

Backcasting/Transferability Concept

Project KNOWING

Work package 2, Deliverable D2.5

Backcasting/Transferability Concept



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List of Acronyms

CIC	Climate Impact Context
CMIP6	Climate Model Intercomparison Project
WP	Work Package
SWF	South Westphalia region
PCA	Principal Component Analysis
toe	Tons of oil equivalent

Glossary

Accompanying measures	Measures meant to reduce and/or avoid possible response risks and to enhance opportunities of specific mitigation or adaptation measures. They are implemented at the same time.
Adaptation	<p>The process of adjustment to actual or expected climate and its effects. In human systems, adaptation seeks to moderate or avoid harm or exploit beneficial opportunities. In some natural systems, human intervention may facilitate adjustment to expected climate and its effects (IPCC, 2014).</p> <p>This can be specific for climate change (United Nations Framework Convention on Climate Change, UNFCCC), but also apply for other challenges such as soil erosion, migration and structural economic changes. Adaptation can occur in autonomous fashion, for example through market changes, or as a result of intentional adaptation policies and plans at International, National or local scale (UNISDR, 2009).</p>
Adaptation measures	Adaptation measures are nature-based solutions, technologies, processes, and activities directed at enhancing our capacity to adapt (building adaptive capacity) and at minimizing, adjusting to and taking advantage of the consequences of climatic change (delivering adaptation) (Climate-ADAPT). Can be separated in: Hard and source-oriented measures, Hard and receptor-oriented measures and Soft measures (Glossary of the Clarity Proposal).
Climate impacts	The consequences of realized risks on natural and human systems, where risks result from the interactions of climate-related hazards (including extreme weather and climate events), exposure, and vulnerability. Impacts generally refer to effects on lives; livelihoods; health and well-being; ecosystems and species; economic, social and cultural assets; services (including ecosystem services); and infrastructure (based on IPCC, 2018)
Climate Impact Contexts (CIC)	Within KNOWING three CICs (heat & health, soil fertility and agriculture, flooding and infrastructure) are investigated, representing emerging risks for the demonstrators due to climate change.
Demonstrators	Regions that are part of the KNOWING consortium and for which the mitigation pathways are developed.
Domain models	A detailed computational model of a domain that covers its relevant structure and interfaces with other domains. A domain model incorporates both behaviour and data. In KNOWING, the used domain models can be classified into three main groups: Sector Models, Climate Models and Climate Impact Assessment Models.
Follower	Regions that are part of the KNOWING consortium and which represent the first regions for testing the transferability of the mitigation pathways developed for the Demonstrators.
Greenhouse gases (GHGs)	Gaseous constituents of the atmosphere, both natural and anthropogenic, that absorb and emit radiation at specific wavelengths within the spectrum of radiation emitted by the Earth's surface, by the atmosphere itself, and by clouds. Includes Water vapour (H ₂ O), carbon dioxide (CO ₂), nitrous oxide (N ₂ O), methane (CH ₄) ozone (O ₃) sulphur hexafluoride (SF ₆), hydrofluorocarbons (HFCs), chlorofluorocarbons (CFCs) and perfluorocarbons (PFCs).
Impact	<p>The impact can be measured in several ways: physical, economic, social, functional etc. and it can be evaluated as direct and/or indirect consequence of the event at a given time (snapshot) or projected in the future</p> <p>In literature impact is defined as "consequences of a hazardous event, on natural and human systems, once it materializes, i.e. actually affects a societal system.</p> <p>The term impacts is used primarily to refer to the effects on natural and human systems of extreme weather and climate events and of climate change. Impacts generally refer to effects on lives, livelihoods, health, ecosystems, economies, societies, cultures, services, and infrastructure due to the interaction of climate changes or hazardous climate events occurring within a specific time period and the vulnerability of an exposed society or system. The impacts of climate change on geophysical systems, including floods, droughts, and sea level rise, are a subset of impacts called physical impacts (IPCC, 2014).</p>
Impact Interaction Modelling Framework	In KNOWING, the Impact Interaction Model Framework (IIMF) consists of a system dynamics model, climate and domain models for integrated assessment of impacts (direct and indirect) of climate change, as well as mitigation and adaptation interventions

Interventions	A specific action that supports reaching defined goals or measures of mitigation or of adaptation (e.g. measure: reducing number of cars within city limits; intervention: increasing the parking fee by 50% within the city)
Land Systems	Land systems constitute the terrestrial component of the Earth system and encompass all processes and activities related to the human use of land, including socioeconomic, technological and organizational investments and arrangements, as well as the benefits gained from land and the unintended social and ecological outcomes of societal activities (van Asselen and Verburg 2012)
Mitigation	<p>In the context of climate change, and in this document, the term is used to indicate "a human intervention to reduce the sources or enhance the sinks of greenhouse gases (GHGs)" (IPCC, 2014), that are the source of climate change.</p> <p>It is also used to indicate the lessening or minimizing of the adverse impacts of a hazardous event (UNISDR, 2017), through actions that reduce hazard, exposure, and vulnerability (IPCC, 2014). However, this is not the meaning that is used in this document.</p> <p>Annotation: The adverse impacts of hazards, especially natural hazards, cannot be completely prevented, but their scale or severity can be substantially reduced by various strategies and actions. Mitigation measures include engineering techniques as well as improved environmental and social policies and public awareness.</p>
Mitigation measures	In climate policy, mitigation measures are technologies, processes or practices that contribute to mitigation, for example renewable energy technologies, waste minimisation processes and public transport commuting practices (IPCC, AR6)
Mosaic	A mosaic of land uses refer to a spatial mixture of different land use types within the same area such as a combination of forested and cropped areas (i.e., 'Mosaic of forest and agriculture')
Response opportunities	Potential for positive side-effects of responses. This can be on the sector associated with the response, or in other sectors, or on other societal objectives, such as the Sustainable Development Goals (SDGs) (IPCC, AR6).
Response (in climate adaptation and mitigation)	Actions or behaviours (including inaction) by individuals, groups, organisations, companies, institutions or governments related to climate adaptation and mitigation. This includes actions meant directly to reduce the impacts of climate change and or emissions (see 'adaptation measures' and 'mitigation measures') as well as actions or behaviours to reduce/capitalize on the intended and unintended consequences of such actions (see 'response risks').
Response risk	<p>Potential for trade-offs or negative side-effects from responses. This can be on the sector associated with the response, or in other sectors, or on other societal objectives, such as the Sustainable Development Goals (SDGs) (IPCC, AR6).</p> <p>Note: response risks may occur in the same sector or in other sectors.</p>
Strategies	Sets of measures, of either mitigation or adaptation. Strategies are commonly generated in advanced (climate-related) planning, at national, regional or local level.

1. Executive Summary

Climate change poses significant threats to global ecosystems, reducing land productivity for agriculture and forestry while negatively impacting human health. Although mitigation and adaptation strategies have been proposed, their real-world effectiveness remains uncertain, necessitating alternative approaches to tailor interventions to specific regional contexts. The suitability of measures such as wind turbines and solar panels varies based on geographic and socio-economic factors, emphasizing the need for fine-scale modelling. Backcasting methodologies enable the identification of necessary conditions for effective climate action, while spatial similarity analysis enhances the transferability of successful strategies to comparable regions.

This deliverable presents a system dynamics-based backcasting approach and a transferability framework, identifying archetypal regions in Europe to support the broader application of climate mitigation and adaptation pathways. Backcasting begins by defining a desired future goal in terms of climate mitigation and adaptation, then works backward to identify the necessary steps and strategies to achieve those goals. Through iterations and calibration, it ensures that the impact of combined mitigation and adaptation measures, forming pathways, is properly assessed and deemed transferable through the identification of exogenous variables. The transferability concept combines these exogenous variables with endogenous variables—categorized as socioeconomic, biophysical, land system, and future climate hazard and mitigation potential—to identify regions in Europe where similar mitigation and adaptation measures would be most relevant. The transferability concept is tested in a proof-of-concept at the European level through archetype and similarity analyses.

