Raw milk	- Wool
Managed forest	Yes	- Forestry			
Natural forest	No				
Savannah/ grassland	No				
Shrubland	No				
Other land	No				
Built-up land	No				

Source: Own illustration. Remark: “Oth.” abbreviates “other”.

2.2.2 *Shared socio-economic pathway quantification*

CGEBox implements the quantifications across all five SSPs as recursive-dynamic baseline scenarios, simulated biennially from 2017 to 2050. From 2025 onwards, these scenarios diverge based on a set of exogenous projections and assumptions tailored to each SSP. Country- and scenario-specific GDP and demographic inputs are sourced from version 3.1 of the OECD Env-Growth model and the WiC-POP model (IIASA, 2024). Based on these inputs, empirically estimated structural change drivers vary across scenarios. Key among them for LULC are changes in calorie intake per dollar spent – reflecting increasing demand for processed and out-of-home food – and the expansion of built-up areas, which intensifies land competition and reduces natural vegetation. GDP and demographic changes themselves are also major LULC drivers: higher incomes disproportionally raise per capita food demand and shift diets towards more land-intensive animal products, while population growth increases total demand for food, feed, fibre and consequently land (Alexander et al., 2015).

G-RDEM also incorporates FAO projections of cropland and yield developments (FAO, 2018) for three scenarios: Towards Sustainability (TSS, SSP1), Business As Usual (BAU, SSP2), and Stratified Societies (SSS, SSP3/4). In this study, SSS is used for SSP3. For SSP4 (MIX), projections are applied differentially across income groups: TSS for high-income countries (HICs), BAU for middle-income countries (MICs), and SSS for low-income countries (LICs), reflecting its unequal development narrative. SSP5 assumes rapid technological advancement without environmental prioritisation and relatively low population pressure, allowing largely unconstrained land conversion and providing little incentive for yield improvements. As a result, the corresponding Fossil-Fueled Development (FFD, SSP5) projection is derived from SSS but assumes slightly lower cropland expansion and yield improvements. While cropland expansion competes with other LUs, yield improvements critically determine the land area needed to meet future demand. Historically, productivity gains have mitigated land pressure, but future yield growth remains uncertain due to biophysical and environmental constraints (Alexander et al., 2015; van Zeist et al., 2020).

Beyond relying on projections, the baselines developed with CGEBox incorporate a broader set of assumptions related to LULC drivers. These assumptions are aligned with the SSP narratives and are grounded in current literature, established IAM implementations, and considerations of technical feasibility. They span five thematic areas: (1) technological progress in agricultural and forestry production, which affects land requirements per unit of output; (2) consumption and preference shifts, which potentially alleviate land pressure through more sustainable dietary patterns; (3) agricultural and environmental policies, which influence LU decisions; (4) energy policies, which affect LULC through bioenergy deployment and carbon stock considerations[9]; and (5) international trade, which can both

[9] CGEBox cannot represent bioenergy dynamics or carbon stock taxation in detail but incorporates implicit assumptions.

promote productivity and drive economic expansion (Alexander et al., 2015; Stehfest et al., 2019).

Table 2.2 below summarises the assumptions on LULC drivers used in the baselines in CGEBox. The first six rows relate to the exogenous projections and core G-RDEM features, while the following rows detail the broader set of scenario-specific assumptions, grouped by the five thematic areas listed above. The table briefly describes the implementation of each driver, visualises its assumed strength across SSPs, and indicates the expected direction of its impact on total forest area. Forest dynamics are shaped by both agricultural expansion and forest management practices. To assess the sensitivity of LULC outcomes to individual assumptions, additional simulations are conducted in which these drivers[10] are sequentially deactivated. Appendix A.2.3 provides the associated General Algebraic Modeling System (GAMS) code for the implementation of the LULC-related SSP assumptions. Further technical details on the integration of these elements into G-RDEM are available in the CGEBox documentation (Britz, 2022a) and the open-source model code.

[10] Excluding socio-economic assumptions required for recursive-dynamic baseline generation.

Table 2.2 Land use and land cover drivers in the shared socio-economic pathway quantifications in CGEBox.

		Assumption	Model Implementation	Development to 2050 SSP1	SSP2	SSP3	SSP4	SSP5	Expected Effect on Total Forest (TF)
Socio-Economics		Gross Domestic Product (GDP)	GDP follows version 3.1 of the SSP-specific projections provided by the OECD (IIASA, 2024).	↗↗↗↗	↗↗↗	↗	↗↗	↗↗↗↗↗	GDP ↗ = Consumption ↗ = TF ↘
		Demographics (DEM)	DEM follows version 3.1 of the SSP-specific projections provided by the Wittgenstein Centre (IIASA, 2024).	↗	↗↗↗	↗↗↗↗↗	↗↗↗↗	↗↗	DEM ↗ = Consumption ↗ = TF ↘
		Calorie Content	Calorie content per dollar spent follows an econometric relation to GDP reflecting changes in food consumption as prosperity increases.	↘↘↘↘	↘↘↘	↘	↘↘	↘↘↘↘↘	Calorie content/ dollar ↘ = Consumption ↗ = TF ↘
		Built-Up Land (BU)	BU follows econometric relations to GDP and DEM as described by Chen et al (2020).	↗↗↗	↗↗	↗	↗↗↗↗	↗↗↗↗↗	BU ↗ = TF ↘
Agricultural and Forestry Production	①	Cropland (CL)	CL follows SSP-specific projections provided by the FAO (2018). These comprise 3 scenarios: TSS, BAU, and SSS. MIX and FFD are created on their basis in line with the SSP narratives.	↘ (TSS)	↗ (BAU)	↗↗↗↗ (SSS)	↗↗ (MIX)	↗↗↗ (FFD)	CL ↗ = TF ↘
	①	Yield	Yield follows SSP-specific projections provided by the FAO (2018). The scenarios are the same as described in the CL row.	↗↗↗↗↗	↗↗↗↗	↗↗	↗↗↗	↗	Yield ↗ = Area to produce same calories ↘ = TF ↗
	②	Irrigation Technology	A GDP and DEM dependent technology shifter is assumed to change the efficiency of water input.	↗↗↗	↗↗	↗	LMH	↗↗	Irrigation technology ↗ = Yield ↗ = TF ↗
	③	Livestock Intensification	A GDP and DEM dependent technology shifter is assumed to change the efficiency of forage and land use.	↗↗	↗	-	LMH	↗↗	Forage/ land use efficiency in livestock production ↗ = Land input ↘ = TF ↗
	④	Forestry Intensification	A GDP and DEM dependent technology shifter is assumed to change the value added (VA) efficiency in forestry.	↗↗↗↗	↗↗↗	↗	LMH	↗↗	VA efficiency in forestry production ↗ = Land input ↘ = TF ↘
	⑤	Timber Utilisation	A GDP and DEM dependent technology shifter is assumed to change the efficiency of intermediate timber use.	↗↗↗↗	↗↗↗	↗	LMH	↗↗	Timber use efficiency ↗ = Timber demand ↘ = TF ↘
	⑥	Total Calorie Consumption	Total calorie consumption increases with GDP. Different upper limits are set.	↗	↗↗	↗↗↗	LMH	↗↗↗↗	Calorie consumption ↗ = TF ↘

Consumption/ Preferences	⑦	Animal Calorie Consumption	Preference shifts between plant- and animal-based calories are implemented by shifting demand system parameters.	↘↘↘	↘↘	↘	LMH	↗	Demand for animal calories ↘ = Efficient calorie intake ↗ = TF ↗
	⑧	Food Processing	A GDP and DEM dependent technology shifter is assumed to change the degree of food processing (FPR).	↗↗↗	↗↗	↗	LMH	↗↗↗↗	FPR efficiency ↗ = Consumption of highly processed food ↗ = TF ↘
	⑨	Food Waste	The relation between calorie supply and demand provided by FAO (2018) enters the demand function. The scenarios are the same as described in the CL row.	↘↘	↘	↗↗	LMH	↗	Food waste ↘ = Food production ↘ = TF ↗
Agricultural/ Environmental Policy	⑩	Irrigation Governance	Access to irrigation water is regulated by adjusting its supply elasticity.	↘↘	↘	-	LMH	↗	Availability of irrigation water ↘ = Yield ↘ = TF ↘
	⑪	Subsidy Shift	Agricultural subsidy payments are redistributed from CL to forest. Arrows indicate the change in CL payments.	↘↘↘	↘↘	↘	LMH	-	Cropland subsidies ↘ = Forest subsidies ↗ = TF ↗
	⑫	Land Buffer	The area of unmanaged land available for conversion is changed manually.	↘↘	↘	-	LMH	↗	Land available for conversion ↘ = TF ↗
	⑬	Meat Tax	A tax on meat products is introduced. In SSP4, the meat tax is limited to the EU.	↗↗	↗	-	LMH	-	Meat tax ↗ = Meat consumption ↘ = Efficient calorie intake ↗ = TF ↗
Energy Policy	⑭	Emission Price	An emission price (excl. carbon stock changes) is introduced, which further impacts the energy production efficiency.	↗↗↗↗	↗↗↗	↗↗	LMH	↗	Emission price ↗ = Production cost ↗ = Consumption ↘ = TF ↗
	⑮	Resource Extraction	Access to natural resources (NR) is regulated by adjusting their supply elasticities.	↘	-	↗	LMH	↗↗	NR access ↘ = Consumption ↘ = TF ↗
	⑯	Renewable Productivity	Power generation from wind, solar, and other renewables is increased by assumed technological progress rates.	↗↗↗	↗↗	↗	LMH	-	Renewable power generation ↗ = Land scarcity ↗ = TF ↘
Trade	⑰	Agricultural Commodities	Assumed tariff changes impact the strength of international trade.	↗↗	-	↗	LMH	↘	Tariff ↗ = Trade ↘ = Consumption ↘ = TF ↗
	⑱	Other Commodities	Assumed tariff changes impact the strength of international trade.	↘↘	-	↗	LMH	↘	Tariff ↘ = Trade ↗ = Consumption ↗ = TF ↘

Source: Own illustration. Remark: Assumption numbers (1-18) correspond to Appendix A.2.4. The abbreviation “LMH” indicates that SSP3/ SSP2/ SSP1 assumptions are assigned to low-/ middle-/ high- income countries.

2.3 Results

This section presents the results generated with CGEBox for each of the SSP scenarios, focusing on food and biomass demand, LULC trajectories, and greenhouse gas (GHG) emissions. These results are shown at the global scale for two main reasons. First, the global perspective offers an overview of long-term development trends, providing a foundation for subsequent regional and sub-regional analysis. Second, it enables a direct comparison of the new projections with existing assessments, as discussed in Section 2.4. Presenting sub-national detail is beyond the scope of this paper; for this, refer to Goebel and Britz (2025a). Appendix A.2.4 provides a graphical summary of a sensitivity analysis in which the assumptions on LULC drivers are sequentially deactivated.

2.3.1 Food and biomass demand results

The five SSP baselines reflect divergent trajectories of global economic and demographic development, with all scenarios projecting increases in per capita real GDP – a proxy for aggregate consumption potential – by 2050. The strongest growth occurs under SSP5 (+127.74%), followed by SSP1 (+97.56%), SSP2 (+73.54%), SSP4 (+67.03%), and SSP3 (+43.69%). Expenditure allocation across product groups including food is simulated using an empirically grounded MAIDADS, calibrated to reproduce observed relationships between per capita income and calorie intake. Scenario-specific adjustments are incorporated to reflect the qualitative narratives of each SSP (as detailed in Table 2.2). In addition, the calorie content per dollar spent varies across income levels, capturing income-driven shifts in dietary preferences – such as increasing consumption of processed or convenience foods. As a result, food demand in CGEBox is responsive not only to income but also to broader, narrative-consistent drivers.

The first panel in Figure 2.4 shows projected increases in global per capita calorie demand, with scenarios ranked as follows: SSP5 > SSP3 > SSP2 > SSP4 > SSP1. This ordering reflects both the empirically estimated income-calorie relationship and scenario-specific adjustments implemented in the MAIDADS through exogenous shifts in consumer preferences and calorie targets. The highest increase in per capita calorie demand found under SSP5 is driven primarily by quite high per capita real GDP growth, which – consistent with empirical evidence – translates into higher calorie intake. This effect is amplified by an upward shift in the income-calorie relationship, aligned with SSP5's narrative of low environmental concern. Similarly, for the other SSPs, the main drivers of per capita calorie demand are the exogeneous GDP and demographic projections, modulated mainly by scenario-specific adjustments to dietary preferences.

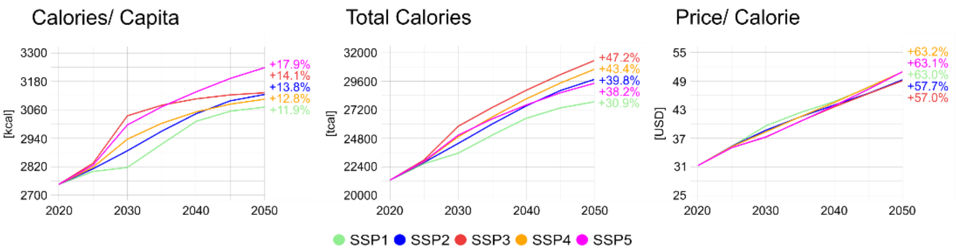

Figure 2.4 Global calorie consumption and prices in the shared socio-economic pathway quantifications in CGEBox.

Source: Own illustration.

Changes in calorie intake are accompanied by shifts in the composition of food demand, which vary substantially by scenario. Besides the income dynamics captured by the demand system, SSP5 assumes increased consumption of meat, dairy, and out-of-home foods, resulting in a notable decline in demand for plant-based calories and a shift away from diets aligned with planetary health targets. Per capita staple food demand also decreases in the other SSPs, consistent with the empirical patterns embedded in the MAIDADS. This effect is least pronounced in SSP3, where modest economic growth is accompanied by narrative-driven assumptions of increased calorie intake beyond what the income-calorie relationship alone would predict. Scenario assumptions – such as (dietary) preference shifts and meat taxation – result in declining per capita consumption of animal products and meat in SSP1, SSP2, and SSP4. Out-of-home consumption increases across all scenarios in line with higher per capita purchasing power. Detailed outcomes by product group are provided in Appendix A.2.5.

Reflecting demographic trends, total calorie demand projections diverge from per capita patterns, as illustrated in the second panel in Figure 2.4. SSP3 exhibits the largest absolute calorie demand increase, followed by

SSP4, SSP2, SSP5, and SSP1. Notably, SSP5 is the only scenario in which total staple calorie demand declines, despite decreases in per capita terms across all SSPs. Reductions in absolute calorie intake from meat are observed in SSP1 and SSP2. However, only SSP1 shows a decline in calories from other animal products, reflecting stronger sustainability assumptions and lower population growth. In contrast, SSP3, SSP4, and SSP5 record increases in total calorie intake from both animal products and meat, with the most significant rise occurring under SSP5. Total demand for vegetable oils, processed foods, and out-of-home consumption increases across all scenarios, in line with both per capita consumption trends and demographic projections.

Calorie prices as quantified in CGEBox rise significantly in all scenarios (+57.03% to +63.15%, see third panel in Figure 2.4) due to increasing land scarcity and land rents. These pressures persist despite technological progress, agricultural yield improvements, land expansion into natural vegetation, and changes in dietary composition. Food affordability – defined by the increase in calorie prices above the increase in per capita real GDP – improves in SSP1 and SSP5, remains near-stable in SSP2 and SSP4, and deteriorates in SSP3. These outcomes are consistent with the underlying scenario narratives.

Beyond its role in food provision, agricultural and forestry biomass constitutes a critical input across numerous economic sectors. Figure 2.5 presents total biomass demand (in constant USD) and its sectoral composition under the SSP scenarios, as quantified in CGEBox. Changes in per capita demand are noted in square brackets. By 2050, all SSPs project increases in both total biomass demand (SSP5 > SSP3 > SSP4 > SSP2 > SSP1) and per capita biomass demand (SSP5 > SSP3 > SSP2 > SSP1 > SSP4). These outcomes reflect a combination of the underlying socio-economic projections and the qualitative assumptions embedded in each SSP in line with its narrative. Analysis of sectoral composition further reinforces this connection. In the sustainability-oriented SSP1, demand for high-impact biomass sources (livestock and fish) rises significantly less than demand for more sustainable alternatives (crops), in line with more conscious consumption, not only in terms of food demand. The concurrent rise in forest-based biomass demand under SSP1 is indicative of increased substitution of non-renewable materials with renewable biomass, supporting a broader sustainability agenda. In contrast, SSP5 illustrates a markedly unsustainable consumption pattern, underscored by a +45.24% increase in per capita biomass demand. At the aggregate level, biomass demand in SSP5 increases substantially more than calorie demand, driven by a pronounced shift towards animal-based diets. Given the high crop input requirements of livestock production systems, the biomass intensity per delivered calorie is substantially higher for animal products than for plant-based foods. Additionally, the sharp increase in forest-based biomass demand under SSP5 does not reflect material substitution, as in SSP1, but rather an overall increase in the consumption of wood and timber, including non-essential uses such as furniture and other consumer goods.

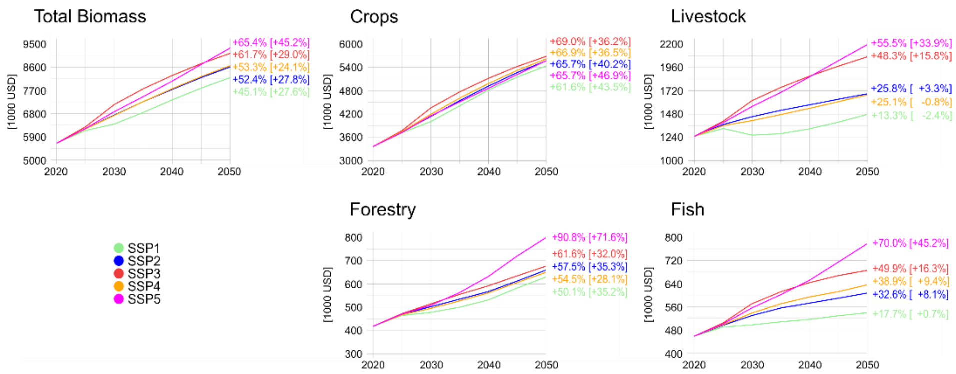

Figure 2.5 Global biomass demand and composition in the shared socio-economic pathway quantifications in CGEBox.

Source: Own illustration. Remark: The values in square brackets indicate the change in per capita demand over time for comparison. The aggregation behind total biomass, crops, livestock, forestry and fish can be found in Appendix A.2.6.

The remaining SSPs fall between these two extremes. SSP3 still exhibits a considerable increase in total biomass demand, driven by both increasing total calorie demand and limited technological progress in land saving practices. The majority of this increase originates from crop-based biomass, as lower income growth limits the expansion of more land-intensive animal-based products. Nonetheless, demand for livestock, fish, and forestry products also rises in SSP3. This trajectory reflects assumptions of slower innovation in agriculture, forestry, and food processing (see Table 2.2), which restrict productivity gains and compound biomass demand growth. Although SSP2 and SSP4 both are associated with higher environmental awareness, they project increasing demand for livestock-based biomass. This pattern stems not only from growing household demand for meat and animal products, but also from increased intermediate demand by the food industry. This is driven particularly by increased consumption of processed and out-of-home foods, contributing to higher livestock biomass use. Scenario-specific assumptions related to food processing efficiency and food waste further influence these outcomes. Biomass demand from fish, forestry, and crop sectors also increases in SSP2 and SSP4. Overall, these two SSPs produce broadly similar aggregate trends, driven by comparable GDP trajectories and compensating effects between LICs and HICs in SSP4. Nonetheless, per capita and regional differences between these scenarios are more pronounced. SSP4 records the lowest per capita increase in total biomass demand, reflecting a world in which HICs adopt sustainable consumption patterns as in SSP1, while MICs and LICs experience more modest gains in per capita real GDP and consequently in consumption.

2.3.2 Land use and land cover results

In addition to demand-side dynamics, LC developments are strongly influenced by the exogenous FAO projections (see Section 2.2), which determine the evolution of cropland area. As illustrated in Figure 2.6, cropland area expands in SSP2, SSP4, SSP5, and SSP3, while it contracts in SSP1. Notably, SSP5 exhibits the second-largest cropland expansion despite showing the second-lowest increase in crop-based biomass demand. This seemingly contradictory outcome reflects relatively modest improvements in yield and irrigation efficiency, continued cropland subsidies, and extensive conversion of natural vegetation. Together, these factors incentivise land extensification rather than intensification, leading to disproportionate cropland expansion. In the other SSPs, the cropland projections align more closely with crop-based biomass demand and the scenario-specific assumptions. The sustainability-focused SSP1, for example, records a reduction in cropland area as a result of significant yield improvements, robust technology adoption, stringent environmental regulation, and reductions in food waste. Coupled with only moderate growth in crop-based biomass demand, these drivers enable land sparing. Conversely, SSP3 sees cropland expansion due to limited technological progress, increased food waste, and high crop-based biomass demand, consistent with its narrative.

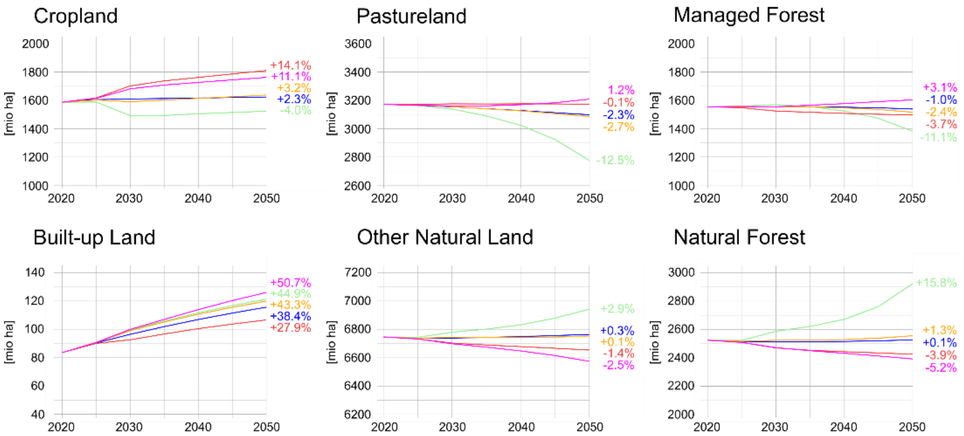

Figure 2.6 Global land cover in the shared socio-economic pathway quantifications in CGEBox.

