ForestPaths

Co-designing holistic forest-based policy pathways for climate change mitigation

D3.2 Fully calibrated agent-based model of European forest owners

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Key takeaway messages

- The fully calibrated CRAFTY-EU model is an advanced tool for modelling land-use dynamics at a European scale, providing insights into decision-making processes of forest practitioners and the impacts of forest management on ecosystem service provisioning.
- The model can account for the competing influences on forest practitioners' management decisions from socioeconomic, environmental and policy drivers
- By coupling within the LandSyMM modelling framework, CRAFTY ensures high-resolution simulations that dynamically reflect interactions between human activities and biophysical processes in forests.
- Socioeconomic influences are represented through availability of socioeconomic capital, calibrated using empirical datasets, and through the incorporation of a new behavioural model, calibrated using forest practitioner survey data. This allows for forest practitioners' attitudes and values to be better represented.
- The development of an exogenous institutional model and coupling with CRAFTY-EU will enable the exploration of policy pathways and sustainable forest management strategies to meet climate change mitigation, forest production and biodiversity goals.

Summary

Deliverable 3.2 details the development and calibration of the CRAFTY-EU agent-based model (ABM), extending the CRAFTY agent-based framework for modelling large-scale land-use changes. By integrating empirical data, advanced modelling routines, and enhanced representations of public policy institutions, CRAFTY is able to represent how European forest practitioners manage land and make decisions that are influenced by socio-economic, environmental, and policy factors. The refined model captures the heterogeneity of forest practitioner behaviours through Agent Functional Types (AFTs), which are influenced by human, social, financial, manufactured and natural capitals. A new behavioural model enables the simulation of social influences on practitioner management decisions, whilst the integration of a newly developed institutional model enables the simulation of policy pathways to climate, biodiversity and other policy goals. CRAFTY-EU incorporates an increased range of mechanisms to simulate ecosystem services, including carbon sequestration, biodiversity, and flood control, while dynamically adjusting to changing scenarios. The integration of the Shared Socio-economic Pathways (SSPs) and the Representative Concentration Pathways (RCPs) allows for comprehensive scenario analyses that project land-use dynamics under diverse climatic and socio-economic futures. Coupled with the LandSyMM framework, CRAFTY enables high-resolution modelling of the land system, allowing the assessment of how changes in forestry and forest management influence the broader land system. Methodological advances include calibration using empirical datasets and coupling with LPJ-GUESS to enhance the representation of natural and socio-economic interactions. This deliverable provides a detailed account of the full calibration of the CRAFTY-EU model, ensuring its readiness for application in various future forest and forestry-related analyses and modelling efforts.

List of abbreviations

CRAFTY	Competition for Resources between Agent Functional Types
SSPs	Shared Socio-economic Pathways
RCPs	Representative Concentration Pathways
MSA	Mean Species Abundance, an indicator for biodiversity intactness
EU	European Union
EU27+3	European Union + UK, Switzerland and Norway
LPJ-GUESS	Lund-Potsdam-Jena General Ecosystem Simulator
GLOBIO	Global biodiversity model for policy support

1 Introduction

Forests cover approximately 31% of the world's land area and are under increasing environmental and socio-economic pressures (FAO and UNEP, 2020). As a result, forest practitioners face a wide array of complex and evolving management challenges (European Commission, 2021; Regulation (EU) 2024/1991, 2024). In Europe, forest practitioners' decision making is also being influenced by the increasing number of environmental and climate policies imposed both by the European Union (EU) and national governments. These require forests to contribute to climate change mitigation and biodiversity goals, and the increasing demand for timber, whilst simultaneously managing the impacts associated with climate change and the increasing number of associated disturbances, such as droughts (Schuldt *et al.*, 2020; Senf and Seidl, 2020), storms, wildfires and bark beetle outbreaks (Seidl *et al.*, 2014; Patacca et al., 2022). Therefore, sophisticated modelling approaches are needed to represent, understand and simulate how forest practitioners make management decisions in response to varying environmental, socio-economic and policy conditions.

This deliverable (D3.2) presents a fully calibrated version of the CRAFTY modelling framework applied to the European land system, defined within the scope of Task 3.2. Guided by empirical data and informed by updated management routines from LPJ-GUESS (Smith *et al.*, 2014; Lindeskog *et al.*, 2021), CRAFTY-EU now incorporates newly calibrated representations of forest management intensities that can be fed back to LPJ-GUESS to calculate carbon sequestration. It also better represents the institutional influences on forest practitioners and the decision-making processes in response to policy drivers. These enhancements enable CRAFTY to simulate how distinct forester types respond dynamically to climatic, social, policy, and market signals. Key developments in this calibrated version include enhanced representation of both intensive and close-to-nature management practices, ecosystem service provision, public policy institutions, and their influence on land-use decisions through various instruments, such as subsidies, regulations, and taxes. These improvements enable the simulation of how different types of forest practitioners adapt their practices - including wood removals, and cutting regimes - in response to changing climatic and socio-economic conditions.

This enhanced CRAFTY-EU model will serve as a crucial tool for analysing policy pathways and evaluating European forest mitigation potential within WP5. The integration of improved forest management options, ecosystem service provision, and institutional modelling capabilities allows for dynamic projections that account for climate change, policy interventions, and socio-economic constraints in generating maps of land-use and forest management types and intensity.

This report details the model calibration steps and the final configuration of the refined CRAFTY-EU forester and other land manager agents, including their improved coupling to underlying ecosystem models. These advancements, developed through iterative refinements and evaluation, result in a robust modelling tool that is now ready for application.

2 Overview of the CRAFTY Model and LandSyMM Framework

The CRAFTY (Competition for Resources between Agent Functional Types) modelling framework is an agent-based model (ABM) designed to simulate large-scale land-use changes (Murray-Rust *et al.*, 2014). At its core, CRAFTY represents the land system as a spatially explicit grid of cells, each with varying levels of resources or "capitals" (natural, human, social, financial and manufactured) (see Section 3 for more detail). These capitals determine the potential productivity of an array of ecosystem services. Land managers, represented as autonomous agents, are categorized into Agent Functional Types (AFTs) (detailed in Section 4) that differ in their capacities to exploit the available capitals for producing bundles of ecosystem services (Arneth, Brown and Rounsevell, 2014; Brown, Seo and Rounsevell, 2019). Through a dynamic process of competition, agents vie for control of cells, adjusting management strategies to best meet regional demands for ecosystem services. Key components of this approach include demand-driven competition, responsiveness to environmental and socio-economic feedbacks, and explicit modelling of institutional influences on land managers' decision-making.

AFTs form the building blocks of CRAFTY's representation of heterogeneity among land managers. Each AFT is parametrized with specific productivity functions, capital sensitivities, and behavioural parameters (Section 4.2). Productivity is based on capital levels and moderated by factors such as climate scenarios, socio-economic pathways, and policy interventions. The resulting spatially explicit competition between AFTs drives emergent patterns of land use and land management, including forest management regims, agricultural practices, and conservation strategies.

As part of an integrated modelling effort, CRAFTY is embedded within LandSyMM (Land System Modular Modelling framework; landsymm.earth), a scalable system designed to capture sub-national to global land-system dynamics (Brown, Seo and Rounsevell, 2019; Kok *et al.*, 2019; Merkle *et al.*, 2023). LandSyMM couples modules of land use decision making, macro-economics & global trade, ecosystem processes, biodiversity and the climate system to represent integrated Earth system dynamics. Within LandSyMM-EU—its European-scale configuration—CRAFTY-EU simulates land-use dynamics at a 1 km resolution for the EU27+3 region (EU Member States plus Norway, Switzerland, and the UK). This regional application draws on consistent storylines represented by European versions of the Shared Socioeconomic Pathways (SSP) (Kok *et al.*, 2019) and integrates scenario-driven changes in capitals, demands, and policy interventions. Updated approaches to modelling ecosystem service supply have allowed a more nuanced representation of both provisioning (e.g., timber), regulating (e.g., flood control), and cultural (e.g., recreation) services (Section 5) (Brown, Seo and Rounsevell, 2019; Saxena *et al.*, 2023).

A critical advantage of the LandSyMM framework is its capacity to allow multiple models and modules to interact. For example, natural capital inputs, such as biomass potential in response to a changing climate, is derived from LPJ-GUESS (van Vuuren *et al.*, 2011; O'Neill *et al.*, 2014), while socio-economic capitals and service demands are influenced by the PLUM model of macroeconomic and trade dynamics (Alexander et al. 2018). This coupling ensures that changes in one subsystem—such as altered forest productivity under climate change—trigger adaptive responses in the ABM, thus bridging biophysical processes with human decision-making.

In the next sections of this deliverable, the design and calibration of five main components of CRAFTY-EU are described: climatic and socio-economic scenarios, AFTs, capitals, ecosystem services, and the institutional and policy mechanisms. Through these detailed examinations, the underlying logic and assumptions of the CRAFTY approach will be made explicit, providing the basis for scenario applications and climate change mitigation and biodiversity-related policy evaluations.

3 Capitals

CRAFTY represents the landscape as a grid of spatial units, each characterized by a set of "capitals" that encapsulate the resources and conditions influencing the production of ecosystem services. These capitals (natural, human, social, financial, and manufactured) not only define the resource availability of each spatial unit for land managers, including forest practitioners, but also directly influence land-use dynamics through their integration into AFT productivity calculations. The productivity of each AFT (Section 4.2) is determined by a Cobb-Douglas-style function that links the available capitals with the AFT's inherent capabilities, defining their ability to generate ecosystem services and their competitiveness with other AFTs. The capitals evolve over time in response to socio-economic and environmental changes, shaping long term forest management, land use transitions, ecosystem service provision, carbon sequestration and biodiversity. In the sections that follow, we detail the calibration of these capitals, distinguishing between socio-economic and natural capitals.

3.1 Scenario framing

CRAFTY-EU has been parametrized for 5 SSP-RCP scenario combinations (Kok *et al.*, 2019), including the three scenarios (SSP1-RCP2.6, SSP2-RCP4.5 and SSP3-RCP7.0) required in WP5 and detailed in the ForestPaths Milestone 7. Characteristics of these scenarios, and a summary of their behavioural influences within CRAFTY-EU, are as follows:

- **SSP1-RCP2.6:** Represents a more sustainable future in which limited climate change occurs, and socio-economic conditions gradually improve through economic growth that focusses on human wellbeing, stable governments, high social cohesion and international cooperation.
- **SSP2-RCP4.5:** Represents a world in which the current social, economic and technological trends do not change substantially from historical trends. Inequality in growth and development continue to exist. There are some improvements in resource and energy use, as institutions strive for mitigating climate change, but progress is slow and environmental degradation takes place.
- **SSP3-RCP7.0:** Represents a future in which medium-high climate change occurs, and regional conflict within, and between, countries, pushes countries to focus on more localised issues, such as economic difficulties, rather than global climate change mitigation. Living conditions widely deteriorate and society begins to disintegrate, along with the environment.
- **SSP4-RCP4.5:** Represents a future in which low-medium climate change occurs, and large economic inequalities and fluctuations develop and contribute to low social cohesion. Nevertheless, substantial technological investment is made and environmental protection is prioritised with increasing financial and manufactured capitals.

- **SSP5-RCP8.5:** Represents a future in which high-end climate change occurs. Substantial emphasis is placed on social and economic development, fossil fuel exploitation and technology, with increases in all capitals, at the expense of the climate and the environment.

3.2 Socio-economic capitals

Socio-economic capitals here are defined as representing the availability of socioeconomic resources for land managers and encompasses four dimensions – financial, manufactured, human and social.

3.2.1 Baseline data

The process of deriving socio-economic capitals for CRAFTY began with the collection of baseline datasets, with the best available data coverage for the year 2018, from pan-European sources, including Eurostat and the European Social Survey (ESS). 2018 was selected due to the higher data availability than more recent years, particularly in the ESS database, and can be seen as representative of a 2020 baseline for modelling studies given the minimal changes seen in these datasets between 2018 and 2020. The indicators chosen were intended to represent different aspects of the relevant socioeconomic capitals and the specific datasets used were selected based on their spatial coverage of the EU27+3 region. These data are available at various administrative scales (NUTS0–NUTS3) and were harmonized to a uniform spatial resolution (a 1-km grid). Any data gaps were addressed using data from the nearest available year or by consulting complementary national statistics (Figure 1). Table 1 shows the selected indicators, their data source and the socioeconomic capital they contribute to.

As in Merkle *et al.* (2023), we used a fuzzy set approach (Dunford *et al.*, 2015; Tinch *et al.*, 2015; Pedde *et al.*, 2018) to quantify the projections for all data from Eurostat and ESS. Using the baseline (2018) data distribution, we created thresholds - very low, low, medium, high and very high - and minimum and maximum limiting values to provide plausible constraints on the semi-quantitative trends. We then used the baseline data and the thresholds alongside the European-SSP narratives (Kok *et al.*, 2019), to create central projection trends for Europe for each indicator from 2020-2100, at 20-year time steps. Specifically, we individually assessed the direction and strength of change for each indicator in the time steps described, before discussing and agreeing the overall European trajectory for each indicator. These were then converted to scenario-dependent multipliers.

3.2.2 Regional scenario-based adjustments

Inter-regional scenario adjustments were then made based on descriptions within the European-SSP narratives. Specifically, we identified two types of geographic adjustment: linear convergence and linear divergence, such that the spread of values in Europe either decrease over time or increase, respectively. For example, references to reductions in inequality (e.g. as in SSP1) were interpreted as convergent trajectories, whilst references to increases in the gap between poorer and richer countries and increased social disparity (i.e. SSP3) were interpreted as divergent factors. Using the narratives, we ranked each indicator-scenario combination as high divergence, low divergence, no change, low convergence or high convergence. An adjustment was then applied to each indicator-scenario combination for each grid point, at each of the 20-year time steps. Between the 20-year time steps, linear interpolation was then used to obtain annual time steps. Where projected values went beyond the maximum and minimum threshold values defined, these values were subsequently replaced with the threshold values. Figure 2 is an illustrated example of indicator distribution in the baseline year and last year for different scenarios, here for education attainment.

The derived scenario-based capital indicators were then standardized to a 0–1 scale. Related indicators (see Table 1) were then combined into composite socio-economic capitals (human, social, financial, and manufactured) by averaging their standardized values (Figure 1.2). The three health indicators were combined into one value, before being combined with the other human capital indicators. This approach resulted in a consistent and comparable set of socio-economic capitals that reflect evolving conditions. These projected capitals have been integrated into CRAFTY's agent-based framework, allowing AFTs to respond dynamically to changing socio-economic environments across European regions.

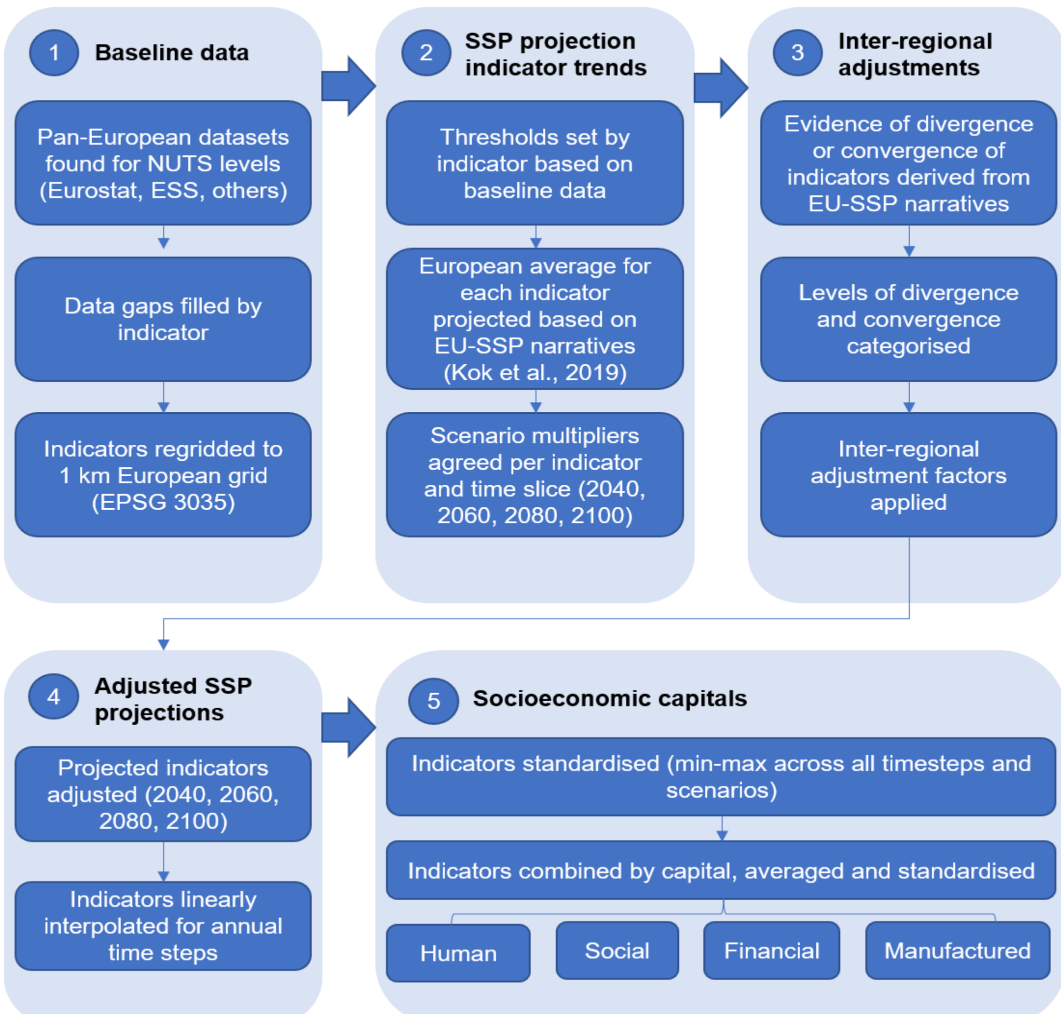


Figure 1: Flowchart of socioeconomic indicators and capital creation. NUTS refers to Nomenclature of Territorial Units for Statistics, a set of administrative units used by the EU. ESS refers to the European Social Survey.

Table 1. Socio-economic capitals and the contributing indicators. Indicators were selected based on their pan-European availability for the year 2018 and derived from Eurostat and European Social Survey datasets. Where there was missing data for specific regions of Europe, additional datasets were used e.g. from national databases to fill these gaps.

Capital	Explanation	Indicators	Sources
Human	Availability of human resources	Working population (% total population 15-64)	Eurostat dataset: Statistics | Eurostat (europa.eu) (02.04.23)
		Education (at least upper secondary level)	Eurostat dataset: Statistics | Eurostat (europa.eu) (02.04.23)
		Health (subjective general health, life expectancy at birth, doctors per capita)	ESS dataset (round 9, edition 3.1, 10.21338/ess9e03_1): Search European Social Survey (nsd.no) (31.05.23) ESS dataset (round9-Romania, 10.21338/ess9roe01): Search European Social Survey (nsd.no) (31.05.23) ESS dataset (round10, edition 3.0, 10.18712/ess10e03_0): Search European Social Survey (nsd.no) (01.06.23) European Social Survey European Research Infrastructure (ESS ERIC). (2023). ESS10 integrated file, edition 3.0 [Data set]. Sikt - Norwegian Agency for Shared Services in Education and Research. https://doi.org/10.18712/ESS10E03_0 Eurostat dataset: Statistics | Eurostat (europa.eu) (03.04.23) Eurostat dataset: Statistics | Eurostat (europa.eu) (25.06.23) Population dataset: Statistics | Eurostat (europa.eu) (26.06.23) UK-dataset (NUTS2): Stenning *et al.*, 2021 (07.02.22, *the link of the UK Climate Resilience Programme is not working now)* Germany dataset (NUTS3): Laufende Raumbeobachtung des BBSR; Kassenärztliche Bundesvereinigung, 2019 Der Deutschlandatlas - Homepage - Indikatoren auf Ebene der Kreise und kreisfreien Städte (bund.de) (30.05.23)
Social	Social support for land uses	Social cohesion	ESS dataset (round 9, edition 3.1, 10.21338/ess9e03_1): Search European Social Survey (nsd.no) (31.05.23) ESS dataset (round9-Romania, 10.21338/ess9roe01): Search European Social Survey (nsd.no) (31.05.23) ESS dataset (round10, edition 3.0, 10.18712/ess10e03_0): Search European Social Survey (nsd.no) (01.06.23) European Social Survey European Research Infrastructure (ESS ERIC). (2023). ESS10 integrated file, edition 3.0 [Data set]. Sikt - Norwegian Agency for Shared Services in Education and Research. https://doi.org/10.18712/ESS10E03_0 Eurostat dataset: Statistics | Eurostat (europa.eu) (03.04.23)
		Equality (reversed Gini inequality index)	Eurostat dataset: Statistics | Eurostat (europa.eu) (02.04.23)
Manufactured		Road density	Downscaled from Meijer *et al.* (2018). Data already projected 2020-2100 at 10-year time steps.