This proof-of-concept identified 16 archetypes of regions that capture Europe's diverse land-use structures and climate hazards, potentially aiding in determining where climate adaptation and mitigation strategies would be most effective. Urban archetypes highlight potential risks such as the urban heat island effect, while forest archetypes address concerns like wildfire risks and carbon sequestration potential. Agricultural archetypes distinguish between intensive and mixed land-use types, identifying areas for targeted mitigation efforts such as crop diversification and reduced livestock density. The transferability analysis identifies regions similar to South Westphalia (SWF), where climate mitigation pathways—such as afforestation—could be applied to other areas.

However, this proof-of-concept has limitations, including gaps in policy data, spatial resolution constraints, and the need for improved and more numerous datasets on existing mitigation efforts and other contextual variables. Future refinements could enhance the framework's applicability by incorporating more detailed regional policies, sector-specific economic data, and additional climate hazards such as coastal flooding and wildfires. The project's findings support policymakers in designing adaptable, region-specific climate strategies while ensuring broader scalability across similar regions.

2. KNOWING Summary

Climate change has been globally recognised as an existential threat requiring urgent action to avoid catastrophic consequences. Hence, the EU's Green Deal has been proposed “to make Europe the first climate neutral continent in the world”. This includes not only the elimination of net emissions of greenhouse gases by 2050; this is to be achieved while decoupling economic growth from resource use and striving for a fair implementation, leaving no person and no place behind. This ambitious goal is additionally challenged by the need to adapt to unavoidable impacts.

According to the EU's Climate Adaptation Strategy (COM(2021) 82), “improving knowledge and managing uncertainty” is key for realising the vision of a climate neutral and climate-resilient Union, as “Climate change is having such a pervasive impact that our response to it must be systemic”. Thus, there is an **urgent need for an integrated approach for enhanced understanding of the interaction, complementarity and trade-offs** between adaptation and mitigation measures, especially regarding the expected increase in regional mean temperature, changing precipitation pattern and soil moisture (IPCC AR6 WG I). Furthermore, this **understanding and knowledge needs to be provided to a broad audience to support local authorities** in EU countries for developing regional programmes. To achieve this

KNOWING aims to develop a **modelling framework to help understand and quantify the interactions** between impacts and risks of climate change, mitigation pathways and adaptation strategies. The framework will be used to assess the **interrelations between public and private adaptation and mitigation strategies** in order to **identify mitigation pathways along optimised combinations of interventions** in different sectors (e.g. energy, mobility, land use, construction, agriculture). The framework will focus on **three main Climate Impact Contexts (CICs)**: (1) Heat waves & health, (2) Soil fertility & agriculture, and (3) Flooding & infrastructure (including river and coastal flooding). It be applied **in four Demonstrator and five Follower Regions by involving authorities, stakeholders and citizens** to develop **enhanced activation and empowerment services, providing target-group-specific awareness, education and decision support tools** to improve the comprehensibility of complex interrelations and support strategic planning of combined adaptation and mitigation measures.

goal, KNOWING will produce the following **key exploitable results (KERs)**::

- KER1 an **Impact Interaction Knowledge Base** comprising causal relations of climate and intervention impacts, rebound effects, coping strategies, etc. to inform Climate-ADAPT and IPCC Working Groups I, II & III
- KER2 an **Impact Interaction Model Framework** consisting of a system dynamics model, climate and sector models for integrated assessment of impacts (direct and indirect) of climate change and countermeasures
- KER3 a Typology of transferable **Climate Mitigation Pathways** including optimised bundles of adaptation and mitigation measures for different typical Climate Impact Contexts (heat waves, soil fertility, flooding)
- KER4 **Climate Activation and Empowerment Services** addressing different target groups (citizens, businesses, authorities) to enhance climate literacy, provide playful trainings and support decision making

These results, developed with the support of an External Expert Advisory Board (EEAB) and a Stakeholder Reference Group (SRG), will **accelerate the transition to a climate-neutral and resilient society and economy** enabled through advanced climate science, mitigation and adaptation pathways and behavioural transformations. This Deliverable is part of WP2 and depicts the backcasting approach to analyze change in external drivers required to reach specific target and the transferability concept that analyze where local conditions in Europe could allow the implementation of similar pathways of measures.

3. Objectives of the Deliverable

The main objective of this deliverable is to document the backcasting methodology including specific conditions and the transferability concepts developed in Task T2.4.

- The backcasting methodology aims to optimize pathways from the present to a desirable, climate-neutral future by defining development corridors for Demonstrator Regions. The approach integrates quantified visions of desirable futures, ensuring that the combined measures are suitable, desirable and effective. The methodology will incorporate multi-sectoral modeling to identify potential interactions and countereffects between climate mitigation measures. It will establish clear backcasting conditions within a sustainable development framework, defining specific intervention corridors that align with stakeholder-defined visions. The process will be informed by Demonstrator Dialogues, where stakeholders and citizens outline regional priorities, adaptation needs, and suitable measures for achieving climate neutrality. These priorities will be quantified using indicator values related to environmental, economic, and social goals, including public health, infrastructure resilience, and local economic stability.
- The transferability concept aims to enhance the transferability of the model framework to other geographic areas. By analyzing the results from the Demonstrator Regions, a generalized framework will be developed to support adaptation in Follower Regions across Europe primarily and beyond in areas that would be suitable for mitigation and adaptation measure. This transferability will involve defining demonstration conditions that enable comparability and ensure that findings can be applied in different contexts. Follower Regions have committed to testing the roadmaps within their contexts, modeling their impacts, and validating results. The objective is to determine which measure-effect relationships are broadly generalizable and which require location-specific adaptations.

Ultimately, the deliverable aims to establish a robust framework for guiding regional development toward climate neutrality, ensuring that insights gained are scalable and applicable in diverse geographic settings.

4. Introduction

Major global environmental changes threaten the livelihoods of human beings on the planet (Callaghan et al., 2021). Among these changes, climate change is likely to reduce the capacity of land for agricultural and forest production (van Dijk et al., 2021), while also having negative impacts on people's health (Whitmee et al., 2015). The IPCC has been producing global and national estimates of climate change pathways, impacts, and associated solutions to address it through mitigation and adaptation practices (IPCC, 2022). However, although average estimates of effects have been generated for these mitigation and adaptation practices, empirical evaluations of their significant implementation are still lacking. It is crucial to determine whether these practices can genuinely help achieve global and regional targets, such as the average reduction of human carbon emissions to 1.6–2.8 tCO₂ of CO₂ equivalent per capita per year to limit warming to 1.5–2 °C (Bruckner et al. 2022) or the protection of 30% of land for biodiversity (Maxwell et al. 2020). However, considering the inner diversity of regions worldwide and even within continents, a fine-scale modelling approach for all regions is not possible. Alternative approaches are then needed to find ways to determine what mitigation and adaptation measures (interventions) can be effective in different contexts.

The success of mitigation and adaptation interventions depends on the potential effects of those interventions. For instance, wind turbines are effective in reducing electricity production from non-renewable sources that emit GHG, but not all areas are suitable for wind turbines due to land and human settlement constraints. The relevance of interventions also depends on their ability to produce significant impacts. Solar panels are virtually suitable in many areas, but their ability to produce energy will depend on the amount of radiation in the regions. When it comes to adaptations, capturing the likelihood of different regions of experience certain climate hazards is of outermost need in order to tailor interventions that can decrease the risk of impacts. For instance, climate change is likely to increase the average temperature which will result in increased risk of urban heat island effects with detrimental effect on urban population in different areas (Mentaschi et al. 2022).

Generic models of regional functioning that connect different sectors are also of relevance to capture the chain of causes and consequences that one intervention can have on an entire system. Several system dynamics models operating at global scale have been proposed to show the effect of climate change mitigation or adaptation interventions like the En-ROADS model that allow for online simulation to test and explore cross-sector climate solutions. This type of model simulates measures at global scale, but its functioning does not allow to explore the potentials of interventions on regional or city scale as it does not allow for accounting for regional key characteristics in terms of land use, energy system, particular climate hazard, and local trade-offs associated with mitigation or adaptation pathways.