Source: Own illustration. Remark: “Other natural land” groups savannah/ grassland, shrubland, rock, ice, and desert.

Despite rising aggregate demand for livestock-based biomass in all scenarios, pastureland area projections decline in all SSPs except SSP5. The most substantial reduction occurs in SSP1, driven by falling demand for meat and dairy, intensified production systems, and technological innovation. SSP2 and SSP4 experience more moderate declines of pastureland area, reflecting modest demand growth for livestock products and modest technological advancements. Additionally, a significant share of livestock-based biomass demand comes from non-grassland-fed systems. In SSP3, pastureland area contracts only marginally, while in SSP5 it increases slightly. Although livestock-based biomass demand rises substantially in SSP5, its effect on pastureland is partially offset by technological progress. This is not the case for SSP3, where limited productivity gains fail to mitigate land pressure. Managed forest area projections are shaped by multiple forces. SSP1 experiences the largest decline due to increased production efficiency offsetting moderate demand increases, innovation in wood processing, and strong environmental governance. In SSP3 and SSP4, the decline in managed forest area is driven by the strong cropland and pastureland expansion and the limited availability of land for conversion. Some previously managed forest is thus converted to agricultural use. SSP2 shows a slight decline in managed forest area, consistent with its intermediate trajectory. Conversely, SSP5 registers a substantial increase in managed forest area, driven by high forest-based biomass demand and the absence of environmental constraints on land conversion. Built-up land expands in all scenarios, in line with projected GDP and demographic growth (SSP5 > SSP1 > SSP4 > SSP2 > SSP3). These four LC categories – cropland, pastureland, managed forest, and built-up land – compete directly with natural land cover (NLC). Consistent with the SSP narratives, SSP1 yields a substantial increase in NLC (natural forest and other natural land) of +6.27%. SSP2 and SSP4 show modest gains (+0.42% and +0.22%), whereas SSP3 and SSP5 experience pronounced declines (-2.05% and -3.27%). Beyond the LC dynamics outlined above, the scenario-specific assumptions regarding land availability and LU regulations play a critical role in determining NLC outcomes.

Figure 2.7 presents projected changes in LU between 2020 and 2050. Among cropland categories, other oilseeds and soy beans account for the largest absolute area increases across all SSPs. This growth is driven by their role as high-protein feed inputs and sources of vegetable oils – both of which are highly income-elastic commodities. Although these trends are broadly consistent across scenarios, the magnitude and composition of cropland expansion vary. In SSP1, which experiences a net decline in cropland area, reductions are observed across numerous crop categories. In the other SSPs, individual crop LUs may decline, but these reductions are typically less widespread and less pronounced. In relative terms, other oilseeds and soy beans remain among the primary drivers of cropland expansion. Additionally, LU for cocoa beans, coffee beans, and teas increases in all scenarios, reflecting rising demand for higher-value, income-elastic commodities. Consistent with pastureland developments, all scenarios project absolute reductions of land used for ruminant meat production. Pastureland for raw milk production declines in SSP1, SSP2, and SSP4, while pastureland for wool production increases modestly in all scenarios except SSP3, albeit from a low base. Forestry follows broader LC trends: it declines in all SSPs except SSP5, in line with the scenario-specific drivers and LC trends discussed above.

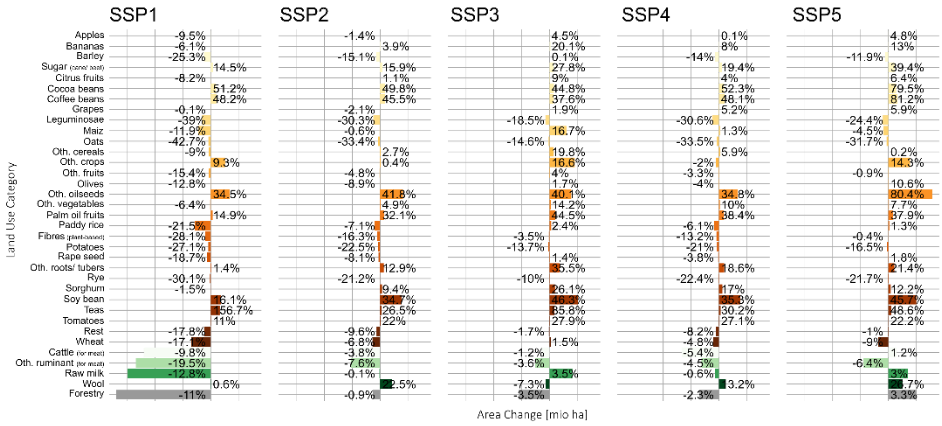

Figure 2.7 Global land use changes in the shared socio-economic pathway quantifications in CGEBox.

Source: Own illustration. Remark: Irrigated and rainfed land uses are aggregated. Bars indicate absolute land use changes; relative changes are provided as additional information. “Oth.” abbreviates “other”.

2.3.3 Greenhouse gas and carbon emission results

Figure 2.8 (upper left) presents cumulative GHG emissions as quantified in CGEBox, including emissions from agriculture but excluding carbon stock changes. Across all SSPs, emissions rise substantially by 2050. The same trend applies to annual emissions, with the respective percentage changes given at the end of the bars. Among the scenarios, SSP5 records the highest emissions, followed by SSP3, SSP2, SSP4, and SSP1. These results are shaped by a policy environment characterised by only moderate carbon pricing and conservative progress in renewable energy productivity in all SSPs, but with differences according to their narratives. These conservative assumptions reflect a continuation of current emission reduction efforts rather than the implementation of ambitious climate mitigation policies. As such, emission outcomes are primarily driven by the absence of transformative energy or LU interventions in combination with the demand-side dynamics described above. Disaggregating total GHG emissions by gas type reveals a consistent scenario ranking across CO_2, N_2O, CH_4, and F-Gas emissions, in line with the aggregate results. CH_4 emissions exhibit the smallest increase across all scenarios, whereas N_2O, F-Gas, and CO_2 emissions rise more substantially. Focusing specifically on carbon emissions from LU change (Figure 2.8, lower left), all SSPs project declining annual emissions in 2050 as the availability of remaining natural vegetation for land expansion declines, population growth rates decrease over time, and yields improve. Despite these trends, cumulative outcomes diverge. Only SSP1 achieves a net increase in carbon stocks over the simulation period. In all other scenarios, carbon stocks continue to fall – most notably in SSP3, closely followed by SSP5. These divergent outcomes largely reflect LULC dynamics described above, particularly changes in NLC and managed forest, which play a central role in carbon fluxes.

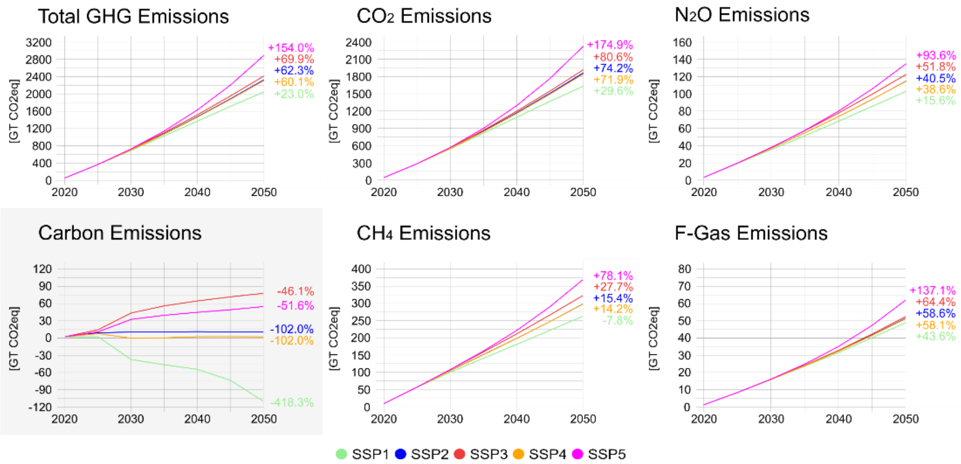

Figure 2.8 Global cumulative emissions and composition in the shared socio-economic pathway quantifications in CGEBox.

Source: Own illustration. Remark: The percentage changes at the end of the bars indicate the change in annual emissions over time.

2.4 Discussion

LULC projections are widely acknowledged to involve substantial uncertainty, arising from differences in input data definitions and quality, as well as from the diversity of modelling frameworks employed (e.g., Alexander et al., 2017; Prestele et al., 2016; Schmitz et al., 2014). This study presents a new modelling framework for generating globally consistent LULC projections, applied across the five SSPs. Both the underlying data and the modelling approach differ substantially from those used in previous IAM-based LULC assessments of the SSPs. IAMs are simulation frameworks that couple models from multiple disciplines – such as climate science, economics, LULC, and energy systems – to represent interactions between human behaviour and Earth system dynamics. Economic modules, implemented via general equilibrium or cost-optimisation approaches, are at the core of these frameworks as they shape energy, LULC developments, and emissions pathways, and enable the evaluation of policy costs, benefits, and trade-offs. The biophysical components provide detailed complementary projections of climate and environmental impacts. IAMs typically operate at global or regional scales with relatively coarse spatial and temporal resolution, ensuring computational tractability despite the high computational demands of integrating multiple sub-systems and running large scenario ensembles[11] (Hare et al., 2018; IPCC, 2022).

In contrast, this study presents an approach to quantify LULC among the five SSPs based on an open-source, stand-alone economic model focused on structural economic change. This unified modelling architecture avoids many of the complexities associated with multi-model coupling (e.g., Britz, 2008; Delzeit et al., 2020) and supports large-scale applications with high regional and sectoral resolution. The modelling platform CGEBox addresses common limitations of stand-alone economic models by including dedicated modules for LULC and energy accounting, and by integrating cropland and yield projections. Like IAMs, it adopts SSP-specific projections for GDP and demographics but compared to available IAM results integrates the latest available versions (IIASA, 2024). Additionally, scenario-specific assumptions relevant for LULC are implemented in a manner consistent with detailed sectoral models. CGEBox cannot replicate the full biophysical detail of IAMs. Rather, its strength lies in capturing key structural features

[11] For more information on the structure of the IAMs applied in the original SSP quantification, please refer to Fujimori et al. (2017) for AIM, Calvin et al. (2017) for GCAM, van Vuuren et al. (2017) for IMAGE, Fricko et al. (2017) for MESSAGE-GLOBIOM, Kriegler et al. (2017) for REMIND-MAgPIE and Popp et al. (2017) for details and a comparison of LULC-related assumptions.

of the economy, which shape LULC and emission outcomes. To facilitate a focused comparison, we contrast CGEBox global-scale projections with those from the five so-called marker IAMs[12], which were central to the original SSP quantifications and whose results are publicly accessible via the SSP database (IIASA, 2025; Popp et al., 2017). The CGEBox projections are published via a Mendeley data repository (Goebel and Britz, 2025b). Despite notable methodological and data-related differences, the CGEBox projections align with IAM-based trends in global LULC and emissions, as illustrated in Figure 2.9.

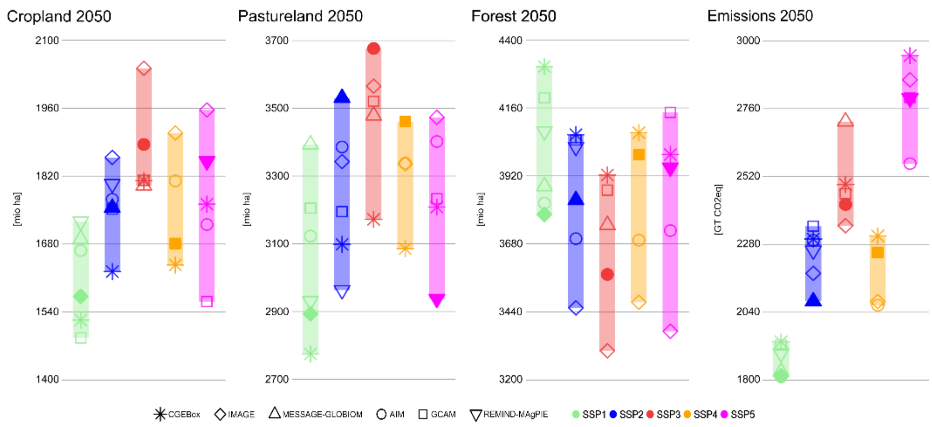

Figure 2.9 Comparison between CGEBox and integrated assessment model quantifications of the shared socio-economic pathways.

Source: Own illustration. Remark: The “marker model” for each shared socio-economic pathway is indicated by a filled point. MESSAGE-GLOBIOM and REMIND-MAgPIE do not quantify all shared socio-economic pathways.

IAM-based projections for global cropland area in 2050 vary considerably, ranging from 1487 million hectares in GCAM (SSP1) to 2042 million hectares in IMAGE (SSP3). Importantly, only a small portion of this variation stems from differences in input data: in 2005[13], GCAM and IMAGE report comparable cropland areas (1522 and 1548 million hectares, respectively). Divergence becomes more pronounced by 2020, reflecting differing model specifications and scenario assumptions in the SSPs – GCAM (SSP1) projects 1489 million hectares and IMAGE (SSP3) 1709

[12] AIM, GCAM, IMAGE, MESSAGE-GLOBIOM, and REMIND-MAgPIE.
[13] 2005 is the start year of the IAM simulations.

million hectares. CGEBox starts from a global cropland area of 1586 million hectares in 2020, placing it in the lower-middle of the IAM range. By 2050, CGEBox projections – except under SSP5 – consistently fall at the lower end of the IAM range and most closely align with GCAM. In contrast, IMAGE and REMIND-MAgPIE report substantially greater cropland expansion. Drawing on the FAO projections (FAO, 2018), CGEBox presents a more moderate cropland outlook, particularly under SSP2, where it estimates the lowest 2050 cropland area of all models. The projected spread in 2050 cropland area across SSPs also varies substantially within IAMs. MESSAGE-GLOBIOM and REMIND-MAgPIE exhibit narrow ranges (110 and 120 million hectares, respectively), while IMAGE shows a much wider variation (470 million hectares). With an internal spread of 290 million hectares, CGEBox falls in between. The scenario ranking in CGEBox follows the commonly observed pattern – SSP1 < SSP2 < SSP4 < SSP5 < SSP3 – consistent with IMAGE, MESSAGE-GLOBIOM, and REMIND-MAgPIE. Although CGEBox's higher SSP5 projection deviates from its general position at the lower end of the IAM range, it remains defensible given this shared scenario hierarchy. By contrast, GCAM and AIM display different internal rankings for SSP2, SSP4, and SSP5.

For global pastureland area in 2050, IAM projections range from 2893 million hectares in IMAGE (SSP1) to 3677 million hectares in AIM (SSP3). In 2020, IMAGE (SSP1) estimates 3143 million hectares, while AIM (SSP3) projects 3613 million hectares – up from 3188 and 3376 million hectares, respectively, in 2005. As with cropland, these differences largely reflect model-specific assumptions and mechanisms. CGEBox starts from a global pastureland area of 3172 million hectares in 2020, placing it at the lower end of the IAM range, a position it maintains through 2050. This is particularly notable under SSP1, SSP3, and SSP4. The scenario spread in CGEBox reaches 398 million hectares – intermediate between the narrow ranges of MESSAGE-GLOBIOM (90 million hectares) and REMIND-MAgPIE (30 million hectares), and the broader variation projected by IMAGE (680 million hectares). Scenario rankings within CGEBox follow the order SSP1 < SSP4 < SSP2 < SSP5 < SSP3, which aligns to the sequence of AIM, IMAGE, and MESSAGE-GLOBIOM, except for SSP3 and SSP5. In contrast, GCAM and REMIND-MAgPIE diverge from this ranking.

Across models, a consistent pattern emerges: greater agricultural expansion by 2050 is generally associated with reductions in forest area, and vice versa. However, the magnitude of this trade-off varies by model, reflecting differing assumptions about substitution between cropland and pastureland, as well as about the conversion of NLC. While CGEBox differentiates between natural and managed forests, the SSP database reports only total forest area, limiting the comparison to this indicator. By 2050, global forest area projections span from 3303 million hectares in IMAGE (SSP3) to 4196 million hectares in GCAM (SSP1) and 4306 million hectares in CGEBox (SSP1). CGEBox consistently places at the upper end of the model range, a tendency already evident in 2020 when IAM projections range from 3560 to 4152 million hectares and CGEBox reports 4078 million hectares. This outcome reflects CGEBox's reliance on historically observed land transition patterns and scenario-specific assumptions governing NLC changes, which together produce more conservative forest loss estimates compared to most IAMs. The range of forest area outcomes across SSPs also varies widely by model. MESSAGE-GLOBIOM and REMIND-MAgPIE exhibit narrow spreads (130 million hectares), IMAGE projects the widest range (480 million hectares), and CGEBox falls in between (382 million hectares). Despite these differences, all models agree on the scenario extremes, projecting highest forest cover under SSP1 and lowest under SSP3. However, the rankings of SSP2, SSP4, and SSP5 differ across models, reflecting divergent interpretations of the SSP narratives and their implications for LULC change.

Projected cumulative GHG and carbon emissions by 2050 vary considerably across IAMs, ranging from 1812 Gt CO_2eq in AIM (SSP1) to 2862 Gt CO_2eq in IMAGE (SSP5). Annual emissions in 2020 span from 51 Gt CO_2eq in GCAM (SSP1) and 66 Gt CO_2eq in MESSAGE-GLOBIOM (SSP3), compared to 44 to 49 Gt CO_2eq in 2005. These variations reflect underlying differences in economic assumptions, which influence production levels and technological developments. They also stem from divergent expectations about the evolution of energy systems, even under baseline scenarios without explicit climate policies. CGEBox reports 2020 emissions of 56 Gt CO_2eq, placing it within the mid-range of the IAM estimates. Its relative position by 2050 varies across SSPs: it ranks at the high end in SSP1, SSP4, and SSP5; in the upper-middle in SSP2; and centrally in SSP3. This pattern may reflect a more conservative approach to emission pricing in CGEBox, compared to the more rapid decarbonisation embedded in some IAM baseline assumptions. Notably, lower emissions in SSP3 in CGEBox may also reflect the influence of slower economic growth, given the model's detailed representation of economic dynamics. Across models, internal scenario spreads for cumulative emissions vary from 754 Gt CO_2eq in AIM to 1046 Gt CO_2eq in IMAGE, with CGEBox exhibiting a comparatively wide spread of 1011 Gt CO_2eq. However, all models agree on the scenario ordering, projecting 2050 cumulative emissions in the sequence: SSP1 < SSP4 < SSP2 < SSP3 < SSP5.

Despite the absence of dedicated LULC or energy system models, CGEBox produces LULC and emissions projections, which are broadly consistent with those of leading IAMs. As discussed, CGEBox tends to assume greater substitution between managed land categories and less conversion of NLC, drawing on historically observed land transition patterns. Consequently, cropland and pastureland projections are at the lower end of the IAM projection range, while maintaining the ordering of the SSPs. It also adopts more moderate baseline climate policy assumptions than many IAMs, resulting in relatively high emission projections. Overall, CGEBox LULC and emission projections fall within the range of IAM outcomes, demonstrate scenario spreads of comparable magnitude, and mostly replicate the relative ordering of SSP-specific results. This positions CGEBox as a viable alternative for quantifying LULC across the SSPs.

Beyond this validation, CGEBox offers several advantages. It's open-source, well-documented code increases transparency and facilitates replication and further development, such as refining scenario assumptions or adding regional detail outside Europe. Compared to IAMs, its relatively low computational requirements allow for timely updates when input data – such as GDP or demographics – are revised. With its strong economic orientation, CGEBox is particularly well suited to support extended economic assessments, including trade, food security, or distributional analysis. Counterfactual scenarios can be readily compared against the SSP baselines, while retaining full sectoral and regional detail. Furthermore, any time point along the CGEBox SSP quantifications can be converted into a full CGE database, enabling further disaggregation or the testing of alternative model set-ups, such as multiple household formulations or different international trade specifications. The CGEBox framework supports comprehensive post-model analyses, including the quantification of a broad range of SDG indicators (Wilts and Britz, 2024), and reports not only the land categories addressed here but also built-up land and various NLC types, with managed areas further disaggregated into detailed LU classes. A companion publication presents CGEBox's projections at full regional and sectoral resolution (Goebel and Britz, 2025a). With regard to transferability, it is to be noted that sectoral disaggregation has already been successfully applied in various contexts (e.g., Wilts and Britz, 2024; various ongoing projects with different regional focuses and resolutions). The sub-national data are currently available only for Europe, but the methodology has also been tested for African countries (Ferrari et al., 2019).

Nonetheless, some limitations – particularly in comparison to the model-coupling approach used in IAMs – should be acknowledged. CGEBox does not explicitly simulate biophysical processes such as carbon sequestration, vegetation dynamics, or climate feedbacks, which are core components of IAM frameworks. As a result, its capacity to evaluate land-based mitigation strategies or ecosystem services in a fully integrated manner is limited. Additionally, CGEBox relies on exogenous projections for key drivers such as cropland and yields, which introduces a dependency on external assumptions. The projections also depend on the model parameterisation. Part of this uncertainty is already captured by constructing five different baselines and by sensitivity simulations in which one SSP-specific LULC-driver assumption is removed at a time. Nevertheless, further testing of parameter choices would be a valuable avenue for future research. These limitations underscore CGEBox's role as a valuable complement to IAMs – particularly for economically focused assessments – rather than a replacement. Future work could explore the model's potential for representing specific policy interventions building on the SSP baselines presented here. It may also be worthwhile to investigate opportunities for linking CGEBox with biophysical, sector-specific, or downscaling tools to support more integrated and comprehensive assessments.