	Technological resources	Gross fixed capital formation	Eurostat data: Statistics | Eurostat (europa.eu) (02.04.23) UK GFCF data: (Merkle *et al.*, 2023) Eurostat national GFCF data: Statistics | Eurostat (europa.eu) (23.04.23) Eurostat population data: Statistics | Eurostat (europa.eu) (23.04.23) UK population data: ons.gov.uk (23.05.23)
		Research and Development expenditure	Eurostat data: Statistics | Eurostat (europa.eu) (13.04.23) Additional Eurostat national data: Statistics | Eurostat (europa.eu) (23.05.23)
Financial	Financial resources	GDP per inhabitant	Eurostat data: Statistics | Eurostat (europa.eu) (13.04.23) UK data: ons.gov.uk (08.05.23)
		Disposable income	Eurostat dataset: Statistics | Eurostat (europa.eu) (12.04.23) Additional Eurostat dataset: Statistics | Eurostat (europa.eu) (15.04.23)

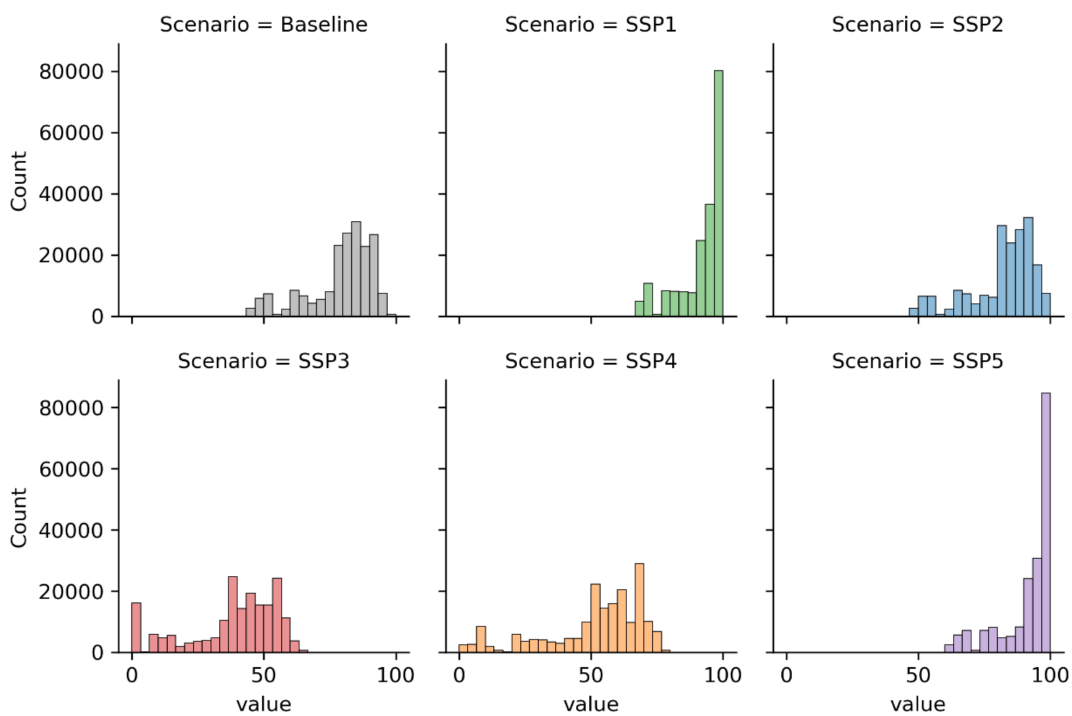


Figure 2: Using the education indicator (Table 1) as an example, histograms show how indicator values vary between the baseline year and the projected year 2100 in the different scenarios, after restricting the value range by the minimum and maximum thresholds. In the case of education attainment, the thresholds were 0% and 100%.

The evolution of socio-economic capitals (human, social, financial, and manufactured) varies substantially across SSP-RCP scenarios, as shown in the Figure 3. These capitals, derived from baseline indicators and projected forward under different pathways, reflect the socio-economic and policy-driven contexts influencing land management. Human capital, for instance, demonstrates strong growth in SSP1-RCP2.6, where stable governance and cooperative international policies foster investments in education, healthcare, and workforce development. In contrast, SSP3-RCP7.0 shows a marked decline in human capital, indicating fragmented progress and regional inequalities. SSP5-RCP8.5, characterized by rapid socio-economic and technological advancements, exhibits steep increases in human and financial capitals, although with potential environmental trade-offs. Social capital trends vary similarly, increasing under SSP1-RCP2.6 due to enhanced social cohesion, while declining sharply in SSP3-RCP7.0 due to socio-political instability and not increasing in RCP5-RCP8.5. Financial capital sees robust growth in SSP5-RCP8.5, driven by technological investments and economic expansion, whereas SSP1-RCP2.6 reflects more balanced development. Manufactured capital exhibits pronounced growth under SSP5-RCP8.5, aligned with rapid infrastructure development, while SSP1-RCP2.6 shows moderate, sustainable increases.

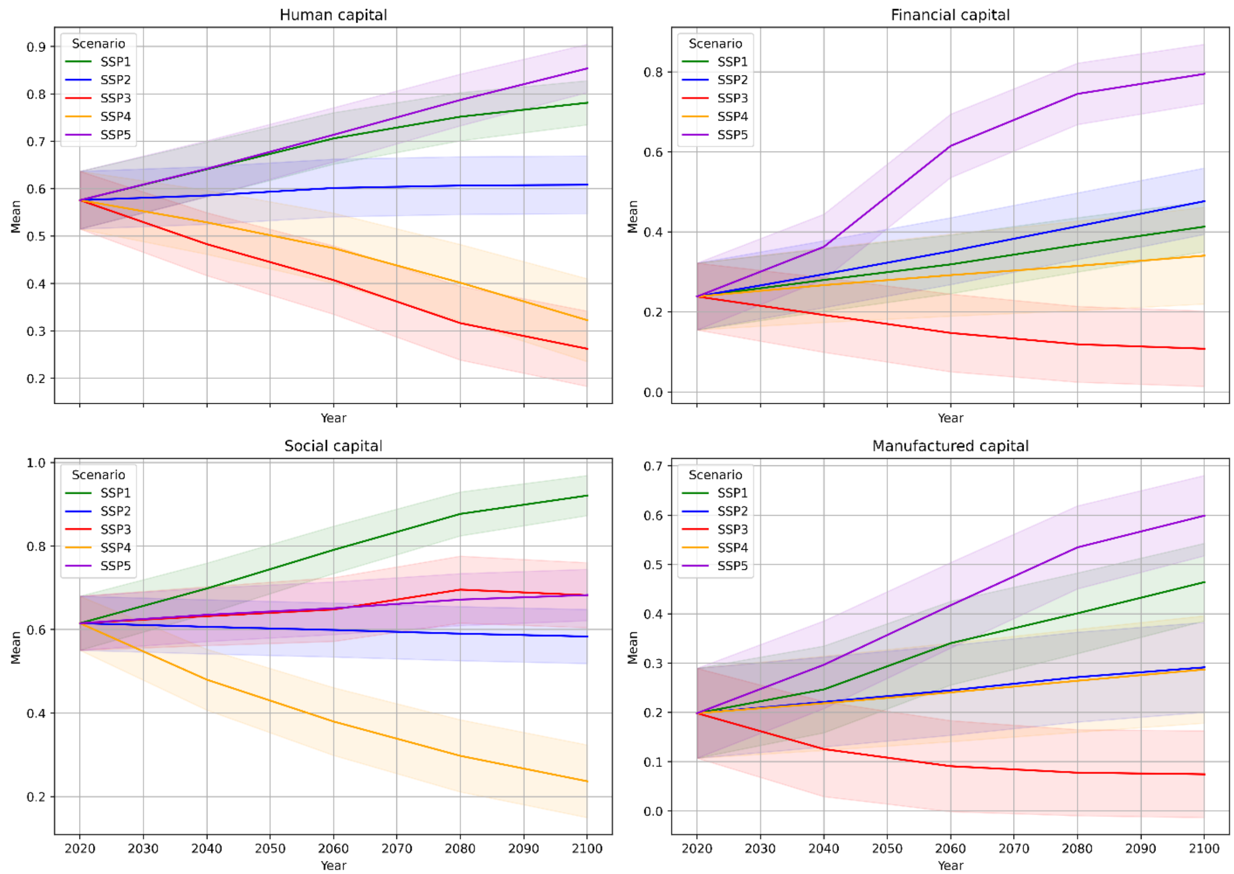


Figure 3. Trends of mean socio-economic capital values available to the land managers for each SSP-RCP scenario considered in CRAFTY-EU from 2020 to 2100.

3.3 45Natural capitals

As part of the LandSyMM framework, the natural capital inputs that underpin CRAFTY's simulations are derived from the LPJ-GUESS dynamic global vegetation model (Smith *et al.*, 2014; Lindeskog *et al.*, 2021). These natural capitals describe the potential productivity of a range of goods and services that different forest and land managers can produce (Table 2). LPJ-GUESS is a process-based ecosystem model that simulates vegetation dynamics and ecosystem functioning across a range of biomes, including forested, agricultural, grassland, pasture, and peatland systems, under changing environmental conditions such as climate, atmospheric CO2 concentrations, and nitrogen deposition. By incorporating both natural processes and management interventions, LPJ-GUESS can produce spatially explicit, time-dependent projections of vegetation structure, productivity, and resource availability. For the European application of LandSyMM-EU, LPJ-GUESS has been refined and calibrated for European forest conditions, making use of project-specific data and external datasets (see Pugh *et al.,* 2024).

The outputs of LPJ-GUESS, such as forest biomass productivity, vegetation composition, and related ecological indicators presented in Table 2, were integrated into CRAFTY. These natural capital inputs provide the essential biophysical context in which agents operate, and are the core part of calibration of service production in CRAFTY-EU.

Table 2. *Natural capitals derived from LPJ-GESS. Each capital gives a yield (weight) or Net Primary Production (NPP) value based on climatic conditions and management (fertilizer (tonnes/ha) and irrigation for crops, and percentage thinning over 30 years for forests). Note that capitals for managed forests are averages of 2 thinning intensities.*

Capital	Description	Model output	Indicator	Management	PFT
Intensive C3 cereal crop suitability	C3 cereals / C3 crops sown in winter (Wheat, barley, rye) with intensively managed	LPJG_crop	Yield	fertilizer: 250; irrigation: yes	CerealsC3
Extensive C3 cereal crop suitability	C3 cereals / C3 crops sown in winter (Wheat, barley, rye) extensively managed	LPJG_crop	Yield	fertilizer: 100; irrigation: no	CerealsC3
Intensive C3 oil crop suitability	C3 oil crops (Rapeseed, Sunflower, Linseed, Soybeans) intensively managed	LPJG_crop	Yield	fertilizer: 250; irrigation: yes	OilNfix, OilOther
Extensive C3 oil crop suitability	C3 oil crops (Rapeseed, Sunflower, Linseed, Soybeans) extensively managed	LPJG_crop	Yield	fertilizer: 100; irrigation: no	OilNfix, OilOther
Extensive C3 pulses suitability	C3 pulses (Peas, Lentils, Chickpeas, Beans) extensively managed	LPJG_crop	Yield	fertilizer: 100; irrigation: no	Pulses
Intensive C3 starchy roots suitability	C3 non-cereals / C3 crops sown in summer (Sunflower, soybeans, peanuts, rapeseed, canola, potatoes, sugarbeet) with maximum fertilizer	LPJG_crop	Yield	fertilizer: 250; irrigation: yes	StarchyRoots, Sugarbeet

Extensive C3 starchy roots suitability	C3 non-cereals / C3 crops sown in summer (Sunflower, soybeans, peanuts, rapeseed, canola, potatoes, sugarbeet) extensively managed	LPJG_crop	Yield	fertilizer: 100; irrigation: no	StarchyRoots, Sugarbeet
Intensive C4 crop suitability	C4 crops (Maize, millet, sorghum) for food/feed production with maximum fertilizer	LPJG_crop	Yield	fertilizer: 250; irrigation: yes	CerealsC4
Extensive C4 crop suitability	C4 crops (Maize, millet, sorghum) for food/feed production extensively managed	LPJG_crop	Yield	fertilizer: 100; irrigation: no	CerealsC4
Intensive fodder crop suitability	C3/C4 crops cultivated for feeding domestic livestock, managed intensively	LPJG_crop	Yield	fertilizer: 250; irrigation: yes	CerealsC4, CerealsC3, OilNfix, OilOther
Extensive fodder crop suitability	C3/C4 crops cultivated for feeding domestic livestock, managed extensively	LPJG_crop	Yield	fertilizer: 100; irrigation: no	CerealsC4, CerealsC3, OilNfix, OilOther
Bioenergy G1 suitability	Food Crops (Rapeseed, Wheat, Maize, Sugar Beet, Barley) cultivated for bioenergy production.	LPJG_crop	Yield	fertilizer: 250; irrigation: yes	CerealsC4, CerealsC3, Sugarbeet, OilOther
Bioenergy G2 suitability	Non-food crops or grasses used in the production of biofuels or biomass, e.g. Miscanthus, Short Rotation Coppice (SRC) Willow	LPJG_crop	Yield, NPP	fertilizer: 100; irrigation: no	CC4G_MEG
Intensive C3 pasture suitability	C3 grass, farmers managing intensively for livestock and bioenergy	LPJG_crop	NPP	fertilizer: 250; irrigation: yes	C3G_pas
Intensive C4 pasture suitability	C4 grass, farmers managing intensively for livestock and bioenergy	LPJG_crop	NPP	fertilizer: 250; irrigation: yes	C4G_pas
Extensive C3 pasture suitability	C3 grass, farmers managing intensively for livestock and bioenergy, managed extensively.	LPJG_crop	NPP	fertilizer: 100; irrigation: no	C3G_pas

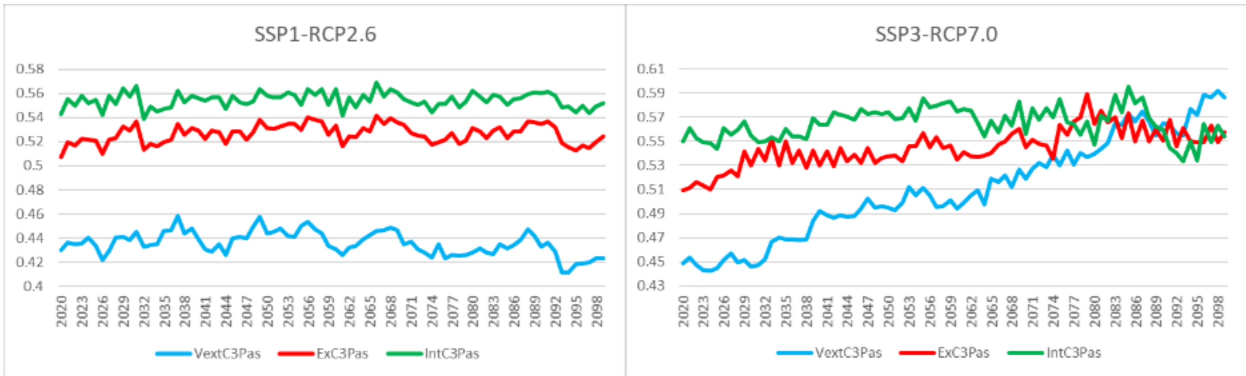
Extensive C4 pasture suitability	C4 grass, farmers managing intensively for livestock and bioenergy, managed extensively.	LPJG_crop	NPP	fertilizer: 100; irrigation: no	C4G_pas
Very extensive C3 pasture suitability	C3 grass, farmers managing intensively for livestock and bioenergy, managed very extensively.	LPJG_crop	NPP	fertilizer: 0; irrigation: no	C3G_pas
Very extensive C4 pasture suitability	C4 grass, farmers managing intensively for livestock and bioenergy, managed very extensively.	LPJG_crop	NPP	fertilizer: 0; irrigation: no	C4G_pas
Conifer forest suitability (intensive)	Needleleaved trees with intensive forest management	LPJG_forest	NPP	Average of thinning 25% and 40% of trees over 30-year period	BINE, BNE, TeNE
Conifer forest suitability (extensive)	Needleleaved trees with extensive forest management	LPJG_forest	NPP	Average of thinning 10% and 25% of trees over 30-year period	BINE, BNE, TeNE
Broadleaf forest suitability (intensive)	Broadleaved trees with intensive forest management	LPJG_forest	NPP	Average of thinning 25% and 40% of trees over 30-year period	IBS, TeBE, TeBS
Broadleaf forest suitability (extensive)	Broadleaved trees with extensive forest management	LPJG_forest	NPP	Average of thinning 10% and 25% of trees over 30-year period	IBS, TeBE, TeBS
Conservation forest suitability (very extensive)	Needleleaved trees or broadleaved trees without forest management	LPJG_forest	NPP	NE_unmanaged, BD_unmanaged	BINE, BNE, TeNE, IBS, TeBE, TeBS

3.3.1 Management intensities

In CRAFTY, land management intensity levels are critical to understanding how AFTs operate and compete for resources. Agents' ability to succeed in land competition is determined by the availability of capitals within the land (intensity level). These capitals serve as inputs for the production of ecosystem services. To better account for variability in land-use intensity, we define distinct levels of capital intensities. For example, LPJ-GUESS provides inputs distinguishing between three levels of forest management areas with different intensities such as *Broadleaved trees with intensive forest management, Broadleaved trees with extensive forest management, and Needleleaved trees or broadleaved trees without forest management.*

These intensities define different levels of biophysical productivity and land management potential, acting as independent capitals that AFTs can utilize. These differentiated capitals serve as independent inputs to CRAFTY, meaning that AFTs can interact with one or multiple intensities of the same natural capital type, depending on their management strategies and sensitivity to different capital availability. A second aspect of intensity is related to capital utilization: while natural capitals define the baseline potential of the landscape, their actual utilization depends on how AFTs interact with these capitals based on their specific productivity functions and their ability to integrate socio-economic capitals. Each AFT has a distinct capital sensitivity, determining how effectively it can use different intensities of natural capital in combination with other available resources. For example, ExtBF (Extensive Broadleaf Forest) and IntBF (Intensive Broadleaf Forest) both utilize the same natural capital type (Broadleaved forest suitability), but IntBF has a higher sensitivity to financial capital as it requires more economic inputs, resulting in higher harvest levels. This distinction ensures that management intensity is not only a function of natural capital availability but also of the AFT's capacity to utilize and optimize different capital inputs. The availability of each capital intensity is influenced by the socio-economic and climatic context defined by the SSP-RCP scenarios. Figure 4 illustrates how normalized capital intensities for pastures (very extensive, extensive, and intensive) and forest capitals vary across three scenarios: SSP1-RCP2.6, SSP3-RCP7.0, and SSP5-RCP8.5. Note that the natural capital values are derived from LPJ-GUESS under potential vegetation productivity conditions, meaning that land use is switched off in these simulations. Consequently, while RCP components such as climate and atmospheric CO_2 concentrations directly influence natural capital projections, the only SSP-related factors affecting natural capital in these scenarios are those impacting emissions, such as population and GDP growth. No scenario-based assumptions for land use change are applied to these inputs.

The comparative analysis of these scenarios highlights how socio-economic pathways and differing levels of climate change shape the distribution and utilization of capital intensities by AFTs. In SSP1-RCP2.6, the balanced capital availability allows for diverse management strategies, supporting ecosystem service multi-functionality. Conversely, in SSP5-RCP8.5, the predominance of higher-intensity capitals reflects a trade-off, where socio-economic priorities drive intensification, potentially at the expense of ecological sustainability.



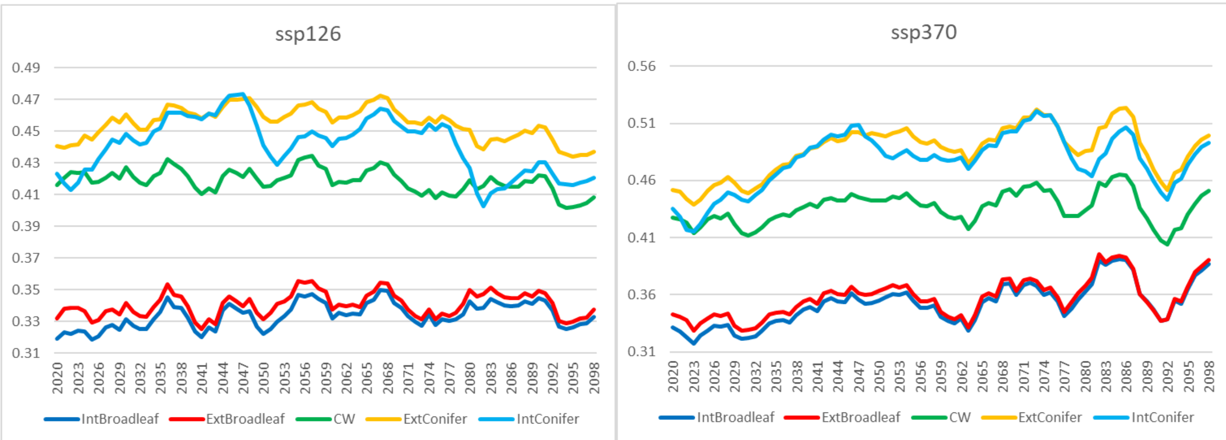


Figure 4: Variation in the normalized capital intensities for pastures (very extensive, extensive, and intensive) and forest capitals across the two scenarios SSP1-RCP2.6 and SSP3-RCP7.0. This capital is one of the inputs to CRAFTY-EU.