Scaling out place-based knowledge can help the design of scenarios in support of sustainability transformations (Ehrensperger et al. 2019). For example, the transfer of solutions through learning could be directly explored in locations that are contextually similar to the case studies where the solutions are

generated (Diogo et al. 2023). As scenario analysis are conducted in specific geographical location, the genericity of their outcomes can be questioned for other regions. We consider that similar regions would behave similarly, making the scenario outcomes also relevant for them. It is then necessary to characterize the level of similarity in regions and the level at which similar characteristics lead to relevance for scenario outcomes. By modelling the implementation and potential efficiency of adaptation and mitigation measures at local scale, we are able to identify the relevance of some characteristics that drive this efficiency. We can then spatialise these characteristics at large scale to identify areas where the set of conditions for efficiency and success of implementation of mitigation and adaptation measures is met.

In this deliverable, we present a SD-based backcasting concept to learn from case studies in terms of determining factors that can drive the success of interventions in various areas. We later produce a transferability concept based on multidimensional statistics to identify regions where pathways could be successful in terms of mitigation and adaptation to climate change. We illustrate this transferability with the identification of archetype regions in Europe and areas similar to the KNOWING Demonstrator regions, namely South Westphalia, Tallinn, Naples and Granollers, in terms of key characteristics.

5. Methodology

The methodology described here takes stock of the different Demonstrator regions by integrating their functioning in terms of ability to meet mitigation and adaptation goals in time (e.g., reduction of emissions by 80% by 2050) and identifying the key system variables to meet these while looking at the current values of such parameters across Demonstrator regions.

5.1. Overview of the methodology

The methodology in this deliverable is split into two main parts namely the backcasting (in red in Fig.1) and the transferability analysis (in green in Fig.1). The backcasting approach addresses the problem of identifying suitable pathways (sequences and combinations of policy interventions) to approach predefined mitigation and adaptation targets for a specified region; the transferability approach addresses the question how far such pathways can then also be applied to other regions.

The backcasting approach uses a system dynamics (SD) model that allows representing the links between the different sectors (forest, energy, agriculture, transport, etc.) within a certain region. The derivation of important set of contextual drivers (i.e., the socioecological variables) from the backcasting approach can allow to identify areas where the set of conditions is the same that would then allow for the potential transfer of successful pathways. The backcasting uses target-based objectives and explores what is the combination of contextual variables (in particular those that can be influenced by policy interventions) that makes it possible to meet the targets set by the user.

The transferability analysis uses a framework of adaptation and mitigation to climate change which comprises a set of variables representing the socioecological systems: socioeconomic drivers, biophysical variables, land systems and climate change mitigation potential and risks. The variables are used for producing a representation of regional archetypes found in Europe which are an ensemble of regions with similar socioecological functioning where we assume that within the same archetype the same pathways of climate change adaptation and mitigation measures would be relevant. In parallel, a similarity analysis is conducted to gauge the similarity of all regions within Europe to our KNOWING Demonstrator regions, tested here in South Westphalia assuming that the more similar the more relevant pathways in Demonstrator regions will be. This similarity analysis provides a complementary quantitative indication of the similarity in regions compared to our demonstrators.

While the methods for transferability analysis have already been applied in a proof-of-concept that will be described in chapter 6, the backcasting concept can only be covered in a theoretical way within this deliverable, since the calibration is currently still ongoing in Task T2.3. Examples of applying this approach to the final calibrated SD model will be included in Deliverable D2.4.

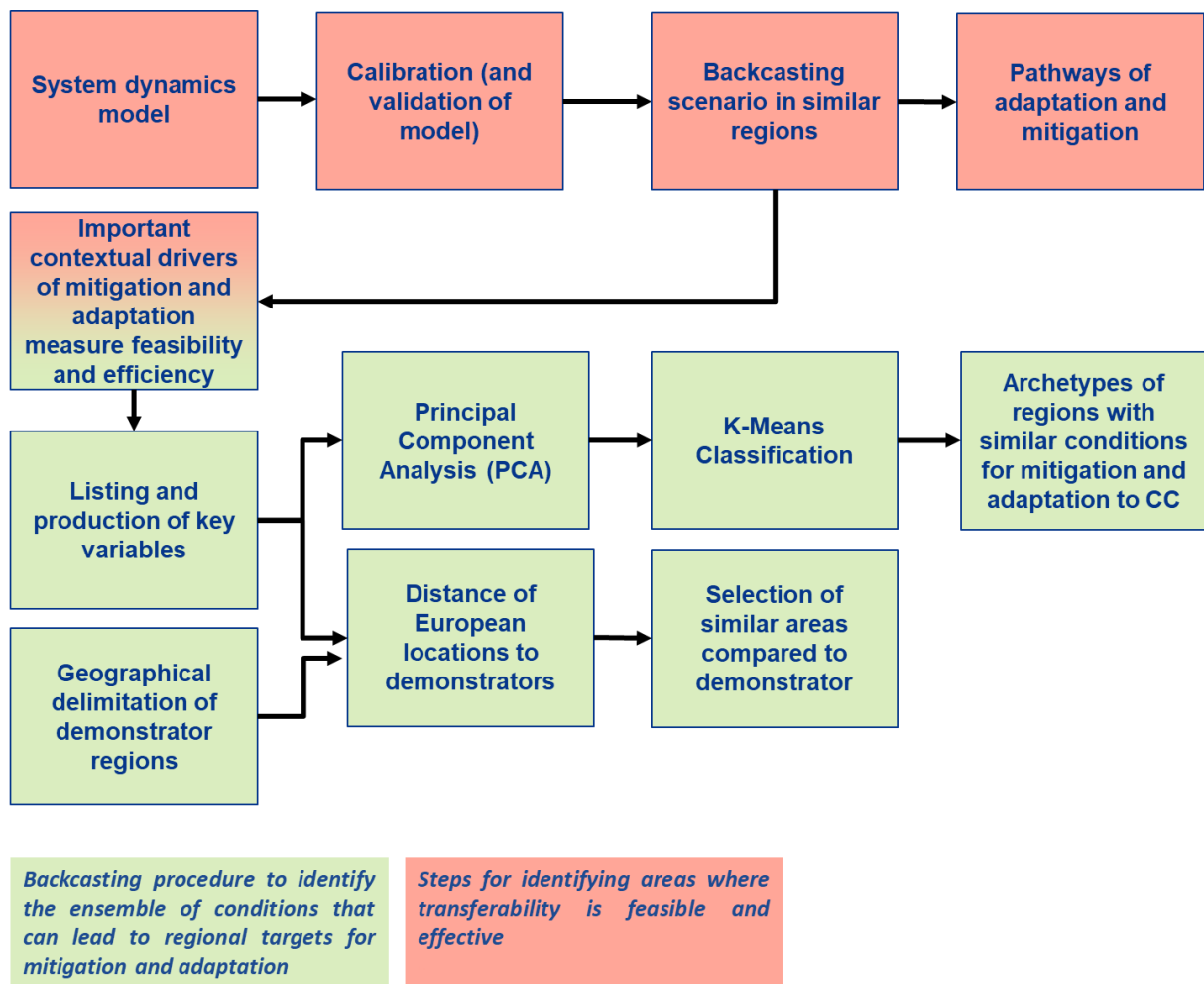


Figure 1: Methodological framework to explore potential areas where mitigation and adaptation pathways can be locally relevant in comparison to KNOWING Demonstrator regions.

5.2. Backcasting concept

As outlined in the previous section, the backcasting approach in KNOWING is based on the development of a system dynamics (SD) model that comprises the various cross-dependencies between sectors and domains¹, and that is informed by the results of all the domain model runs applied for the four KNOWING demonstrators in WP3.

In the following sub-sections, the basic concepts of this approach will be described in some more detail.

¹ The term „domain“ extends the originally used term “sector”, since it comprises parts of the overall system (sub-systems) in a more general way than just sectors, often interpreted in an economic sense. The specialised models applied in KNOWING are therefore referred to as “domain models” and comprise sector models, climate models and impact assessment models.

5.2.1. Definition of backcasting

Backcasting is widely understood as a planning method today that starts with defining a desired future goal and then works backwards to identify the necessary steps and strategies to achieve that goal. Unlike forecasting, which projects future developments based on current trends, backcasting focuses on what needs to be done today to reach a specific long-term vision.

The term “backcasting” was originally coined by Robinson as a method to define future scenarios and to investigate their effects (Robinson 1982). Backcasting means defining future goals without current restrictions in order to be able to answer the following questions: “What shall we do today to get there, and what measures may lead into blind alleys and should be avoided? (Bibri, 2018).”