2.5 Conclusion

This study presents a new modelling framework for generating globally consistent LULC projections, applied to the five SSPs through 2050. This framework combines a recursive-dynamic core with highly disaggregated data and dedicated model extensions to capture integrated assessment features, implemented via the open-source modelling platform CGEBox. Benchmarking against leading IAMs demonstrates that CGEBox produces plausible LULC outcomes while offering new insights into the complex interactions between socio-economic drivers and land system dynamics – with high regional and sectoral detail and full transparency. These features position CGEBox as a valuable complement to IAMs, particularly for supporting economically grounded assessments of LULC change and its implications. By delivering transparent, replicable baselines, this work supports more inclusive and adaptable policy analysis – especially in contexts where timely updates, distributional effects, or regional and land use details are essential. While CGEBox is not designed to simulate climate-biosphere feedbacks, its ability to generate robust, scenario-based LULC and emissions trajectories makes it a practical and policy-relevant tool for integrated LU planning under socio-economic uncertainties, contributing to more informed decision-making in the pursuit of global sustainability.

2.6 Acknowledgement

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Chapter 3
NUTS2 level dataset on land use and land cover projections for Europe under the shared socio-economic pathways through 2050[1]

Abstract

This dataset provides projections of land use and land cover from 2020 to 2050, spanning an uncertainty range consistent with the five Shared Socio-Economic Pathways. For Europe, results are reported at both the national and the sub-national level of administrative NUTS2 regions, while regions outside Europe are represented at the national or aggregated level. The dataset distinguishes eight land cover types (e.g., cropland, pastureland, shrubland) and 65 corresponding land use categories (e.g., individual crops) and is available at two- and five-year intervals. The projections are generated using G-RDEM, a recursive-dynamic global Computable General Equilibrium model designed to capture long-term structural change on both the supply and demand sides. Implemented via the modelling platform CGEBox, G-RDEM simulates economic and land use dynamics directly at

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the NUTS2 level, eliminating the need for multi-model coupling and post-model downscaling used in existing SSP-based LULC quantifications. The modelling framework is open-source, reproducible, and transparent, and enables researchers to build upon or extend the projections. By outlining land transitions across socio-economic scenarios, the dataset supports research requiring detailed LULC projections as input, for example in climate impact or biodiversity conservation studies. The projections are particularly valuable for researchers and policymakers working on economically grounded assessments of long-term land system change in Europe. As an independent, scenario-based projection set grounded in a distinct economic approach, the dataset contributes to uncertainty analysis in land use and land cover futures, supports multi-model comparisons and ensemble modelling, and broadens the understanding of regional land use and land cover developments.

Keywords: Computable General Equilibrium (CGE) modelling, recursive-dynamic baseline generation, scenario analysis, sub-national detail, land use detail, land cover detail.

Specifications table

Table 3.1 Specifications table

Subject	Earth & Environmental Sciences
Specific subject area	NUTS2 level projections of European land use and land cover under socio-economic scenarios for environmental assessments.
Type of data	Tabular time-series data by region, land use and land cover, and each of the five Shared Socio-Economic Pathways.
Data collection	Projections are generated using G-RDEM, a recursive-dynamic global Computable General Equilibrium (CGE) model implemented in the open-source modelling platform CGEBox. Economic and land use dynamics are simulated at the NUTS2 level under the five Shared Socio-Economic Pathways from 2020 to 2050, covering eight land cover types and 65 corresponding land use categories, reported at two- and five-year intervals.
Data source location	Geographic extent: Europe at NUTS2 and national levels; rest of the world at national or aggregated level. Main input data locations for 2017 as the benchmark point: • CGE input data:

	https://www.gtap.agecon.purdue.edu/databases/default.asp • Land use and land cover disaggregation: https://www.cia.gov/the- world- factbook/field/area/country-comparison https://www.fao.org/faostat/en/#data/LC https://land.copernicus.eu/en/products/corine- land- cover https://www.fao.org/faostat/en/#data/FBS • NUTS2 level disaggregation: https://ec.europa.eu/eurostat/databrowser/view/nama_10r_3gva/default/table?lang=en https://ec.europa.eu/eurostat/databrowser/view/AGR_R_ACCTS/default/table?lang=en https://ec.europa.eu/eurostat/databrowser/view/SBS_R_NUTS06_R2/default/table?lang=en https://ec.europa.eu/eurostat/databrowser/view/lfst_r_lfe2en2/default/table?lang=en https://ec.europa.eu/eurostat/databrowser/view/ef_lus_allcrops/default/table?lang=en https://ec.europa.eu/eurostat/databrowser/view/PROJ_19RP3/default/table?lang=en https://ec.europa.eu/eurostat/databrowser/view/ef_mp_irri__custom_119320 0 0/ default/table
Data accessibility	Repository name: NUTS2 Level Land Use and Land Cover Quantifications under the Shared Socio-Economic Pathways, 2020–2050 Data identification number: 10.17632/x4xfh2kcdy.1 Direct URL to data: https://data.mendeley.com/datasets/x4xfh2kcdy/1
Related research article	Goebel, T., Britz, W., 2025. Global land use and land cover projections under the shared socio-economic pathways: An integrated computable general equilibrium analysis with sub-national resolution for Europe. Glob. Environ. Change Adv., 5, 1000127.

Source: Own illustration.

3.1 Value of the data

- The dataset provides land use and land cover (LULC) projections for European (NUTS2 and national level) and non-European (national or aggregated level) regions under the five Shared Socio-Economic Pathways (SSPs) from 2020 to 2050.
- The projections distinguish eight land cover types (e.g., cropland, pastureland, shrubland) and 65 corresponding land uses (e.g., individual crops), reported at two- and five-year intervals.
- The projections are generated with G-RDEM, a recursive-dynamic global Computable General Equilibrium (CGE) model implemented via the modelling platform CGEBox.

- The model set-up eliminates the need for multi-model coupling and post-model downscaling used in existing SSP-based LULC quantifications.
- The modelling framework is open-source, reproducible, and transparent, and enables researchers to build upon or extend the projections.
- The dataset supports research requiring detailed LULC projections as input; enables economically grounded assessments of long-term land system change in Europe; and contributes to uncertainty analysis, multi-model comparisons, and ensemble modelling of LULC futures.

3.2 Background

To address uncertainty in LULC developments, the climate research community explores contrasting futures by varying socio-economic trends according to the predefined narratives of the SSPs, which are graphically summarised in Figure 3.1. Existing SSP-based projections derived from Integrated Assessment Models lack sufficient detail for regional and sectoral analyses. To bridge this gap, the present dataset provides LULC quantifications for the five SSPs from 2020 to 2050, offering high sectoral detail globally and sub-national resolution for Europe. The projections are generated using an open-source, recursive-dynamic global CGE model, which builds on highly disaggregated input data and includes dedicated modules for land use and energy accounting. Tailored for long-term analysis, the model explicitly considers key drivers of structural change and integrates SSP-specific projections on gross domestic product (GDP), demography, cropland, and yields. In addition, the projections reflect quantified assumptions on LULC drivers consistent with the SSP narratives.

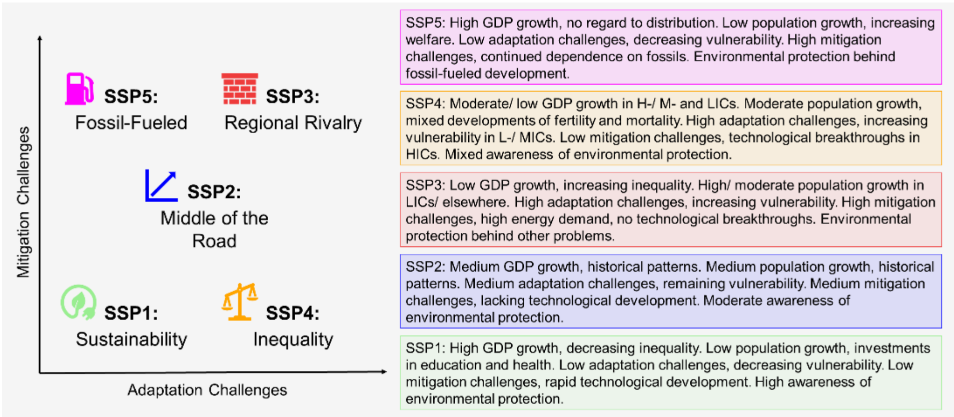

Figure 3.1 Overview of the shared socio-economic pathways.

Source: Goebel and Britz (2025a). Remark: L-/ M-/ HIC stands for low-/ middle-/ high-income country.

3.3 Data description

The dataset follows the methodology described in Goebel and Britz (2025a) and provides LULC projections at the level of administrative NUTS2 regions for the five SSPs (Riahi et al., 2017) for the period 2020 to 2050. European Union (EU) member states follow the 2016 NUTS2 classification (EC, 2016), while European Free Trade Association (EFTA) countries and EU accession candidates follow the 2008 classification (EC, 2008). Overseas territories are excluded. In total, the dataset covers 317 NUTS2 regions for Europe, which are listed and mapped in the accompanying data explanation document. In addition to the sub-national projections, the dataset includes matching national level results and covers the rest of the world at national or aggregated level. The projected LULC categories are based on version 11 of the Global Trade Analysis Project (GTAP) Power dataset (Chepeliev, 2023), with further disaggregation as detailed in Goebel and Britz (2025a). Table 3.2 lists the LULC categories included, while Figure 3.2 illustrates the projected changes in managed land covers across Europe. The dataset is available via Mendeley Data (Goebel and Britz, 2025b) in both .csv and a .xlsx formats, with two- and five-year resolution. It is accompanied by a data explanation document, also available in .csv and .xlsx formats.

Table 3.2 Land use and land cover detail in the shared socio-economic pathway quantifications in CGEBox.

Land Cover	Managed	Land Use
Cropland	Yes	- Apples - Bananas/ plantains - Barley - Citrus fruits - Cocoa beans - Coffee beans - Grapes - Leguminosae - Maize - Nuts - Oats - Olives - Oth. cereals - Oth. crops - Oth. fruits - Oth. oilseeds - Oth. roots/ tubers - Oth. vegetables - Paddy rice - Palm oil fruit - Plant-based fibres - Potatoes - Rape seed - Rye - Sorghum - Soy bean - Sugar cane/ beet - Teas - Tomatoes - Wheat All as irrigated and rainfed variants.
Pastureland	Yes	- Cattle for meat - Oth. ruminants for meat - Raw milk - Wool
Managed forest	Yes	- Forestry
Natural forest	No	
Savannah/ grassland	No	
Shrubland	No	
Other land	No	
Built-up land	No	

Source: Goebel and Britz (2025a). Remark: "Oth." abbreviates "other".

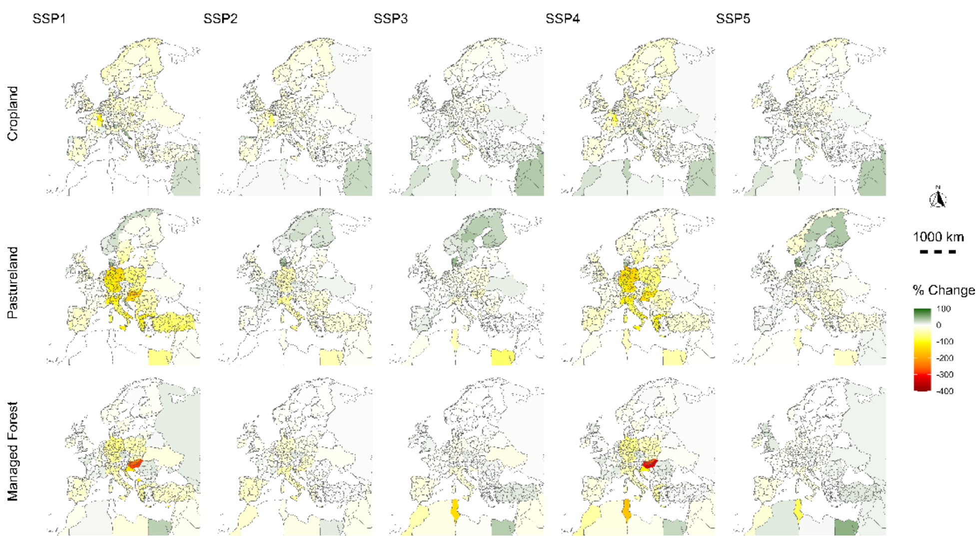

Figure 3.2 Projected changes in managed land cover under the five shared socio-economic pathways from 2020 to 2050.

Source: Own illustration. Remark: The maps are projected in the coordinate reference system WGS 84 (EPSG:4326).

3.4 Experimental design, materials and methods

This dataset provides LULC projections at the level of administrative NUTS2 regions for the five SSPs from 2020 to 2050. Each projection is part of a recursive-dynamic CGE baseline generated with G-RDEM (Britz and Roson, 2019), the GTAP-based recursive-dynamic economic model. Global CGE models represent the entire economy, including international trade, and are therefore well-suited to analyse the impact of interrelated socio-economic drivers on LULC dynamics. However, they typically operate at coarse regional and sectoral resolution. This limitation is addressed in this study by operating G-RDEM via the open-source modelling platform CGEBox (Britz, 2022a; Britz and van der Mensbrugghe, 2018)[2]. This set-up enables the simulation of economic and land use dynamics directly at the NUTS2 level and allows the integration of model extensions that enhance LULC representation and enable energy accounting. The CGE baselines underlying the projections differ according to the SSP narratives, which describe contrasting socio-economic developments associated with different challenges to climate change adaptation and mitigation. They are incorporated as follows:

(1) **Macro-economic developments** (GDP and demographics) follow country- and scenario- specific projections from version 3.1 of the OECD Env-Growth model and the WiC-POP model (IIASA, 2024).

(2) **LULC drivers** are parameterised using an SSP-specific assumption catalogue consistent with the SSP narratives (Goebel and Britz, 2025a).

The benchmark dataset underlying the CGE simulations builds on the GTAP v11 Power database (Chepeliev, 2023), which provides a snapshot of the global economy in 2017. For this study, the full sectoral detail of this database is maintained, while electricity products and labour-related production factors are aggregated. Land use is further disaggregated to the detail shown in Table 3.2, and irrigation water is introduced as an additional

[2] The model documentation provides necessary information for downloading and using CGEBox. The related research article (Goebel and Britz, 2025a) adds information on the model version used for the LULC quantifications, on the database generation process, and on the model set-up. In the following, reference is made to relevant code sections referring to the respective directory in CGEBox.

production factor to distinguish between irrigated and rainfed cropland production. Outside this study's focus region[3], countries are aggregated into larger model regions to facilitate comparison with existing global projections. Within the European focus region, production and factor use, including land use, are disaggregated to the level of administrative NUTS2 regions. A detailed description of the disaggregated CGE input data, the model set-up, and the SSP implementation is provided in Goebel and Britz (2025a)[4]. This article focuses on the processing of LULC and NUTS2 level data for the use in long-term baseline generation and publishes the resulting NUTS2 level LULC projections.

3.4.1 Land use and land cover representation

To improve the representation of LULC, the simulations use CGEBox's Agro-Ecological Zone (AEZ) module, which builds on the GTAP-AEZ model (Lee et al., 2009), but extends it in three ways (Britz, 2022a):

(1) **Land supply** is modelled by a nested multi-level Constant Elasticity of Transformation (CET) function. At the top level, an additive functional form is used to preserve physical area balances[5].

(2) **Cropland nesting** includes an additional layer to differentiate transformations between annual and perennial crops.

(3) **Cropland conversion** from pastureland, managed forest, or unmanaged land is determined based on a statistically estimated correlation in historical regional land conversion data.

The GTAP v11 AEZ dataset (Baldos and Corong, 2025) provides the base LULC input data. It links physical LULC to the GTAP v11 Power database by dividing land into 18 AEZs with similar cultivation conditions and distinguishes seven land cover types and 13 land uses[6]. Our work systematically improves the LULC input during database generation in

[3] The study's focus region is the EURO–CORDEX domain (WRCP, 2024).

[4] Goebel and Britz (2025a) provide a detailed description of how to replicate this work.

[5] At the lower levels, projections are scaled retrospectively to add up to the top levels.

[6] GTAP v11 AEZ land cover comprises cropland, pastureland, forest, savannah and grassland, shrubland, other land (rock, ice, desert) and built-up land. GTAP v11 AEZ land use comprises eight cropland, four pastureland and one forest production activity/ sector. For more detail see the data explanation document.

CGEBox to produce consistent CGE-based LULC projections[7]. A set of a-priori target values is constructed for four key corrections:

(1) **Total area adjustment:** GTAP v11 AEZ total areas are compared with World Factbook statistics (CIA, 2025). Country level areas are replaced by official statistics, and AEZ level areas are recalculated based on GTAP v11 AEZ shares[8].

(2) **Unmanaged forest land:** The GTAP v11 AEZ data underestimates forest area, as it only includes managed forest within ten kilometres of infrastructure (Baldos and Corong, 2025). The difference between GTAP v11 AEZ reported total land areas and official statistics is filled by introducing an "unmanaged forest" land cover category, informed by FAOSTAT tree cover statistics (FAO, 2024). Remaining total area discrepancies are assigned to the land cover type "other land".

(3) **European land cover refinement:** Detailed 2018 CORINE land cover data (COPERNICUS, 2024) are aggregated to country and AEZ level using GIS analysis in R, replacing the GTAP v11 AEZ data for Europe[9].

(4) **Data inconsistencies:** Several internal inconsistencies in the GTAP v11 AEZ data are corrected, including removal of economic returns without corresponding land cover, estimation of missing land use entries using proportionality assumptions, and deletion of unmatched records.

The corrected GTAP v11 AEZ data is rebalanced by solving a non-linear programming (NLP) problem that minimises the squared relative differences to the a-priori target values using a highest posterior density (HPD) objective function. The rebalanced dataset satisfies six conditions:

(1) Posterior land rents for each sector aggregated over the AEZs equal the sum of land rents reported in the GTAP v11 Power database.

(2) Posterior land rents per hectare, multiplied by areas, equal posterior activity level land rents.

[7] The code correcting GTAP v11 AEZ data can be found in CGEBox\gams\gtapAgg\aggAez.gms.

[8] Data wrangling is conducted in R. Target values are provided to the model via CGEBox\data\aezArea_v11.gdx.

[9] The mapping between CORINE and GTAP land cover classes is shown in the data explanation document. Target values are provided to the model via CGEBox\data\CORINE_AEZ.gdx.

(3) Posterior managed land area equals the sum of all posterior land use activity areas.
(4) Posterior total area equals the sum of all related posterior land covers.
(5) Posterior total forest area equals posterior managed plus posterior unmanaged forest area.
(6) Each region includes at least one percent of posterior unmanaged land to avoid numerical issues.

After correction of the input data, two data disaggregation steps are applied to enhance LULC detail:

(1) **Agro-food split:** Following Britz (2022b)[10], the eight GTAP v11 cropland production activities and sectors are disaggregated into 30, and the four pastureland production activities and sectors into eight. A detailed mapping between GTAP v11 and the disaggregated entries is provided in the data explanation document provided in the data repository.
(2) **Irrigation split:** The production factor land is split to introduce irrigation water as a new production factor and the 30 cropland production activities are disaggregated into irrigated and rainfed variants using FAO irrigation statistics (FAO, 2018) and a methodology similar to the one used in the agro-food split.

The final database distinguishes eight land covers and 65 land uses (Table 3.2), corresponding to the LULC level of detail in the dataset presented here.

3.4.2 NUTS2 representation

Harmonised economic activity data at sub-national level reported by EUROSTAT are limited, and not available for demand and bilateral trade. To address this, CGEBox includes a module that integrates sub-national detail where data is available, while solving the remaining model domains at the national level. Specifically, production functions and commodity output are represented at the sub-national (NUTS2) level, while market clearing including commodity demand is represented at the national level.

[10] Based on more recent input data from FAO (2025).

To satisfy equilibrium conditions and reflect quality differences, sub-national production volumes are aggregated to the national level using a Constant Elasticity of Substitution (CES) aggregator. Factor markets are represented at sub-national level: land and water are region specific, while capital and labour are sluggishly mobile across regions. Accordingly, factor availability, mobility, and prices differ sub-nationally based on CET factor supply functions, while national intermediate input prices apply uniformly across sub-regions as sub-national trade margins are not considered. Taxes are modelled exclusively at the national level and therefore apply uniformly across all sub-regions. As a result, the sub-national data requirements are relatively modest, consisting essentially of output quantities and cost shares net of taxes. Prior to database generation in CGEBox, three categories of sub-national data are collected and prepared[11]:

(1) **Gross value added (GVA) data for all GTAP sectors at NUTS2 level:** Since national accounts do not provide sectoral production values at sub-national level, this work relies on NUTS2 GVA data together with the assumption of equal sectoral cost structures across regions. EUROSTAT provides GVA data at NUTS3 level for eleven broad sectors (EUROSTAT, 2024d), which are aggregated to NUTS2 level. These broad sector data are then disaggregated to GTAP sector detail using additional data sources:

- *Agriculture (part of sector A):* NUTS2 level production shares are taken from the Economic Accounts for Agriculture (EAA; EUROSTAT, 2024a). Where unavailable, disaggregation is based on NUTS2 level land cover shares derived from a GIS intersection of CORINE 2018 land cover data (COPERNICUS, 2024) with 2016 NUTS2 boundaries (EUROSTAT, 2025).
- *Manufacturing (sector C), energy/ utilities/ waste (sector BDE), construction (sector F), retail/ logistics/ hospitality (sector GI), information and communication (sector J), finance and insurance (sector K), real estate (sector L), business*

[11] The code preparing NUTS2 level data can be found in CGEBox\gams\GTAPNuts2\createNUTS2_V11.gms.

services (sector MN), and community/ social/ personal services (sector RU): disaggregation is based on NUTS2 level salary shares from EUROSTAT (2024e).

- *Public services (sector OQ):* disaggregation uses NUTS2 level employment shares (EUROSTAT, 2024b).

Where no NUTS2 level data is available, disaggregation of the broad GVA data to GTAP sectoral level is inferred from related sectors or GVA records are distributed evenly across GTAP sectors. Figure 3.3 illustrates the GVA data preparation process.

(2) **LULC data at NUTS2 level:** Production factor stocks are disaggregated to NUTS2 level using the equal cost structure assumption: national stocks by sector are allocated according to NUTS2 production shares. For land, this procedure is refined by overwriting factor stocks with GIS-derived land cover information from CORINE 2018 land cover data (COPERNICUS, 2024) intersected with the 2016 NUTS2 boundaries (EUROSTAT, 2025). Where available, NUTS2 level Farm Structure Survey (FSS) data (EUROSTAT, 2024c) are used to further refine cropland and pastureland entries and to provide land use information at NUTS2 level.