3.3.2 Solar capital: Photovoltaic potential in Europe

Solar capital was derived from the PV potential model of (Saxena *et al.*, 2023) for Europe. Accounting for photovoltaic energy generation potential in future scenarios is important for understanding synergies and land competition among PV energy generation, agriculture, forest, conservation and other uses of land. Higher solar capital indicates greater technical potential for PV installations, and accounts for a range of environmental and technological factors. Inputs for the PV model were obtained from ISIMIP3b (Lange and Büchner, 2021) and CMIP6 (Müller *et al.*, 2018; Mauritsen *et al.*, 2019). These datasets were processed using a downscaling algorithm to apply high-resolution climatologies to the Earth's land surface, creating 1 km resolution tiles from the original datasets (CHELSA) (Karger *et al.*, 2017). In addition to climate data (solar radiation, temperature), factors such as panel orientation and solar panel performance estimates were included in the PV potential calculations (see Saxena et al 2023 for full details). The processed inputs were then fed into the PV potential model to estimate the technical PV potential across Europe at a 1 km resolution.

The dataset spans the baseline period (1990–2014) and future projections (2015–2100) under three scenarios: SSP1-RCP2.6, SSP3-RCP7.0, and SSP5-RCP8.5.

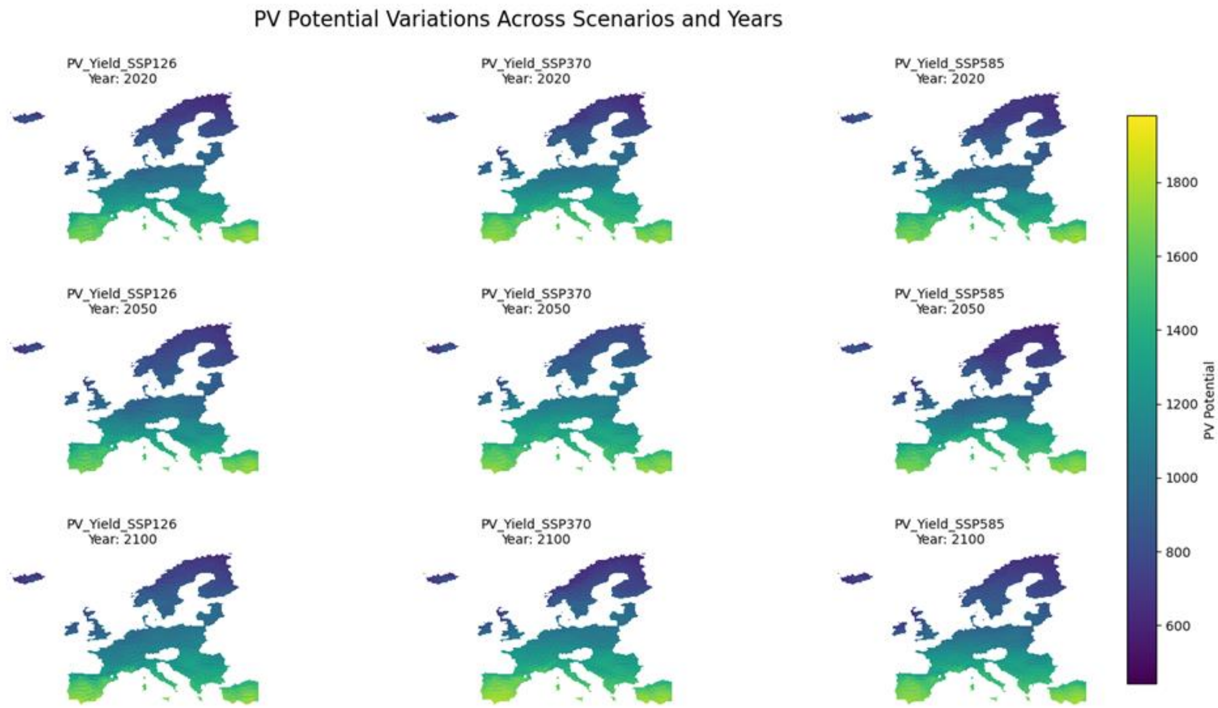


Figure 5: Photovoltaic (PV) potential (kWh) across scenarios and years. Photovoltaic potential is part of the natural capital that agents can use in CRAFTY-EU.

To develop a standardised capital dataset, we applied a min-max normalization approach to scale the data between 0 and 1 across different years and scenarios. The results reveal notable spatial and temporal variations across Europe, influenced by its diverse geographical and climatological conditions. For instance, southern Europe shows consistently higher PV potential due to greater solar radiation, whereas northern and central Europe exhibit more variability tied to regional climatic shifts under different SSPs (Figure 5).

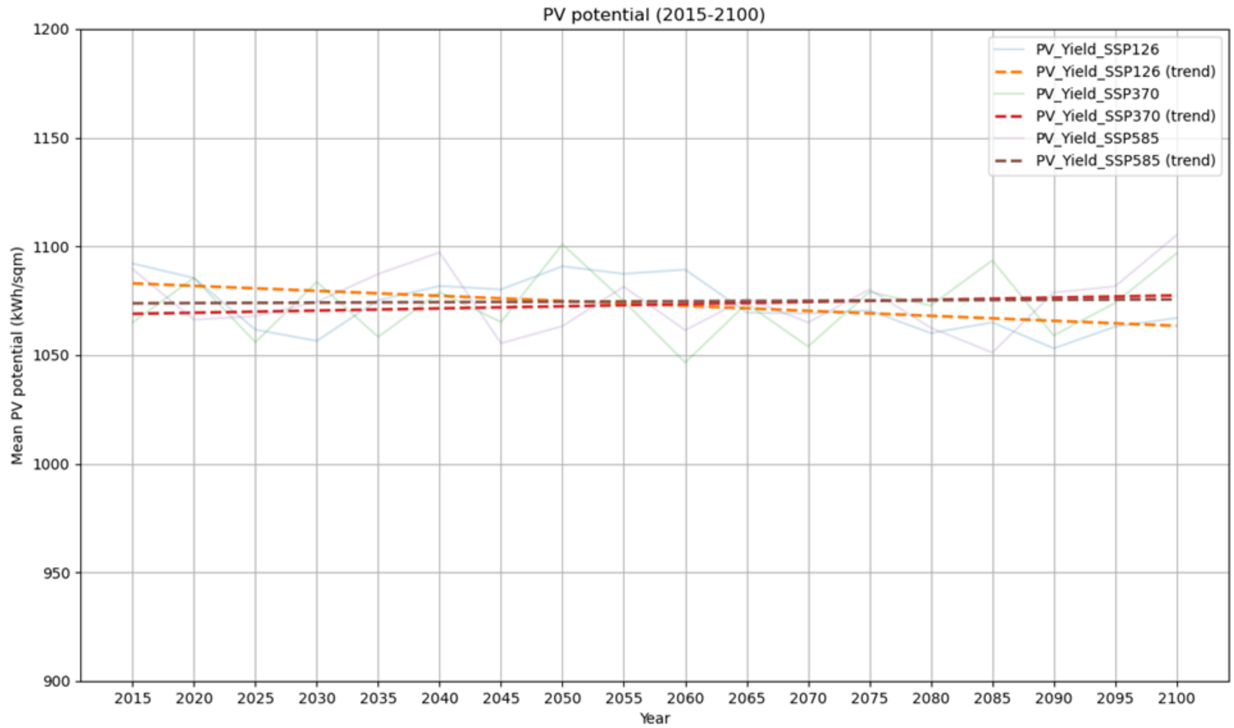


Figure 6: Trends for PV potential across scenarios and years for Europe. Photovolataic potential is part of the natural capital that agents can use in CRAFTY-EU.

4 Agent Functional Types (AFTs)

CRAFTY represents land managers through AFTs, which capture key variations in behaviour, productivity, and decision-making. Each AFT is defined by a combination of productivity, behavioural, and competitiveness parameters that shape how agents respond to the capitals available, produce a range of ecosystem services, and compete for land. While agents within the same AFT share broad characteristics, individual agents may differ in specific parameters, allowing for realistic diversity in land management strategies.

CRAFTY-EU includes a range of agent types that represent the main types of land uses, divided between arable, pastoral, forest and combined classes. They also represent different management intensities and degrees of multi-functionality (Table 3), with the ability to supply a range of ecosystem services.

Table 3. Overview of Agent Functional Types in CRAFTY-EU

Land use type	Label	Agent Functional Type	Description
Agriculture	IntC3C	Intensive C3 cereal crops	Intensive cereal cultivation (wheat, rye, barley, etc.) for food production (high fertilization <250 kg N/ha)
	IntC3oil	Intensive C3 oil crops	Intensive oil crops (rapeseed, sunflower, linseed, soybeans) for food production (high fertilization <250 kg N/ha)
	IntC3fruitveg	Intensive C3 fruit and vegetables	Intensive fruit or vegetable crops (leeks, onion, carrots, strawberries, grape etc.) for food production (high fertilization <250 kg N/ha)
	IntC3star	Intensive C3 starchy roots	Intensive starchy root crops (potatoes, sugarbeet) for food production (high fertilization <250 kg N/ha)
	IntC4	Intensive C4 crops	Intensive maize cultivation for food production (high fertilization <250 kg N/ha)
	IntFodder	Intensive C3/C4 fodder crops	Intensive crops (cereals, starchy roots, maize) cultivated for feeding domestic livestock (high fertilization <250 kg N/ha)
	ExtC3C	Extensive C3 cereal crops	Extensive cereal cultivation (wheat, rye, barley, etc.) for food production (low fertilization <100 kg N/ha)
	ExtC3oil	Extensive C3 oil crops	Extensive oil crops (rapeseed, sunflower, linseed, soybeans) for food production (low fertilization <100 kg N/ha)
	ExtC3fruitveg	Extensive C3 fruit and vegetables	Extensive fruit or vegetable crops (leeks, onion, carrots, strawberries, grape etc.) for food production (low fertilization <100 kg N/ha)
	ExtC3puls	Extensive C3 pulses	Extensive pulses cultivation (peas, lentils, chickpeas, beans) for food production (low fertilization <100 kg N/ha)
	ExtC3star	Extensive C3 starchy roots	Extensive starchy root crops (potatoes, sugarbeet) for food production (low fertilization <100 kg N/ha)
	ExtC4	Extensive C4 crops	Extensive maize cultivation for food production (low fertilization <100 kg N/ha)
	ExtFodder	Extensive C3/C4 fodder crops	Extensive crops (cereals, starchy roots, maize) cultivated for feeding domestic livestock (low fertilization <100 kg N/ha)
	IntP	Intensive pastoral	Intensive pasture for livestock (maximum fertilization < 250 kg N/ha)
	ExtP	Extensive pastoral	Extensive pasture for livestock (moderate fertilization <50 kg N/ha)
	VExtP	Very extensive pastoral	Very extensive pasture for livestock (minimum fertilization 0 kg N/ha, e.g. mountain areas)
	BioenergyG1	1st generation bioenergy (intensive)	Food crops (rapeseed, wheat, barley, maize, sugar beet) cultivated for bioenergy production (high fertilization <250 kg N/ha)
	BioenergyG2	2nd generation bioenergy (intensive)	Non-food crops or grasses used in the production of biofuels or biomass (e.g. miscanthus, Short Rotation Coppice willow)
Forest	AF	Agroforestry	Agroforestry systems with a mix of trees and grazing
	IntBF	Broadleaf forest (intensive)	Broadleaf trees with intensive forest management for timber

	IntCF	Conifer forest (intensive)	Conifer trees with intensive forest management for timber
	ExtBF	Broadleaf forest (extensive)	Broadleaf trees with extensive forest management for timber and other services
	ExtCF	Conifer forest (extensive)	Conifer trees with extensive forest management for timber and other services
	MW	Multifunctional mixed woodland (extensive)	Mixed trees with extensive forest management for a range of services
	CW	Conserved Woodland	Protected forests with no/low active management
Solar	Solar	Dedicated solar farm	Large-scale installation of solar panels for solar energy production
	Agrovoltaic	Agrovoltaic farm	Combination of cropland (cereals, maize, starchy roots or fruit and vegetables) and solar energy production
Unmanaged	UL	Unmanaged	Unlabelled, sparsely or un-managed land (mining areas, wetlands, shrubs, barren land, rocks and ice)
Masked	Urban	Urban land	Masked
	Water	Water areas	Masked

4.1 Forest Agent Functional Types and their distribution

Establishing, the baseline distribution of AFTs is a key part of model calibration, and is shown in Figure 7. The baseline distribution is based on the HILDA+ dataset (Winkler *et al.*, 2021) in conjunction with the EU land systems map (Dou *et al.*, 2021). Urban and water areas are masked out, and these areas do not produce ecosystem services. AFTs were distributed according to broad HILDA+ classes in the first place, to ensure consistency with the LPJ-GUESS runs that provide inputs to CRAFTY, and which initialise with historical HILDA+ data. In this step, arable, pastoral, forest, urban and unmanaged areas were assigned. Intensities within these were then taken from the EU land systems map of Dou et al., and crop types were distributed spatially randomly but in quantities determined by supply levels in the baseline year. The forest tree genus distribution map (see De Keersmaecker et al., 2024) was then used to distribute forest types (conifer, broadleaved, mixed), with a 70/30 threshold taken as indicative of one type or another.

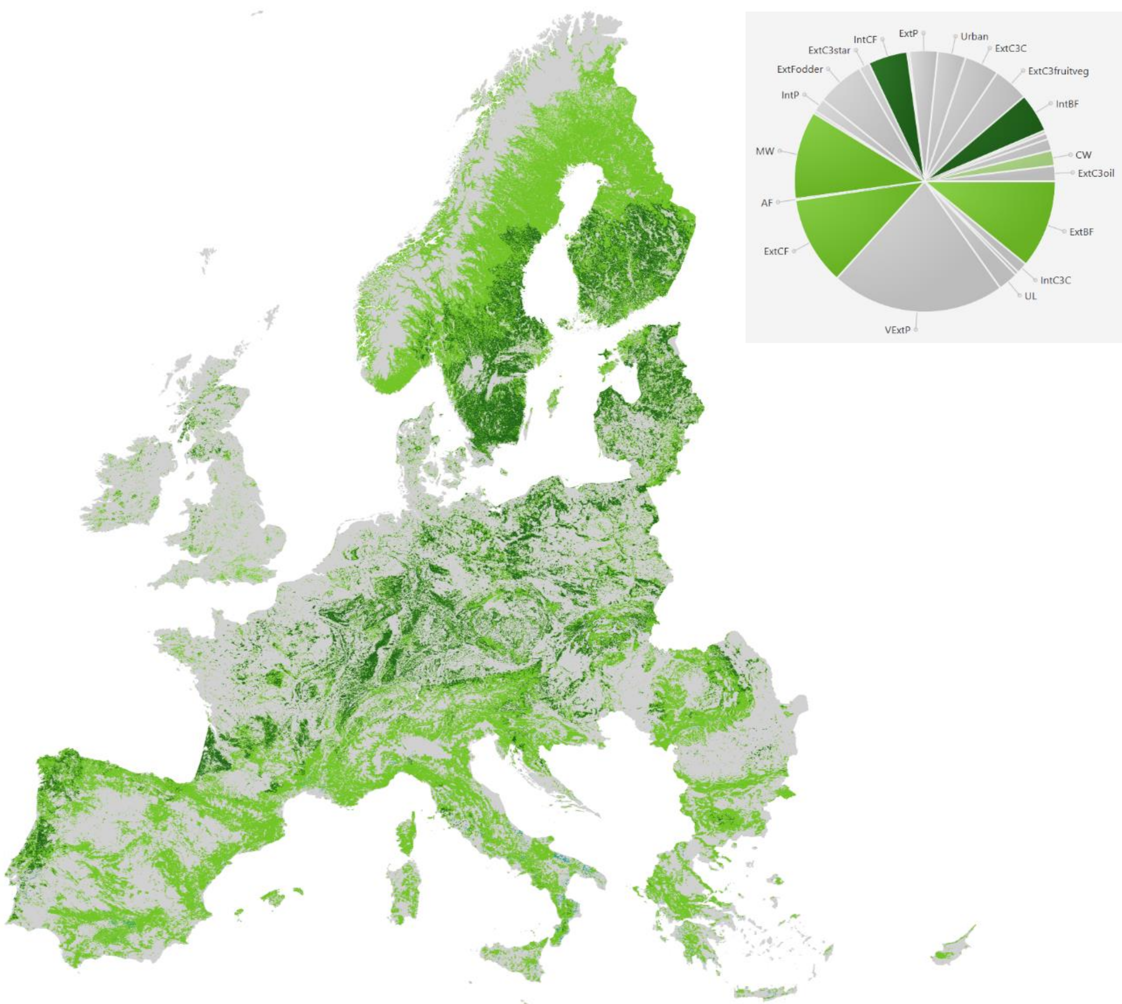


Figure 7. The distribution of forest AFTs in the baseline year 2020. The descriptions of each AFT can be found in Table 3.

4.2 Productivity parameters of AFTs

The abilities of an AFT $A_{\omega_{t_\tau}}$ in a land ω_{t_τ} to utilise capitals $c = (c_1, \ldots, c_n)$ and produce ecosystem services $s = (s_1, \ldots, s_n)$ were defined via capital sensitivity $\lambda_{i,j}$. For each AFT, the sensitivity is represented as a matrix which links each service with capital sensitivity weight. Relationships are quantified between the extremes of linear relationships (which were assigned a sensitivity value of 1.0) and random relationships (which were assigned a sensitivity value of 0.0). Modelled production of ecosystem services occurs subject to capital and productivity levels, according to the equation

$$p_{s_i}\left(A_{\omega_{t_\tau}}\right) = o_i(A) \prod_{j<n} c_j^{\lambda_{i,j}\left(A_{\omega_{t_\tau}}\right)} \qquad (2)$$

Where $p_{s_i}\left(A_{\omega_{t_\tau}}\right)$ represents the level of production of ecosystem service s_i by AFT $A_{\omega_{t_\tau}}$ in the land ω at time t_τ, calculated as the product across all capitals $(c_1, \ldots, c_n)$. Each cell-specific capital levels c_j weighted by the sensitivity $\lambda_{i,j}$, multiplied by the maximum level of production $o_i(A)$ that the AFT is able to produce. Maximum production levels $o_i(A)$ and capital sensitivities $\lambda_{i,j}$ are constant throughout simulations, while capital levels c_j vary according to scenario.

The maximum productivity level $o_{s_i}(A)$ indicates the upper limit of an AFT's production for a given service (i.e. when all required capitals are at their maximum value), and are set as described in Table 3. However, actual productivity also depends on the capital sensitivity matrix. To visualize this relationship, we generated a set of random capital vectors and compute the resulting productivity for each. Because the productivity values can span different orders of magnitude, we used a logarithmic scale to display their frequency distribution, allowing for clearer comparisons across the entire range of outcomes. Figure 8 represent the productivity frequency of softwood, hardwood and carbon by different forest AFTs. The AFT parametrization used in this analysis is calibrated for Europe, while all capital values in figure 8 are assigned random values between 0 and 1 to assess productivity under a standardized capital distribution to explore the relative productivity of different AFTs. The x-axis represents unitless productivity values, as the goal is to compare relative productivity across AFTs rather than report absolute values. By normalizing capital values, the analysis isolates differences in AFT-specific capital sensitivities, allowing a direct comparison of how different forest AFTs contribute to softwood, hardwood, and carbon production under varying capital conditions.

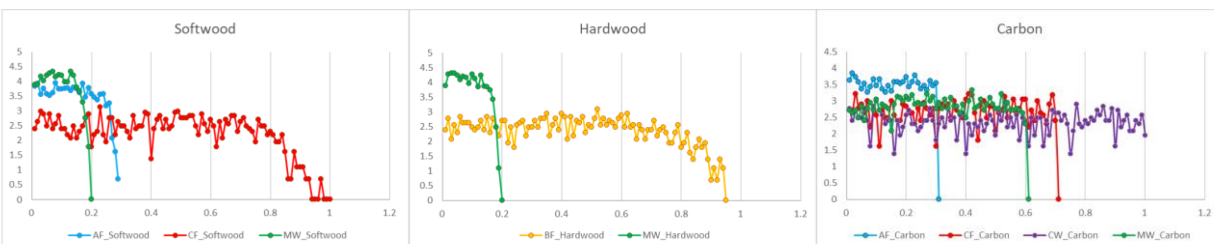


Figure 8. Productivity frequency of softwood, hardwood and carbon by forest AFTs (AF = agroforestry, CF = conifer forest, MW = mixed woodland, BF = broadleaf forest) using a sample of random capital values (1,000 points), to explore the relative productivity potential of different AFTs under varying capital conditions. The x-axis is the productivity values and y-axis are the logarithm of frequency.

4.3 Behavioural Parameters

A new behavioural model is currently being integrated into CRAFTY, incorporating intrinsic attitudinal and social factors into land managers' decision-making processes regarding changes in land use intensity. This enhancement builds upon the existing framework, which accounts for demand-driven competition, responsiveness to environmental and socio-economic feedbacks, and institutional influences. An overview in the form of a simplified flowchart of the behavioural model integrated into CRAFTY is shown in Figure 9.