A paper by (Höjer, 2000) demonstrates four backcasting steps as following:

1. the setting of a few long-term targets
2. the evaluation of each target against the current situation, prevailing trends, and expected developments
3. the generation of images of the future that fulfil the targets
4. the analysis of images of the future in terms of feasibility, potential, and pathways toward images of the future (Akerman, 2006)

While there has been wide adoption of backcasting as a participative (and more qualitative) method in the past, the combination with more formal methods within modelling (supporting quantitative outputs) is not very present in the literature. This seems a bit surprising, since a system dynamics-based modelling approach is particularly suitable for backcasting due to its inherent support of modelling long-term behaviour of the overall system along a certain pathway, avoiding the traps of local, sector-specific or short-term optimisations.

There is a widely used concept, however, in system dynamics that corresponds to the basic ideas of quantitative backcasting – Policy optimisation: Supported by SD Modelling platforms like Vensim, optimising engines can search through a large space of parameter values (representing all possible interventions), looking for “optimal solutions”. These optima are defined by means of payoff variables. Efficient algorithms then search through the parameter space looking for the largest cumulative payoff. In principle, there are no limits on the numbers of payoff variables or policy parameters to search over; in practice such optimisation problems in complex systems can become extremely challenging, however, due to the high number of dimensions. Also, the time dependency of policy parameters (interventions) adds to this complexity: Some interventions might be most critical right now, others will only contribute decades later, when the system has undergone a series of transformations.

Common to both a participative qualitative backcasting approach and a quantitative policy optimisation is the importance of a planned future development towards specific long-term goals, emphasizing a structured, step-by-step progression over time – the concept of Pathways that will be elaborated in the next sub-section.

5.2.2. KNOWING Pathways

In analogy to a physical pathway (towards a destination point) several key aspects of goal-oriented development are important for the understanding of pathways:

- **Sequential Steps & Directionality:** A pathway suggests a logical sequence of actions that must be taken in a particular order to reach a desired outcome. Just like walking along a path, each step builds on the previous one, preventing abrupt jumps or unrealistic leaps forward.
- **Adaptability & Course Corrections:** Paths can have alternative routes (e.g., which interventions to prioritize first), detours, or adjustments, reflecting the flexibility needed in real-world planning. If conditions change (e.g., new technologies, policy shifts, unexpected obstacles), the pathway can be adjusted continuously, while still aiming for the original goal.
- **Long-Term Perspective:** A pathway typically covers an extended period, recognizing that meaningful progress, especially in areas like climate change mitigation and adaptation, economic development, or urban planning, takes time. The idea of a pathway underscores that transformation is gradual and cumulative.
- **Milestones & Waypoints:** Just as physical paths have checkpoints (e.g., road signs, landmarks), planned pathways include milestones—key achievements that indicate progress. These could be intermediate targets like carbon reduction benchmarks.²
- **Complexity & Interdependence:** Many development goals involve multiple interacting factors (e.g., policies, technologies, behaviours). A pathway captures this complexity by laying out a coherent, interconnected sequence rather than isolated actions.
- **Predictability & Risk Management:** A well-planned pathway allows for better forecasting and risk assessment, making it easier to anticipate challenges and develop strategies for overcoming them.

For illustrating this long-term perspective of pathways, the key inputs and outputs of the KNOWING SD Model are shown in a schematic way in Figure 2. This is also referred to as “Reference Mode” in System Dynamics – it is used to describe the historical and – in this case more important - expected future behaviour of a system as a whole over time. The main message here is that the key outputs (CO2 emissions at one hand, and various impacts from climate change hazards on the other) are influenced by mitigation and adaptation interventions as the key input variables, where these causal relationships get more complex due to the mutual cross-dependencies. From a backcasting perspective, this causal direction can be reversed in the policy process: Starting from defined targets at a certain time point in future (visualised as green dots for 2050), the SD model should answer the question which mitigation and adaptation interventions (as a function of time) will result in the achievement of these target values.

² Some targets might be a “must” to reach, for others a range could be used, resulting in minor adjustments of the pathway.

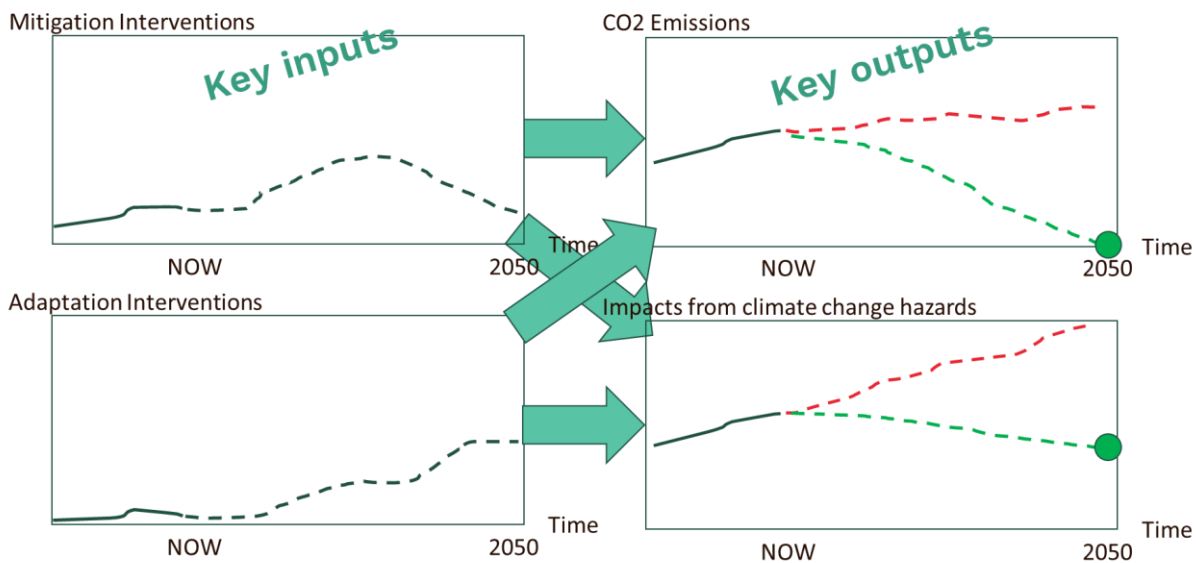


Figure 2: Basic inputs and outputs of the KNOWING SD Model (reference mode)

While the resulting pathway can be quantitatively described by such behaviour-over-time graphs (both for input and output variables), it can also be visualised in a geometrically more intuitive way, highlighting the analogy with physical pathways shown on a two-dimensional map. Think of the two “orthogonal” key output variables depicted above, which might also be reformulated as positive variables (“more” is better) directly corresponding to “targets” (e.g. *emission reductions* as mitigation target and *resilience against flooding events* as adaptation target). Then a pathway can be represented as a line in the two-dimensional target space, connecting the present with the point representing the desirable future (the “Vision”).

The method of displaying pathways in a two-dimensional target space also offers an intuitive way to:

1. Modify an initial pathway in such a way that its endpoint moves closer to (and ultimately coincides with) the defined vision – this process can be achieved with the policy optimisation described before, defining a payoff based on the targets,
2. Compare different pathways, which already lead to the desired vision but take alternative routes – such alternative pathways might result from different starting conditions and stakeholder priorities in the backcasting process. The simplified visualisation in a two-dimensional space might help stakeholders to understand better the consequences of their decisions, and to reconsider their priorities.

The iterative refinement of a pathway in two-dimensional target space is depicted in a schematic way in Figure 3. Note that it must be ensured that the SD model can represent the whole pathway connecting the present with a desired vision of the future. If the calibration of the SD Model [cf. Deliverable D2.3] has been performed along the initial pathway only, additional calibration points might be beneficial if the final pathway covers other regions in the parameter space. These relationships are also discussed in the next subsection.