(3) **Additional data for optional use:** Population projections at NUTS2 level (EUROSTAT, 2021) are provided, which can be used to disaggregate SSP-specific population projections to sub-national level during baseline generation. Further, NUTS2 level irrigation areas (EUROSTAT, 2020) are included for applications involving water splits, and NUTS2 level AEZ shares are provided based on GIS analysis.

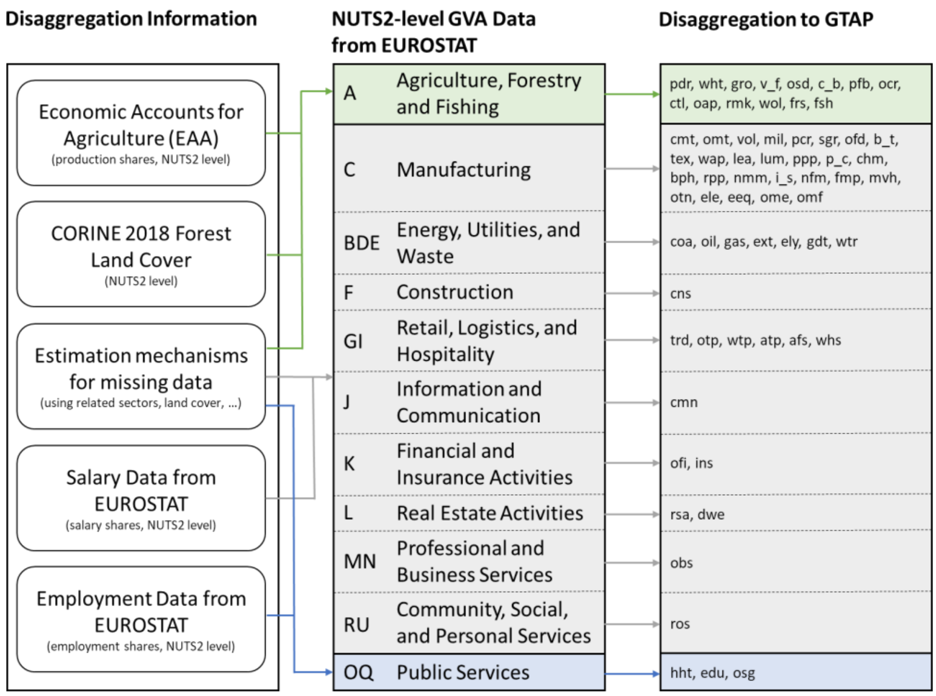

Figure 3.3 Processing of NUTS2 gross value added data.

Source: Own illustration.

The processed NUTS2 data are stored in a GAMS Data Exchange (GDX)[12] file and are automatically imported when the CGEBox framework generates a database that contains European countries as single entities[13].The model first adjusts the NUTS2 GVA data to the current aggregation and performs consistency checks. For example, NUTS2 data entries are deleted if no corresponding national production exists in the GTAP v11 database, and very small data entries are removed to avoid numerical issues. As at the national level, NUTS2 LULC data are rebalanced by solving a NLP problem minimising the squared relative differences to the a priori target values, equivalent of maximising the posterior density under normally distributed relative errors. The rebalanced data meet the following conditions:

(1) Posterior AEZ and NUTS2 level land rents aggregated over AEZs equal NUTS2 level land rents.

[12] CGEBox\gams\GTAPNuts2\gams\GTAPNuts2\gdp_NUTS2_V11.gdx

[13] For numerical reasons, the disaggregation of a database at NUTS2 level is only carried out in the final step of multi-step data processing procedures.

(2) Posterior NUTS2 level land rents aggregated over NUTS2 equal national land rents.
(3) Posterior NUTS2 level managed land area aggregated over NUTS2 equals national managed land areas.
(4) Posterior NUTS2 level unmanaged land area aggregated over NUTS2 equals national unmanaged land areas.
(5) Posterior total area equals the sum of all related posterior land covers.
(6) Posterior areas aggregated over AEZs, NUTS2, and land cover equal national total land areas.

The production side of the LULC-modified GTAP data is disaggregated to sub-national level by applying NUTS2 shares to national entries. The final input dataset comprises 47 countries or regions, 317 NUTS2 regions, 143 production activities, 103 products, and six production factors, forming the basis for the projections presented here.

3.5 Limitations

The dataset provides detailed projections of LULC under the five SSPs from 2020 to 2050. These projections depend on exogenous projections, assumptions on SSP-specific LULC drivers, the CGE input data, and the model's mechanisms and parameterisation. Each of these elements carries uncertainties, though projections remain internally consistent according to CGE balancing and accounting conditions. The SSPs illustrate contrasting futures without implying that these five narratives are the only plausible ones or attaching probabilities to them. Our scenario-based projections therefore reflect potential LULC developments rather than exact predictions. Sub-national data follow the 2016 NUTS2 classification, consistent with the 2017 base year of the GTAP v11 database. However, users should note that more recent NUTS2 classifications (2021 and 2024) differ slightly and that overseas territories are excluded from the projections. The equal cost structure assumption across sub-national units and uncertainties in secondary data sources (e.g., CORINE 2018 land cover) may reduce precision at sub-national level. Model parameters – particularly elasticities in CES and CET structures – are uncertain and influence projected LULC dynamics. Outside Europe, regions are represented at national or aggregated levels, which masks local heterogeneity. Users should consider these factors when applying the dataset for research, modelling, or policy support.

3.6 Acknowledgement

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Chapter 4
Linking socio-economic dynamics across regional scales to assess land-atmosphere feedbacks of land cover change[1]

Abstract

Anthropogenic land cover change is a potentially important driver of regional climate dynamics, yet its integration into climate assessments remains limited. This study showcases a new approach that allows socio-economic development assumptions to propagate from global economic dynamics to local land-atmosphere feedbacks. The framework loosely couples (1) land cover projections consistent with the five Shared Socio-Economic Pathways from a global economic model, (2) a high-resolution land cover downscaling model, and (3) a physically consistent regional

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[1] This chapter is submitted to Global Environmental Change as:

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CRediT Statement:

Theresa Goebel: Conceptualisation, Formal analysis, Methodology, Project administration, Software, Visualisation, Writing – original draft, Writing – review & editing. Marco Ferro: Conceptualisation, Formal analysis, Methodology, Software, Writing – original draft. Chiara Colesanti-Senni: Conceptualisation, Formal analysis, Methodology, Visualisation, Writing – original draft. Justin Andrew Johnson: Conceptualisation, Methodology, Software, Supervision, Writing – review & editing. Wolfgang Britz: Conceptualisation, Methodology, Software, Supervision, Writing – review & editing. Jan Börner: Conceptualisation, Methodology, Software, Supervision, Writing – review & editing.

climate model depicting land-atmosphere interactions. Moderate land cover changes (2.7% to 7.9% of the study area) produce measurable biophysical feedbacks leading to three key findings. First, deforestation and urbanisation emerge as dominant drivers of regional temperature increases. Second, land-atmosphere feedbacks of land cover change are strongest during the crop growing season (April to October). Third, these feedbacks are particularly relevant in low-emission mitigation scenarios involving substantial land cover interventions. Overall, this study's results demonstrate that socio-economic drivers of land cover change, even if moderate, can significantly influence regional climate patterns. Integrating land-atmosphere feedbacks into climate assessments through coupled socio-economic and biophysical modelling is therefore essential for robust regional climate projections and for informed adaptation and mitigation planning.

Keywords: Land cover change, Computable General Equilibrium (CGE) modelling, spatial downscaling, Earth system modelling, land-atmosphere feedbacks, human-Earth system interactions.

4.1 Introduction

Land cover (LC) change is a potentially important driver of climate dynamics. Beyond greenhouse gas (GHG) releases through land management and carbon stock changes, land affects climate through alterations of biophysical processes such as albedo and evapotranspiration, which modify land-atmosphere interactions and potentially affect the ecosystem's capacity to regulate the climate (Foley et al., 2005; IPCC, 2019; Pielke et al., 2016). A substantial body of literature has investigated the climate impacts of future LC change using scenarios based on abrupt and large-scale LC conversions (e.g., Cherubini et al., 2018; Davin et al., 2020; Rydsaa et al., 2015). However, such rapid and extensive transformations are unlikely to occur in Europe over the coming decades. This highlights the need for more realistic LC scenarios that reflect plausible trajectories of LC change. To address the inherent uncertainty in future LC developments, climate research commonly explores contrasting futures driven by alternative socio-economic pathways aligned with predefined narratives (Stehfest et al., 2019). The five Shared Socio-Economic Pathways (SSPs) constitute the most recent set of such narratives, describing potential developments across economic, environmental, and social dimensions (Figure 4.1; O'Neill et al., 2014, 2017; Riahi et al., 2017). LC under the SSPs has been quantified by comprehensive Integrated Assessment Models (IAMs; Popp et al., 2017) and downscaled for use in Regional Climate Models (RCMs) to investigate land-atmosphere feedbacks of LC change (Hurtt et al., 2020). However, IAMs typically operate at supra-national scales with coarse sectoral and temporal resolution (IPCC, 2022; Johnson et al., 2025), and the downscaled LC data represents areas ranging from tens to several hundred square kilometres (Doelman et al., 2018; Hurtt et al., 2020; Zeng et al., 2022). These characteristics limit the representation of national and sub-national socio-economic interactions in RCM simulations and constrain assessments of local land-atmosphere responses to LC change.

This study addresses these limitations by applying a new approach that links sub-national, SSP-based LC scenarios to regional climate responses through a sequential modelling chain. This chain loosely couples (1) endogenous, SSP-based LC projections from a global Computable General Equilibrium (CGE) model with sub-national detail and integrated assessment features, (2) high-resolution spatial downscaling of LC changes relying on an efficient two-stage approach, and (3) physically consistent climate simulations with a high-resolution RCM depicting land-atmosphere interactions. Together, these three components allow socio-economic assumptions embedded in the SSPs to propagate from global economic dynamics to local land-atmosphere interactions, improving the representation of regional socio-economic processes and the precision of LC downscaling. Applied to a test region in Central Europe, this study assesses the climate signal of alternative LC futures stemming from changes in biophysical processes. The guiding research question is: *"How do socio-economically driven LC changes influence regional climate through biophysical land-atmosphere interactions?"*. The remainder of the paper is structured as follows: Section 4.2 outlines the conceptual framework and modelling chain components; Section 4.3 presents the results; Section 4.4 discusses the findings; and Section 4.5 concludes with a summary and implications.

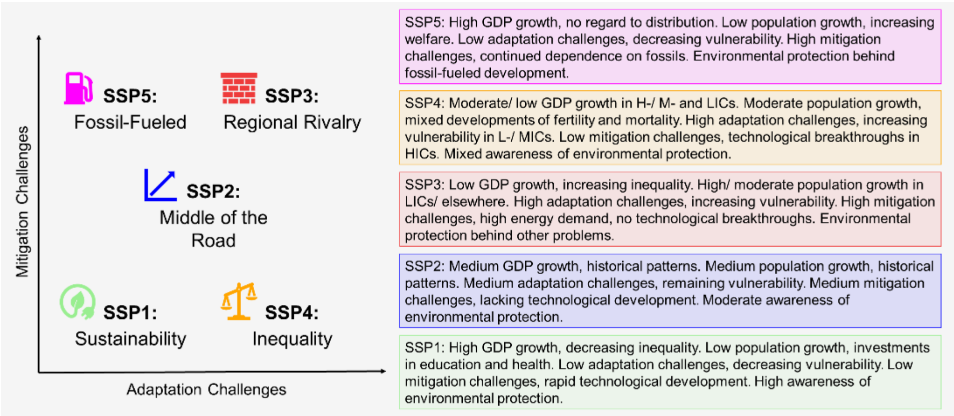

Figure 4.1 Overview of the shared socio-economic pathways.

Source: Goebel and Britz (2025a). Remark: L-/ M-/ HIC stands for low-/ middle-/ high-income country.

4.2 Conceptual framework and methods

This section provides an overview of the new approach to assess local land-atmosphere feedbacks of alternative LC futures under average and dry climate conditions in Central Europe (Figure 4.2). It starts from endogenous SSP-based LC projections generated using the open-source CGE modelling platform CGEBox (Britz, 2022; Britz and van der Mensbrugghe, 2018). These projections are globally consistent and available for all five SSP scenarios, at bi-annual resolution from 2020 to 2050, and cover eight LC types: cropland, pastureland, managed forest, natural forest, shrubland, savannah and natural grassland, built-up land, and other land (rock, ice and desert; Goebel and Britz, 2025a, 2025b). The selected study region – an area of 450 km x 450 km roughly corresponding to Northern and Central Germany that has undergone considerable LC changes in the past (Ferro et al., 2025) – comprises CGEBox LC projections for 37 sub-national NUTS2[2] regions. For those regions, CGEBox LC outputs for the years 2020 and 2050 are passed to the open-source Spatial Economic Allocation Landscape Simulator (SEALS) model (Jeetze et al., 2025; Johnson and Thakrar, 2024). SEALS covers seven LC classes: cropland, grassland, forest, other natural land, urban, other, and water. The mapping between CGEBox and SEALS

[2] NUTS (Nomenclature des Unités territoriales statistiques) is a regional classification administrated by the Statistical Office of the EU. Level 2 covers districts with the same regional policy (EU, 2025).

LC classes can be seen in Figure 4.2. To downscale the CGEBox LC projections to a 10 arc-seconds (~300 m) grid, SEALS operates through a two-stage hierarchical approach, combining the regional projections with spatial patterns from the Land Use Harmonization 2 (LUH2) dataset and afterwards applying a machine learning based downscaling algorithm to determine pixel-level transitions. The resulting high-resolution LC maps then serve as input for the Terrestrial Systems Modeling Platform (TSMP or TerrSysMP; Shrestha et al., 2014). TSMP distinguishes LC in the form of different plant functional types (PFTs): Bare ground; needleleaf evergreen and deciduous trees of boreal and temperate zones; broadleaf evergreen and deciduous trees of boreal, temperate, and tropical zones; broadleaf evergreen and deciduous shrubs of boreal and temperate zones; C3 and C4 grass; and C3 and C4 crops. Figure 4.2 shows the PFTs relevant to the analysed study region and the applied LC mapping. TSMP uses the 2020 LC from CGEBox and downscaled by SEALS as a reference point and simulates changes in key bioclimatic variables resulting from 2050 LC changes under the five SSPs under average and dry climate conditions.

While conceptually related approaches exist (e.g., Hirsch et al., 2018; Hoffmann et al., 2023; Huang et al., 2020), the new framework is distinguished by several features. First, the LC projections originate from a globally consistent CGE model accounting for global, regional, and sub-regional socio-economic dynamics. Second, the CGEBox projections stand out in terms of a coherent and transparent treatment of underlying assumptions and their high level of economic, regional, and sectoral detail. Third, SEALS enables LC change simulations over large regions with higher resolution than previous studies due to efficient and parallel computation. Fourth, both CGEBox and SEALS are open-source and require limited computational resources, allowing flexible transfer to other scenarios and regions. Finally, TSMP provides physically consistent simulations of land-atmosphere feedbacks of LC change, linking global socio-economic scenarios to regional and local climate impacts in a robust way. The following sections provide methodological insights into the individual components of the conceptual framework.

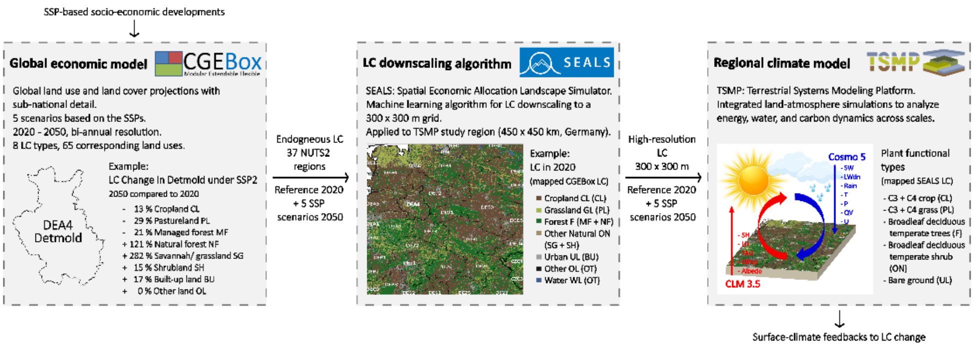

Figure 4.2 Conceptual framework.

Source: Own illustration. Remark: The central panel shows the study region and the 37 NUTS2 units included in the analysis. A zoomed view and a complete list of these NUTS2 regions are provided in Appendix A.4.1. Appendix A.4.2 summarises land use and land cover as classified by CGEBox. Appendix A.4.3 provides an enlarged view of Figure 4.2. SSP abbreviates Shared Socio-Economic Pathway. LC abbreviates land cover.

4.2.1 NUTS2 level land cover projections from CGEBox

CGEBox (Britz, 2022; Britz and van der Mensbrugghe, 2018) is an open-source CGE modelling platform that builds on the General Algebraic Modeling System (GAMS) implementation of the Global Trade Analysis Project (GTAP) standard model, version 7 (van der Mensbrugghe, 2018). The GTAP standard model is a multi-regional, comparative-static CGE framework that represents the global economy by linking countries or regions through trade, production, consumption, and factor markets. It is widely used to analyse the impacts of policy changes or economic shocks on trade flows, prices, and welfare across regions and sectors (e.g., GTAP, 2026). A key feature of CGEBox is its modular structure, which allows the GTAP standard model to be coupled with additional CGE modules tailored to specific analytical purposes, e.g., including land use and land cover (LULC) dynamics.

Goebel and Britz (2025a, 2025b) apply CGEBox to quantify LULC under all five SSPs with sub-national resolution for Europe. Their analysis builds on a processed version of the GTAP v11 Power database (Aguiar et al., 2022; Chepeliev, 2023; GTAP, 2023), comprising 47 countries or regions, 317 NUTS2 sub-regions, 143 production activities (65 of which are land-related), 103 products (35 of which are land-related), and six production factors. The CGE simulations are based on the GTAP-based Recursive-

Dynamic Economic Model (G-RDEM; Britz and Roson, 2019; Roson and Britz, 2021), an extension of the GTAP standard model designed for long-term economic baseline generation and analysis. To enhance its integrated assessment capabilities, G-RDEM is complemented with additional CGEBox modules. These improve the representation of the production factor land through enhanced land input data, locally determined substitution options, and finer distinctions between LULC classes. They also enable the tracking and taxation of climate-relevant emissions and allow production functions and factor markets to be disaggregated to the sub-national level. Quantifications of the SSPs are implemented as five recursive-dynamic baseline scenarios, simulated biennially from 2020 to 2050. From 2025 onwards, the scenarios diverge according to SSP-specific assumptions regarding exogenous projections (gross domestic product, demographics, cropland, yields), as well as consumption, policy, and technology developments. The CGEBox LULC projections for Europe are publicly available as a dataset (Goebel and Britz, 2025c). The corresponding publications also document in detail the steps required to replicate the analysis and transfer the approach to other regions or sectors.

Compared to existing LULC quantifications, the CGEBox projections offer four key advancements for their use within a conceptual framework assessing land-atmosphere feedbacks of LC change. First, the use of an open-source, stand-alone economic model with integrated assessment features enhances transparency and facilitates updates and transfers to other regions and scenarios. Second, the ability to disaggregate a global economic framework to the sub-national level allows, for the first time, a consistent representation of both global and regional socio-economic processes. Third, the explicit modelling of key economic structural change drivers within a recursive-dynamic framework improves the representation of long-term socio-economic processes. And fourth, the high sectoral resolution of LULC projections generated with CGEBox enables a detailed analysis of land-atmosphere feedbacks as RCMs capabilities continue to advance.

4.2.2 Spatial downscaling with SEALS

SEALS (Jeetze et al., 2025; Johnson and Thakrar, 2024) is an open-source LC downscaling model that converts regional or global LC projections into fine-resolution maps by allocating changes based on observed historical patterns, land suitability, and adjacency effects. It is calibrated empirically and simultaneously distributes multiple LC classes, producing high-resolution maps suitable for ecological and environmental modelling. To downscale the NUTS2 level CGEBox LC projections to a 10 arc-seconds (~300 m) grid, SEALS uses a two-stage hierarchical approach. First, NUTS2 level net hectare changes for each LC class are allocated to a coarse grid (~0.25°) using the CGEBox projections in combination with LUH2 within-region spatial patterns. These patterns are available for SSP-RCP (Representative Concentration Pathway) combinations reflecting how historical land use dynamics vary across space under different socio-economic and climate contexts. In SEALS, each CGEBox scenario is linked to the corresponding LUH2 SSP-RCP pattern (e.g., SSP2 projections use SSP2-4.5 spatial patterns), ensuring that coarse economic outputs are allocated spatially in a way consistent with empirical observations. Second, the medium-resolution projections (~0.25°) are allocated to 10 arc-seconds (~300 m) pixels using SEALS's machine-learning allocation algorithm. This starts from the European Space Agency (ESA) Climate Change Initiative (CCI) LC baseline, which provides observed historical LC distributions. Pixel-level suitability is calculated as a weighted combination of spatial covariates, including adjacency to existing LC (via Gaussian convolutions at multiple kernel sizes), slope, soil characteristics, and distance to infrastructure. Allocation respects conversion eligibility constraints, excluding protected areas and disallowed transitions (e.g., urban cannot revert). Eligible pixels are ranked by suitability and converted sequentially until the coarse-cell LC budget is exhausted. Model coefficients are calibrated using ESA CCI data from 1992 to 2010 via iterative optimisation that minimises differences between observed and predicted transitions (Johnson et al., 2023; Suh et al., 2020). SEALS is comprehensively documented (Johnson, 2026) and can be replicated on a conventional laptop.