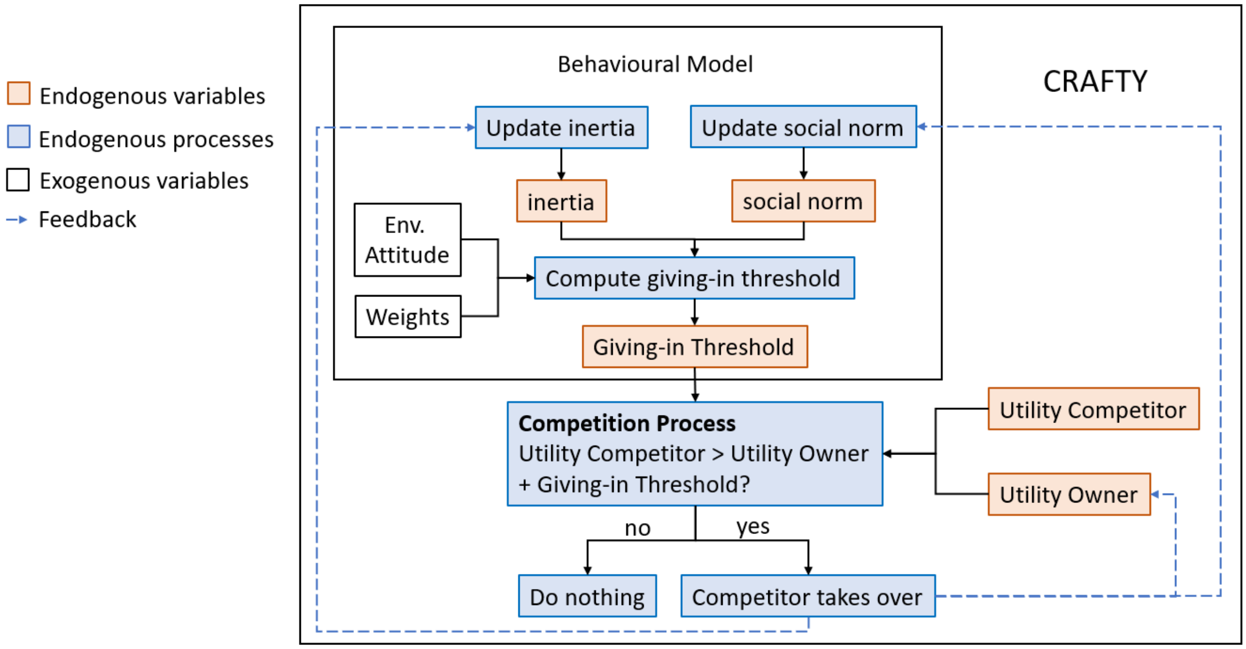


Figure 9. Simplified flowchart of the behavioural model integrated into CRAFTY. Weights include here the weight between the social norm and the environmental attitude, the strength of the inertia to large shifts in intensity and the upper limit of the giving-in threshold. The social norm is calculated and dynamically updated based on the behaviour of neighbouring land managers within a social network. The inertia to large shifts in intensity is calculated dynamically based on the difference in land use intensity between competitor and owner. Only the elements of CRAFTY that are relevant for the behavioural model integration are shown.

The decision-making model is grounded in the Theory of Planned Behaviour (TPB), a well-established framework in cognitive psychology that predicts and explains human behaviour. According to the Theory of Planned Behaviour, human decision-making is guided by three factors: attitudes, subjective norms, and perceived behavioural control. Together, these factors shape an individual's intention to engage in a behaviour, which is the strongest predictor of actual behaviour, assuming sufficient control over it.

In the CRAFTY modelling framework, behavioural control is integrated as a necessary condition for the adoption of a new land use behaviour via the demand-driven competition process and via the legal framework imposed on the land managers by an institutional model. The intention to adopt a new land management practice will be built by the economic benefits incorporated through the competition process, the perception of policies stemming from the institutional model and the motivational factors that will be incorporated through the new behavioural model. These motivational factors will encompass environmental attitudes and social norms:

- **Environmental Attitude**: In general, attitudes towards a behaviour describe the personal evaluation of a behaviour (e.g., whether it is perceived as positive or negative). In the context of decisions on changing land use intensity in CRAFTY, the environmental attitude reflects the positive or negative assessment of the considered transition in land use intensity, based on personal environmental objectives.
- **Social Norm**: Here social norms refer to the social pressure or perceived expectation from others to perform or not perform a behaviour. In the behavioural model, social norms will focus on the influence within land management communities, particularly within

agricultural and forestry practitioner communities. Social norms will be modelled endogenously in CRAFTY as an emergent characteristic resulting from interactions between land managers within a social network.By integrating these motivational factors, the enhanced behavioural model aims to capture the complex, dynamic interactions that drive land use decisions. The incorporation of endogenous social norms will allow for more realistic representations of how peer influences and collective behaviours evolve over time. This approach enhances the capacity of CRAFTY to explore policy implications and adaptive strategies for sustainable land management by better reflecting the human behavioural dimension of land use change.

The legal framework and land managers perception of market mechanisms such as regulations and subsidies are included into CRAFTY through a different model component, involving the institutional model (Section 6). Additionally, the influence of different organizational structures such as forestry networks will be part of the institutional modelling.

Detailed Implementation

In CRAFTY, the decision-making process of land manager agents on changing land use intensity is modelled through a cell level demand driven competition process between two land manager agents. During this process, a representative agent from a randomly selected AFT B competes with the current owner of AFT A of a randomly chosen cell α. The incumbent manager will relinquish control of the cell only if the competitor's utility U_B^α exceeds its own utility U_A^α by more than a specific giving-in threshold $GIT_{(AB)}^\alpha$,

$$U_B^\alpha - U_A^\alpha > GIT_{(AB)}^\alpha.$$

The giving-in threshold is dependent on behavioural cell parameters as well as on characteristics of the owner and competitor. Throughout this section, α denotes characteristics of the cell while A and B denote characteristics of the owner's AFT and the competitor's AFT respectively. With the integration of the new behavioural model, the giving-in threshold is dynamically calculated based on cell specific behavioural factors, representing characteristics of the individual person managing a cell. These factors are location specific and stored as cell variables. Through the competition threshold, agents can be parameterized as active intermediaries in the demand/supply chain equipped with a set of behavioural attributes or as non-behavioural land use optimisers if the giving-in threshold is set to zero.

Within the behavioural model, the competition threshold for transitions in land use intensity $GIT_{(AB)}^\alpha$ is calculated by a logistic function based on different behavioural factors $x_{(AB)}^\alpha$, influencing the decision-making on changing land use intensity,

$$GIT_{(AB)}^\alpha = \frac{L_\alpha}{1 + e^{\left(k \cdot x_{(AB)}^\alpha\right)}},$$

with L_α defining the upper limit of the giving-in threshold and k the growth rate of the logistic function. The bounded nature of the logistic function ensures that the giving-in threshold remains within a predefined range defined by the upper limit L_α, facilitating integration with the economic components. Furthermore, the characteristic S-shaped curve of logistic functions effectively models threshold effects and saturation points, which are specific for real-world adoption processes where changes initially occur slowly, accelerate upon reaching a tipping point, and then stabilize as saturation is reached. Logistic regression is commonly applied in social sciences to predict binary outcomes by utilizing this function as a link between predictor variables and probability space.

The behavioural factors $x^{\alpha}_{(AB)}$ include the influence of descriptive social norms from neighbouring land managers $S^{\alpha}_{(AB)}$, the influence of the land manager's environmental attitude $A^{\alpha}_{(AB)}$ and the land manger's inertia to perform large changes in intensity λ_{α}, see Figure 10,

$$x^{\alpha}_{(AB)} = w_{\alpha} \cdot S^{\alpha}_{(AB)} + (1 - w_{\alpha}) \cdot A^{\alpha}_{(AB)} - \lambda_{\alpha} \cdot |I_B - I_A|,$$

with w_{α} denoting the weight of the social influence in comparison with the attitudinal influence and I_X the land use intensity of agent X.

Environmental Attitude

The environmental attitude A_{α} describes the positive or negative evaluation of intensifying or extensifying land use, respectively, based on environmental values. These environmental values show, for instance, in the importance given to regulatory land use objectives such as climate change, soil quality, water quality, and biodiversity. We assume that more extensive land use practices are perceived as more environmentally friendly by the land managers. Hence, a higher environmental attitude leads to a higher probability of extensifying land use, which is modelled through a lower giving-in threshold for transitions to more extensive land use practices. A pro-environmental attitude is modelled through positive values of the environmental attitude, while negative values represent an anti-environmental attitude. We calculate the attitudinal influence on the decision-making based on the alignment of the environmental attitude with the considered land use intensity transition, represented through the change in intensity $I_B - I_A$,

$$A_A B^{\alpha} = -\text{sign}(I_B - I_A) \cdot A_{\alpha}.$$

Social Norms

In our model, social norms represent the social pressure or perceived expectations from others to engage in or refrain from certain behaviours. Specifically, we focus on descriptive norms, which capture the observable behaviours of others—such as the land management practices of neighbouring farmers or forestry practitioners. The behavioural model incorporates social norms as an endogenous characteristic that emerges from interactions between land managers within a structured social network.

To represent the influence of social norms within land management communities, we model interactions using a small-world network constructed via the Watts-Strogatz approach Duncan (1998). The network originates from a regular grid based on spatial proximity, to which random links are added to reduce the average path length. This structure ensures that the network maintains small-world properties while adhering to spatial constraints characteristic of agricultural and forestry communities. Furthermore, the social network is exclusively formed between land managers who belong to the same land use category such as agriculture and forestry.

New land use practices spread through the social network based on a social contagion model. Specifically, we implement a network-based adaptation of Granovetter's threshold model, following Wiedermann et al. (2020). In Wiedermann et al., an agent's likelihood of adopting a new behaviour increases as more of their neighbours exhibit the behaviour. Unlike Wiedermann et al., our approach accounts for a spectrum of possible actions by considering a structured hierarchy of land use intensities rather than a binary adoption decision.

We define behavioural transitions based on the proportion of neighbours demonstrating a particular land use intensity. The decision to intensify or extensify land use follows these principles:

- **Intensification of Land Use $I_B > I_A$:** If the proportion of neighbours $p_{(N_A^\alpha)}(I \geq I_B)$, exhibiting at least the intensity level of the prospective behaviour, exceeds a critical threshold CM_α (e.g., 50%), the willingness to adopt the new behaviour increases. Mathematically, this condition is expressed as follows:

$$S_A B^\alpha = p_{(N_A^\alpha)}(I \geq I_B) - CM_\alpha.$$

- **Extensification of Land Use $I_B < I_A$:** If the proportion of neighbours $p_{(N_A^\alpha)}(I \leq I_B)$, exhibiting at most the intensity level of the prospective behaviour, exceeds a critical threshold CM_α (e.g., 50%), the willingness to adopt the new behaviour increases. Mathematically, this condition is expressed as follows:

$$S_A B^\alpha = p_{(N_A^\alpha)}(I \leq I_B) - CM_\alpha.$$

Behavioural inertia

We include an inertia to large shifts in land-use intensity $\lambda_\alpha \cdot |I_B - I_A|$, which scales with the considered amount of change in intensity. Empirical evidence suggests that land managers generally favour gradual changes over abrupt changes due to risk management, economic constraints, and adaptation processes. Larger changes often come with higher transaction costs and uncertainties, reinforcing the preference for stepwise transitions rather than drastic modifications in land management practices. This can be regulated in the model through the inertia coefficient λ_α.

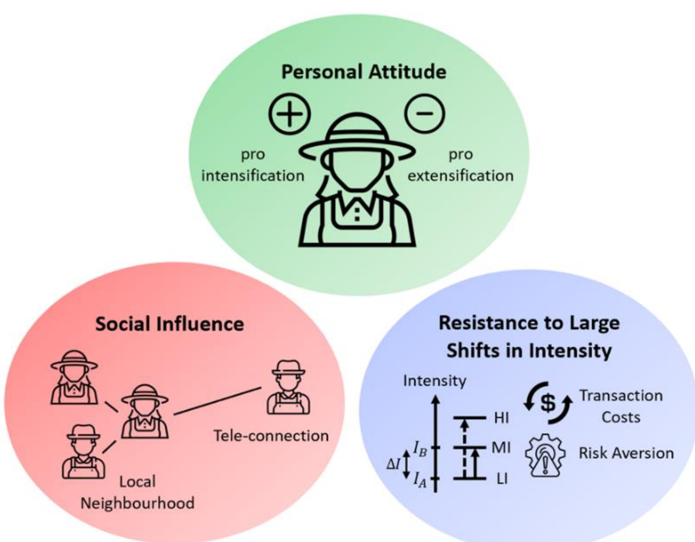


Figure 10. Illustration of the new behavioural factors included in the behavioural model. The personal attitude describes here an environmental attitude.

Integrating results from WP1 survey

An important dimension to improving the representation of forest practitioners in Europe

the diversity of forest practitioners in Europe and the management decisions they within CRAFTY-EU is through the incorporation of empirical data on forest management decisions. The ForestPaths-Fowards-Holisoils forest practitioner survey results, described in ForestPaths deliverables 1.2 (D1.2) (Franzini et al., 2024) and 1.3 (D1.3) (Feliciano et al., 2025), provide valuable input for this. The survey targeted forest practitioners across 13 countries in Europe and included sections on the forest practitioners and their forest holdings, ongoing management activities across Europe and their perceptions towards their forest management practices. The survey also employed the theory of planned behaviour, the same theory used in the CRAFTY behavioural model, drawing on the three dimensions: attitude, subjective norm, and perceived behavioural control. This theoretical alignment means there are multiple ways that the survey output can be used within CRAFTY and the behavioural sub-model.

A main result of the survey is the five forest practitioner typology groups (D1.3, Table 2.5). These typologies are based on the degree of importance of a set of behavioural factors: regulating ecosystem services (RES) objectives, income objectives, amenity objectives, forestry networks, society and market mechanisms (D1.3, Tables 2.6, 2.7). There exist statistical differences between the management practices implemented by the five typologies (D1.3, Table 2.8) and how the typologies are distributed across the European regions (D1.3, Table 2.9), forest holding size (D1.3, Table 2.10) and forest practitioner type (private or public, manager or owner) (D1.3, Table 2.11).

We considered two potential methods for incorporating the survey results: through value-based AFTs, or using values as cell characteristics, in a similar mechanism to the capitals, in which AFT behaviour is influenced by the values in that cell, allowing for spatial variation in attitudes and social norms of the AFTs across Europe. We take the latter approach, in which the typologies are distributed as cell characteristics, based on the frequency of their distribution within the survey across countries.

There are three main steps to including the survey output as values in the cells: 1. distributing the typologies, 2. defining how the typologies interact with the behavioural model, and 3. defining how the typologies interact with the institutional model. Given the survey does not cover all the countries within CRAFTY-EU, we will assume that those countries included in the survey and clustered into European regions, are representative for the countries not included in the survey but typically classed as being in those regions.

1. *Distributing the typologies:*

For each grid cell (including non-forest cells in the baseline map), we use a probabilistic method to allocate one of the five practitioner typologies found in D1.3 Table 2.5 (environmentally conscious passive, environmental implementer, traditionalist, maximiser, social satisfier).

- Grid-cell allocation is based on probabilities of that typology being present in that cell. We utilise multiple probabilities, derived from the survey, to calculate the overall cell probabilities and subsequently assign the typology
  - P_C = **Country-based typology probability**: We use the % of typologies per European region to calculate a probability a cell is a particular typology in each

country. This information is extracted from D1.3 (Table 2.9), to obtain the total practitioner respondents per region and for each region, the percent of each typology. For example, in North Europe, 17.20% of respondents were classified as Environmentally Conscious Passives, and so $P_c = 0.172$ in this region.

- P_T = **Forest practitioner type typology probability**:
  - We use regional forest ownership data (Pulla *et al.*, 2013) to statistically distribute publicly and privately owned forests as a cell attribute
  - Table 2.11 (D1.3) details the country breakdown of respondents and the forest practitioner type. We group these countries into the European regions as previously, to get a break down per region of what % of respondents working in privately owned forest that are a. The owner, or b. The manager or c. both
  - We then use Table 2.11 (D1.3) to calculate the probability within a privately-owned forest cell, of that cell being privately owned, privately managed or both

Drawing on these probabilities, a typology has been allocated to each grid cell. By using this method, we introduce the assumption that all cells with private ownership in a specific country have the same likelihood of being a certain typology. Whilst we acknowledge that this does not represent the real world and there exists variation regionally and locally within countries, the lack of sub-national data on this means that we cannot account for this variation, hence the assumption made.

In future simulations, there is the option to introduce changes in the typologies across scenarios, for example in a more sutainable SSP1-RCP2.6 scenario, the frequency of the environmentally conscious passives and the environmental implements could increase.

2. The interaction of the cell-based typologies with the behavioural model:

We then use some of the assigned cell typology to determine the behavioural parameters for each cell. Specifically, we use the values of the typology in that cell – regulatory ecosystem service (RES) objectives, income objectives and society – to introduce variation in the behavioural model parameter combinations, including environmental attitudes, the importance of social norms in comparison to the environmental attitude and the upper limit of the giving-in threshold which represents the importance of the new behavioural factors in comparison to the competition process. The weightings of the influence vary based on the typology, as summarised in Table 4 (adapted from Table 2.14, D1.3). The other values from the survey will be used to parametrize other parts of CRAFTY. Market mechanisms and forestry network can be integrated through the institutional model. Amenity objectives could be used in a next step to parametrize the preference of land managers to adopt AFTs which have high cultural ecosystem service production such as recreation and cultural landscapes.

In our model, we use regulating ecosystem service (RES) objectives as a proxy for land managers' environmental attitudes. A positive perception of RES outcomes translates into a positive attitude toward behaviours associated with RES benefits, which is reflected in the model's environmental attitude parameter. We assume that more extensive land use practices have higher expected RES benefits. In this survey, RES include climate change regulation, soil quality, water quality, biotic and abiotic disturbance.

Additionally, we use the relative importance of society and RES objectives to parametrize the weight between the social influence and the environmental attitude in our model. In the survey results, society encompasses influences from neighbours, friends and general public. Survey results indicate that practitioners perceive these influences as roughly equal, allowing us to use this measure to parametrize the social influence from neighbouring forestry practitioners in our model.

Furthermore, we use the relative importance of income objectives, RES objectives and society to parametrize the upper limit of the giving-in threshold, which moderates the impact of demand-driven competition on decision-making. If income objectives dominate, the model reflects this by assigning a low giving-in threshold, meaning decision-making is primarily competition-driven. Conversely, when RES and social objectives carry more weight than income considerations, the upper limit of the giving in threshold is higher, meaning decisions are more influenced by social and attitudinal alignment rather than competition alone.

In the following, we explain the behavioural parametrization for the five different forestry practitioner types:

- **Environmentally conscious passives**: Environmental Conscious Passives place high importance on RES objectives, which we use as a proxy for a positive environmental attitude. Furthermore, they are ambivalent towards income objectives and society. As this group places higher importance on RES objectives than on the opinion from society, we choose a low weight for the social norm compared to the environmental attitude. We choose the upper limit of the giving-in threshold to be slightly higher than medium, making sure that RES objectives are more important than income objectives.
- **Environmental implementers**: Environmental Implementers place high importance on RES objectives while income objectives and society are seen as unimportant. Hence, we choose a positive environmental attitude and give all weight to it. We choose a very high upper limit of the giving in threshold making sure that the environmental attitude restricts the competition process.
- **Traditionalist**: Traditionalist have high RES objectives and perceive the influence from society as important, while being ambivalent towards income objectives. We choose a positive environmental attitude and an equally balanced weight for social norm and environmental attitude with a high upper limit of the giving-in threshold.
- **Maximisers**: Maximizers place high importance on income objectives while RES objectives and society are seen as unimportant. Hence, we choose that the decision-making of this group is only guided by the competition process, by setting the upper limit of the giving-in threshold to zero. This group will be only influenced by economic profitability and policies including subsidies and regulations from the institutional model.
- **Social satisfiers**: Social satisfiers are highly influence by the opinion of society, while being ambivalent towards RES and income objectives. We choose a high weight for the social norm and a neutral environmental attitude. We choose the upper limit of the giving-in threshold to be slightly higher than medium, making sure that the influence from society is more important than income objectives.

Table 4: Draft summary of values per typology and the associate CRAFTY behavioural parameters, adapted from Table 2.14 (D1.3). The value range for the upper limit of the giving-in threshold still needs to be determined through a sensitivity analysis.

Typology	**Values**	**Upper limit of giving-in threshold**	**Weight of env. attitude**	**Weight of social norm**	**Environmental attitude**
1. Environmentally conscious passives	**RES objectives +** **Income objectives +/-** **Amenity objectives -** **Forestry network +/-** **Society +/-** **Market mechanism -**	Slightly Higher than Medium	0.75 (High)	0.25 (Low)	0.5 (High)
2. Environmental implementers	**RES objectives +** **Income objectives -** **Amenity objectives +/-** **Forestry network ++** **Society –** **Market mechanism +**	Very High	1 (Very High)	0 (Very Low)	0.5 (High)
3. Traditionalist	**RES objectives +** **Income objectives +/-** **Amenity objectives +/-** **Forestry network –** **Society +** **Market mechanism +/-**	High	0.5 (Balanced)	0.5 (Balanced)	0.5 (High)
4. Maximisers	**RES objectives –** **Income objectives +** **Amenity objectives –** **Forestry network +/-** **Society -** **Market mechanism ++**	Zero	No Weight	No Weight	No Weight
5. Social satisfiers	**RES objectives +/-** **Income objectives +/-** **Amenity objectives +** **Forestry network +** **Society +** **Market mechanism +/-**	Slightly Higher than Medium	0.25 (Low)	0.75 (High)	0 (Ambivalent)

This then influences the behaviours of the agents through methods described in the behavioural model description and through the weightings given in Table 4.