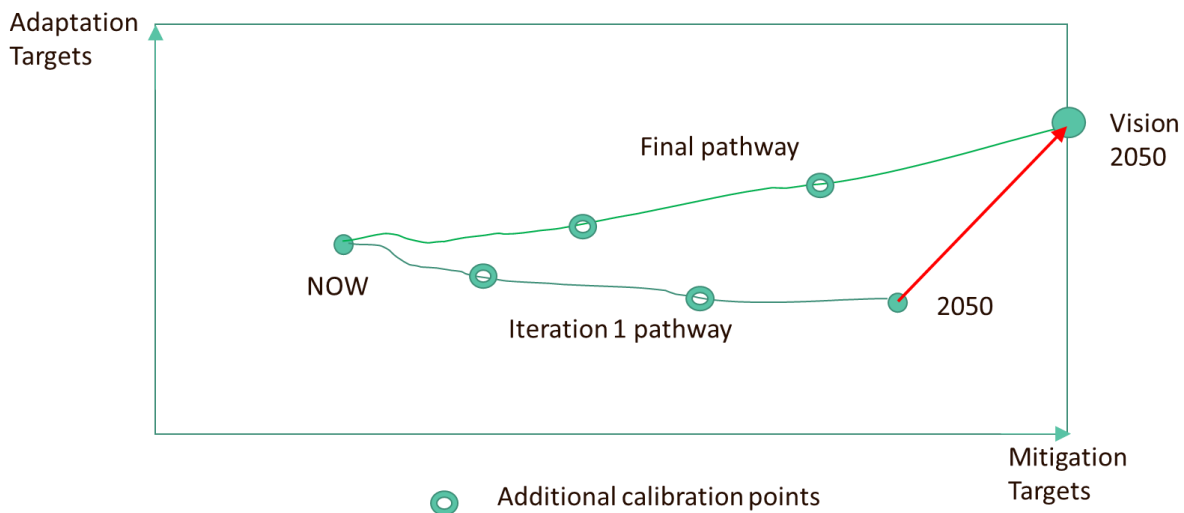


Figure 3: Visualisation of a pathway and its refinement in the backcasting process in the two-dimensional mitigation-adaptation target space

5.2.3. Integrated consideration of calibration, backcasting and transferability

Calibration, backcasting (or policy optimisation) and transferability are usually seen as separated steps in the modelling process. From the SD modelling approach followed in KNOWING, it is useful, however, to consider these steps in an integrated way and discuss how they relate to each other.

As any SD model, the KNOWING SD model contains a variety of exogenous model variables, i.e. variables that do not depend on any other model variables. These, in general, can still vary over time (e.g. population size, with some assumed growth rate over the next decades); some of these variables are time independent, however (constants), or their time dependency is neglectable for the purpose of the model.

Analysing variations of *all* these exogenous input variables gives valuable insights to model behaviour, the interpretation differs significantly, however, between three different types of these variables (corresponding to three main steps in the KNOWING modelling process):

1. *Calibration parameters* are varied to find out the best match between results of SD (sub-) models and domain models. Once their values have been determined in the calibration process (as described in Deliverable D2.3), it can be assumed that the SD model captures the overall system behaviour reasonably well along the (initial) pathway corresponding to the individual domain model runs.
2. *Intervention variables* (all model variables representing mitigation and adaptation policy interventions) are varied to analyse and optimise the initial pathways resulting from the model after step 1 (the calibration). This variation might comprise both “policy optimisation” runs (as supported by the Vensim platform) and a participative process with the stakeholders, in order to

figure out which modifications of policy strategies might be acceptable. The application of such a backcasting approach in the final calibrated SD Model will be described in Deliverable D2.4.

3. Finally, there are *other exogenous variables* which are specific to a certain demonstrator, and which have been taken over in the SD model from the various domain models. Under the pre-conditions that (i) the values of these variables are known for other regions, and (ii) these regions can be considered as “similar” according to the similarity analysis as described in section 5.5, a corresponding (small) variation of the pathway might be applicable for these other regions. Extending the application of the SD Model in such a way to “Follower regions” goes beyond the originally planned scope of the project; nevertheless, this approach will be tested in the context of Task T3.5 (Generalise Climate Mitigation Pathways).

Two additional “feedbacks” within that process might be mentioned here: As already discussed in the previous subsection, a recalibration might be useful after a pathway is significantly altered in step 2 (backcasting), compared to the initial pathway. And finally, the similarity analysis as described in this deliverable might also be used to connect step 3 (transferability) back to step 1 (calibration), estimating the unknown values for calibration parameters when no domain model runs are available for calibration, and then re-iterate step 2 (backcasting) to obtain adjusted pathways.

A schematic view of this approach is shown in Figure 4.

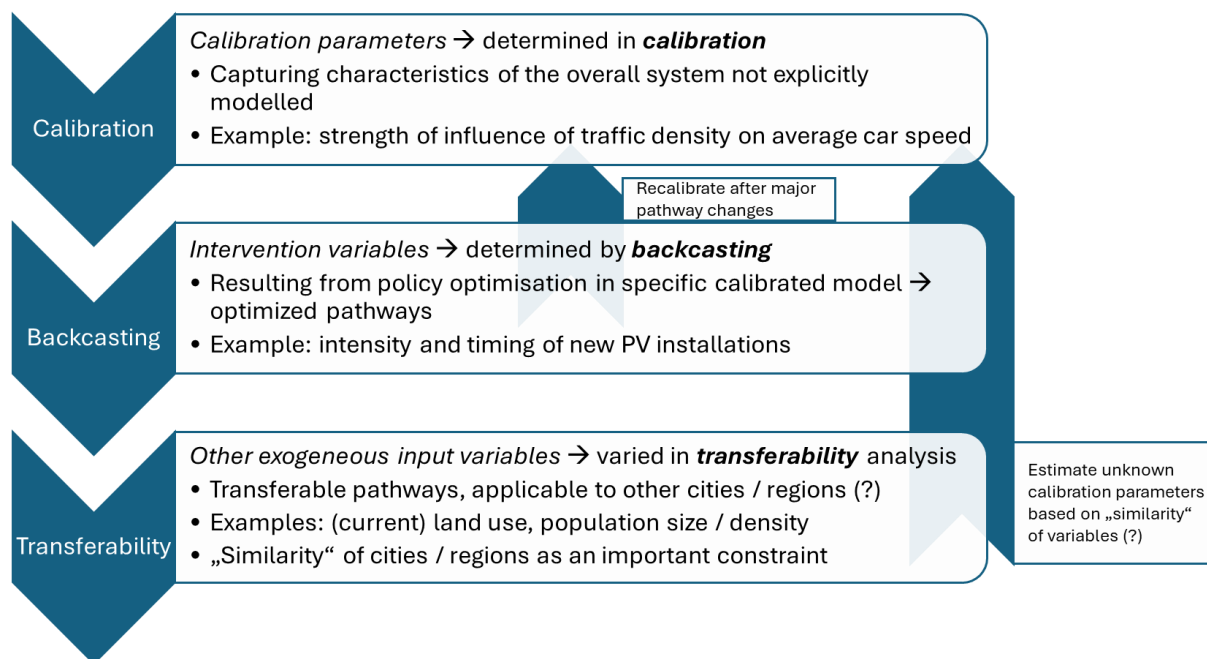


Figure 4: Schematic view of the three steps calibration, backcasting and transferability – and how they are related to each other within the SD modelling approach

5.2.4. Enhanced methods

Finally, two potential enhanced methods are briefly presented here that might support the backcasting process. Note that these have been tested or applied in other contexts already, but a proof of concept

within the KNOWING approach is still outstanding – because the current state of both the calibrated SD model and the dataset for the transferability analysis is not yet mature enough.

1. Analysis of Dynamic Models by Optimization (ADMO) (Moxnes and Naumov 2024): ADMO can evaluate the influence of exogenous variables and nonlinearities, leading to new understandings of endogenous behaviour and providing insights for policy design. It can in particular help to highlight which interventions are critical at which time along the pathway to reach the final vision.
2. Entity embeddings / collaborative filtering: This technique might be applied for estimating the unknown values for calibration parameters when no domain models runs are available for calibration (as mentioned in the previous subsection). It would be based on complementing the similarity concept of regions discussed in this deliverable with a similarity concept of variables. Variables which are “similar” would show a high level of correlation: If the value for variable A is very high in a specific region, then the value for a similar variable B could also be expected to be very high. Basically, collaborative filtering can be considered as an approach based on linear algebra that fills in the missing values in a matrix and therefore can address the problem of data scarcity. This technique is well supported by state-of-the-art machine learning platforms (see , refer e.g. to (Gugger and Howard 2020; Chapter 8).