4.2.3 Climate simulation with TSMP

TSMP (Shrestha et al., 2014) is a modular modelling framework that simulates interactions between the atmosphere and the land surface by coupling high-resolution convective-permitting RCMs. The modelling framework is widely used for regional climate studies, hydrological research, and land-atmosphere interaction analysis (Gasper et al., 2014; Shrestha et al., 2014). TSMP is ideal for testing our proposed framework because – compared to other RCMs – it has a higher resolution and is thus more sensitive to small LC changes, such as those occurring in our study region. To simulate local land-atmosphere feedbacks of the LC changes projected by CGEBox and downscaled by SEALS, this study uses TSMP version 1.4.0 with a CLM3.5-COSMO5.0-OASIS3MCT3 model configuration (Baldauf et al., 2011; Craig et al., 2017; Oleson et al., 2008). The land-surface component CLM (Community Land Model) represents vegetation dynamics, soil hydrology, surface energy balance, and carbon-nutrient cycling. Through the OASIS coupler, land-surface processes interact with atmospheric dynamics in COSMO (Consortium for Small-scale Modeling), including cloud microphysics, turbulence, radiation, convection, and land-atmosphere exchanges.

Our study region spans a 450 km × 450 km domain in Central Europe (Figure 4.2), roughly corresponding to Northern and Central Germany. TSMP has been successfully tested for this domain in previous analyses (e.g., Iakunin et al., 2022; Kollet et al., 2018). Lateral atmospheric boundary forcing conditions are taken from the ERA5 reanalysis for the years 2017 and 2018 (Copernicus Climate Change Service, Climate Data Store, 2023). The horizontal grid spacing is approximately three km (dx = dy = 0.0275°) across all model components, resulting in 150 grid points x 150 grid points. Vertically, CLM includes 10 levels, while COSMO includes 50 levels. CLM operates with a time step of 3600 seconds, while COSMO uses a time step of 25 seconds. The simulation period covers a full annual cycle to capture seasonal variability. For each scenario, we initialise the soil and land surface with a 17-year (2000–2016) model spin-up to equilibrate soil moisture, temperature, and carbon pools. All model simulations can be replicated by configuring TSMP (HPSC-TerrSys, 2023) with the aforementioned forcing data and model set-ups. However, due to the computational power and data storage required, using a high-performance computer is recommended for coupled simulations. Due to mismatches between the SEALS downscaled LC data and the PFT classification, it is assumed that the “other natural” LC class from SEALS represents broadleaf deciduous temperate shrub, and that the “forest” class represents broadleaf deciduous temperate trees, as can be seen in Figure 4.2.

To assess local land-atmosphere feedbacks of LC change, the focus is on three commonly assessed bioclimatic variables: 2-metre air temperature, total precipitation, and topsoil temperature. 2-metre air temperature represents near-surface air temperature and is commonly used as an indicator of atmospheric warming relevant for human and ecosystem impacts. Total precipitation denotes the accumulated precipitation over the simulation period and reflects changes in the regional hydrological cycle associated with land-atmosphere interactions. Topsoil temperature refers to the temperature of the upper soil layer and serves as an indicator of land-surface thermal conditions and soil-atmosphere energy exchange. Together, these variables capture key components of the surface energy and water balance and are frequently employed to quantify biophysical climate responses to LC change. The atmospheric forcing is held constant for all scenarios and differences in the outcome variables between the baseline scenario (2020) and the projected SSP scenarios (2050) are calculated. This allows to isolate the climate signal attributable solely to these LC changes. The selected atmospheric forcing years represent different conditions within the domain. For example, 2018 experienced particularly dry conditions, while 2017 is a rather average year (Bastos et al., 2020).

4.3 Results

This section first presents the CGEBox LC projections for the study region after downscaling with SEALS, using 2020 as the reference year and examining the changes over time for all five SSPs. It then reports the land-atmosphere feedbacks of LC change simulated by TSMP.

4.3.1 Land cover transitions

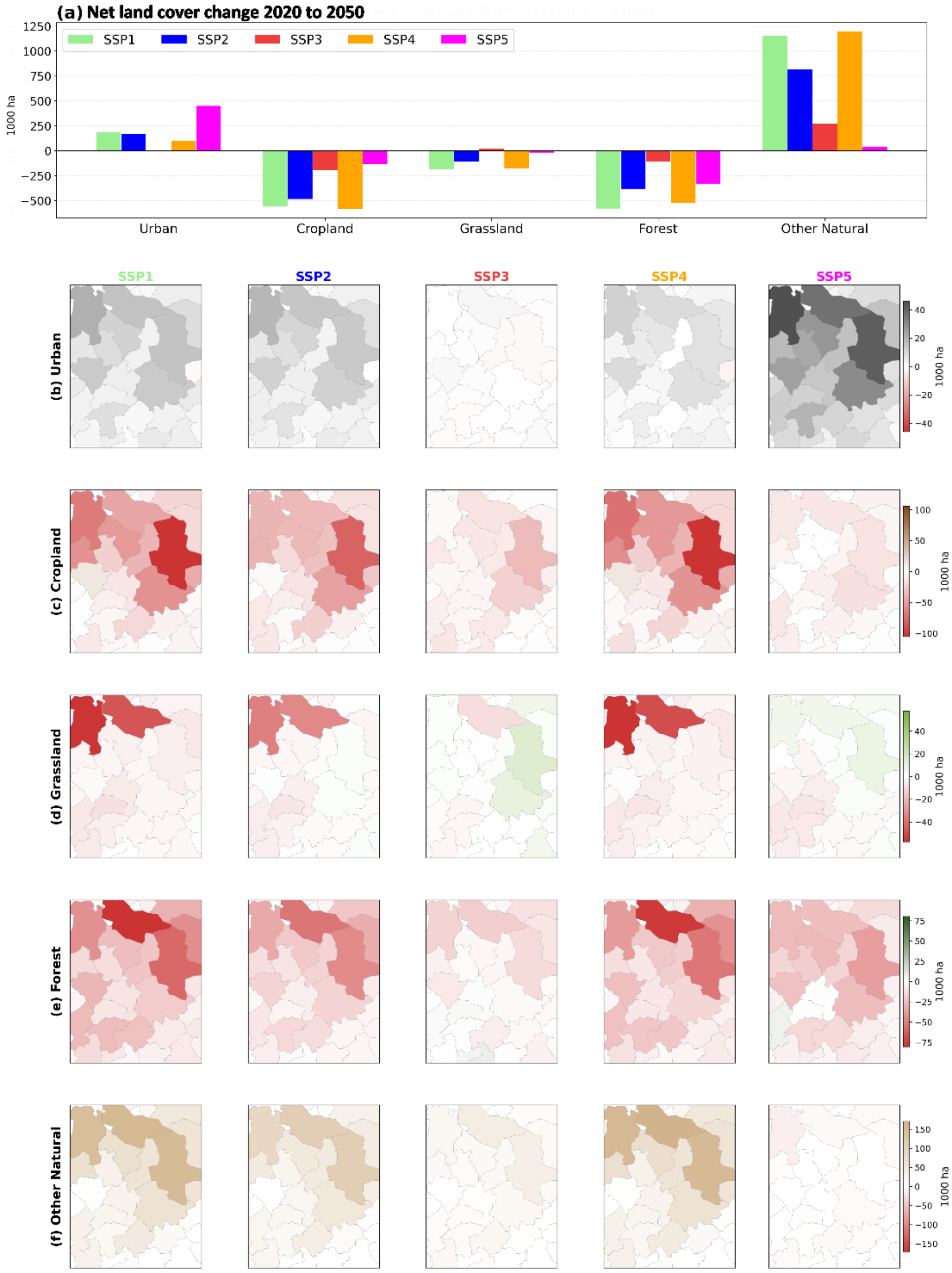

Figure 4.3 Net land cover change across the shared socio-economic pathways.

Source: Own illustration.

Our reference is given by the 2020 LC specified by CGEBox at NUTS2 level and downscaled by SEALS. In this year, cropland accounts for 47.2% of the 20.2 million hectares study region, other land for 33.1%, grassland for 12.0%, urban area for 6.8%, other natural land for 1.2%, and water for 0.9%. Figure 4.3 presents net LC changes from 2020 to 2050 across all five SSP scenarios, with panel (a) showing aggregated changes by LC class and panels (b) to (f) illustrating spatial change patterns across NUTS2 regions. Urban area and other natural land increase in all scenarios, whereas cropland, grassland, and forest generally decline. Overall, SSP1 and SSP4 exhibit the most pronounced LC changes, SSP2 shows intermediate shifts, and SSP3 and SSP5 display comparatively minor changes. Urban expansion is an exception, with SSP5 showing the largest increase. In general, LC changes are most pronounced in northern and eastern sub-regions.

Figure 4.4 summarises the main LC transitions from 2020 to 2050 for each SSP scenario. Arc size represents the total transitions (inflows + outflows) for each LC class, and ribbon width indicates the magnitude of each transition flow, with ribbon colour corresponding to the source class. SSP1 and SSP4 exhibit the largest total transition volumes (7.88% and 7.65% of pixels changed; see Appendix A.4.4), dominated by conversions from cropland and forest to other natural land. These flows are also prominent in SSP2, whereas SSP3 shows fewer transitions between LC classes. In SSP5, transitions from forest and grassland to urban area dominate. While the chord diagrams illustrate the magnitude of LC transitions, they do not provide spatial detail. Figure 4.5 examines the distribution of LC changes at multiple resolutions for contrasting transition patterns under SSP1 and SSP5. Panel (a) shows the total percentage change in area of interest, with higher regional variability under SSP1. Panel (b) presents the fine-resolution (10 arc-seconds, ~300 m) SEALS output, highlighting different spatial clustering patterns: the change hotspot occurs in the eastern part of the domain for SSP1 and in the north-western part for SSP5. Panel (c) zooms into these hotspots, revealing distinct transition compositions: under SSP1, conversion to other natural land (73.3% of transitions) and under SSP5, conversion to urban area (53% of transitions).

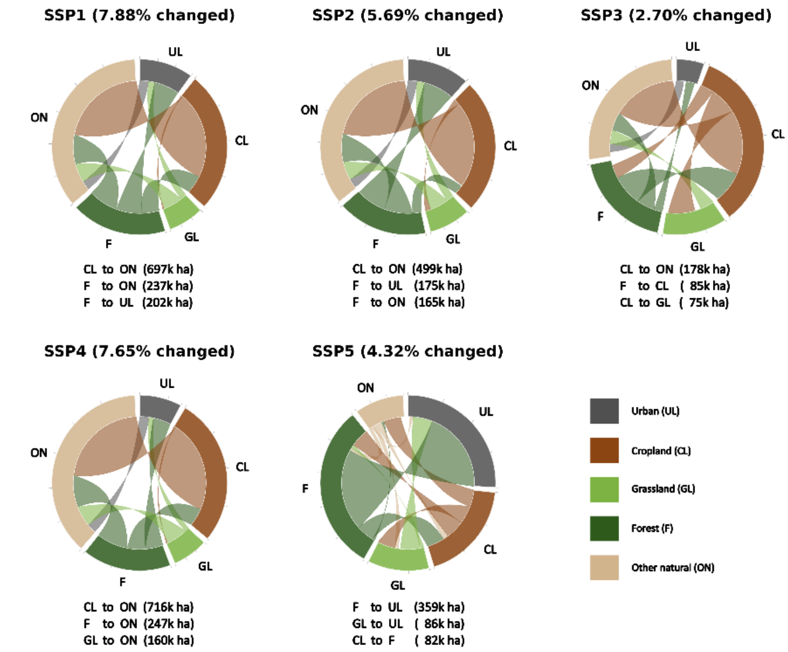

Figure 4.4 Land cover transitions chord diagram.

Source: Own illustration. Remark: The arc size for each class represents outflows and inflows for that class. Only LC transitions exceeding 10,000 hectares are shown. Below each pie chart, the three largest transition flows are indicated.

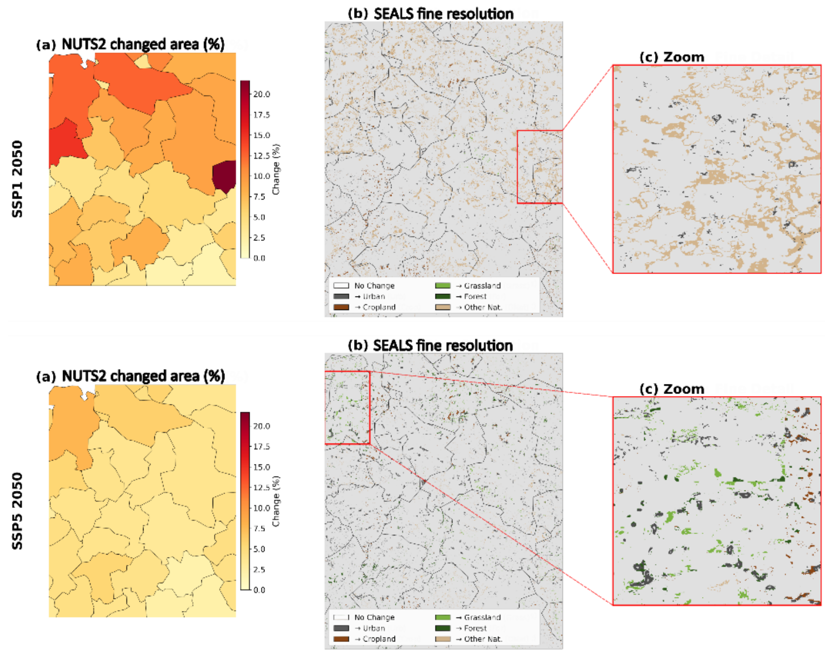

Figure 4.5 Spatial change.

Source: Own illustration.

4.3.2 Land-atmosphere feedbacks

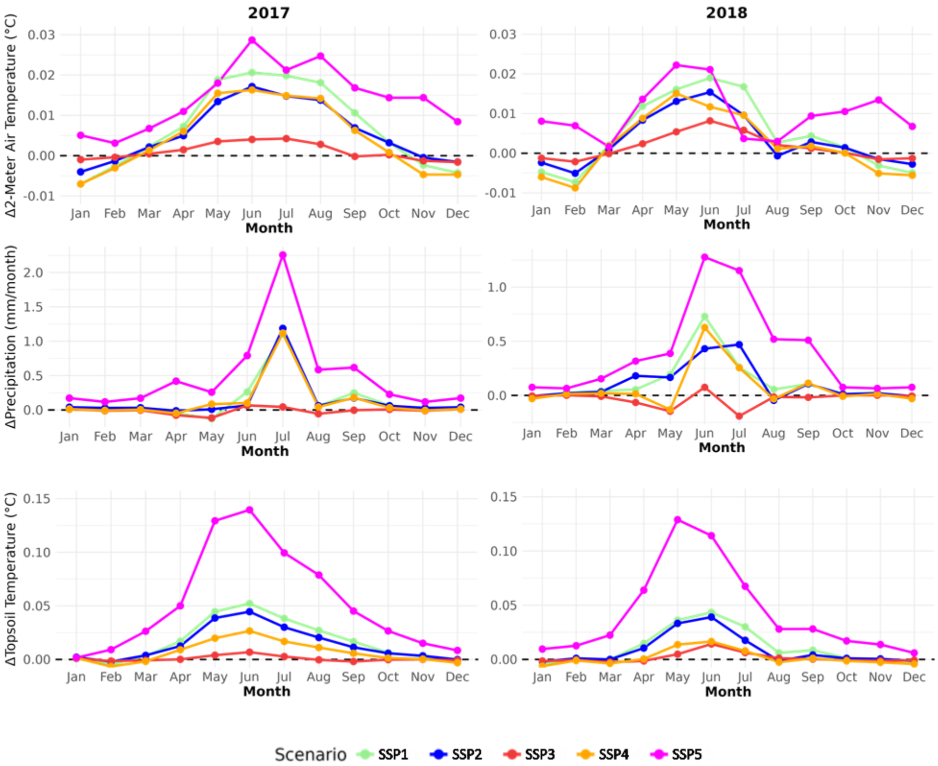

Figure 4.6 Mean differences in key bioclimatic variables between the 2020 baseline and the shared socio-economic pathway scenarios, simulated under 2017 and 2018 ERA5 atmospheric conditions.

Source: Own illustration.

Figure 4.6 provides monthly mean differences in 2-metre air temperature, total precipitation, and topsoil temperature resulting from LC changes between the 2020 reference and the five SSP scenarios in 2050. Results are shown for two atmospheric forcing years, 2017 (average) and 2018 (dry), with atmospheric conditions held constant to isolate land-surface feedbacks of LC change. Overall, the simulated responses are small, ranging from -0.01 and +0.03 degrees for 2-metre air temperature, from -0.25 to +2.25 mm/month for total precipitation, and from -0.05 to +0.15 degrees for topsoil temperature. Except for precipitation, the magnitude of changes is generally lager under 2017 forcing conditions than under 2018 forcing. Among the scenarios, SSP5 exhibits the strongest impacts in both forcing years, with increases in all three bioclimatic variables and all months. SSP1 shows the second-largest effects (except for total precipitation under 2017 forcing), while SSP2 and SSP4 generally produce intermediate responses. SSP3 consistently exhibits the smallest impacts. Seasonally, individual months show isolated instances of cooling or reduced precipitation. However, these represent exceptions.

Table 4.1 Annual mean and standard deviation of key bioclimatic variables under 2017 and 2018 ERA5 atmospheric forcing for the 2020 reference and the five shared socio-economic pathway scenarios.

		Topsoil Temperature [in °C]		Total Precipitation [in mm/month]		2-metre Air Temperature [in °C]	
		Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
2017	**Reference**	10.1336	7.0662	53.2951	39.5104	9.9492	7.0488
	SSP1	10.1505	7.0794	53.3889	40.6822	9.9564	7.0579
	SSP2	10.1479	7.0767	53.3911	40.6692	9.9550	7.0553
	SSP3	10.1344	7.0661	53.2430	40.4485	9.9503	7.0505
	SSP4	10.1404	7.0709	53.3788	40.7042	9.9540	7.0564
	SSP5	10.1863	7.1056	53.7268	40.9425	9.9637	7.0551
2018	**Reference**	11.1429	8.3477	30.9452	28.5283	10.8352	8.0153
	SSP1	11.1538	8.3552	32.3625	28.7390	10.8398	8.0213
	SSP2	11.1515	8.3525	32.3572	28.5980	10.8385	8.0188
	SSP3	11.1445	8.3497	32.2129	29.5219	10.8368	8.0177
	SSP4	11.1444	8.3479	32.3098	28.6620	10.8373	8.0201
	SSP5	11.1857	8.3707	32.6300	28.8864	10.8452	8.0154

Source: Own illustration.

As summarised in Table 4.1, all three bioclimatic variables increase on an annual mean basis in all scenarios (except for total precipitation under SSP3 under 2017 forcing) and under both forcing years. Variability differs across scenarios: the standard deviation of topsoil temperature and total precipitation is highest under SSP5, whereas the standard deviation of 2-metre air temperature is highest under SSP1. SSP3 tends to exhibit the lowest variability across variables (except for total precipitation under 2018 forcing). Appendix A.4.5–A.4.7 present monthly mean differences for selected NUTS2 regions with pronounced LC changes, together with corresponding means and standard deviations, including for the growing season. At the sub-regional scale, deviations from domain-wide patterns are rare. Even during the growing season, spatial responses largely mirror the overall patterns described above.

4.4 Discussion

This section discusses the findings of the study, beginning with an interpretation of the results presented in Section 4.3 and their implications for the relationship between socio-economically driven LC changes and simulated land-atmosphere feedbacks. Section 4.4.2 then critically evaluates the conceptual framework and the methodological choices underpinning the analysis.

4.4.1 Discussion of the results

LC projections are subject to substantial uncertainties related to input data, model structure, and study focus (e.g., Alexander et al., 2017; Prestele et al., 2016; Schmitz et al., 2014). Consequently, the CGEBox LC projections differ from other commonly used datasets, such as the IAM-based LC projections underlying LUH2 (Popp et al., 2017). Nevertheless, CGEBox LC projections have been shown to fall within a realistic global range (Goebel and Britz, 2025a). In addition, given that LC in Germany is strongly shaped by spatial planning, conservation policies, and agricultural regulation, and that demographic stagnation and limited availability of unused land constrain large-scale transformations (Weingarten, 2020), projected LC changes between 2.7% and 7.9% appear plausible.

The land-atmosphere feedbacks simulated by TSMP are small compared to effects reported in extreme LC change scenarios (e.g., Cherubini et al., 2018; Davin et al., 2020; Rydsaa et al., 2015). However, these magnitudes are entirely reasonable in the context of the moderate LC changes examined here and still result in measurable biophysical feedbacks, reinforcing the need to include these processes in regional climate projections. While the magnitude of biophysical responses varies slightly between the two forcing years analysed to account for variability in background climate, the overall spatial and seasonal patterns remain consistent. Changes in total precipitation are particularly small, likely because precipitation in TSMP is not primarily controlled by local surface conditions but by large-scale atmospheric circulation. This behaviour is consistent with previous TSMP studies (Vries et al., 2022). Simulated temperature effects depend on the type and extent of LC changes as well as on regional climate conditions, with spatial and seasonal heterogeneities. Notably, the strength of 2-metre air temperature and topsoil temperature responses does not scale linearly with the total amount of LC changes. Although SSP3, which exhibits the smallest overall LC change, also shows the weakest biophysical response (with a few regional exceptions), the remaining scenarios do not follow a simple ranking by LC change magnitude. Instead, the direction and type of LC transitions appear more influential than their aggregate extent, reflecting a trade-off between albedo- and evapotranspiration-driven warming or cooling that varies by region and transition type.