3. The interaction of the cell-based typologies with the institutional model:

To integrate the influence of forestry networks on forest practitioners' decisions requires combining the survey output with the institutional model (described in section 6). This interaction is two-fold: through the influence of market mechanisms on the uptake of subsidies, and through the influence of forestry networks and organisations on decisions.

Firstly, we can utilise the "market mechanisms" factor scores to represent forest practitioners' perception of policies. One example is whether a forestry AFT uptake the available subsidies or not. The environmentally conscious passives see market mechanisms as unimportant for the group, and as such may be uninfluenced by the introduction of subsidies for ecosystem service provision or otherwise. Meanwhile, the traditionalists show some tendencies towards it being important, and could be more likely to receive subsidies.

Secondly, we can use the information within Table 2.6 (D1.3) to define how forest AFTs respond to forestry networks. For example, we see that for the environmental implementers, forestry networks are more important, whereas for the traditionalist these are not all. There is the option to include forestry networks and organisations - for example Forest Europe - as one of the institutions within the institutional model. By doing so, we can vary how strongly agents, depending on their cell typology, respond to these networks. This includes how well information diffuses between agents (affecting management decisions) or as an additional social influence as in the behavioural model.

By using the cell value-based approach, rather than value-based AFTs, we are able to integrate the survey and see what effect using this information has on forest management decisions within the model and the resultant forest management, and land use, distribution, whilst also keeping the ability to run the model without using the survey results, to enable a comparison without this information.

5 Ecosystem services

Several additions have been made to the list of ecosystem services provided by CRAFTY AFTs leveraging the capitals available within their cells. A description of these services, and how they have been calibrated, is provided in Table 5. These include cultural ecosystem services, such as identity and recreation, provisioning services including food and timber (see above), supporting services such as soil formation, and regulating services such as carbon sequestration. These allow improved assessment of how different forest management scenarios impact ecosystem services provision.

In modelling the production of crops and livestock products, we assume divisions between crop production for direct human consumption, crop production for livestock consumption, and grass-fed livestock production. We assume that pastoralist agents produce grass-fed milk (intensive pastoral only) and grass-fed red meat, while ‘arable for fodder’ agents effectively produce crop-fed red and white meat, and milk. Monogastrics are graminivorous, so are fed only from crop-land. The PLUM bio-economy and global trade model provides the demand levels for foods and timber. Non-food agricultural demands are scenario-based.

Table 5. Ecosystem services and other benefits to people supplied by agents within CRAFTY-EU.

Service	Explanation	Description
Food crops	Crops for human consumption: C3 cereals, starchy roots, oil crops, pulses, fruit and veg, C4 crops	The supply of these services comes directly from LPJ-GUESS, based on the natural productivity, as well as the access and sensitivity an agent has to the socioeconomic capitals
Fodder crops	Crops for livestock	
Grass-fed	Pasture-fed (intensive)	

Bioenergy fuel	First generation – food crops e.g. maize, Second generation – non-food crop e.g. miscanthus	
Wood	Divisible into softwood and hardwood	
Sustainable production	Abstract service as proxy for organic demand	Abstract attribute of sustainable/extensive/organic systems represent scenario-based demand for those management practices (as opposed to specific services)
Solar energy	Energy provided by solar power installations	Agents leverage solar capital to produce solar energy. Solar capital is derived from photovoltaic potential (Saxena *et al.*, 2023), described in more detail in 2.1.2.
Carbon sequestration	Potential GHG sequestration by ecosystems (climate regulation)	CRAFTY has a basic ranking of land uses for carbon sequestration. For more detailed calculation of carbon sequestration, the annual AFT maps for the model runs are fed back to LPJ-GUESS
Biodiversity	The degree of naturalness, indicating the anthropogenic influence on biodiversity.	Ranking of land use types, based on the degree of naturalness . AFT categories were mapped onto the land use types within the naturalness classification.
	Mean Species Abundance – see van 't Veen et al., 2024	See section 5.1
Flood control	Flood control expressed by the potential runoff generated by rainfall	Flood control is expressed in terms of potential water runoff generated by rainfall. This is quantified by the curve number (CN) on a scale from 0-100, whereby low CN values indicate low water runoff (i.e., high water retention and thus good flood control) and high CN values indicate high water runoff generated by rainfall. CRAFTY follows the approach by Vallecillo *et al.* (2020) to calculate the CN number for each cell grid. CN number is influenced by soil type, slope, riparian zone status and land use. Novel to the CRAFTY approach is the dynamical adjustment of CN values based on land use change over time.
Soil erosion	Soil loss due to water run off i.e., (inter)-rill-erosion	Soil erosion arising from sheet and rill erosion processes. This is quantified as the annual average soil erosion at a specific site given by the (multiplicative) RUSLE equation from Borrelli *et al.* (2017).
Pollination & seed dispersal	Potential diversity & abundance of animal pollinators & seed dispersers	Ranking approach based on literature evidence and Species Distribution Model results
Landscape heterogeneity	Diversity within and/or between land uses in a landscape	Shannon Diversity Index calculated for each 1km² grid cell in Europe based on EUNIS habitat level 2 data (100m spatial resolution) and averaged per AFT and country for the baseline year.
Rural employment	Potential employment in forestry and agriculture	Relationship between number of forestry agents and forest employment derived from Eurostat employment in forestry and forestry-related jobs dataset for each country. Agricultural employment will be derived using statistical methods to obtain estimates for agricultural employment per square kilometre for each aft using the FADN data of agricultural employment.

Cultural ecosystem services	**Experience/inspiration**: the possibility to conduct physically and psychologically beneficial activities, healing, relaxation, recreation, and aesthetic enjoyment based on contact with nature. It also includes capabilities developed through education, knowledge acquisition, and inspiration by nature for art and technological design (Brauman *et al.*, 2020) **Recreation**: characteristics of living systems that enable activities promoting health or enjoyment through active or immersive interactions	To calculate the supply of **Experience and Inspiration**, we approximated the activities conducted by people in nature by using crowd-sourced, geotagged photos from the photo-sharing website Flickr. This is a well-established approach (e.g., (Figueroa-Alfaro and Tang, 2017; Schirpke *et al.*, 2018; Le Clec'h *et al.*, 2019) and accounts well for activities conducted by people in nature (Wood *et al.*, 2020; Ghermandi, 2022). We used artificial intelligence (AI) to ensure that photos are related to experiences in nature as manual classification is not feasible in this large and diverse study area. We also ran the model to identify which of these photos were related to **Physical Recreation**, a subset of Experience and Inspiration. Lastly, we spatially analysed how the photos relate to AFTs to identify the supply of the services by each respective AFT.
	Cultural landscapes: cultural landscape index	Cultural landscapes have been mapped for Europe (Tieskens *et al.*, 2017) Tieskens et al. (2017). Both the Cultural landscape indices for forests and agricultural lands were spatially analysed to see how cultural landscapes are related to AFTs in Europe to identify the supply of cultural landscapes by each respective AFT.
	Identity: Rootedness and sense of place associated with stability of the environment/land cover	Land use stability was estimated from historical data from 1960 to 2020 using HILDA+ (Winkler *et al.*, 2021) and identified the land use transitions that might have significant impacts on identity, for example, from agricultural uses to forestry uses. Then, these changes were contrasted with changes in social variables such as attachment to the country, community or social participation and permanence in the country (European Social Survey European Research Infrastructure (ESS ERIC), 2023a, 2023b) to define a score of land use types to produce the service identity.

5.1 Integrating land use and climate change effects on biodiversity in CRAFTY

As part of ForestPaths Task 3.3, and to better represent the effects of land use and climate change on biodiversity, we have coupled CRAFTY with GLOBIO, a global biodiversity model. GLOBIO determines the impacts of six anthropogenic pressures on biodiversity, based on pressure-impact relationships derived from empirical datasets (Schipper *et al.*, 2019). The impact is quantified through the mean species abundance (MSA) metric, calculated by dividing the abundance of each species present under pressured conditions (impacted sites) by the abundances of the same species within unpressured conditions (reference sites) (Alkemade *et al.*, 2009; Schipper *et al.*, 2019). The relationships for the two biggest anthropogenic drivers of biodiversity loss - land use change and climate change - have been incorporated into CRAFTY. Van 't Veen *et al*. (2024) (D3.3) section 5 provides details of how these two models have been coupled together, including how the land uses classes were matched Appendix K), and the pressure-impact relationships integrated (D3.3 section 5.1).

One of the discrepancies between the two models is that CRAFTY has annual time steps, whereas GLOBIO makes calculations on changes in MSA over more extended time periods e.g. 2015 to 2030 or 2050. Based on the current method described in D3.3, a transition in AFT e.g. from an intensive cereal agent to a conservation woodland agent, would result in an unrealistic increase in MSA from one year to the next. To prevent this, we have added MSA response times, to better represent the recovery or degradation of biodiversity associated with land use change.

Below, we describe the rules-based mechanism used to capture how MSA (Mean Species Abundance) transitions when an AFT shift occurs in CRAFTY. Each AFT is associated with a MSA value, based on the previously calculated GLOBIO land use MSA values. When land use changes from one AFT to another, the MSA does not switch instantaneously. Instead, it gradually moves from the original value, MSA_1, to the new value, MSA_2, over one year, reflecting either a recovery (increase in MSA) or a degradation (decrease in MSA).

$$MSA_{t_2} = \begin{cases} \min\left(MSA_1 + \frac{(MSA_2 - MSA_1)}{\alpha}, MSA_2\right) \; if \;\; \alpha < 1 \\ \hline \max\left(MSA_1 + \frac{(MSA_2 - MSA_1)}{\alpha}, MSA_2\right) \; if \;\; \alpha > 1 \end{cases}$$

Here, α determines the rate at which the MSA changes. If $\alpha < 1$, the transition occurs more rapidly but is capped at MSA_2. If $\alpha > 1$, the transition is slower, with a lower bound of MSA_2. Negative values of (MSA_2 - MSA_1) represent degradation, while positive values represent recovery. This formulation ensures that MSA moves stepwise toward the new equilibrium value, rather than jumping instantly upon an AFT change.

Using a simplified example, if we define the recovery time as 50 years from arable to forest AFTs, this would give us α=50. The MSA value would increase by 1/50 per time step. If the forestry AFT then changes again before the end of the 50 years e.g. to urban, the change in MSA would then convert to that at the rate for forest to urban e.g. 5 years of degradation so 1/5 time step until it reaches the MSA value for pasture. The MAX and MIN function ensure that the MSA does not go beyond the pre-defined MSA values for each AFT per scenario.

The equations for the MSA time lag (1) have been implemented in the CRAFTY code. To parametrise α, we are currently exploring how data and equations used for and within GLOBIO can be used. Where there are gaps in α values from this approach, we will undertake a literature assessment to define the recovery and degradation times for the required AFT transitions.

Figure 11 represents an example of MSA evolution during a run of CRAFTY. For these runs, we used an up-scaled dataset with a lower resolution than the original data to enable faster testing. In future simulations, these outputs values will be compared to the GLOBIO model runs in which CRAFTY AFT maps are to be incorporated to enable additional MSA components to be calculated, including fragmentation and the effects of nitrogen deposition.

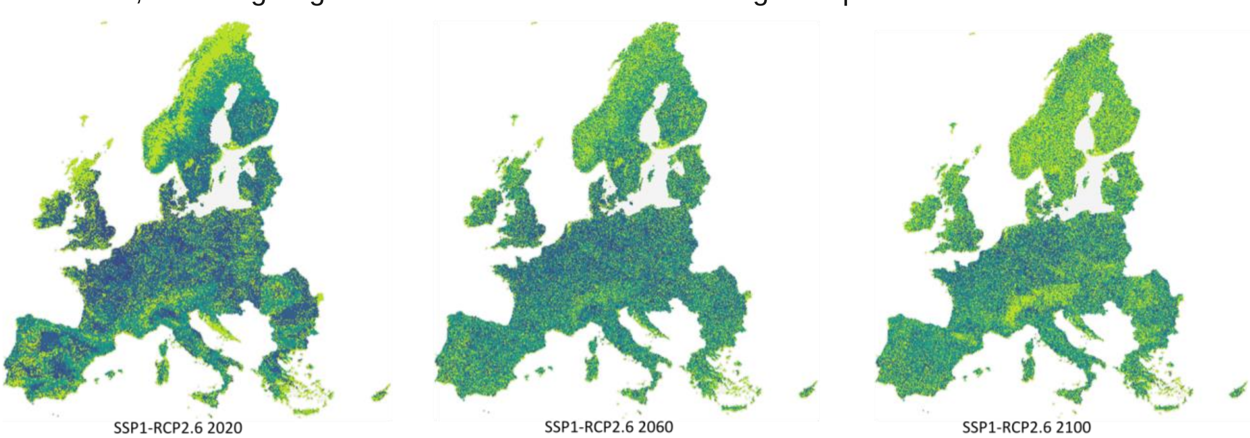


Figure 11. An example of MSA evolution in SSP-RCP2.6 scenario using an upscaled version of CRAFTY-EU-1km. High values are yellow, low values are blue.

6 Improving the representation of public policy institutions

An integral part of CRAFTY-EU development for the ForestPaths project has been the establishment of an endogenous institutional model to enable an improved representation of public policy institutions. Within CRAFTY, institutional agents, such as government departments or forestry organisations, can monitor changes in the environment, measure the changes against policy objectives and implement policy actions to better achieve those objectives. This will enable the simulation of policy pathways towards important forest and other land-based policy objectives. Here we present a detailed description of the institutional model. A use case of this model can be found in Zeng et al. (2025). The application of this model to forestry sectors will take place within WP5.

6.1 Model overview

Inspired by the work of Easton (1965) and Wlezien (1995), the role of endogenous institutions can be depicted as a sophisticated controller mechanism from a system perspective. Macroscopically, the outline structure of the endogenous institutional model within CRAFTY-EU is a closed-loop control system, where an institution is populated with a sequence of components forming a decision entity. Within this system, institutions can observe and influence land use processes to achieve policy goals. Figure 12 offers an overview of operational procedures within the loop. For illustrative clarity, these operational procedures are categorized into three parts, including the institutional model, the land use change model, and the part that solely represents the policy implementation procedure, the juncture where the two models tightly intersect.

Within the institutional model, we adopted two further methodological approaches from control theory: Proportional-Integral-Derivative (PID) and fuzzy control (Misir, Malki, and Guanrong Chen, 1996; Carvajal, 2000; Kaur and Singh, 2019). A PID controller continually adjusts the disparity between a set point (e.g., a policy target) and the system's existing state by factoring in three sources of error. In pursuit of policy goals, institutions can be modelled to adapt their decisions based on: 1) The current gap between the actual and desired policy outcomes (Proportional); 2) The accumulated impact of past policies and their resulting discrepancies (Integral); and 3) The changing speed with which these discrepancies are evolving (Derivative). Simulating policy adaptations based on these three types of gap between the outcomes of interest and policy targets provides a simple yet systematic approach that mirrors the principle of heuristics and incrementalism in policy-making, enabling institutions to implement continual, small adjustments informed by these factors.

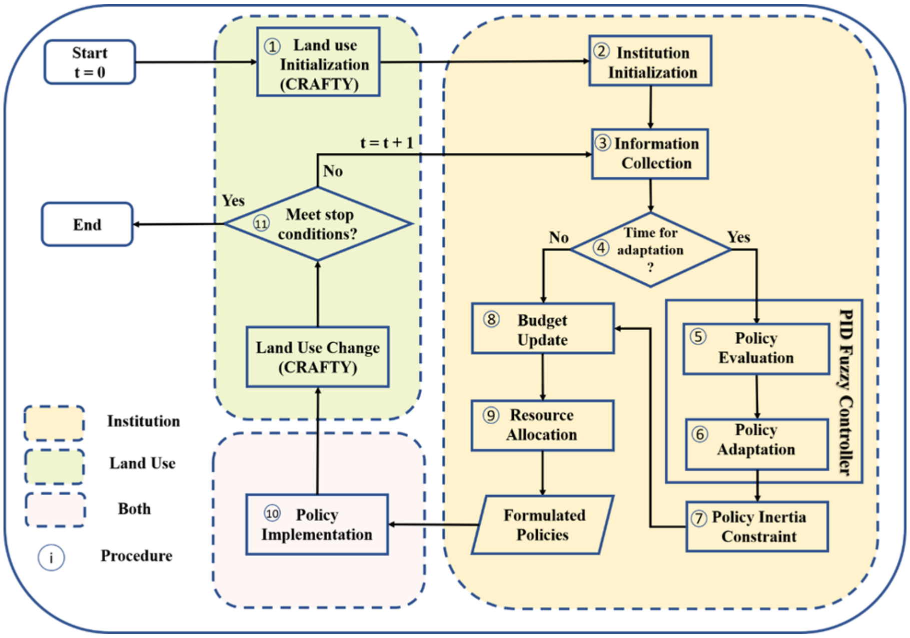


Figure 6: The operational procedures of the institutional model when embedded in a land use modelling framework.

A Fuzzy Logic Controller (FLC) serves as a function approximator that maps the goal-output discrepancies onto policy measures. The merits of coupling the PID and fuzzy control are manifold. An FLC is driven by an inference engine using a set of IF-THEN logic rules (Kaur and Singh, 2019). This rule-based paradigm fosters intuitive comprehension amongst human stakeholders and facilitates the encapsulation of knowledge from model users and policy-makers. Compared with a sole PID controller, the joining of an FLC endows the modelled institutions with the capability of coping with non-linear systems (Brown and Harris, 1995; Carvajal, 2000). Here, the PID controller allows for an adaptive, feedback-orientated approach to evaluating the disparity between an imposed policy goal and the model output, whilst the FLC maps the goal-output discrepancies onto policy measures. These approaches not only resonate with our core principles of institutional modelling but also offer practical algorithms that facilitate the effective operationalization of endogenous institutional behaviours upon a solid theoretical basis.

The complete model sequence includes eleven operational steps as follows:

1. **Initialize the land use model.**

2. **Initialize the institution agents**. This model can simulate many institutions simultaneously. Here, only one institution is shown for illustrative simplicity. Within an institution, one crucial process is to initialize the policies, which includes defining the policy IDs, objectives, policy types, and any other policy characteristics to be included in the model.

3. **Information collection by the institutions** on whichever features of modelled land use are relevant (here, the demands and supplies of ecosystem services such as timber and biodiversity). Uncertainties might accompany the information collection.

4. **Determine if it is time to adapt the policies**. Policies remain unchanged within a set period of time that can represent, for example, election cycles. This step is considered here for three reasons. Firstly, institutions need time to allow the effects of the policies to become manifest and then to evaluate the outcomes. Secondly, institutions might have difficulties in responding to the changes with sufficient speed. Thirdly, policies might be designed in this way to gain more consistency.

5. **If it is time to adapt the policies, the institution evaluates the performance of existing policies based on the collected information**. The evaluation procedure uses the PID controller that considers the errors between the policy goals and actual outcomes. Optionally, the institution may also incorporate predicted errors into the evaluation.

6. **Using the evaluation results, the institution conceives policy adaptations**. A fuzzy logic module is applied to allow the integration of real-world policy-makers' knowledge into decision-making. The fuzzy logic module serves as a function that maps the evaluation results to policy adaptation.

7. **A policy inertia constraint limits the magnitude of policy changes at each time step**, which reflects the non-monetary (e.g., public opinion, interested parties, legislation) resistance to policy changes.

8. **Subsequently, the institution deals with monetary constraints, i.e., budgets**. In reality, institutional budgets can come from multiple sources and vary over time. The incorporation of a dynamic budget update process adds another layer of realism to the institutional model.

9. **After updating the budget, the institution allocates the budget** among different policies and outputs the formulated policy interventions.

10. **The institution implements the policies** in the land use system to push land use changes in the desired direction.

11. **After the land use model processes the implemented policies, there is a check whether the end conditions are met**. If true, then the simulation is stopped; otherwise, the information collected by the institutions is updated for the next iteration of decision-making.

6.2 Sub-models

Further details about the various sub-models are provided here. To better present these details, the institutional model is segmented into four sub-models. The first sub-model focuses on the preliminary set-up and is limited to procedure 2: institution initialization. The second sub-model, termed "information, evaluation, and adaptation", encompasses procedures 3 to 7 due to their intrinsic link. This sub-model deals with information collection, uncertainty injection, policy evaluation, and adaptation together with the policy inertia constraint. The third sub-model, termed "budget-allocation", deals with updating the budget and allocating resources. The final sub-model focuses on policy implementation.