5.3. Variables of use for Transferability analysis

The choice of spatial variables for assessing geographic representativeness should not be based purely on data availability, but rather address the question: ‘representative for what purpose?’ (Diogo et al. 2023). A list of characteristics can be compiled from many publications addressing the drivers and outcomes of land system change in urban, forest and agricultural areas such as land use intensity in Europe (Levers et al. 2016) or change trajectory (Levers et al. 2018) (see Table 1). A large range of studies also looks at the spatial drivers of location of land systems or some of their characteristics like decision making of actors across land systems (Malek and Verburg 2020). Suitability studies approach gather different factors and assume that combination of factors create niches or areas where some management practices are favourable (e.g., wind turbines implementation, urban green spaces, afforestation) (e.g., Fayet and Verburg 2023). Constructing such archetypes or niches should make it possible to make recommendations for sets of mitigation practices in Europe (Görbig et al. 2024). The geographic representativeness of each individual site in relation to the European context was then assessed separately for different social-ecological dimensions considered in the conceptual framework, specifically: socioeconomic drivers, biophysical context, land system and climate mitigation potential and hazards. A list of all variables used for testing the transferability concept is presented in Table 1. The list of variables is partly constrained by data availability and spatial resolution. The transferability analysis aims to account for different types of data to derive implications for adaptability in various regions. However, for some dimensions, data availability remains limited. This is particularly true for socioeconomic data, which are mostly available only at the NUTS3 level. Conducting the analysis at the NUTS3 level would have been possible, but it would have required using average biophysical and land system information for each NUTS3 region. Yet, within a single NUTS3 region, diverse situations often exist, making such averaging less meaningful. For instance, a NUTS3 region may include large urban areas where small patches of green space could be targeted for carbon sequestration, alongside extensive forested areas where afforestation with mixed species might be more appropriate. Consequently, the choice was made to attempt transferability analysis at a finer spatial scale (5x5km) to capture the heterogeneity of climate intervention opportunities at the landscape level.

The objective of the following transferability analysis was to provide a proof of concept for the proposed approach—both in terms of methodology and resolution/scale. The outcomes are intended to inform subsequent iteration in D3.5, where the approach may be further developed through the inclusion of additional datasets or by adapting the scale to integrate a broader range of data sources.

Table 1 List of potential characteristics driving the behaviour of regions

Category	Name	Description	References
Socioeconomic context	Population density	Number of inhabitants at 1 km resolution	Eurostat - JRC
	GDP density	Gross domestic product as of 2005 downscaled a 1km resolution	(Wang and Sun 2022)
	Energy consumption per capita	The energy demand is expressed in tonnes of oil equivalent (toe)	(European Commission, Joint Research Centre (JRC))
Biophysical external drivers	Elevation	Altitude above sea level in m	(EEA 2016)
	Slope	Slope in degrees derived from the elevation map	(EEA 2016)
	Mean annual precipitation	mm	(Karger et al. 2017)
	Mean annual temperature	Annual mean temperature in degrees Celsius ° C	(Karger et al. 2017)
System variable	Prop. Arable land Prop. Urban Prop. Forest	Corine Land cover dataset with aggregated land use categories	(European Environment Agency (EEA) 2018)
	Land use intensity	Application of mineral nitrogen fertilizers from CAPRI	(Britz and Witzke 2008, p. 2)
	Grazing	Probability of grazing	(Malek et al. 2024)
	Road density	GRIP Global roads database	(GLOBIO, 2018)
Climate hazards and mitigation and adaptation potential	Vegetative cooling	Proportion urban green space. We found NDVI as a reliable proxy of UGS coverage relative to other UGS characteristics (Ju et al. 2024)	Copernicus (2020)
	Risk of river flooding	Areas affected by a flood with 100-year return interval	(Baugh et al. 2024) (JRC)
	Heatwave days	The count of climatological hot days in a year. A climatological heat wave is a period of at least three consecutive days exceeding the 99th percentile of the daily maximum temperatures of the May to September season during a reference period.	(Copernicus Climate Change Service (C3S) 2024)
	C sequestration potential	Soil Organic Carbon - Saturation Capacity in Europe	(Lugato et al. 2016) (JRC)

5.3.1. Socioeconomic context variables

Socioeconomic context variables represent variables that will impact the way regions will develop their agricultural/forest production, energy system set up, transportation, industrial and housing systems. Typically, the characteristics of the population shape the socioecological system in several ways. For instance, higher population lifestyle, increases demand for goods and services, leading to intensification in use and consumption of resources. So high lifestyle with emissions will be potential characteristics associated with the relevance of climate mitigation measures related to lifestyle like transport mode or energy consumption. This information is generally heterogeneous within the population of a single area and is also rather difficult to approach especially beyond single individuals. In order to summarize this

information, we have integrated three variables that capture this simply through the population number, the GDP and the energy demand.

Population data represents the number of inhabitants in region which is of use to represent the number of population potentially affected by climate change stressors occurring in the future. Population was represented using population density data for the number of people per 1x1 km from 2018 JRC census data, which were then upscaled to 5x5 km resolution.

Economic data: GDP is the most commonly used indicator to assess and compare economic development within and across countries. The data used in our study (Wang and Sun 2022) uses Gridded GDP estimates can be obtained using a spatially explicit gridded population dataset and/or satellite-derived nighttime light (NTL) images to better support current research.

Electricity demand: This dataset consists of a series of maps of the EU in TIFF format with the demand of the main groups of energy products from each category of economic activity, according to the energy balances for 2019 and the 1x1 km reference grid from EUROSTAT.

5.3.2. Biophysical variables

Biophysical variables which describe the physical attributes of the landscape and climate regime, are important driving factors for what challenges are present or what solutions could be available in each location.

Topography: elevation (m above sea level) and slope ($^{\circ}$) (especially at their extremes) dictate what types of activity are possible in a location. These datasets were derived from an EU DEM³ at 30m resolution from the EEA based on remote sensing data, then upscaled to 5x5km.

Annual climate: similarly, mean annual temperature ($^{\circ}$ C) and precipitation (mm) dictate what plant species (either agricultural or forest) are suited to that location. These were sourced from the CHELSA climate dataset, which is created using terrain-based downscaling of global reanalysis data at 30 arcsecond resolution, and then upscaled to 5x5km (Karger, 2017). Seasonal temperatures could be also used if we had a good sense of their influence on their suitability of mitigation measures.

5.3.3. Land System variables

Land system encompass all processes and activities related to the human use of land, including socio-economic, technological and organizational investments and arrangements, as well as the benefits gained from land and the unintended social and ecological outcomes of societal activities (van Asselen and Verburg 2012). Land systems are represented in a simplified way in this proof-of concept by means

³ Digital Elevation Model

of proportions of different land use types and the intensity of their use. The type of land system variables that provide information regarding the intensity of land use is also an indicator of potential implementation of mitigation measures to ensure reduction in GHG emissions.

Land use proportion: Land use proportion for agriculture, urban and forest were obtained by using Corine Land Cover 2018 after reclassifying each land use type under those broad categories (see Appendix 10.3). CORINE land cover maps are derived from satellite data from Sentinel-2 and Landsat-8, provided at 100m (1 ha) resolution.

Land use intensity: Nitrogen input data from land nitrogen budgets for European agriculture by various modelling approaches downscaled to 40,000 Nitrogen Calculation Units (NCUs) from a combination of soil, land use and slope (de Vries et al. 2021).

Road density: roads also act as a structural force on the landscape and constrain changes in those locations. Here road density is represented as the number of roads per 5x5 km, downscaled from the Global Roads Inventory Project (GRIP) at 8x8 km resolution.

5.3.4. Future Climate Mitigation via sequestration and Adaptation

These variables aim to depict the current state and future capacity of locations to adapt to and mitigate future climate change by way of carbon sequestration in this proof-of-concept. Selection was intended to best represent the sectors under investigation within the KNOWING project, within the bounds of data availability.