Our results are in line with previous research on historical LC changes in our study region (e.g., Ferro et al., 2025) and they support three key hypotheses from the literature. First, deforestation and urbanisation emerge as dominant drivers of regional temperature increases. Although SSP5 exhibits only moderate LC change (4.32%), its transitions are dominated by forest loss and urban expansion. As a result, SSP5 produces the strongest increases in 2-metre air temperature and topsoil temperature at both regional and sub-regional scales across nearly all month. This finding is consistent with previous studies: deforestation tends to increase average maximum temperature in Germany due to reduced evapotranspiration resulting in increased sensible heat flux despite potential albedo increases (e.g., Hu et al., 2019; Huang et al., 2020; Lejeune et al., 2018), while urbanisation substantially enhances surface warming, particularly at regional scales, highlighting the strong biophysical influence of impervious surfaces (Huang et al., 2020; Liu et al., 2025). Second, land-atmosphere feedbacks of LC change are strongest during the crop growing season (April to October), when evapotranspiration, canopy density, and soil moisture actively modulate surface energy fluxes, amplifying temperature responses (Lawrence and Chase, 2010). This emphasises the importance of interannual temporal resolution in regional climate impact assessments. Third, land-atmosphere feedbacks are particularly relevant in low-emission mitigation scenarios. Ambitious climate pathways often involve extensive LC interventions, such as bioenergy expansion and reforestation, which can induce substantial climate effects (e.g., Hirsch et al., 2018; Seneviratne et al., 2018; Pielke et al., 2016). In line with this, the sustainable SSP1 scenario coupled with RCP 2.6 shows the highest overall LC change (7.9%) and produces only slightly weaker bioclimatic effects than the high-emission SSP5 scenario coupled with RCP 8.5. Overall, these findings indicate that even under identical GHG forcing, regional climate responses can differ substantially depending on the type and spatial distribution of LC changes. This highlights the critical importance of accounting for land-atmosphere feedbacks in regional adaptation planning and in the evaluation of mitigation scenarios.

4.4.2 Discussion of the methodology

This study presents a new approach to analyse land-atmosphere feedbacks of socio-economically driven LC changes. To assess the robustness of the modelling framework, we first look at its individual components. CGEBox provides the socio-economic foundation of the framework by generating LC projections consistent with global developments in line with the SSP narratives. The model offers a highly detailed representation of agricultural production and land use, and its LC projections have been shown to fall within a plausible global range (Goebel and Britz, 2025a). Its open-source implementation and detailed documentation further ensure transparency and reproducibility. Nevertheless, CGEBox LC projections depend on exogenous assumptions regarding economic growth, demographics, crop yields, and cropland demand, as well as on qualitative interpretations of SSP-specific LC drivers, input data, and model parameterisation. The resulting LC trajectories therefore represent internally consistent scenario outcomes spanning an uncertainty range, rather than exact predictions of future LC.

SEALS performs the spatial allocation of these projected LC changes. Its hierarchical structure and optimised algorithms allow computationally efficient downscaling to high spatial resolution, and its open-source design and structed user guide facilitate application to other regions and alternative scenario frameworks. Compared with alternative allocation approaches, SEALS preserves NUTS2 level LC totals while introducing spatial heterogeneity based on empirical suitability relationships. This ensures consistency between economic projections and spatially explicit LC patterns. Limitations include the reliance on a historical calibration (1992 to 2010) and a one-way downscaling approach. As a result, SEALS may be less suitable for capturing LC dynamics outside the observed historical range and does not provide feedback to the upstream economic projections.

TSMP represents the biophysical component of the conceptual framework by coupling an atmospheric model (COSMO) and a land-surface model (CLM), enabling a physically consistent representation of surface energy and water fluxes at very high horizontal grid spacing. This makes it well-suited for analysing climatic responses to spatially explicit LC changes. For instance, by better representing convective processes which are particularly relevant for vegetation changes (Hong et al., 1995). However, TSMP is not applied in a fully coupled configuration with an explicit groundwater model. As a result, the simulated land-atmosphere feedbacks primarily reflect changes in surface albedo, aerodynamic roughness, evapotranspiration, and soil moisture dynamics within the land-atmosphere scheme, while lateral groundwater flow or deeper soil-groundwater interactions are not represented. These omitted processes can influence the persistence and spatial coherence of land-atmosphere feedbacks, particularly during dry periods. Their exclusion constitutes a limitation for interpreting the magnitude of the simulated biophysical effects but does not affect the qualitative assessment of how spatially explicit LC changes impact land-atmosphere feedbacks.

The full conceptual framework successfully links SSP-consistent LC projections, spatially explicit LC downscaling, and physically consistent RCM simulations to assess land-atmosphere feedbacks of socio-economically driven LC change. It allows joint consideration of global and regional socio-economic drivers and biophysical processes within a coherent modelling chain. The open-source, well documented, and computationally efficient design of CGEBox and SEALS facilitate transferability to other regions and scenario frameworks and allows for rapid regeneration of RCM input data. Currently, the three model components are coupled via a soft-linking approach, with data exchange conducted manually between modelling steps. A hard-linking of CGEBox and SEALS appears technically feasible as demonstrated in related frameworks such as the World Bank's MANAGE model coupled with SEALS (Ragchaasuren et al., 2025). Such integration could enhance internal consistency, reduce manual intervention, and support broader environmental assessments. Full integration of TSMP remains more challenging due to computational demands and the specialised infrastructure required for its operation. A further challenge lies in translating socio-economic LC categories into PFTs required by RCMs. While CGEBox distinguishes multiple cropland and pastureland uses and differentiates between irrigated and rainfed agriculture, forest representation remains comparatively aggregated. In contrast, RCMs employ detailed forest classifications but simplify agricultural land use into a limited number of PFTs (see Figure 4.2). Approaches such as Hoffmann et al. (2023) work on high-resolution translators from LUH2 LC data into PFT distributions for Europe, generating historical and future PFT maps at fine temporal resolution (1950 to 2100). Compared to this work, our approach relies on economically more detailed LC projections, enabling a more coherent representation of socio-economically driven LC changes. Bridging the conceptual and technical mismatch between socio-economic LC categories and PFTs remains an active area of research and introduces uncertainty into the coupling between socio-economic and biophysical model components.

4.5 Conclusion

In conclusion, our results show that socio-economic drivers of LC changes, though moderate in magnitude, exert a significant influence on regional climate patterns. Incorporating land-atmosphere feedbacks of LC change through integrated socio-economic and biophysical modelling is therefore essential for robust regional climate assessments and informed adaptation and mitigation planning. Especially under sustainable, low-emission scenarios, LC interventions such as reforestation or bioenergy expansion can contribute significantly to regional climate outcomes, sometimes producing effects comparable to high-emission scenarios with lower LC changes. The approach presented here successfully links SSP-consistent, sub-national LC projections, high-resolution spatial downscaling, and physically consistent RCM simulations, providing a coherent approach to explore the biophysical consequences of socio-economic development trajectories. Our work highlights key methodological challenges, including the translation of socio-economic LC categories into PFTs, the missing representation of sub-surface hydrological processes, and the high computational demands of RCMs. By addressing these challenges, future applications could further improve the accuracy and relevance of regional climate projections, supporting both scientific understanding and practical decision-making in LC planning and climate adaptation and mitigation.

4.6 Acknowledgement

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Chapter 5
Discussion and conclusion

This dissertation aims to develop land use and land cover (LULC) projections for the five Shared Socio-Economic Pathways (SSPs) that complement existing Integrated Assessment Model (IAM) projections by combining global economic consistency with detailed regional and sectoral resolution, while extending the representation of socio-economic processes. This work enables the analysis of how socio-economic uncertainty affects regional LULC dynamics and supports economically grounded environmental and climate assessments, as well as LULC, adaptation, and mitigation planning. The remainder of this chapter summarises the major contributions of the thesis, discusses the applied methodology and its limitations, highlights implications for future research and policy, and concludes.

5.1 Major contributions of the thesis

The major contributions of this dissertation are threefold. First, it makes a methodological contribution by introducing a new approach to generate consistent and highly detailed LULC projections aligned with the SSP narratives using a global, open-source Computable General Equilibrium (CGE) model. Second, it contributes a novel, publicly available dataset of global SSP-based LULC projections through 2050, with European coverage at national and sub-national (NUTS2) levels and high LULC detail. Third, it offers a conceptual and integrative contribution by demonstrating how socio-economic development pathways propagate from global economic dynamics to local climate effects through a loosely coupled modelling framework linking the new LULC projections with regional climate simulations.

The methodological contribution of this thesis builds on the modelling platform CGEBox (Britz, 2022; Britz and van der Mensbrugghe, 2018) and extends it to integrate advanced recursive-dynamic baseline generation, detailed LULC representation, sub-national resolution, and SSP-consistent scenario implementations within a stand-alone, globally consistent, and open-source CGE framework. Thereby, it broadens the scope and accuracy of CGE-based LULC analysis and provides an alternative to coupled IAM-based approaches for SSP quantification. Through CGEBox's modular structure, the proposed approach combines the specialised GTAP-based recursive-dynamic economic model (G-RDEM; Britz and Roson, 2019; Roson and Britz, 2021) with highly disaggregated input data and dedicated modules for LULC dynamics, energy systems, emissions accounting, and sub-national production structures.

G-RDEM extends standard recursive-dynamic CGE models by moving beyond a primary reliance on capital accumulation and exogenous GDP growth. Instead, it captures many additional key dynamics, including income dependent variations in household consumption, sector-specific productivity growth, and debt accumulation. As a result, G-RDEM improves the representation of long-term socio-economic processes. The LULC data underlying the simulation are systematically disaggregated and refined to provide accurate, detailed, and internally consistent input information. The corresponding CGEBox module preserves physical area balances and models LULC change based on empirically grounded relationships. In addition, the integration of sub-national production structures within an advanced recursive-dynamic modelling set-up with global economic coverage represents a key methodological advancement. This approach enables the analysis of regional heterogeneity in LULC dynamics while maintaining global economic consistency and capturing cross-border interactions and feedbacks, and can, in principle, be applied to all regions where suitable input data are available. For Europe, this dissertation delivers harmonised input data at the NUTS2 level.

In CGEBox, the SSPs are operationalised as recursive-dynamic baselines through 2050. They are initialised in 2017 in line with the GTAP v11 input data (Aguiar et al., 2022) and begin to diverge from 2025 onwards, reflecting SSP-specific assumptions. These incorporate projections of demographic development, GDP growth, cropland expansion, and yields derived from specialised external models (FAO, 2018; IIASA, 2024), as well as a mechanism linking built-up land expansion to the macroeconomic developments (Chen et al., 2020). These inputs are complemented by an extensive set of assumptions on key drivers of LULC change, ensuring consistency with the qualitative SSP narratives and enabling a comprehensive scenario quantification.

Together, these features enable a coherent representation of socio-economic processes and their influence on LULC dynamics across regions and sectors, at a level of detail typically not achieved in global economic models. The high regional and sectoral detail and the comprehensive implementation of the SSP scenarios provide new insights into the interactions between socio-economic drivers and land system dynamics. At the same time, the strong economic foundation of the new approach supports a wide range of downstream applications, including counterfactual policy analysis, distributional assessments, and the evaluation of trade and food system dynamics. Another key strength of the proposed framework lies in its flexibility and transparency. Compared to multi-model coupling applied in IAMs, the unified modelling architecture underlying CGEBox reduces structural and computational complexity. It therefore facilitates timely updates and iterative model development, including refinement of input data, scenario assumptions, and regional disaggregation. The open-source structure and comprehensive documentation of CGEBox further enhance reproducibility and accessibility.

Benchmarking against leading IAM-based frameworks demonstrates that CGEBox produces plausible LULC outcomes. The model shows a slightly greater tendency towards land substitution and a reduced tendency towards land conversion compared to IAM-based results. Nonetheless, its projections remain within the range of IAM outcomes, exhibit comparable scenario spreads, and broadly reproduce the relative ordering of SSP-specific results. This positions CGEBox as a valuable complement to IAMs, particularly for applications requiring economically grounded assessments of LULC change and its implications, timely updates, and detailed analyses of distributional effects and regional LULC dynamics.

A second major contribution of this thesis is the provision of a novel, publicly available dataset of SSP-based LULC projections. This covers all five SSPs from 2020 to 2050 at two- and five-year intervals and ensures global economic consistency while including a sub-national (NUTS2) disaggregation for Europe. Compared to existing SSP-based LULC projections (e.g., Doelman et al., 2018; Hurtt et al., 2020; IIASA, 2025), which typically rely on aggregated land cover (LC) classes or plant functional types (PFTs) at coarse regional resolutions, this dataset provides an unprecedented level of regional and sectoral detail. It distinguishes eight LC types with 65 corresponding land use categories and represents 47 global regions, including 40 individual countries and 317 NUTS2 regions. This level of detail enables a wide range of new applications, including climate modelling, biodiversity assessments, and economically grounded analyses of long-term LULC change in Europe. In addition, the dataset contributes to ensemble-based uncertainty analyses by providing a complementary, economically consistent perspective on LULC futures under the SSPs.

Finally, this thesis contributes a new and integrative conceptual framework to assess how socio-economic developments propagate from global economic dynamics to local land-atmosphere interactions. This framework downscales the new SSP-aligned LULC projections to a 300 m x 300 m grid by loosely coupling the high-resolution LC downscaling model SEALS (Jeetze et al., 2025; Johnson and Thakrar, 2024). The resulting spatially explicit LC data serve as input to the physically consistent regional climate model (RCM) TSMP (Shrestha et al., 2014), which explicitly depicts land-atmosphere interactions. Applied to a 450 km x 450 km test region in Northern and Central Germany, the new conceptual framework demonstrates that even moderate LC changes can produce significant regional climate feedbacks. Changes in LC patterns, including deforestation or urbanisation, emerge as particularly important drivers of regional temperature responses, with land-atmosphere feedbacks being most pronounced during the crop-growing season. These effects are especially relevant under sustainable, low-emission scenarios involving substantial LULC changes, where resulting climate impacts can be comparable to those observed under high-emission scenarios.

By relying on the NUTS2 level LULC projections combining global economic consistency with high regional and sectoral detail, the new conceptual framework improves the representation of socio-economically driven LULC dynamics in RCM simulations. The open-source and computationally efficient design of the upstream modelling components CGEBox and SEALS facilitates the transferability to other regions and scenario frameworks. It further allows for a rapid generation of consistent RCM input data. TSMP is well suited for analysing climatic responses to spatially explicit LC change, as it integrates atmospheric and land-surface processes at high spatial resolution. Overall, the integration of precise socio-economic modelling, high-resolution spatial LC downscaling, and physically consistent regional climate simulations enables the joint analysis of socio-economic and biophysical processes across scales and contributes to more robust regional climate simulations and informed policy support.

Building on these contributions, the following section critically reflects on the applied methodology, discusses its limitations, and outlines directions for future research.

5.2 Methodological discussion and research outlook

To develop globally consistent LULC projections for the five SSPs that provide high regional and sectoral detail and improve the representation of socio-economic processes, a CGE-based methodological approach is adopted. Economic simulation models are well suited for ex-ante analyses of LULC developments, as shifts in consumption and production – driven by economic and population growth, income levels, consumer preferences, resource availability, technological change, and policy frameworks – determine the demand for land (e.g., Schmitz et al., 2014; Riahi et al., 2017). While global CGE models may offer less sectoral detail than specialised partial equilibrium (PE) models, they provide a comprehensive and internally consistent representation of the entire economy, including international trade. This allows for capturing interactions between multiple socio-economic drivers of LULC change and their implications for macro-economic developments – mechanisms that are typically not covered in PE frameworks. Compared to single-country CGE models, global set-ups further enable the explicit integration of cross-border linkages and global feedback effects (e.g., Burfisher, 2020; Delzeit et al., 2020; Pisu et al., 2023). Together, these features justify the choice of a CGE-based modelling approach in this dissertation.

CGE models are originally designed in a comparative-static framework to support short-term policy analysis based on recently observed economic structures (e.g., Britz, 2022; Burfisher, 2020). However, generating SSP-aligned LULC projections requires a long-term perspective that captures structural adjustment processes. To address this, the projections developed in this thesis build on G-RDEM, a model specifically designed for the construction and analysis of long-term economic baselines and capable of capturing a wide range of key dynamics (Britz and Roson, 2019; Roson and Britz, 2021). Within this framework, the limitation of lower sectoral detail is addressed by extending relevant production activities and products to PE level resolution. This is implemented within the modelling platform CGEBox, which enables the use of highly disaggregated input data (Britz, 2022; Britz and van der Mensbrugghe, 2018). In particular, the approach incorporates sub-national information at the NUTS2 level and systematically disaggregates and refines the underlying LULC data, complemented by dedicated modules for LULC, energy, and emissions accounting. Compared to existing CGE applications that typically focus either on advanced recursive-dynamic baseline generation, detailed land representation, or sub-national resolution, the CGEBox approach combines these features within a globally consistent framework. This extends the scope of CGE-based LULC analysis without losing detail in other model domains or relying on model coupling.

Existing SSP-based LULC projections are primarily generated using IAMs, which at their core also rely on economic simulation tools. However, the integration of different specialised models within IAM frameworks requires extensive harmonisation. As a result, the economic components of IAMs typically operate at a higher level of aggregation in terms of regional and sectoral detail and provide a more stylised representation of structural adjustment processes. At the same time, IAMs explicitly simulate biophysical processes, which cannot be captured within a purely CGE-based framework (IIASA, 2025; IPCC, 2022; Popp et al., 2017; Riahi et al., 2017). The flexible integration of specialised modules in CGEBox improves the representation of key domains such as LULC, energy systems, or emissions accounting, and enables the quantification of LULC developments under the SSPs within a unified modelling system. However, the approach remains simplified and does not capture biophysical details such as carbon sequestration, vegetation dynamics, or climate feedbacks. This reflects a fundamental trade-off in model design, with the two approaches placing different emphasis on the explicit simulation of detailed socio-economic versus environmental and biophysical processes.

Despite these methodological differences, both approaches are comparable in their implementation of the SSPs. Both rely on SSP-specific projections for demographic and economic development from specialised external models and translate key drivers of LULC change into internally consistent assumptions aligned with the SSP narratives. As demonstrated by the benchmarking of global-scale results in Chapter 2, both approaches produce comparable LULC outcomes and rank the SSP scenarios consistently. In this context, the CGE-based approach developed in this dissertation can be understood as a valuable complement to IAMs, offering additional insights into socio-economic drivers and regional dynamics. It is not intended as a replacement for IAMs, but as an extension of the available modelling toolbox for analysing future LULC dynamics.

While the proposed CGE-based approach offers clear advantages and complements IAM-based quantifications, several limitations also need to be considered. First, it should be emphasised that the SSPs are internally consistent but stylised narratives for future development (O’Neill et al., 2014, 2017). The LULC projections presented in this dissertation therefore illustrate plausible development pathways rather than precise predictions of future LULC outcomes. Ex-ante analyses inherently rely on strong assumptions regarding model structure, parameterisation, and functional relationships. In addition, long-term scenario projections depend on uncertain future developments across a wide range of socio-economic variables, while LULC input data are themselves subject to inherent uncertainties (e.g., Alexander et al., 2017; Burfisher, 2020; Schmitz et al., 2014). The reliance on exogenous projections for key drivers such as GDP, demographics, cropland, and yields introduces additional dependencies on external data sources and modelling assumptions. While part of this uncertainty is addressed through the construction of five SSP baselines outlining contrasting development pathways, substantial uncertainty remains, particularly at more disaggregated levels of analysis.

As a further limitation, it should be acknowledged that the recursive-dynamic baseline approach focuses on long-term structural developments and does not explicitly capture short-term economic disruptions, such as the COVID-19 pandemic or geopolitical shocks, such as recent wars or trade conflicts. Consequently, the new projections smooth over short-term volatility and should be interpreted as representations of long-term development trends in line with the SSP narratives rather than near-term fluctuation analyses.

With respect to the inclusion of high regional and sectoral detail within a global CGE simulation, data availability is a key constraint, and complexity and tractability need to be balanced. Despite the introduced disaggregation and refinements, the LULC input data cover only a single forest-related land use and do not include land uses related to (bio-)energy production due to data limitations. Natural land cover categories are represented in aggregated forms, and their dynamics are implicitly driven by socio-economic determinants rather than explicitly modelled natural disturbances or biophysical processes. The sub-national data exclude overseas territories, and the use of underlying assumptions and secondary data sources may reduce precision at finer spatial scales. In addition, the sub-national data follow the 2016 NUTS2 classification (EC, 2016), consistent with the 2017 base year of the GTAP v11 input data (Aguiar et al., 2022), while more recent classifications are already available. Outside Europe, regions remain represented at national or aggregated levels, which masks local heterogeneity and limits the ability to capture region-specific dynamics in these areas.

Beyond the CGE-based approach and the resulting SSP-based LULC projections, the proposed conceptual framework to analyse land-atmosphere feedbacks of LC changes is also subject to several limitations. It is realised as a loosely coupled system, which does not capture potential feedbacks from climate impacts back to the economic system over time. In addition, the high computational requirements of the RCM constrain the spatial extent and limit the feasibility of large-scale or global applications. Finally, the translation of socio-economic LULC categories into PFTs requires simplifications, which may affect the representation of land surface processes in the climate model.

Future research could extend and strengthen the proposed CGE-based methodological approach and its applications along several dimensions. First, uncertainty in the new SSP-based LULC projections could be addressed through large-scale and systematic sensitivity analyses. This would enable a more comprehensive evaluation of parameter choices, functional relationships, and the influence of exogenous SSP-specific projections and LULC driver assumptions on model outcomes. In addition, future work could explore validation strategies, such as back casting or comparisons with historical LULC developments, to assess model performance and improve confidence in the projections.

Second, updates to input data, further disaggregation, and refinements of model specifications could broaden the scope and robustness of the analysis. Building on the recently released GTAP v12 database (Aguiar et al., 2025) with the reference years 2019 and 2023, would provide a simulation starting point that more accurately reflects global developments compared to GTAP v11 (Aguiar et al., 2022) with the reference year 2017. In this context, the simulation horizon could also be extended, for example to 2055 or 2060, to capture longer-term dynamics. Further disaggregation of input data, combined with targeted model extensions, would enable a more detailed representation of emerging land uses, including bioenergy production and land requirements associated with renewable energy infrastructure such as photovoltaic systems or wind turbines. This would improve the representation of LULC trade-offs in the CGEBox framework and is particularly relevant in regions such as Europe, where these land uses are increasingly promoted by policy frameworks (e.g., EU, 2021; EC, 2025). Future work could also explore more refined representations of forest and natural land cover and the associated dynamics, potentially incorporating improved linkages to biophysical processes or external ecological information to better capture non-economic drivers of LULC change.