Sub-model 1: Initialization

Each institution has a unique ID to distinguish itself from other institutions, a set that contains all policies available to this institution, a container to collect information, a variable to control the uncertainties, a set of variables and conditions defining its budget, and a set of decision rules (Figure 13). A crucial task in this step is to initialise the policies and add them to the policy set. Each policy is essentially a group of attributes that can be adapted by the institution. The attributes/behaviours of institutions and policies as well as their relationships are shown in Figure 13. The meanings of these behaviours and attributes are summarized in Table A1 and Table A2 in Appendix A.

Of crucial significance is the setting of unambiguous policy goals, as these lead to institutional adaptation throughout the simulation. Real-world examples of clearly stated policy goals can be found in the Paris Agreement (2015) regarding carbon emission reductions. Some specific examples include that, the United States and European Union have set goals to reduce greenhouse gas emissions by 2030 by 50-52% compared to 2005 levels and by at least 55% compared to 1990 levels, respectively (Zhao *et al.*, 2022). In line with this target and as part of a portfolio of targets in the new EU Nature Restoration Law (REGULATION (EU) 2024/1991), the EU is also committed to planting 3 billion trees by 2030 and restoring forests.

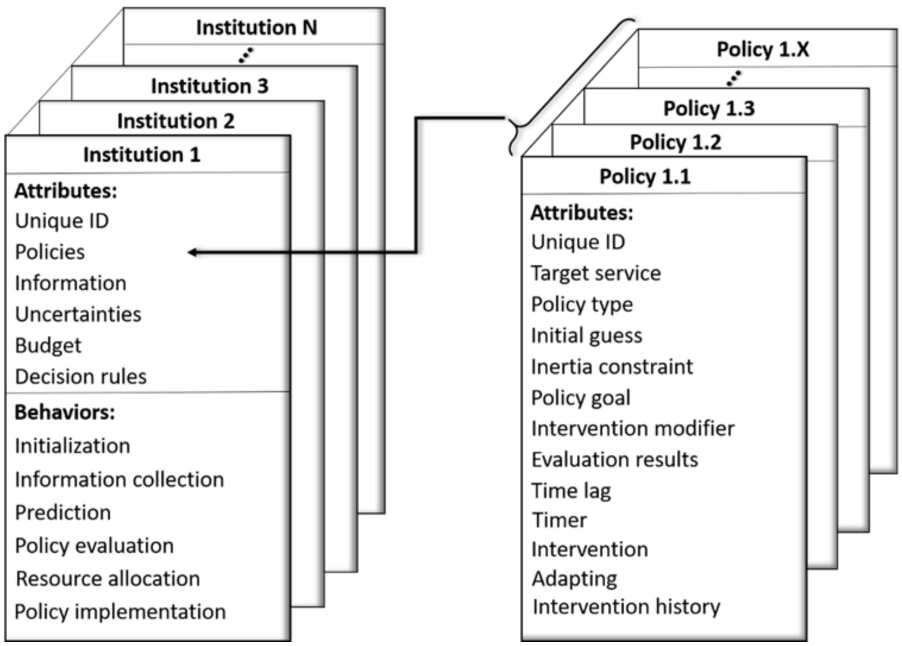


Figure 7: Institution and policy structures

These policies consistently specify a reference time, a deadline, and a targeted quantity. We use vector

$$\mathbf{G}^{\mathbf{ij}} = [T_s^{ij}, T_e^{ij}, Q^{ij}] \tag{3}$$

to represent the goal of institution i's policy *j*, which contains three components: T_s^{ij} the time when the policy starts, T_e^{ij} the time when the policy ends, and Q^{ij} the quantity a policy is meant to change from T_s^{ij} to T_e^{ij}. During the process of achieving a policy target, the institution conducts a series of constrained actions, which form a policy pathway. For instance, an institution might plan to increase carbon stocks in forests over 50 years by 10%. It might use extremely strict policies, such as high taxes, penalties, and restrictions, to achieve the target within a very short period of time. However, extreme policy changes normally face high resistance. A compromise outcome usually turns out to be much less strict and results in incremental interventions over a long period to allow the public and interested parties to accept the change gradually. These compromise policy changes consist of the policy pathway during the pursuit of the policy target.

With the policy goals clearly defined, an appropriate initial policy intervention needs to be set up, which could be a real-world policy. For instance, if a simulation starts from the year 2020, the initial policy intervention could be the actual taxes and subsidies implemented in that year. The initial intervention can also be derived from model users' intuitive estimation or deliberate calculation.

Sub-model 2: Information, evaluation, and adaptation

Institutions can have access to a wide range of information to support decision-making processes. Within the context of CRAFTY, when examining land use changes, pertinent data encompasses the supply and demand of various ecological services, land use type distributions, and the allocation of ecosystem service productions and the use of capitals, among others. While there are multiple sources of information available, gathering information can be resource-consuming, and the forms and extent of information can be limited as a result. Within the model, each category of information is represented as a distinct data container, labelled appropriately and filled with specific data points. Uncertainties can arise during information collection, and so the collected data can be varied using defined value distributions, reflecting relevant forms of bias or error.

Based on the information, institutions evaluate the state of the land use system relative to their goals. In reality, policies normally do not change frequently; it takes time for existing policies to manifest their impact and for institutions to respond to recent changes (Hocherman et al., 2024). Hence, a time lag is added to periodically trigger the evaluation and adaptation procedures for each policy (e.g. see Brown *et al.* (2019) for a discussion of time lags in the land system). Time lags can be fixed or changed over time to reflect different triggering mechanisms of policy adaptation. A common example of the time lags in policy adaptations is election cycles.

The evaluation of policy performance is a challenging task due to the complex nature of land use systems. It is difficult to attribute an outcome to a specific institutional action (Blanco, 2016). We adopt a heuristic approach to mimic institutional behaviour using a PID controller that adjusts the input based on the evaluation of three types of output-goal errors: proportional, integral and derivative. In this model, the proportional, integral, derivative errors, and their weighted sum are calculated using Equations (4), (5), (6), and (7) respectively:

$$\varepsilon_{t_n}^{(P)} = \frac{Q^{ij} - o_{t_n}^{ij}}{|Q^{ij}|} \tag{4}$$

$$\varepsilon_{t_n}^{(I)} = \frac{1}{k} \sum_{m=n-k}^{n} \frac{Q^{ij} - o_{t_m}^{ij}}{|Q^{ij}|} \tag{5}$$

$$\varepsilon_{t_n}^{(D)} = \frac{\left(Q^{ij} - o_{t_n}^{ij}\right) - \left(Q^{ij} - o_{t_{n-k}}^{ij}\right)}{|kQ^{ij}|} \tag{6}$$

$$E = C^{(P)}\varepsilon_{t_n}^{(P)} + C^{(I)}\varepsilon_{t_n}^{(I)} + C^{(D)}\varepsilon_{t_n}^{(D)} \tag{7}$$

where $\mathrm{t_n}$ represents the specific time at which the institution evaluates the errors; $o_{t_n}^{ij}$ is the output intended to be adjusted by institution i's policy j at the time t_n; k is the time interval of interest; $\varepsilon_{t_n}^{(P)}$, $\varepsilon_{t_n}^{(I)}$, $\varepsilon_{t_n}^{(D)}$respectively denote the proportional, integral, and derivative errors of policy j regarding its outcome $o_{t_n}^{ij}$ at time t_n. The weight vector $[C^{(P)}, C^{(I)}, C^{(D)}]$, where $C^{(P)} + C^{(I)} + C^{(D)} = 1$ and $C^{(P)}$, $C^{(I)}$, $C^{(D)} \in [0,1]$, can be applied to depict the policymakers' sensitivity to these errors. The summation *E* of these errors, factoring in their respective weights compose the evaluation of the institution in terms of the performance of policy *j*. It is noteworthy that these errors can involve predicted outcomes, and thus, consider predicted errors in the calculation, depending on how institutions consider the reliability of the predictions.

The FLC uses the weighted sum of errors E as an input, representing the performance evaluation of implemented policies. This controller works by mapping output errors onto policy adaptations, a crucial feature since institutions typically cannot directly influence the output but do so through policy instruments. As the FLC receives the input E, it is processed through three modules: fuzzification, inference engine, and defuzzification (Dadios, 2012). Fuzzification is the process that converts the crisp value of E into a set of fuzzy variables. Fuzzy inference maps the fuzzified input onto fuzzy output based on user-defined decision rules that are formatted in the IF-THEN structure. These rules are linguistic representations of experts' knowledge, such as that of policymakers and researchers who have domain-specific interests. For example, a rule might be "IF E is low THEN the change of intervention of Policy j is small". Another crucial user-defined component is the membership functions, which numerically define the adjectives "high", "low", "medium", etc. Typical membership functions include triangular, trapezoidal, and Gaussian functions (Dadios, 2012). The third process is defuzzification, which translates the fuzzy output back to crisp real numbers again to allow the computer to process.

Technically, the institutional agents' behaviour in approaching policy goals is analogous to iterative approaches such as Newton's method in solving ordinary differential equations (Cajori, 1911; Ypma, 1995; Galántai, 2000), but a critical difference is that the institutions do not know the precise mathematical representation of the target system and hence need to conduct a series of constrained trial and errors to approach the policy goals. Also, it should be noted that the FLC is used to map the errors onto the incremental quantity of policy interventions rather than onto a direct value indicating the intensity of the policy interventions, reflecting the approach of incrementalism.

Let F denote the function of FLC and $F(E)$ indicates policy variation. The policy variation is constrained by the policy inertia constraint N^{ij}. The constrained policy variation at $t+1$ is denoted as $A_{t+1}^{ij}$and calculated using Equation (8). The sign function outputs the sign of its input. A_{t+1}^{ij} is accumulated to form a policy modifier denoted as M_{t+1}^{ij}, as shown in Equation (9). It might be convenient to use normalized policy variation together with a fixed step size for iterative policy adaptation. In this way, the policy modifier is a coefficient of the step size. As shown in Equation (10), η^{ij} is the step size, and V_{t+1}^{ij} is the modified policy intervention for the $(t+1)$-th iteration.

$$A_{t+1}^{ij} = sign\big(\mathrm{F}(E)\big) \times \min\big(|\mathrm{F}(\mathrm{E})|, N^{ij}\big) \tag{8}$$

$$M_{t+1}^{ij} = M_t^{ij} + A_{t+1}^{ij} \tag{9}$$

$$V_{t+1}^{ij} = \eta^{ij} \times M_{t+1}^{ij} \tag{10}$$

Sub-model 3: Budget allocation

In modelling an institution with multiple policies, it is crucial to understand how much budget each has access to, because the distribution of budget among institutions or policies is related to the power they can leverage to impact land use change or even other institutions. Hence, a process that updates the budget for an institution has been included in the model. The budget update process tracks the institution's income and expenditure whenever a policy is applied.

The institution can allocate the budget across multiple policies. It is assumed here that policy interventions are quantitively measurable, and their absolute values are positively correlated to the budget the institution uses to implement a policy. As seen in Equation (11), f is a monotone function that maps the absolute value of a policy intervention V_{t+1}^{ij} to the resource R_{t+1}^{ij} consumed. For simplicity, in the simulation section below, function f can be approximated as a linear function, and only subsidies are considered budget-consuming.

$$f\big(|V_{t+1}^{ij}|\big) = R_{t+1}^{ij} \tag{11}$$

The allocation of the budget can be treated as an optimization problem in quadratic form, which is a convex optimization problem:

$$\min_{\boldsymbol{r}\in(\boldsymbol{r_{min}},\boldsymbol{r_{max}})} \sum_j \xi_{ij}\left(r_{t+1}^{ij} - R_{t+1}^{ij}\right)^2 \tag{12}$$

$$s.t.\ \ 0 \le \sum_j r_{t+1}^{ij} \le B_t^i \tag{13}$$

$$\sum_j \xi_{ij} = 1 \tag{14}$$

where R_{t+1}^{ij} denotes the resource needed by institution *i*'s to implement policy *j*; r_t^{ij} is the decision variable determining the resource allocated to implement policy *j*; ξ_{ij} is a weight reflecting the comparative importance of policy *j* perceived by institution i; B_t^i is the total budget of the institution i at t. The optimizer is intended to find a combination of r_t^{ij} that minimize the objective function. Alternatively, one might consider using IF-THEN rules instead of optimization to determine the resource allocation or modifying the weights to add more dynamics. However, treating the budget allocation as a convex optimization problem provides a unique optimal solution, making this process manageable and understandable even if the number of policies is large. Meanwhile, this treatment allows model users to focus on the customization of the policy adaptation process.

After finding the optimal resource allocation, it has to be transformed back to the policy intervention using the inverse function of f, as shown in Equation (15):

$$V_{t+1}^{*ij} = sign(V_{t+1}^{ij}) f^{-1}(r_{t+1}^{*ij}) \tag{15}$$

where r_{t+1}^{*ij} is the optimal resource for V_{t+1}^{ij}; the *sign* function returns the sign of V_{t+1}^{ij}; V_{t+1}^{*ij} is the resultant optimal policy intervention. Because the policies consume the budget, the budget B_t^i should be updated accordingly using Equation (16):

$$B_t^i \leftarrow B_t^i - \sum_j r_{t+1}^{*ij} \tag{16}$$

Sub-model 4: Policy implementation

The policy implementation sub-model is an intersection of the institutional model and the land use change model. There is a diversity of policy instruments that can influence land use changes, among which economic measures play a crucial role. In this model, we focus on the intervention of economic policies within the land use system represented by CRAFTY-EU.

Typically, economic policies include taxes and subsidies. In real-world cases, when economic policies come into play, the equilibrium of demand and supply is determined by both the elasticities of the demand and supply, even if the policies are imposed on one side of the market. For instance, subsidies on the supply side may cause a price drop, which in turn induces more demand and adds resistance to the price drop. Because the current land use change model is focused on the supply side of different land use types and uses prescribed demands for different ecosystem services, it is assumed that taxes and subsidies are only imposed on the land users rather than the ecosystem service consumers.

That is, the demand is assumed to be completely inelastic. The economic policies are implemented as follows:

$$c_{xy} = \sum_S (p_S (\sum_i V_{t+1}^{iS} + m_S)) \tag{17}$$

where c_{xy} denotes the competitiveness of a land use agent at the land cell whose coordinates are (x, y); S is the ecosystem service the land user produces. V_{t+1}^{iS} is the institution *i*'s economic policy that targets ecosystem service S; m_S is marginal utility brought by ecosystem service *S*. p_S is the production level of ecosystem service S.

A use case of this model can be found in Zeng et al. (2025). The application of this model to forestry sectors will take place within WP5 to identify policy pathways to current EU policy targets and targets proposed by stakeholders in WP6.

7 Simulation Output

Here, we present example results of CRAFTY-EU to demonstrate the model's capabilities. These results are precursors to the full exploratory analysis to be undertaken within ForestPaths, and are presented in condensed form, for four SSP-RCP combinations: SSP1-RCP2.6, SSP3-RCP7.0, SSP4-RCP4.5, and SSP5-RCP8.5.

Key outcomes are presented in Table 6, while Figure 14 illustrates the spatial distribution of forest AFTs and Figure 15 the AFT transitions. Across all four scenarios, the distribution of AFTs changes from 2020 to 2085, but dominant land use types vary.

Forest cover increases from 45% in 2020 to 55% under SSP1-RCP2.6 and 53% under SSP5-RCP8.5. However, it remains stable in SSP4-RCP4.5 and declines to 38% in SSP3-RCP7.0, reflecting the specific demands for forests and climate mitigation within each scenario. By 2085, the expansion of Extensive Broadleaf Forestry in SSP1-RCP2.6 is driven predominantly by the conversion of land previously classified as Very Extensive Pasture, Mixed Woodland, and Extensive Conifer Forestry (Figure 15). In contrast, under SSP3-RCP7.0 and SSP4-RCP4.5, Very Extensive Pasture remains relatively stable compared to 2020, with only minimal contributions from other AFTs. The growth of Mixed Woodland in SSP5-RCP8.5 primarily arises from transitions from land formerly occupied by Very Extensive Pasture, Extensive Conifer Forestry or Extensive Broadleaf Forestry. Figure 16 highlights a selection of the demand and supply curves for simulated ecosystem services, showing the impacts of these land use changes on service provision.

The CRAFTY framework has previously been used to develop a comprehensive protocol for land system model evaluation (Brown et al. 2023). Table 7 summarises this protocol and its application to the newly developed version of CRAFTY-EU described in this document. The protocol is intended to provide a menu of evaluation options rather than a compulsory list, and to emphasise the range of useful approaches beyond the most common, but relatively uninformative, fit to historical data. While some of these options (e.g. involving participation) are currently not feasible due to the stage of development of CRAFTY-EU, a wide sample have been applied during model development and calibration (Table 7).

Table 36. Dominant AFTs, land use types and their coverages.

Year	Scenario	Dominant AFT	Coverage	Overall forest coverage
2020	-	Very Extensive Pasture	10.90%	45%
2085	SSP1-RCP2.6	Extensive Broadleaf Forestry	14.10%	55%
2085	SSP3-RCP7.0	Very Extensive Pasture	13.30%	38%
2085	SSP4-RCP4.5	Very Extensive Pasture	15%	45%
2085	SSP5-RCP8.5	Mixed Woodland	27.60%	53%

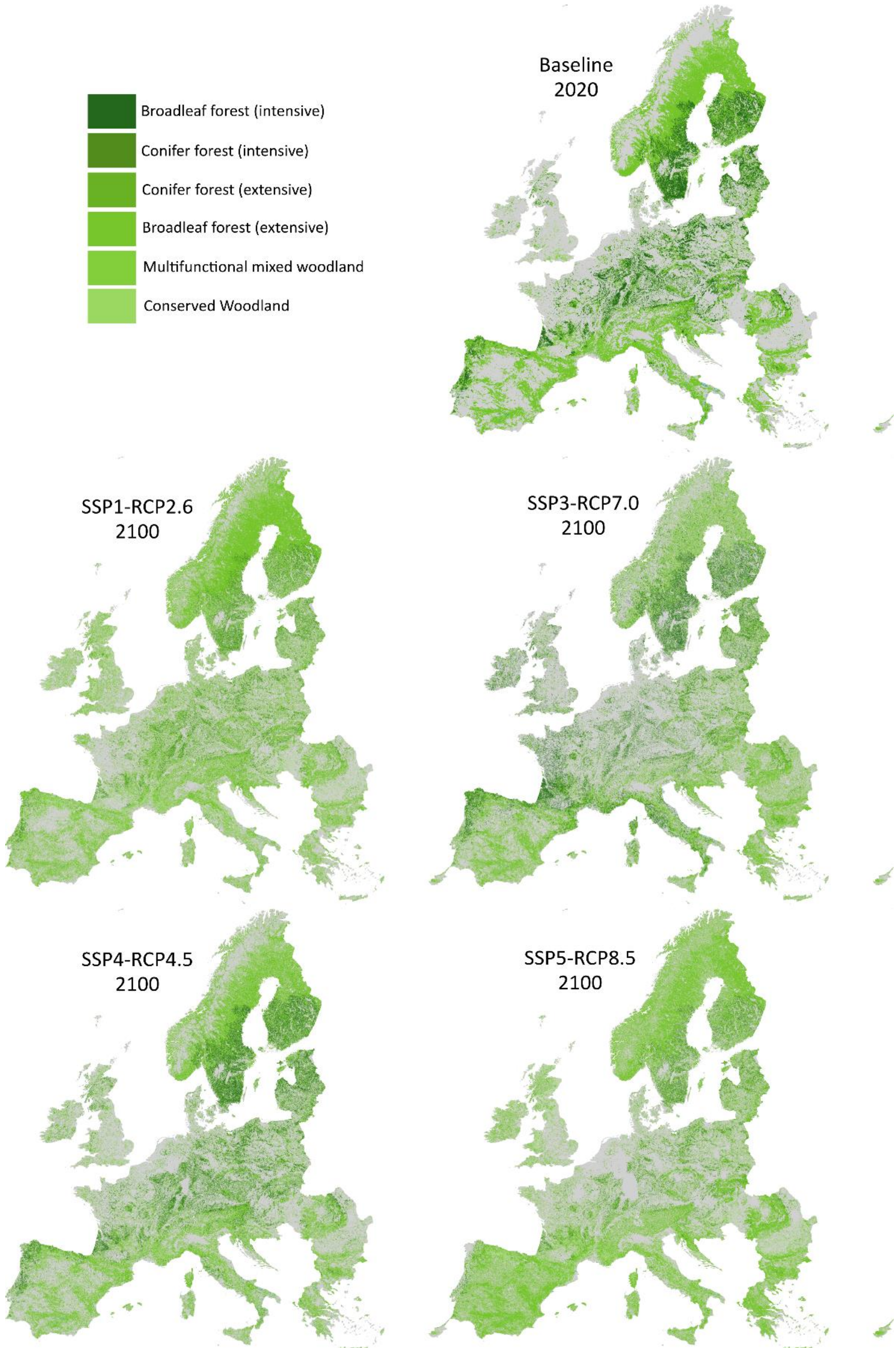


Figure 148: Distribution of forest Agent Functional Types (AFTs) in the CRAFTY baseline year 2020 and four scenarios for 2100.