River flood hazard: to represent the flood mitigation and adaptation interventions tested in KNOWING, flood hazard maps were created from a gridded dataset of inundation levels (m) produced using the JRC's LISFLOOD model along river networks for Europe and the Mediterranean Basin, for a 100-year return period flood (Baugh et al., 2024).

Heatwave days: to represent interventions focused on heat stress, projections of the number of heatwave days in 2050 (for RCP 4.5) from Copernicus climate data projections at 25x25 km resolution (0.25° by 0.25°) were transferred to a 5x5km resolution (Copernicus Climate Change Service (C3S) 2024).

Cooling potential: Furthermore, NDVI, sourced and formatted as described previously, can be used as a rough proxy for vegetative cool effects that help alleviate heat stress (Copernicus, 2021). Hence, this relation to heat stress is another reason for its inclusion.

Carbon sequestration potential: to represent interventions on soil fertility and natural carbon sequestration, the ratio between actual and potential soil organic carbon (SOC) between 0 and 1 at 250 m resolution was upscaled to 5x5 km (Lugato et al., 2016). This dataset represent the actual SOC stock estimated from a Pan-European simulation of the biogeochemical CENTURY model. A low value means

that there is still potential for further carbon sequestration while a high value close to 1 indicate that carbon is close to soil saturation.

5.4. Archetype definition

The archetype definition is based on a statistical approach using the set of initially defined variables (Table 1). The statistical archetype definition is done by performing a K-means classification based on Principal Component Analysis (PCA) using the 16 initial variables. In this, we are essentially taking a two-step approach to grouping similar 5 by 5 km areas in Europe based on key patterns in the data. As our 16 variables in Table 1 come from four different categories, biophysical characteristics, socioeconomic context, system-related variables, and climate adaptation and mitigation measures, they may vary significantly in scale, influence, and correlation with one another. To make sense of this complex dataset, we first apply Principal Component Analysis (PCA). PCA is a mathematical technique that helps reduce the number of dimensions while retaining as much of the original information as possible. Instead of working directly with 16 variables, which might be highly correlated or redundant, PCA transforms them into a new set of uncorrelated variables called principal components (PCs). These components are ranked based on how much variance they explain in the data, meaning the first few components capture most of the meaningful patterns. This step simplifies the dataset, making it easier to visualize and analyse while also preventing issues like multicollinearity. In this transferability concept, we retained 3 PCs that explained 50% of the variance, beyond this number only small incremental increases were made per additional PC.

Once we have the transformed dataset, we proceed with K-means clustering, which is a method used to classify observations into distinct groups. K-means works by partitioning the data into a predefined number of clusters, with each observation being assigned to the cluster with the closest centroid (a central point representing the cluster). Since we are using PCA-transformed data rather than the raw variables, the clustering is based on the most important patterns extracted from the original variables. By applying this approach, we can identify meaningful clusters that group observations based on shared characteristics across biophysical, socioeconomic, land system, and climate-related dimensions. We have produced several typologies of regions, increasing iteratively the number of groups up until 16 types as the emerging ones provided clear and distinct patterns with homogeneous characteristics. The results can help in understanding how different regions, communities, or systems behave in relation to these factors, potentially guiding policy decisions or targeted interventions in areas such as climate adaptation or resource management.

The use of only quantitative data facilitates a principal component analysis to reduce the multiplicity of variables (i.e., dimensions) and select principal components which explains a certain level of variance in our pixels characteristics (i.e., up to 80% of the variance).

5.5. Similarity analysis of the demonstrators

Spatial similarity indices can also be employed to assess the potential transferability of place-based case-study research to other places in the world (Václavík et al., 2016). The underlying assumption is that the more similar two locations are in terms of land system characteristics, the higher the probability that solutions generated in a case study are also applicable to the other location. In parallel to this classification of pixels in archetypes, we also conduct a similarity analysis to observe the proximity/distance of all EU areas to our demonstrators' regions. Because the considered case studies may cover a large area with significant geographic heterogeneity (e.g., a country or sub-national region), absolute distance in this case is measured by calculating for every grid cell of the case study area the statistical difference to every 5x5km grid cell in the considered geographic universe (Václavík et al., 2016), as follows:

$$D_m = \frac{1}{g.p.v} \sum_{i=1}^v \sum_{n=1}^p \sum_{m=1}^g |x_{i,n} - x_{i,m}| \quad \text{Eq. A.1}$$

where:

D_m is the absolute distance between the average characteristics of the case site and the land system characteristics of grid cell m , as represented by a set of relevant social-ecological variables (here the ones from Table 1);

$x_{i,m}$ is the normalized value of variable i in grid cell m ;

$x_{i,n}$ is the normalized value of variable i in grid cell n located within the regional case study area;

p is the number of grid cells n located within the regional case study area;

v is the number of considered variables i ;

g is the number of grid cells m in the considered geographic universe.

We get variables from 0 to 1 centred around the variables from our Demonstrator regions. A value of 0 means that for a given indicator the average value in the Demonstrator region is similar to the values observed in the tested cell. A value of 1 means that the observed cell is completely different in terms of characteristics compared to the Demonstrator region. After aggregation of the variables into the four categories, socioeconomic context, biophysical variables, land system variables and future climate mitigation and adaptation, we can see per categories of variable to which extent the different regions in Europe differ from our Demonstrator region. This Min-Max normalization is simple enough to allow scaling the different variable between 0 and 1 and allow aggregation without being influenced by outliers or problematic error points that emerge sometimes, when the method is applied on survey data.

6. Proofs of concepts

6.1. Archetypes identified in Europe

The different archetypes are identified in Table 2 and 3 and mapped in Figure 5.

Table 2: Description of the archetypes 1-8 in terms of average characteristics across the socioeconomic context, biophysical context, land system variable and climate change risks. Dark and light green represent respectively significant and very significant positive deviations from the average

Variables	Dry forest agriculture mosaic	Mountainous forest	Agricultural mosaic	Flood risk urban agriculture	Cold-dry lowland forest	Agriculture-forest mosaic	High density urban	Hilly forest-agriculture mosaic
Annual precipitation (mm/year)	671	1101	639	754	643	807	652	908
Annual temperature (°C)	6.8	6.8	9	9.2	3.4	8.8	10	9.1
GDP (k€)	559	448	650	59000	405	44162	469751	697
Energy demand (toe/yr)	11	3	11	1470	11	89	13900	10
Elevation (m)	153	908	221	124	155	263	112	583
Grazing (%)	1.3	13	1	0.1	0.5	0.8	0.1	10.4
Heatwave risk in 2050	2.2	1.3	0.8	1.2	8.5	0.5	1.1	0.7
NDVI	0.7	0.7	0.6	0.5	0.7	0.7	0.4	0.7
Nitrogen (kg N/ha)	90	38	101	89	84	132	36	82
Population	20	7	25	4451	12	210	13762	25
Prop Agriculture (%)	30%	9%	72%	21%	10%	57%	6%	24%
Prop Forest (%)	48%	48%	16%	7%	60%	23%	1%	40%
Prop Urban (%)	2%	1%	3%	66%	1%	13%	87%	2%
River flooding risk	0.14	0.01	0.15	0.4	0.17	0.14	0.2	0.03
Road Density	125	71	184	1122	44	605	2543	142
Slope (%)	1	15	2	2	1	3	2	10
SOC potential	0.8	0.9	0.6	0.1	0.7	0.6	0	0.9

Table 3: Description of the archetypes 9-16 in terms of average characteristics across the socioeconomic context, biophysical context, land system variable and climate change risks. Dark and light green represent respectively significant and very significant positive deviations from the average