Third, expanding the sub-national resolution beyond Europe to regions expected to experience substantial future LC changes is an important research priority. Results from the climate application indicate that even moderate LC changes can induce significant regional climate impacts, underscoring the importance of analysing regions where more pronounced changes are anticipated. Achieving this will require substantial efforts in data collection and processing, as well as the development of alternative methods to represent LULC dynamics at sub-national scales. In this context, recent advances in spatial disaggregation approaches for CGE-compatible LULC input data (e.g., Cameron-Harp et al., 2025) illustrate potential methodological directions for constructing corresponding inputs for data-scarce regions. At the same time, Europe can be understood as a laboratory region, where high-quality data availability and strong policy engagement provide favourable conditions for developing, testing, and refining modelling approaches before extending them to other world regions.

Fourth, the climate application of the new, SSP-based LULC projections could be further refined. In particular, a more detailed differentiation of forest-related land uses within the CGE-based LULC quantifications would help to reduce inconsistencies in the mapping between socio-economic land use categories and PFTs. More broadly, a tighter integration between socio-economic and biophysical modelling frameworks – including feedback mechanisms between land use and climate systems over time – would allow for a more comprehensive analysis of land-atmosphere interactions.

Finally, the proposed framework offers substantial potential for extended applications. The high-resolution LULC projections can serve as input for more specialised climate, biodiversity, or environmental assessments. Further policy-related applications are discussed in the following section.

5.3 Policy implications

As outlined in Chapter 1, a key societal challenge lies in managing land in a way that simultaneously meets social, economic, and environmental objectives. In response, international and regional policy frameworks increasingly seek to steer LULC towards more sustainable trajectories (e.g., the Sustainable Development Goals (UN, 2015), the Kunming-Montreal Global Biodiversity Framework (UN, 2022), or the European Green Deal (EU, 2021)). Given the inherently uncertain nature of future socio-economic and environmental developments, a systematic exploration of alternative scenarios plays a central role in supporting robust policy designs and informed decision-making. Within this context, the SSPs provide a widely used framework for analysing contrasting but internally consistent future development pathways and their implications for land systems. The SSP-based LULC projections developed in this dissertation build on a new methodological approach and provide globally consistent quantifications of all five SSPs with enhanced regional, sectoral, and socio-economic detail. In doing so, they support methodological comparisons and ensemble-based approaches aimed at improving the robustness and credibility of LULC projections relevant for policy strategies operating under high uncertainty.

Through their detailed representation of land uses, including a distinction between irrigated and rainfed production, the new SSP-based LULC projections improve assessments of agricultural production and input use, along with their implications for food security, climate, biodiversity, and the economy. The sub-national resolution of the new projections is particularly relevant for policy planning, as many political, economic, and ecological processes are determined at these scales rather than at the national level. Accounting for intra-national heterogeneity enables more targeted planning of infrastructure, resource allocation, and land-related policies, especially in the context of food security, environmental protection, and climate change adaptation and mitigation, where spatial patterns critically influence policy effectiveness. At the same time, considering cross-border linkages and global feedbacks is essential for understanding how land-based policies interact within an interconnected global economy. The new projections further allow for more detailed considerations of economic impacts at both sectoral and regional levels.

With full coverage of the European Union (EU) at NUTS2 level, the new LULC projections are particularly relevant for policymaking in the context of the European Green Deal (EU, 2021). A central objective of this framework is the achievement of climate neutrality by 2050, which involves managing competing land demands across food production, biodiversity conservation, carbon sequestration, and renewable energy production. Current and emerging policy initiatives – including reforms of the Common Agricultural Policy (EC, 2023, 2026) as well as strategies such as the EU Soil Strategy (EC, 2021a), the EU Forest Strategy (EC, 2021b), or the Fit for 55 package (EC, 2025) – will significantly shape future LULC trajectories in Europe. A systematic assessment of these policies under alternative socio-economic pathways is therefore essential for robust and forward-looking policy designs. The combination of global economic consistency with detailed NUTS2 level information enables the translation of EU-wide targets into spatially more explicit implementation contexts, thereby supporting targeted evaluations of regional policy impacts, synergies, and trade-offs.

To further support policy analysis, the CGE-based framework developed in this dissertation enables the systematic exploration of policy-relevant counterfactuals, such as changes in land use regulations or trade policies. In addition, it allows for extensive post-model analyses, including micro-simulations at household level or the assessment of a wide range of sustainability indicators. The transparent, open-source structure and the relatively low computational requirements facilitate timely updates and iterative model development, including the refinement of input data or scenario assumptions as well as extensions of regional detail. This makes the CGEBox framework a flexible tool for both scientific and policy-oriented applications, particularly in contexts where distributional effects, regional heterogeneity, and sectoral detail are critical for the design of robust LULC, adaptation, and mitigation strategies.

The coupled modelling framework presented in Chapter 4 integrates the new socio-economically driven LULC projections with spatial downscaling and physically consistent climate simulations and highlights the importance of considering LULC change as an active driver of regional climate dynamics. The results indicate that even moderate LC changes can induce significant regional climate responses. This is particularly relevant for policy contexts in which land-based mitigation strategies – such as afforestation or bioenergy expansion – are assumed to be climate-neutral or beneficial at aggregate scales, while potentially generating substantial regional climate feedbacks. The findings therefore underline the need for more integrated assessment approaches that jointly consider socio-economic development, LULC change, and regional climate impacts when designing and evaluating land-based climate policies.

5.4 Concluding remarks

Overall, this dissertation demonstrates the value of complementing existing IAM-based approaches for analysing future LULC dynamics. It provides new SSP-based LULC projections that combine global economic consistency with a high level of regional and sectoral detail and improves the representation of socio-economic processes. It further highlights the importance of integrating these projections with high-resolution spatial LC downscaling and physically consistent regional climate simulations to enable a coherent analysis of land-atmosphere feedbacks across scales. In doing so, this dissertation contributes to an improved understanding of how socio-economic uncertainties translate into regional LULC dynamics and associated climate impacts, and supports economically grounded LULC, adaptation, and mitigation planning. In a context characterised by multiple, often competing global challenges, where short-term policy priorities may risk overshadowing long-term sustainability objectives, such detailed and integrated assessment approaches are essential for capturing trade-offs, identifying region-specific challenges, and supporting coherent and forward-looking decision-making for sustainable land management.

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Chapter 6
Appendix

6.1 Appendix Chapter 2

6.1.1 Appendix A.2.1: Mapping in the database generation process

A comprehensive table with the database mapping can be viewed at the following link:

https://nbn-resolving.org/urn:nbn:de:hbz:5-91526

6.1.2 Appendix A.2.2: Patch file to guarantee result reproducibility

The Shared Socio-Economic Pathway (SSP) quantifications are generated using CGEBox revision 6281, with a few local modifications. These can be replicated using the patch file available at the following link:

https://nbn-resolving.org/urn:nbn:de:hbz:5-91526

The patch file includes two batch execution files *DB_SSPQuantification* (for database generation) and *MR_SSPQuantification* (for model runs). These can be used to manage the model execution process.

Please note that the land use and land cover results have been retrospectively scaled to ensure consistency between total land use and corresponding land cover (LC). This adjustment is necessary because CGEBox employs the additive functional form only for the top land nests.

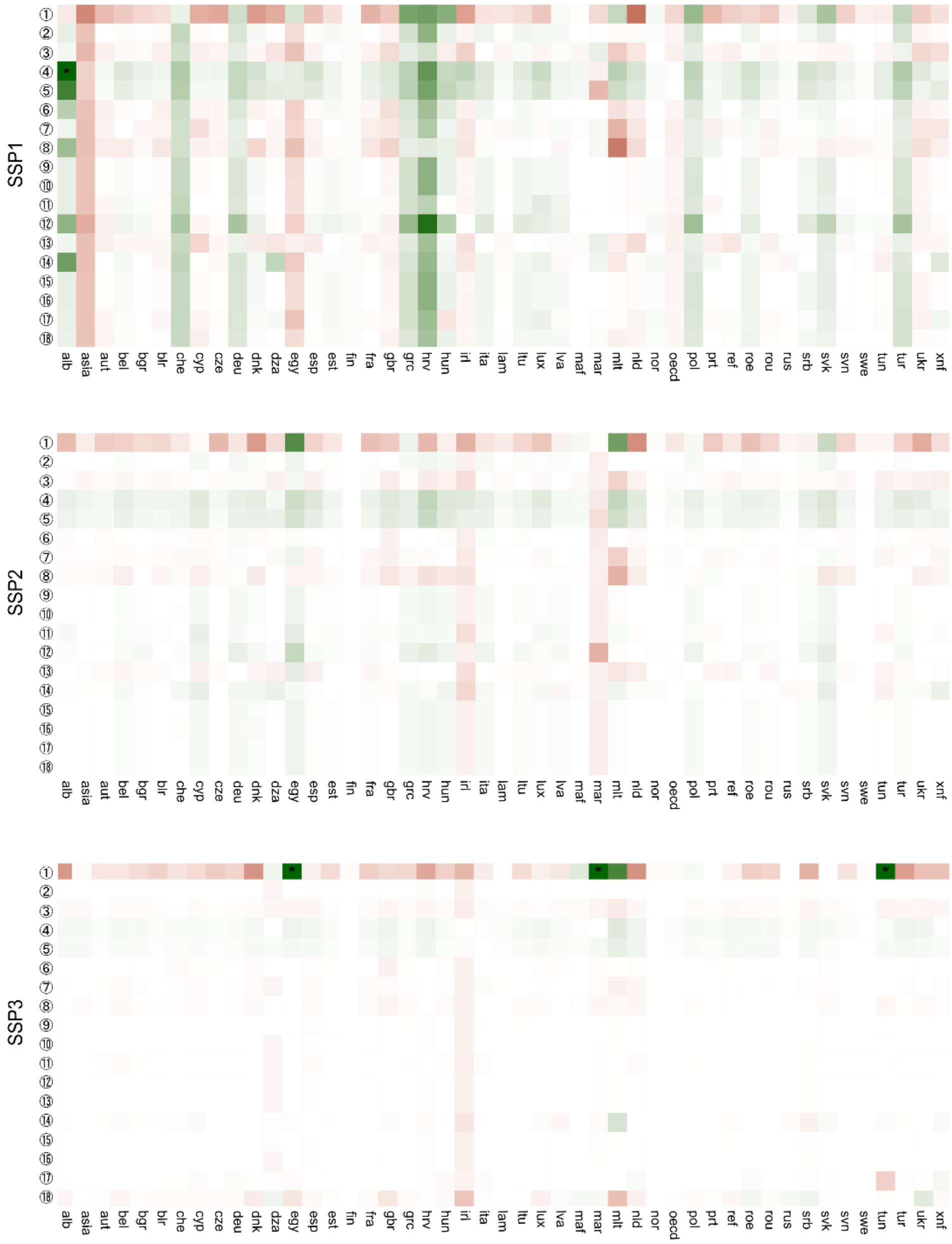
6.1.3 Appendix A.2.3: GAMS Code implementing SSP-specific assumptions

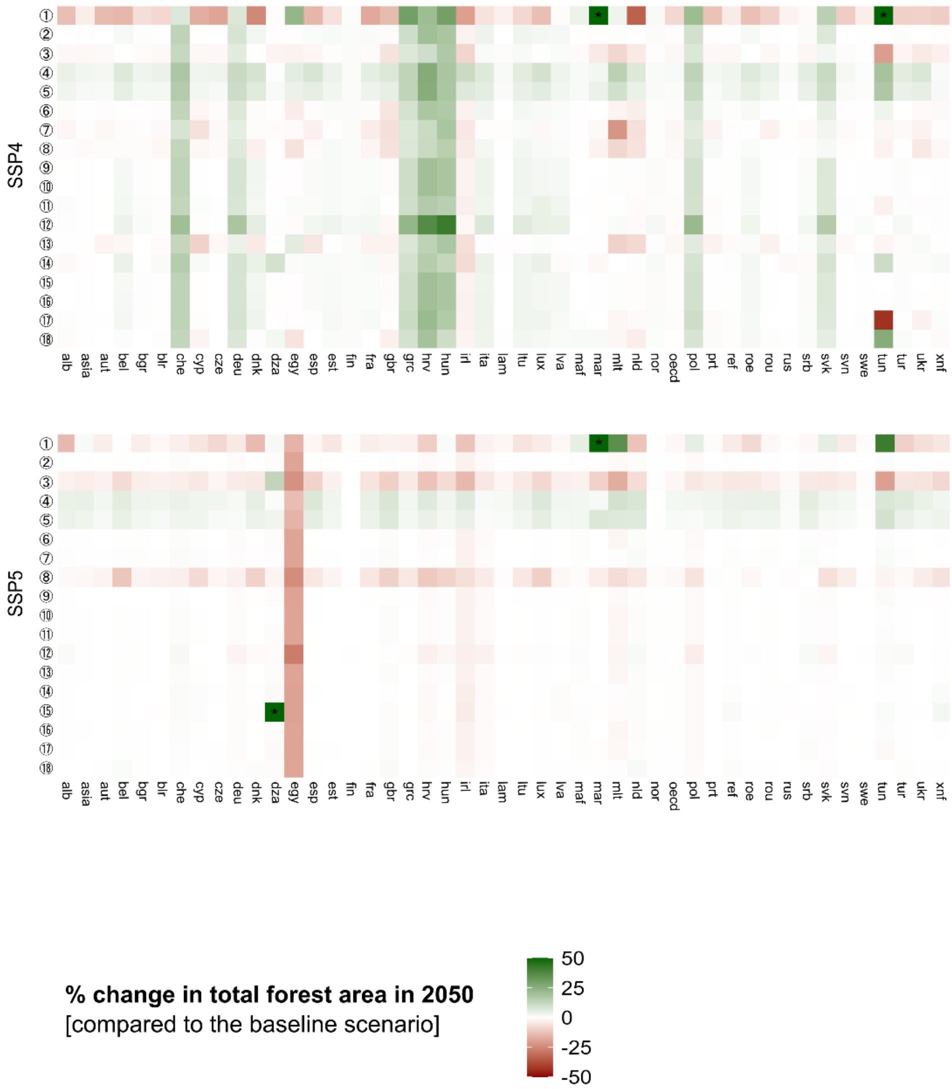
A GAMS code implementing the SSP-specific scenario assumptions can be downloaded under:

https://nbn-resolving.org/urn:nbn:de:hbz:5-91526

It is further available in the open-access application of CGEBox under the directory ..\CGEBox\gams\scen\user_scenarios\ssp.gms.

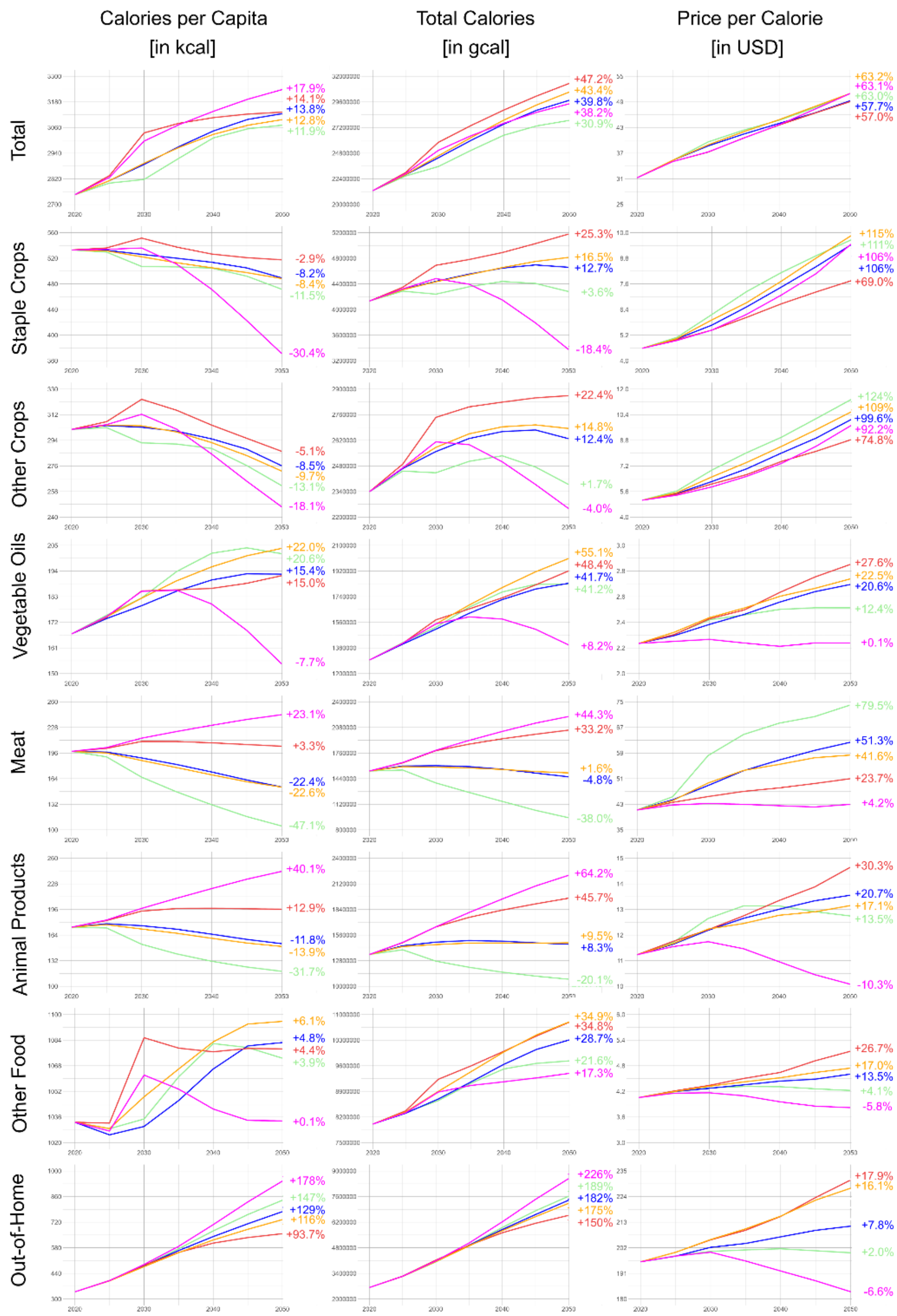
6.1.4 *Appendix A.2.4: Sensitivity run outcomes*





Source: Own illustration.

6.1.5 Appendix A.2.5: Global calorie consumption and prices in the shared socio-economic pathway quantifications in CGEBox by product group



Source: Own illustration. Remark: Appendix A.2.6 details the product group aggregation.

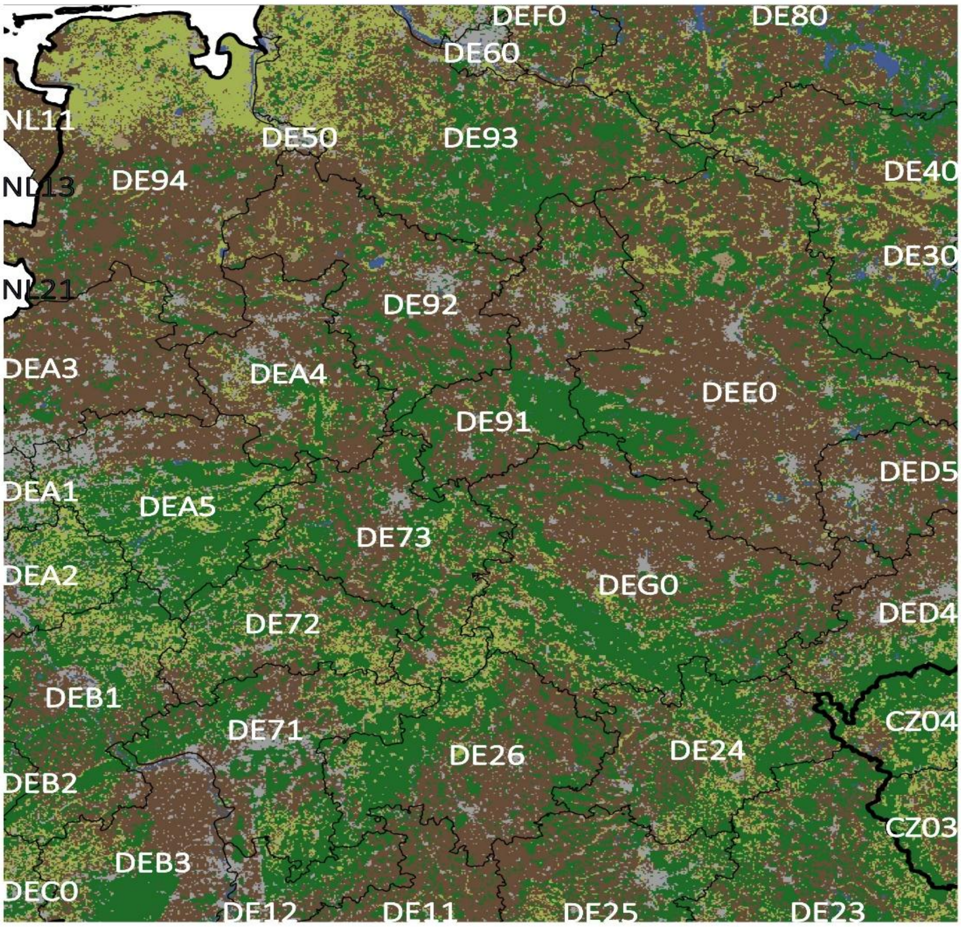
6.1.6 Appendix A.2.6: Mapping in the result visualisation

A comprehensive table with the mapping underlying the result visualisation can be viewed at the following link:

https://nbn-resolving.org/urn:nbn:de:hbz:5-91526

6.2 Appendix Chapter 4

6.2.1 Appendix A.4.1: Study region and included NUTS2 regions



NUTS2 Code	Region
CZ03	Jihozapád
CZ04	Severozapád
DE11	Stuttgart
DE12	Karlsruhe
DE23	Oberpfalz
DE24	Oberfranken
DE25	Mittelfranken
DE26	Unterfranken
DE30	Berlin
DE40	Brandenburg
DE50	Bremen

DE60	Hamburg
DE71	Darmstadt
DE72	Gießen
DE73	Kassel
DE80	Mecklenburg-Vorpommern
DE91	Braunschweig
DE92	Hannover
DE93	Lüneburg
DE94	Weser-Ems
DEA1	Düsseldorf
DEA2	Köln
DEA3	Münster
DEA4	Detmold
DEA5	Arnsberg
DEB1	Koblenz
DEB2	Trier
DEB3	Rheinhessen-Pfalz
DEC0	Saarland
DED4	Chemnitz
DED5	Leipzig
DEE0	Sachsen-Anhalt
DEF0	Schleswig-Holstein
DEG0	Thüringen
NL11	Groningen
NL13	Drenthe
NL21	Overijssel

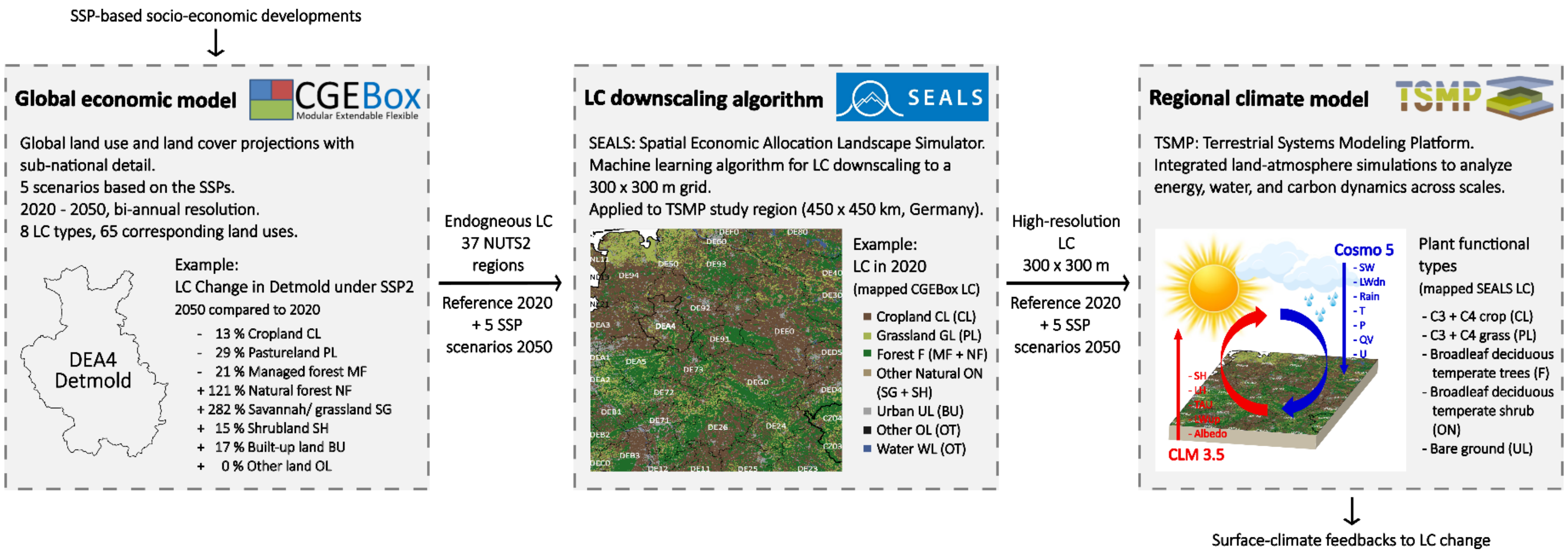
Source: Own illustration.