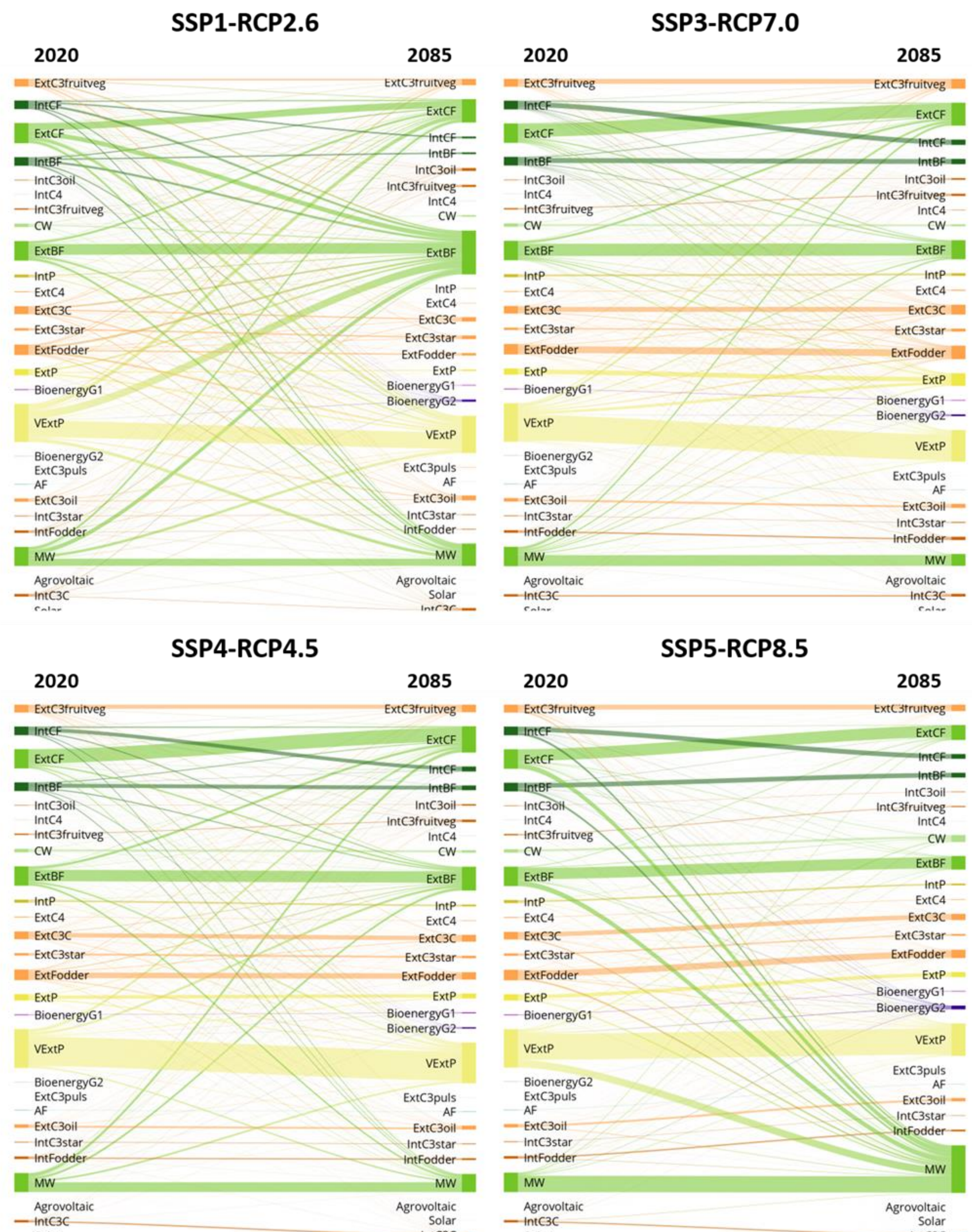


Figure 915: The distribution of AFTs in 2085 for the four scenarios, and associated Sankey diagrams showing land use transitions from 2020 to 2085.

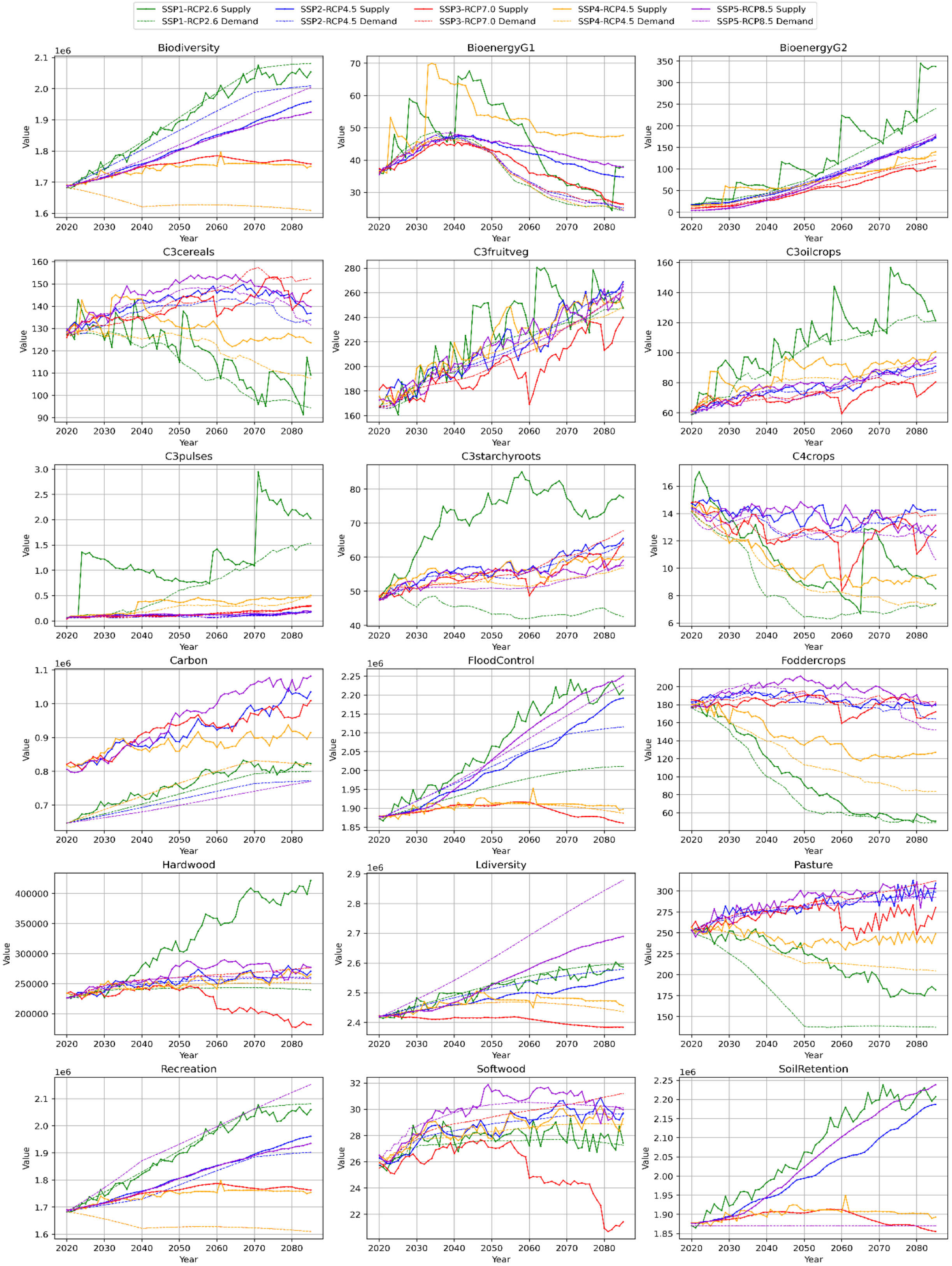


Figure 1016: Supply and demand curves of the ecosystem services in the simulation in relation to the baseline value.

8 Summary of model evaluation steps

In the table below, we summarise the model calibration and evaluation steps undertaken for CRAFTY-EU.

Table 7: Summary of model evaluation using the 'LUC-TRACE' framework (Brown et al. 2023), a model 'evaludation' approach that builds on the TRACE protocol for ecological models to give a comprehensive overview of model utility for land systems simulation. The evaluation steps applied are chosen according to their insight, feasibility and relevance to the model usage (for further details see Brown et al. 2023). The ODD protocol referred to in the table is in Appendix B.

Evaludation **step & substeps**		**Motivating question**	**Application to CRAFTY-EU**
1. Problem formulation		What is the model intended for? (To allow users to judge how appropriate it is)	Done - forms part of model documentation (see ODD protocol)
2. Model description		How does the model work?	Done - forms part of model documentation (see ODD protocol)
3. Data evaluation		What is the nature and quality of the data used to inform, develop, calibrate and evaluate the model?	Done qualitatively, with bulk of calibration work focused on data improvements (see above)
4. Conceptual model evaluation	System conceptualisation	How is the system conceptualised and are there matches & mismatches with the model?	Done – forms part of model documentation (see ODD protocol)
	Model design	How is the model conceptualised as a representation of the system?	Done – forms part of model documentation (see ODD protocol)
	System conceptualisation represented adequately by that design?	Explicitly, how do the system & model conceptualisations align?	Partially done in model documentation, to be completed as part of formal model publication (see Brown et al. 2022 for an example from another application of the CRAFTY framework)
	Problem relevance, e.g. Ability to handle scenario conditions	Can the model be used for its intended purpose given the system & model conceptualisations/designs – are aspects of the problem left out?	Partially done in model documentation, to be completed as part of formal model publication (see Brown et al. 2022 for an example from another application of the CRAFTY framework)
5. Implementation verification	Debugging / code testing (unit testing)	Has there been comprehensive testing of individual sections of code to ensure it (only) functions as intended?	Done
	Software verification/ Testing	Does the model as a whole perform as intended?	Done through extensive testing and calibration

	Usability tools design	Can the model be used and interpreted correctly given its design and description?	Done, for current users
6. Model output verification	Output verification/ Goodness-of-fit: data used in model development	Does the model fit the data used in its development?	Not yet assessed
	Output verification/ Goodness-of-fit: historical timeseries	Can the model reproduce timeseries?	Not yet assessed due to shortage of suitable data
	Calibration; Tests on environmental drivers	How was calibration used to achieve fit to data, and what parts/processes did it involve?	Done, described in this document
7. Model analysis and application	Sensitivity & uncertainty analysis	What are the effects of model parameters on outputs?	Partially done, formal analysis pending
	Robustness analysis; Simulation experiment	'Reasonableness' of model in known situation; do we understand how the outcomes arise?	Done through applications to different scenario conditions, not yet formally described
	Model stochasticity & stability	What effects do model stochasticity and instability have on the results?	Done for current runs, not yet formally described
8. Model output corroboration	Fitting to data "Output corroboration / Validation"	Can the model replicate patterns in independent data, including spatio-temporal, aggregate or otherwise emergent patterns?	Partially done for earlier versions of the model (e.g. Brown et al. 2019, 2021, 2022)
	Benchmarking against other models	Has there been comparison to independent data representing alternative modelling approaches?	Done for earlier versions of the model (e.g. Brown et al. 2021, Perkins et al. 2023)
9. Participatory/ companion modelling	Participatory model development/selec tion	Was the model developed or chosen through a process of user engagement?	N/A
	Details of use in participatory settings	Has the model been used in a participatory setting and what were the outcomes?	To follow
	Communication of results	What methods were used to communicate results, and how well did they work?	To follow
10. Model replication	Repeatability	Does the model produce consistent results across multiple runs?	Done but not yet formally described
	Runnability	Does the model produce consistent results on multiple computers?	Done but not yet formally described
	Reproducibility	Does the model produce consistent results when run by independent researchers?	Done but not yet formally described
	Replicability	Are consistent results produced by entirely independent studies?	Partially done using independent versions of CRAFTY code

9 Next steps

We will then use the fully calibrated CRAFTY-EU for a range of simulations within WP5:

- To analyse how forest coverage and management could differ in different socioeconomic and climate scenarios, according to the range of SSP-RCP scenarios presented in this deliverable.
- Using the behavioural model, we will explore the effect of accounting for the described intrinsic attitudinal and social factors into land managers' decision-making processes on the land use changes.
- To explore the effects of changes in a range of cases specified in Milestone 7, on ecosystem service provision, biodiversity and land use change. In particular, we will look at how changes in Protected Area coverage, deforestation rules and timber demand impact the land system relative to the baseline scenarios (SSP1-RCP2.6 and SSP3-RCP7.0).
- To identify policy pathways to a range of current EU policy targets and those proposed by stakeholders in WP6, using the institutional model described in section 6.

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Appendices

Appendix A

Table A1: Attributes and behaviours of an institution agent

	Name	Explanation
Attributes	Unique ID	A unique label that distinguishes an Institution from the others.
	Policies	A set that contains all policies.
	Information	A container where an institution saves necessary information supporting decision-making.
	Uncertainties	A list of variables determining the noise.
	Budget	A set of conditions that constrain the monetary sufficiency for implementing policies.
	Decision rules	A set of fuzzy rules reflecting how institutions make decisions.
Behaviours	Initialization	Set the initial values of institutional attributes.
	Information collection	Collect information from the target land use system.
	Prediction	Make predictions based on the collected information.
	Policy evaluation	Evaluate the performance of existing policies using PID errors.
	Resource allocation	Allocate the budget among multiple policies based on budget constraints.
	Policy implementation	Apply the resultant policy interventions to the target land use system.

Table A2: Attributes of policy

	Name	Explanation
Attributes	Unique ID	A unique label that distinguishes a policy from the others.
	Target service	In CRAFTY, the target service is the service an institution intends to influence with this policy. Technically, the target can be any modifiable variable in the model.
	Policy type	The type of policies can be taxes, subsidies, administrative orders, information, etc. Different types of policies can have very different ways to impact the target system.
	Initial guess	A value related to the initial policy intervention, which is generated based on the educated guess of model users. The initial guess is crucial for policymaking due to the path-dependency feature of complex systems.
	Policy inertia	Drastic policy changes are prone to encountering resistance from the public, interested parties, and physical limitations. Ideally, the inertia constraint serves as a comprehensive single indicator reflecting all non-monetary resistances to dramatic policy changes.

Policy goal	The ultimate policy goal that the policy is intended to achieve.
Intervention	The policy intervention implemented to influence the target land use system.
Evaluation results	Measured by the PIDs errors that reflect the gaps between the policy goal and target service.
Time lag	It takes time for policy interventions to become fully effective. Institutions also need time to respond to new challenges. The time lag depicts the duration between each two policy adaptations.
Timer	The timer is updated and checked every iteration to judge if it is time for policy adaptation.
Adapting	A Boolean variable signifying if it is the time for this policy to be adapted.
Intervention modifier	A variable that modifies the policy intervention based on the evaluation results.
Intervention history	A container to save the actual policy intervention in each iteration.

Table A3: Nomenclature

Variables	Variable meaning
T_s^{ij}	The time when institution *i*'s policy *j* starts.
T_e^{ij}	The time when institution *i*'s policy *j* ends.
Q^{ij}	The quantity of policy goal that institution *i*'s policy *j* is intended to change.
$\mathbf{G}^{\mathbf{ij}}$	A vector of $[T_s^{ij}, T_e^{ij}, Q^{ij}]$ defining the goal of institution *i*'s policy *j*.
$\varepsilon_t^{(P)}$	Proportional error.
$\varepsilon_t^{(I)}$	Integral error.
$\varepsilon_t^{(D)}$	Derivative error.
o_t^{ij}	Model output under the influence of institution *i*'s policy *j*.
$C^{(P)}$	The weight of proportional error.
$C^{(I)}$	The weight of integral error.
$C^{(D)}$	The weight of derivative error.
k	The time interval used to calculate integral and derivative errors.
E	Weighted sum of proportional, integral, and derivative errors.
F	A function representing a fuzzy logic controller that maps.
A_t^{ij}	The constrained policy variation of institution *i*'s policy *j* at time *t*.
$sign$	A function output -1, 0 or 1 according to the sign of its input.
N^{ij}	The policy inertia constraint of institution *i*'s policy *j*.
M_t^{ij}	A multiplier that modifies the institution *i*'s policy *j*.
η^{ij}	The step size of intervention institution *i*'s policy *j*.
f	A function that maps a policy intervention onto the resource needed for implementing this policy.
$V_{\mathrm{t}}^{\mathrm{ij}}$	Desired policy intervention without considering the budget constraints.
$R_{\mathrm{t}}^{\mathrm{ij}}$	The resource needed for implementing institution *i*'s policy *j*.

ξ_j	A weight reflecting the comparative importance of policy *j* perceived by institution i.
r_t^{ij}	Resource allocated to implement institution *i*'s policy *j*.
$r_{\mathrm{t}}^{*\mathrm{ij}}$	Optimal solution for r_t^{ij} under the budgetary constraints.
$V_{\mathrm{t}}^{*\mathrm{ij}}$	Policy intervention implemented using resource $r_{\mathrm{t}}^{*\mathrm{ij}}$.
B^i	Total budget of institution i.
c_{xy}	An AFT's competitiveness at land cell (x, y).
p_S	AFT production level of ecosystem service S.
V_t^{iS}	Institution i's economic policy that targets ecosystem service S.
m_S	Marginal utility of ecosystem service S.

Appendix B: An ODD protocol for the CRAFTY-EU model

Introduction: technical overview

CRAFTY-EU is an application of the CRAFTY agent-based modelling framework (D. Murray-Rust et al. 2014), which is an Open Source framework built on reusable software components, and is an independent piece of software written in Java. Interactions between components (agents, cells, regions etc.) is specified using interfaces that enable users to create their own configuration of model components. For example, the agent interface specifies that agents have a unique ID, have a current competitiveness and, among other things, belong to a certain Agent Functional Type (AFT; (Arneth, Brown, and Rounsevell 2014). As with other model components, a user may implement new agent types as long as they fulfil the contract of the interface.

To remove the need for high-level programming among model users, the CRAFTY framework and CRAFTY-EU itself can be configured and setup to run through the use of XML files. This is a form of declarative specification – the XML files declare which objects should take part in a simulation, and they are then passed over to a scheduling system. Each XML file defines one or more entities within the simulation, and will typically include other files for subcomponents. Model configuration is based on the principles below:

- A Scenario file encodes overall parameters of the simulation – the number of time steps (years) over which it will run, an ID for the simulation, the means of accessing input data and the required outputs (such as videos, images and tables).
- A World file defines the regions that comprise the simulated world.
- Each Region file specifies:
  - The coordinates and capital levels of the cells in the Region, typically using a CSV or ASCII raster file
  - The Allocation, Competition and Demand models used within the region, often using CSV files to specify time-varying quantities (e.g. changes in capitals and demand)
  - A set of agents and their properties, making use of CSV files as necessary.
  - Various land use raster data to protect or overload externally modelled land use changes such as urbanisation and protected areas.

In each of these cases, the files also specify the Java classes to be used along with their parameters, allowing users to incorporate their own code in the model.

In contrast to the declarative approach taken to configuration, CRAFTY uses a fixed schedule that encodes the flow of operations. To further enhance transparency of model behaviour, CRAFTY includes numeric and graphic displays for model variables. Spatially explicit outputs are also made available and include agent type, capital levels, competitiveness scores and supply of services. Any of these displays can be used to create animations of the model’s behaviour over time.

1. Purpose

CRAFTY-EU is an application of the 'Competition for Resources between Agent Functional Types' (CRAFTY) model framework, which was designed to allow land use changes to be modelled across large spatial extents. **The specific purpose of CRAFTY-EU is to allow exploration of European land system change under a wide range of climatic and socio-economic scenarios**, as outlined in Section 1 (Problem Formulation) above. The model allows the adoption of different land uses, variations in the intensity of land uses, diversification into multifunctional land uses, land abandonment and competition for land.

2. Entities, state variables, and scales

Spatial units CRAFTY-EU is based on a grid of *cells* at 1km^2 resolution. Each cell has defined levels of a range of *capitals*, which describe the availability of particular social, environmental or economic resources. Cells can be grouped into independent or semi-independent *regions*, but these are not applied in the default setup. A non-spatial population is assumed to exist and to generate demands for *services*, such as food, timber and access to nature. These demands are defined exogenously. Each cell may be managed by a single land use *agent.*

Agents Land managers are explicitly represented as agents in CRAFTY-EU (institutional agents can exist as well. Land management agents have functional and behavioural components to describe their forms of land management and decision-making. Agents are able to leverage the *capitals* available in a *cell* to provide a range of *services*. Each agent has a production function that maps capital levels onto service provision levels (see Sub-section 7. *Submodels*, ProductionProduction). An agent's *competitiveness* according to a given level of service provision can be calculated based on societal demands, supply levels and marginal benefit functions that define the economic and non-economic value of service production given the supply-demand difference at that point in the simulation.

Agents have several attributes that directly affect land use change, the two most fundamental being abandonment (*"giving up"*) and competition (*"giving-in"*) thresholds, which interact with other behavioural parameters. If an agent's competitiveness falls below their giving up threshold, which defines the minimum return an agent is willing to accept from a cell, it abandons the cell, which then becomes available to other agents. If an agent that does not currently own a cell has a competitiveness greater than an incumbent agent's, and if the difference is larger than the incumbent's giving-in threshold, the incumbent relinquishes its cell to the competitor – having been, in effect, 'bought out'. An agent searching for land can therefore only take over unmanaged (abandoned) cells, or those on which it can outcompete the existing agent. These processes are mediated by an abandonment probability that determines the likelihood of an agent abandoning their cell at any particular timestep, and search abilities that determine the number and order of cells that are searched for competition at each timestep (Table B1).