6.2.2 *Appendix A.4.2: Land use and land cover detail in the shared socio-economic pathway quantifications in CGEBox*

Land Cover	**Managed**	**Land Use**
Cropland	Yes	- Apples - Bananas/ plantains - Barley - Citrus fruits - Cocoa beans - Coffee beans - Grapes - Leguminosae - Maize - Nuts - Oats - Olives - Other cereals - Other crops - Other fruits - Other oilseeds - Other roots/ tubers - Other vegetables - Paddy rice - Palm oil fruit - Plant-based fibres - Potatoes - Rape seed - Rye - Sorghum - Soy bean - Sugar cane/ beet - Teas - Tomatoes - Wheat All as irrigated and rainfed variants.
Pastureland	Yes	- Cattle for meat - Ruminants for meat - Raw milk - Wool
Managed forest	Yes	- Forestry
Natural forest	No	
Savannah and grassland	No	
Shrubland	No	
Other land	No	
Built-up land	No	

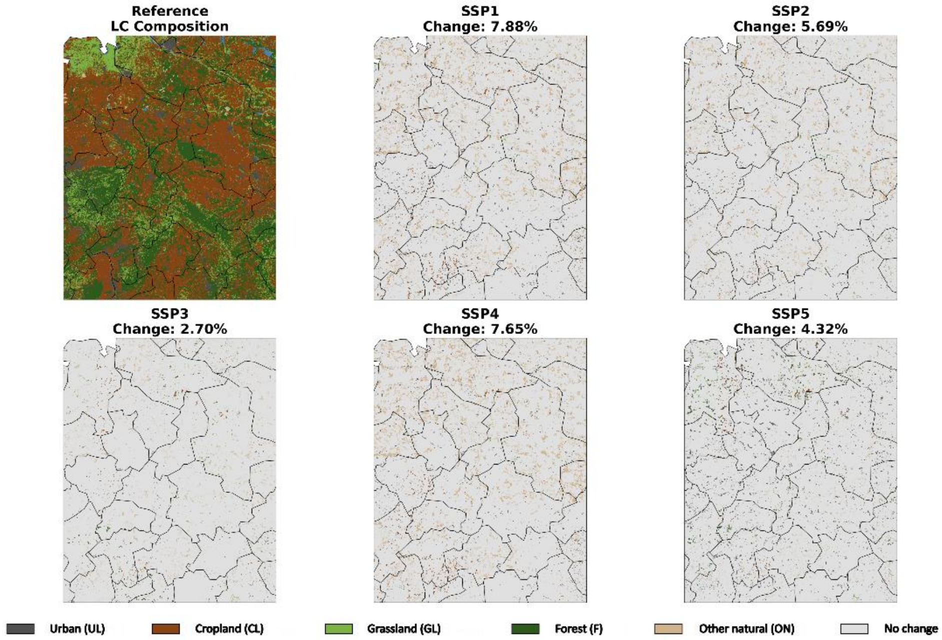
Source: Goebel and Britz (2025).

6.2.3 Appendix A.4.3: Enlarged view of Figure 4.2



6.2.4 Appendix A.4.4: Pixel-level change (Reference to 2050)

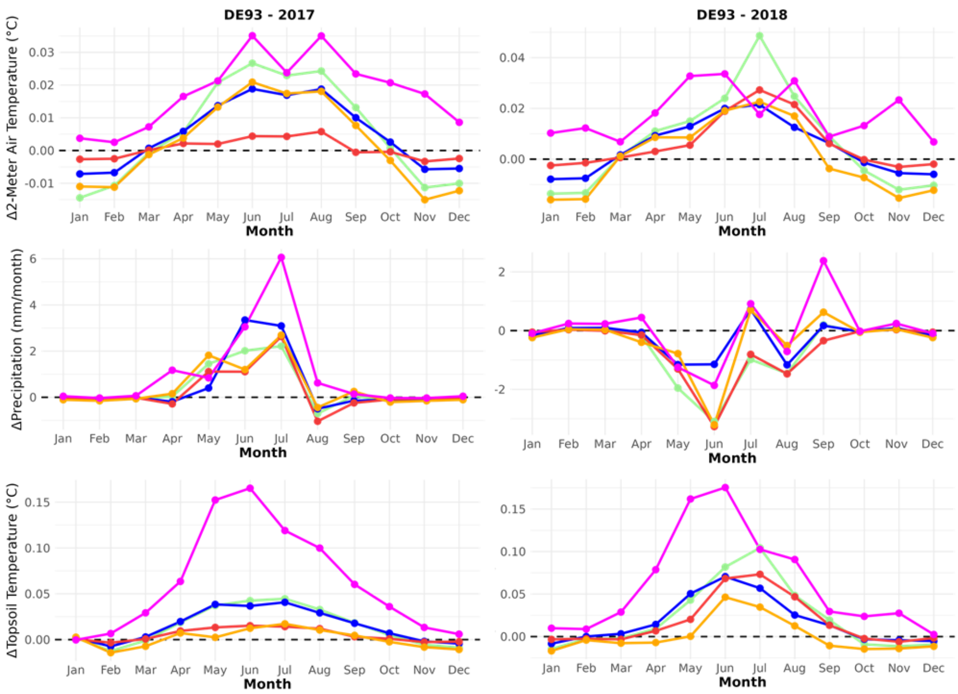
The figure below displays the spatial distribution of LC transitions for each SSP scenario. The first panel shows the reference LC composition (SSP2-RCP45 2020), with cropland and forest dominating the landscape. The remaining five panels show transition maps where grey indicates no change and coloured pixels indicate land that transitioned to a new class (coloured by destination class). Percentage numbers give the proportion of changed pixels.

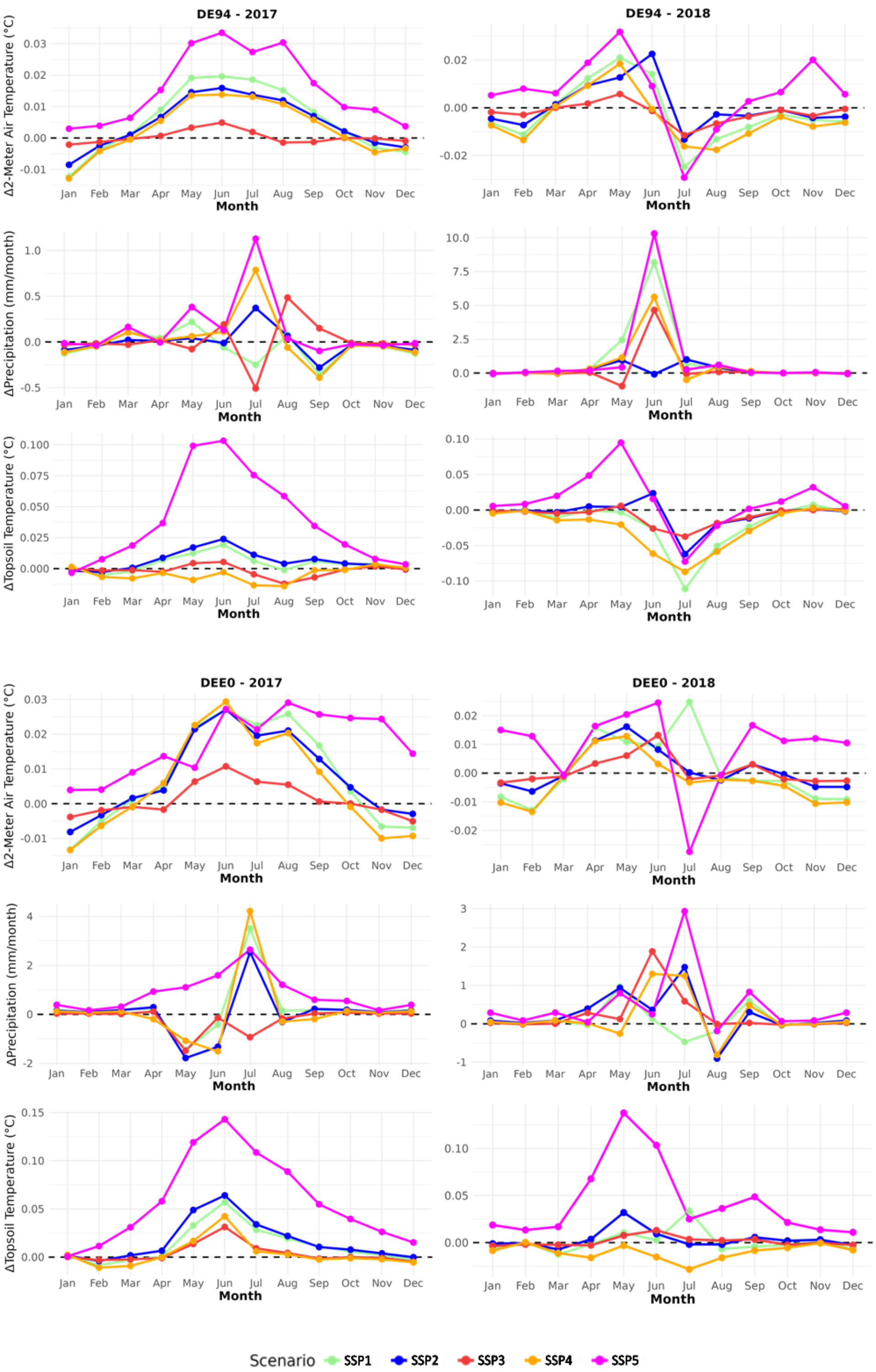


Source: Own illustration.

6.2.5 *Appendix A.4.5: Mean differences in key bioclimatic variables at sub-national NUTS2 level*

The main text shows the mean differences in the three key bioclimatic variables between the 2020 baseline and the shared socio-economic pathway scenarios, simulated under 2017 and 2018 ERA5 atmospheric conditions for the full study domain. Below, we show the results for three selected NUTS2 regions which are characterised by high LC change.





Source: Own illustration.

6.2.6 *Appendix A.4.6: Mean and standard deviation – full year*

			Topsoil Temperature [in °C]		Total Precipitation [in mm/month]		2-metre Air Temperature [in °C]	
			Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
Full Domain	**2017**	**Reference**	10.1336	7.0662	53.2951	39.5104	9.9492	7.0488
		SSP1	10.1505	7.0794	53.3889	40.6822	9.9564	7.0579
		SSP2	10.1479	7.0767	53.3911	40.6692	9.9550	7.0553
		SSP3	10.1344	7.0661	53.2430	40.4485	9.9503	7.0505
		SSP4	10.1404	7.0709	53.3788	40.7042	9.9540	7.0564
		SSP5	10.1863	7.1056	53.7268	40.9425	9.9637	7.0551
	2018	**Reference**	11.1429	8.3477	32.2452	28.5283	10.8352	8.0153
		SSP1	11.1538	8.3552	32.3625	28.7390	10.8398	8.0213
		SSP2	11.1515	8.3525	32.3572	28.5980	10.8385	8.0188
		SSP3	11.1445	8.3497	32.2129	28.5219	10.8368	8.0177
		SSP4	11.1444	8.3479	32.3098	28.6620	10.8373	8.0201
		SSP5	11.1857	8.3707	32.6300	28.8864	10.8452	8.0154
DE93	**2017**	**Reference**	10.4406	6.6717	54.5243	38.1689	10.2083	6.4886
		SSP1	10.4552	6.6856	54.0273	40.7079	10.2140	6.5026
		SSP2	10.4558	6.6842	54.1329	40.9193	10.2136	6.4977
		SSP3	10.4457	6.6761	53.9169	40.5628	10.2089	6.4910
		SSP4	10.4419	6.6749	54.0732	40.8348	10.2107	6.5001
		SSP5	10.5035	6.7197	54.6633	41.4672	10.2263	6.4967
	2018	**Reference**	11.4635	8.3875	27.5852	20.1599	11.0423	7.8275
		SSP1	11.4851	8.4180	26.9312	19.5051	11.0491	7.8442
		SSP2	11.4814	8.4061	27.3530	19.8697	11.0470	7.8359
		SSP3	11.4811	8.4114	26.9645	19.5199	11.0485	7.8366
		SSP4	11.4641	8.3966	27.2499	19.9715	11.0430	7.8387
		SSP5	11.5254	8.4283	27.6075	20.0162	11.0602	7.8311
DE94	**2017**	**Reference**	11.0857	6.9140	44.1763	22.3208	10.5891	6.3895
		SSP1	11.0899	6.9169	42.7309	23.4350	10.5950	6.3989
		SSP2	11.0920	6.9193	42.7729	23.5532	10.5940	6.3964
		SSP3	11.0842	6.9128	42.7883	23.3640	10.5894	6.3906
		SSP4	11.0812	6.9097	42.8038	23.6611	10.5923	6.3972
		SSP5	11.1244	6.9448	42.9103	23.7920	10.6050	6.3985
	2018	**Reference**	11.9666	8.4240	28.5089	25.0263	11.3128	7.5317
		SSP1	11.9475	8.3998	29.4957	27.4565	11.3105	7.5311
		SSP2	11.9607	8.4148	28.7184	25.3375	11.3133	7.5333
		SSP3	11.9586	8.4155	28.8235	25.6244	11.3107	7.5306
		SSP4	11.9419	8.3990	29.0967	26.6927	11.3082	7.5314

		SSP5	11.9790	8.4124	29.5024	27.9381	11.3190	7.5250
DEE0	**2017**	**Reference**	10.3913	7.0891	53.8452	40.6213	10.3811	6.9803
		SSP1	10.4036	7.1015	54.0365	42.4513	10.3889	6.9944
		SSP2	10.4079	7.1039	53.8176	42.0916	10.3892	6.9917
		SSP3	10.3951	7.0950	53.5968	41.7201	10.3824	6.9850
		SSP4	10.3947	7.0949	53.9174	42.5388	10.3866	6.9936
		SSP5	10.4497	7.1293	54.5997	42.4089	10.3985	6.9866
	2018	**Reference**	11.6172	8.6621	26.3059	19.7766	11.2812	8.2264
		SSP1	11.6177	8.6654	26.4132	19.7882	11.2824	8.2335
		SSP2	11.6205	8.6627	26.5453	19.8540	11.2825	8.2288
		SSP3	11.6183	8.6658	26.5528	19.7693	11.2819	8.2292
		SSP4	11.6070	8.6538	26.4873	19.8677	11.2787	8.2299
		SSP5	11.6601	8.6806	26.7908	20.1420	11.2903	8.2209

Source: Own illustration.

6.2.7 *Appendix A.4.7: Mean and standard deviation – April to October*

			Topsoil Temperature [in °C]		Total Precipitation [in mm/month]		2-metre Air Temperature [in °C]	
			Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
Full Domain	**2017**	**Reference**	14.9443	4.4600	63.0507	44.7350	14.5591	4.5714
		SSP1	14.9732	4.4654	64.5744	45.0915	14.5732	4.5766
		SSP2	14.9677	4.4653	64.5713	45.0745	14.5697	4.5756
		SSP3	14.9459	4.4585	64.3319	44.7922	14.5614	4.5725
		SSP4	14.9572	4.4588	64.5664	45.1270	14.5697	4.5754
		SSP5	15.0256	4.4875	65.0869	45.3851	14.5783	4.5759
	2018	**Reference**	16.9625	5.2199	27.8046	22.7982	16.3503	4.8154
		SSP1	16.9824	5.2178	28.0062	23.2913	16.3606	4.8163
		SSP2	16.9773	5.2172	27.9931	22.9871	16.3575	4.8144
		SSP3	16.9660	5.2203	27.7529	22.7764	16.3539	4.8164
		SSP4	16.9675	5.2129	27.9240	23.1187	16.3572	4.8154
		SSP5	17.0263	5.2261	28.4103	23.6382	16.3622	4.8103
DE93	**2017**	**Reference**	15.0684	3.9711	67.0064	44.6011	14.5492	4.0455
		SSP1	15.0969	3.9740	69.0063	45.9733	14.5655	4.0534
		SSP2	15.0955	3.9741	69.1490	46.2614	14.5616	4.0505
		SSP3	15.0781	3.9712	68.7621	45.8526	14.5517	4.0468
		SSP4	15.0758	3.9664	69.0876	46.1395	14.5603	4.0518
		SSP5	15.1679	3.9992	70.0010	46.8388	14.5743	4.0489
	2018	**Reference**	17.3139	5.2408	26.2336	21.0651	16.4364	4.7259
		SSP1	17.3564	5.2708	25.1587	19.9661	16.4547	4.7404
		SSP2	17.3464	5.2545	25.8523	20.5989	16.4480	4.7302
		SSP3	17.3463	5.2661	25.1817	19.9386	16.4482	4.7365
		SSP4	17.3227	5.2473	25.7168	20.7881	16.4457	4.7327
		SSP5	17.4085	5.2629	26.2189	20.8294	16.4586	4.7250
DE94	**2017**	**Reference**	15.8241	4.2568	44.4917	25.0178	14.8092	4.0369
		SSP1	15.8316	4.2578	45.7398	24.9200	14.8223	4.0412
		SSP2	15.8350	4.2593	45.8152	25.1020	14.8195	4.0400
		SSP3	15.8216	4.2563	45.8273	24.8010	14.8104	4.0373
		SSP4	15.8176	4.2534	45.8620	25.2680	14.8182	4.0402
		SSP5	15.8852	4.2778	46.0135	25.4777	14.8327	4.0427
	2018	**Reference**	17.8073	5.4007	23.9490	23.2399	16.4716	4.6255
		SSP1	17.7761	5.3695	25.6574	27.8158	16.4713	4.6179
		SSP2	17.7983	5.3858	24.3182	23.8918	16.4750	4.6219
		SSP3	17.7945	5.3902	24.4980	24.4362	16.4693	4.6229
		SSP4	17.7680	5.3748	24.9735	26.4070	16.4686	4.6195

		SSP5	17.8184	5.3739	25.6402	28.6162	16.4759	4.6133
DEE0	**2017**	**Reference**	15.2981	4.2257	67.3559	46.6961	15.0481	4.3822
		SSP1	15.3203	4.2353	68.9964	47.5707	15.0656	4.3914
		SSP2	15.3258	4.2374	68.6305	47.1318	15.0639	4.3903
		SSP3	15.3061	4.2315	68.3000	46.6528	15.0521	4.3864
		SSP4	15.3073	4.2292	68.8135	47.7546	15.0629	4.3902
		SSP5	15.3856	4.2523	69.8895	47.2489	15.0698	4.3867
	2018	**Reference**	17.6809	5.4075	22.1635	14.9664	16.9762	4.9170
		SSP1	17.6855	5.4083	22.3002	14.9785	16.9840	4.9178
		SSP2	17.6878	5.4004	22.5259	15.1818	16.9813	4.9125
		SSP3	17.6844	5.4119	22.5752	15.0400	16.9791	4.9184
		SSP4	17.6676	5.3965	22.4437	15.2190	16.9783	4.9129
		SSP5	17.7437	5.4037	22.8406	15.7570	16.9848	4.9033

Source: Own illustration.

6.3 References

Goebel, T., Britz, W., 2025. Global land use and land cover projections under the shared socio-economic pathways: An integrated computable general equilibrium analysis with sub-national resolution for Europe. Global Environmental Change Advances 5, 100027. https://doi.org/10.1016/j.gecadv.2025.100027.