Agents are drawn from a typology that defines general characteristics of agents, and which is based on the Agent Functional Types (AFT) approach (see sub-section 4). As well as defining extant agents, the typology allows for new agents to be created, and for the comparison of productivity, benefit and other characteristics of "typical" agents of the type. These "Potential Agents" are used within the allocation process to represent agents who are attempting to find some land to manage, or to analyse the optimum type of agent to manage a given cell. Finally, individual agents of a given type need not be identical – all of the agent's characteristics can be drawn from user-definable distributions to provide within-type heterogeneity. See Table B1 for a complete list of agent variables.

Table B4: Variables of agents

Variable	***Description***
Typological variables (allowing for random individual level variation)	
Competition (giving-in) threshold	If a competing agent's competitiveness is greater than the incumbent agent's by a value larger than the giving-in threshold then the incumbent agent relinquishes that cell to the competitor.
Abandonment (giving-up) threshold	If an agent's competitiveness falls below its giving-up threshold (defines the minimum return an agent is willing to accept from a cell) it needs to abandon its cell(s) (with giving-up probability).
Abandonment (giving-up) probability	Probability for giving up in case the agent's competitiveness falls below the giving-up threshold
Optimal production	Amount of produced service in case of optimal conditions (all relevant capitals maximised)
Capital sensitivities	Sensitivities of production to capital values
Production model	Component responsible for calculation of service provision
Search ability	Comprising three parameters: the number of search iterations an agent type can undertake per timestep, the number of cells considered for competition during each search iteration, and the order (random or ranked) in which those cells are competed for.
Social networks	Comprising two parameters: the size and the effect of neighbourhoods within which agents of the same type benefit one another's capital, production or competitiveness levels.
Individual variables (do not exist at typological level)	
Competitiveness	Denotes the agent's current competitiveness value (calculated in-model)

Environment. CRAFTY-EU represents the European land system. Within this land system, heterogeneity is represented by capitals (economic, social, financial, manufactured, human and natural) that describe the locational attributes of each cell.

Scales. CRAFTY-EU covers the European (EU+3) land system at 1 km resolution. A time step in CRAFTY-EU represents a year by default, but this is not fixed and can vary to match the timescale of land use change decisions. This default is chosen for its consistency with the agricultural cycle, and agent attributes are set accordingly to give realistic rates of change (e.g. with lower likelihood of management change in forestry via increased giving-in and decreased giving-up thresholds). These can be set to match observed rates of change in management, but here a general maximum of 5% of cells is available for change in any one timestep. In the scenario applications of CRAFTY-EU, this is sufficient for the model to track scenario conditions.

3. Process overview and scheduling

At each modelled timestep, the level of service production achieved by an agent is given a benefit value via a function that relates production levels to unmet demand. Agents compete for land based on these benefit values, and this competition is affected by individual or typological behaviour, as defined above. Table B2 gives an overview of the CRAFTY-EU simulation schedule.

Table B2. Basic simulation schedule for CRAFTY-EU.

Timestep
1. Read in masks that constrain land use changes in this timestep (e.g. Urban mask) **2.** For each agent ∈ Agents a. Update competitiveness based on residual demand b. **If competitiveness < giving-up threshold, draw random number on [0,1] and compare against giving-up probability. If lower, abandon cell** **3.** For each region ∈ Regions **allocate-land:** a. Allocate most competitive agent type to unoccupied cells, if consistent with giving-up threshold and masks b. For each agent type *t* ∈ Agent Types, undertake *n* search iterations of *m* cells c. For every searched cell, calculate *t*'s competitiveness d. **If *t's* competitiveness > (cell owner's competitiveness + cell owner's giving-in threshold), and if permitted by masking rules, owner relinquishes cell** e. Agent of type *t* takes cell over, with parameters drawn randomly from typological ranges, if used. **4.** For each agent ∈ Agents Update supply of services produced **5.** (For each region ∈ Regions Update supply and unmet demand)

Figure B1 shows the flow of operation within each tick (or timestep). Each timestep starts by updating the decision-making context for land use agents – the levels of demand, capitals and any restrictions related for example to protected areas. Updates are made to the levels of demand across each region, and levels of capitals within each cell. These are loaded from external files, either as direct values or as functions to be sampled from on a yearly basis. Next, the land use agents respond and adapt to this altered context:

- First, each agent updates its level of supply, based on current capital levels. The total supply of each service is then calculated.
- Next, each agent's competitiveness is calculated on the basis of the difference between total supply and demand, and the valuation per unit unmet demand of each service.
- Any agents who give up are removed from the model.
- The active allocation procedure now runs, allowing new agents to take over unmanaged land and allowing other land transitions to take place.

Once all of the land use agents have been updated, final accounting is carried out, such as calculating total supply and demand, creating output files, displaying model state and creating videos.

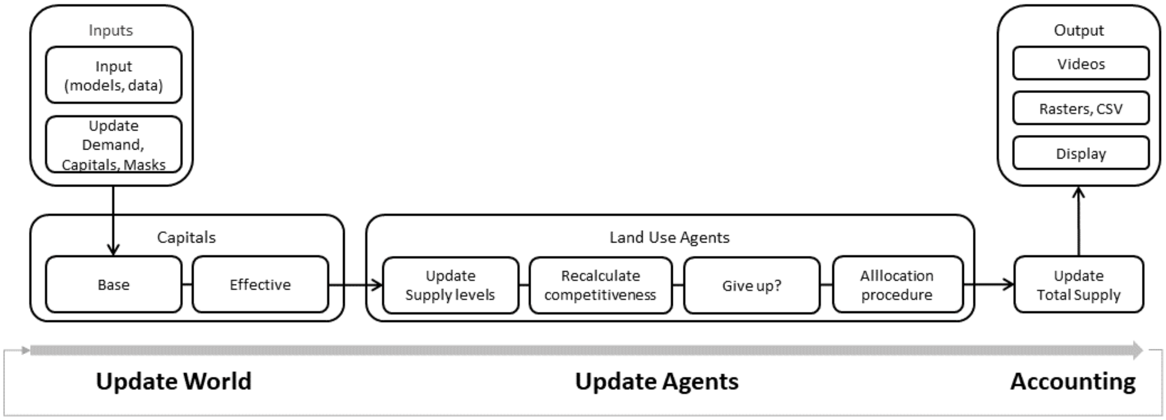

Figure B1. CRAFTY-EU flow diagram. This represents a single timestep for a single region.

4. Design concepts

Basic principles. The concept of Agent Functional Types is used to group land-use agents by their productive and decision-making characteristics. This typology is intended to allow generalisations of the attributes (traits) of individual actors in order to simplify model development and application, and to provide a transparent representation of agent decisional processes and behaviour. The AFT concept derives from a direct analogy with the use of Plant Functional Types (PFTs) in Dynamic Vegetation Models (Arneth, Brown, and Rounsevell 2014).

CRAFTY-EU inherits a number of design criteria from the CRAFTY framework on which it is based. These are:

1) The model must be able to run at 1km^2 resolution across national extent. This requirement holds for runtime costs, complexity, and the availability of data to parameterise and calibrate the model.
2) The model should take into account a wide range of societal demands for ecosystem services, including those that have no direct financial value.
3) The model must be able to represent multifunctional land use, and be responsive to the trade-offs between provision of various services.
4) The model should be able to represent the diversity of human behaviour that determines land management.
5) The model should be easy to refine and extend. This includes incorporating different data on services, capitals, land uses and agents, as well as adding complexity and variation to individual agents.

The decision making submodel (see sub-section 7. *Submodels*) acknowledges the existence of different modes of decision making like habits, heuristics and rule-based behaviour, and deliberative decision making. Decisions are triggered by certain environmental or individual conditions or changes thereof which are checked every time step of the simulation. Table B3 provides an overview of the main assumptions that guided the CRAFTY framework development, and which therefore underpin the operation of CRAFTY-EU.

Table B3: Design assumptions made in CRAFTY-EU

Model assumption	Details	Justification
Potential productivity of land can be represented by a range of capitals	Capitals representing natural productivity (for any good or service such as a specific food or timber crop) and any anthropogenic effects on productivity (such as availability of finance or infrastructure) can be used as a basis for the description of ecosystem services.	Well-established method of characterising and modelling land systems (Boumans et al. 2002; Scoones 1998; Harrison et al. 2013; Pedde et al. 2019).
Production of services by land managers can be described by a function dependent upon access to capitals and productive abilities, subject to individual-level random variation.	The ability of land managers to produce services is dependent on the underlying productivity and attributes of the land, expressed via capitals (above) and their individual or typological productive ability, which may depend upon a number of personal characteristics and behavioural factors. (The form of the production function is not set, but a Cobb-Douglas function is used by default).	An established method that allows for production levels to vary according to context and agent characteristics (Douglas 1976; Fulginiti and Perrin 1998; Martin and Mitra 2001).
The competitiveness of land managers depends upon demand for specific services.	Pre-determined demands exist for ecosystem goods and services, and land managers compete to satisfy these demands (where not satisfied by imports). Land managers are more competitive when they can produce greater (total) quantities of services for which there is unmet demand.	Demands for services are known to be expressed via the economic value of service production, and, in the absence of behavioural factors, land use is driven primarily by economics. Partly, decisions are made on grounds of non-monetary (or indirectly monetary) demands – e.g. for green space - and CRAFTY is designed to be capable of handling these, where they can be parameterised. No fixed assumption about the relationship between unmet (residual) demand and utility values (competitiveness) is made.
Land managers can be classified into Agent Functional Types according to their behaviours and functions.	The management practices and behaviours of land managers allows them to be classified into a typology analogous to the Plant Functional Types used in Dynamic Global Vegetation Models, increasing modelling efficiency.	The use of types increases computational efficiency by providing a description of land management and human behaviour at a level of abstraction that decreases the need for empirical parameterisation but retains the characteristics most important to large-scale land use change (Arneth, Brown, & Rounsevell, 2014).

Three mechanisms of land use change.	Land use (or ownership) changes when agents abandon land, take over unmanaged land, or take over managed land from the current owner.	Analogous to main forms of land use change in the real world.
Each cell is managed by a single agent	Multiple ownership of cells is not supported	The scale of application is not defined and so can be set to the appropriate scale of land holdings in any particular case (the minimum size of holding that is of interest to the modeller). Agents may be permitted to manage multiple cells. In CRAFTY-EU, a 1 km^2 resolution is selected as representative of typical land holdings.
Agents have a fixed set of potential actions	The set of potential actions an agent may select in decision making processes and perform afterwards needs to be defined and assigned beforehand.	The evolution of potential actions during the time span of simulation can be emulated by defining them beforehand and by their dependence on evolving capital and demand levels, which can in turn be affected by other model components.
Wide range of land-use relevant behaviour can be represented by 'giving-in' and 'giving-up' thresholds	Range of personal characteristics and behaviours known to affect land use decisions can be often abstracted in two values giving (relative) willingness of land managers to change land use or abandon land. Believed to be a necessary simplification for large-scale land use models that adequately mimics observed behaviour but can be 'overwritten' by more specific decisions (see sections Agents and Submodels, Decision Making).	Known that numerous factors affect personal decision-making (e.g. (Siebert, Toogood, and Knierim 2006; Gorton et al. 2008; Brown et al. 2020; Bartkowski and Bartke 2018) - too many to model or parameterise. Several studies have suggested that, for modelling purposes, a wide range of behaviours are reducible to a small number of dimensions similar to those used here (Berger 2001; Polhill, Gotts, and Law 2001; Siebert, Toogood, and Knierim 2006; Gorton et al. 2008; Dave Murray-Rust et al. 2011).
Knowledge and social influence flows over geographical social networks.	Land managers are connected via proximity-dependent social ties that transport information, norms and practices.	Adoption of management practices depends on horizontal spatial ties to institutions and organisations (Brown et al. 2020; Bartkowski and Bartke 2018; Brown, Alexander, and Rounsevell 2018).
Demand for urban land is not subject to competition with other land uses	Urban land is allocated externally to the model and acts as a mask for land use change within CRAFTY.	As a relatively small but essential land cover, urban land is likely to take precedence and is not currently modellable in the CRAFTY framework
Protected Areas can be represented as spatial constraints on the intensity of land management	Protected Areas are classified into two levels and used to constrain land use transitions between levels of intensity.	No fixed rules for land use change exist in most European protected areas but limits on intensification are consistent with objectives for environmental protection

***Emergence*.** Emergent effects that could be observed as outcomes of experiments using CRAFTY-EU are spatially explicit changes to land ownership and management, the intensification of land uses, including mono- or multi-functional land uses, changes in productivities and yields of different land uses, and total supply levels.

***Adaptation*.** Individual agents in CRAFTY-EU do not adapt their rules during a simulation run. However, the agent population adapts to changing conditions, and individual variation allows for adaptation in behavioural characteristics within types. Social interaction allows for indirect adaptation through alteration of capital values, allowing land management decisions to evolve and affect one another over time and space.

Learning. Agents can learn from neighbours to whom they are associated in social networks. This learning takes the form of improvements in capitals (e.g. representing knowledge), production or competitiveness, and is scaled by the degree of social networking.

Fitness. Agents' survival in the system depends upon their *competitiveness*, which is determined by an agent's ability to contribute to services for which unmet demands exist.

***Prediction*.** CRAFTY-EU allows for contingent, explorative prediction only – i.e. it provides realisations of outcomes given the set of input conditions and model design. It does not represent an attempt to predict real-world outcomes, although model results can speak to what these real-world outcomes might be, when properly interpreted.

***Sensing*.** Agents in CRAFTY-EU are aware of current demand levels and the production levels required if they are to avoid giving up their cells. They use the capital levels (attributes of a cell) to produce supply of services based on their respective production functions. Potential agents are aware of a defined number of abandoned/vacant cells that they may occupy depending upon their competitiveness. Agents are aware of the competitiveness of other agents in a region and may relinquish their cells to agents that are more competitive. Social networks allow agents to implicitly become aware of advantageous management practices used by their neighbours.

***Interaction*.** Direct interactions occur between new ('potential') and existing agents that compete for cell ownership. Interactions also occur within social networks, allowing changes to production conditions to be shared.

***Stochasticity*.** Agents can have individual variation in giving-up and giving-in threshold parameters, levels of service production, and the importance of each capital to service provision (each agent will have the same values throughout its lifetime, however). The allocation model includes stochasticity (representing agent-heterogeneity) as new agents consider only a limited number of cells on the grid, and the identity of these cells depends upon the random number seed being used. When giving-up probabilities are non-zero, there is stochasticity in giving-up events because the threshold is checked against a randomly drawn value.

Collectives. Two types of 'passive' agent collectives exist during a course of a simulation run. First is the list of agents that possess land parcels (cells) in a simulated landscape (grid), which can be global or regional in nature (covering the entire modelled land surface or some portion of it). Second is the list of potential agents that enter the system to takeover cells from existing agents (if possible) or occupy a vacant or abandoned cell on the grid. 'Active' collectives are those formed through social networks of neighbouring agents, defined by geographical proximity.

Observation. CRAFTY-EU can provide a range of observations and displays to help understand the model behaviour. Each of the submodels has a display, which is either numeric or graphical, showing curves for variables of note. A range of spatially explicit outputs is also available; these include maps of agent types, capital levels, competitiveness scores and supply of services. Any of these displays can be used to create videos of the model's behaviour over time. Output of a number of simulation data is possible in CSV or raster files. Table B4 gives an overview.

Table B4: CRAFTY output matrix

Data	CSV	Raster	Agg.CSV	GUI	Video
Agent ID	✓	-	-	×	-
LandUseIndex	✓	✓	✓	✓	✓
Capital levels	✓	✓	×	✓	✓
Service Demand	-	-	✓	✓	✓
Service Supply	✓	✓	✓	✓	✓
Productivity	✓	✓	×	✓	✓
Service Product.	✓	×	×	✓	×
Competitiveness	✓	✓	×	✓	✓
Giving In Thresh.	✓	×	×	✓	×
Volatility	×	✓	×	×	×
TakeOvers	×	-	✓	×	×
Performed Actions	✓	✓	×	×	×

5. Initialization

Initialisation proceeds through a set of interlinked XML and CSV files to allow the model's configuration by non-programmers. XML files define basic simulation parameters and provide properties for the initialisation of model components coded as Java objects, while CSV files provide data when there are many values required. The approach is highly flexible and extendable.

CRAFTY-EU initialises by reading the Scenario.xml file and follows the links therein to the configuration of outputs and the world configuration, which in turn contains links to regions and these to their model components like agent types, the competition model being used, or the allocation model. A cell.csv file includes the coordinates and capital levels of the cells in a region, the initial allocation of agents on these cells, and agent properties that are applied when these agents are initialised. Figure B2 gives an overview of a standard setting of XML and CSV files.

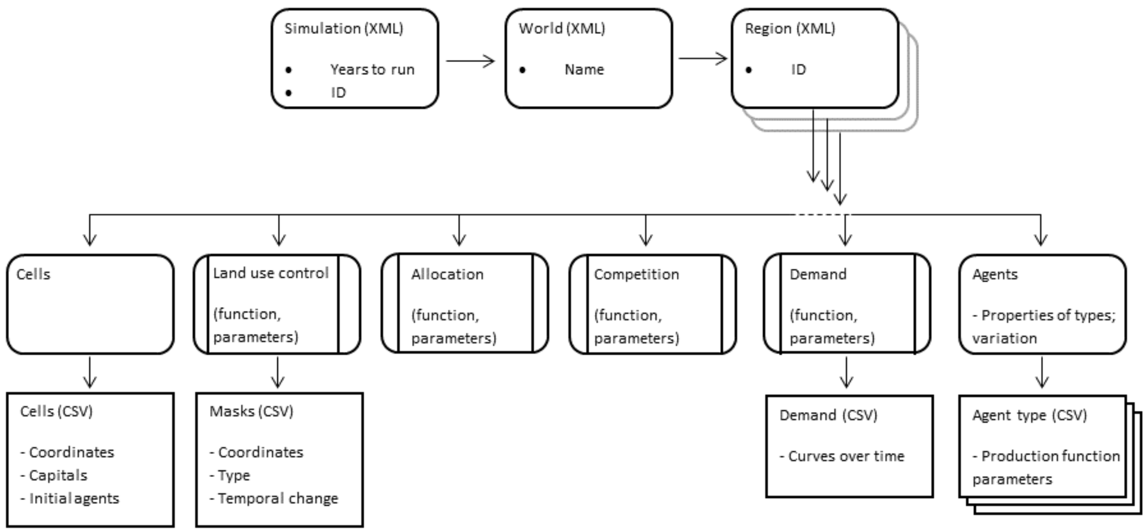

Figure B2: Overview of model configuration, showing relationships between files and what each file provides.

6. Input data

Input data are described in the main text of the report.

Scenarios

We use combinations of the Representative Concentration Pathways (RCP) climate scenarios (van Vuuren et al. 2011) and Shared Socioeconomic Pathways (SSP) socio-economic scenarios (O'Neill et al. 2017).

7. Submodels

Allocation Model. Land ownership within CRAFTY-EU changes according to three different mechanisms, which simulate both individual and collective aspects of land use dynamics. Firstly, agents may leave the model owing to a competitiveness score that falls below an agent's giving-up threshold. Secondly, when land is unmanaged, due to abandonment or lack of managers, it can be taken over by a newly created agent. By default, the set of potential agents is evaluated to determine their competitiveness score on each unmanaged cell ($c_{a,i}$). The agents are sampled such that the probability of an agent of type *a* attempting to take over a cell scales with its competitiveness on a cell with 'perfect' capital levels; $P(a) \propto c_{a,i}{}^{\gamma}$, where γ=0 gives a random selection and $\gamma \to \infty$ tends towards optimal selection. For more general land use transitions, an allocation procedure runs between existing and potential agents to determine ownership changes. This can include direct competition, where incoming agents attempt to take over existing cells; such an attempt succeeds where new agent has a competitiveness on the cell greater than or equal to the existing agent's competitiveness plus giving in threshold: $c_{new} \geq c_{curr} + giving\_up_{curr}$. Different allocation models are possible, however, and can be used to explore the relationships between human behaviour and local or global optimality. Once an agent is located, we assume it does not change location, due to the large costs involved.

Production function. Each agent has a production function, which maps capital levels onto service provision:

$$(1) \qquad P_S = F_A(C_i)$$

There is no limitation on the form of this function, but here a Cobb-Douglas style function is used to combine optimal production levels (o_s) with dependence on each capital to give service productivity:

$$(2) \qquad p_s = o_s \prod_C {c_i}^{\lambda_c} \ ;$$

where λ_c is a weighting factor specific to capital *c*.

***Population, Services, Demand and Utility*.** We assume that there is a population present in any given region with a level of demand for services *D*. At the same time, there is a supply of these services from within the region, and the difference between the two is the residual (or unmet) demand, *R*. The marginal utility of production (i.e., the utility attributed to the production of one additional unit of a service) is a function of this residual demand:

$$(3) \qquad m_s = u_s(r_s);$$

where m_s is the marginal utility, u_s is a function that describes the utility of production, and r_s is the residual demand, for service *s*. The form of the function u_s is linear by default. For a given bundle of service provision, an agents' competitiveness (or utility) is given by:

$$(4) \qquad U_S = \sum_S p_s m_s$$