Variables	Mid-elevation cold forest	Low density urban agriculture	High input agricultural mosaic	High mountain partially forested	Intermediate density urban	High intensity agricultural areas	High SOC agriculture forest mosaic	Cold-dry heatwave-prone forest
Annual precipitation	902	770	753	1382	697	648	838	534
Annual temperature	1.5	8.9	9.3	3.4	9.9	10	9.8	0.5
GDP (k€)	308	26255	10567	411	128659	1333	884	64
Energy demand	0	701	281	1	3954	27	13	1
Elevation (m)	658	144	143	1617	127	139	397	322
Grazing	5.9	0.5	0.4	20.1	0.1	0.3	4.9	0.2
Heatwave risk in 2050	10.3	1.2	0.6	0.7	0.5	0.6	0.7	0.1
NDVI	0.53	0.59	0.61	0.67	0.46	0.56	0.65	0.08
Nitrogen (kg N/ha)	2	121	152	20	46	142	115	43
Population	0	1898	597	0	9391	49	32	0
Prop Agriculture (%)	2%	37%	57%	4%	9%	87%	52%	1%
Prop Forest (%)	43%	12%	12%	37%	4%	5%	28%	55%
Prop Urban (%)	0%	44%	25%	1%	81%	5%	3%	0%
River flooding risk	0	0.3	0.3	0	0.2	0.3	0.1	0.1
Road Density	5	856	799	41	1357	339	252	2
Slope (%)	4	2	2	23	2	1	6	1
SOC potential	1	0.3	0.4	0.9	0	0.5	0.8	0.8

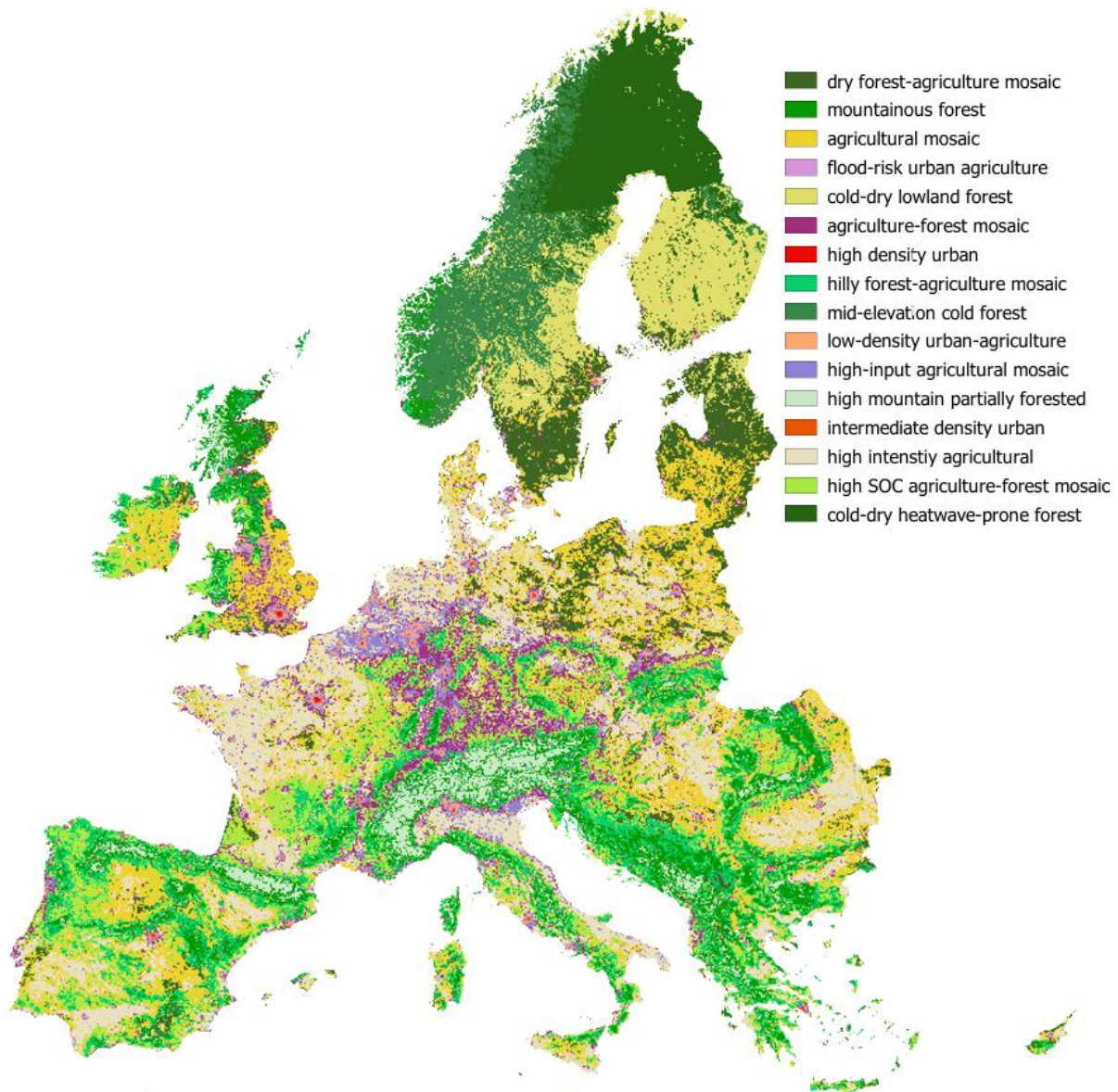


Figure 5: Map of the different 16 archetypes of regions identified across Europe. Archetype analysis resulted in 16 classes of different sizes and distributions throughout Europe.

An interpretation of these archetype classes based on values in table 2&3 and visualization in Figure 5 resulted in several distinct types parsed by their relevance for climate adaptation or mitigation and other characteristics.

Areas with a mosaic of different land covers are named by their primary and secondary land system and other defining features. Forest-agricultural mosaics are a mixture of forest and agriculture with a dominance of forest cover, further separated in this case by precipitation levels and topography. The “***hilly forest-agricultural mosaic***”, found in the foothills of mountainous areas across Europe, is predominantly a mixture of forest (40%) and agriculture (24%) at slightly higher average elevation (583m) on hilly terrain with an average slope of (10.1°). Furthermore, the “***dry forest-agricultural mosaic***” is a mix of majority forest (53%) with some agricultural areas (23%) at relatively low average elevation (152m) and average annual precipitation (671mm). Found primarily in lowland regions of Scandinavia and the

Baltic states. Heatwaves risk is present (2.1 days per year in 2050) but small compared to bordering higher elevation and colder forest dominated classes.

Agricultural-forest mosaics are mixtures dominated by agriculture with smaller areas of forest. The classification of two types of agricultural-forest mosaic is separated based on their % fulfilment of SOC potential. The “**agriculture-forest mosaic**” is a mixture of agriculture (57%) and forest (23%) with a lower 56% fulfilment of SOC potential. This class is found primarily in central Europe typically bordering forest-agricultural mosaics or its high SOC counterpart. Namely, the “**high SOC agricultural-forest mosaic**” class is a mixture of agricultural (52%) and forest (28%) land with high fulfilment of SOC potential (76%) in gentle hilly terrain. Found across Europe, typically bordering other combinations of forest and agricultural mosaic.

Urban dominated areas are separated into high and medium density and then typically bordered by high population urban-agricultural mosaics. The “**high density urban**” class is urban land (86%) with high population (13762 inhabitants/km²), energy demand (toe/yr) and economic density (€469 million) per 5x5 km. This class is typically reserved for the central parts of major cities such as London or Paris. These are also some of the warmest areas likely because of urban heat island effects, and with comparatively low NDVI values (0.36) for vegetative cooling. These areas also have the densest road networks. Furthermore, the “**intermediate density urban**” class also has high (albeit lower) urban proportion (80%) and population (9391), economic (€ 128 million) and road density (1357 roads/km) per 5x5 km; And is typically found surrounding high density urban or representing smaller urban settlements.

Urban agriculture mosaics are separated into two levels of density based on the proportion of urban to agriculture, flood risk and fulfilment of SOC potential. The denser of the two is “**flood-risk urban-agriculture**”, a mixture of dominantly urban (66%) and agricultural (21%) land with a high average relative flood risk (0.4). This class also has relatively high population (4451), economic (€59 million), and road density (1121) per 5x5 km. This class is found near cities all across Europe, especially cities near rivers or the coast. There are particular hotspots of this class in NW Europe in the Benelux region and parts of Western Germany. In comparison, the “**low-density urban agriculture**” has a more even mixture of urban (44%) and agriculture (37%) with a lower population (1897), economic (€26 million) and road density (856) per 5x5 km. Compared to the high flood-risk urban agriculture mosaic, the lower density urban-agriculture mosaic has a more intermediate flood-risk (0.31) and greater (but still low) fulfilment of SOC potential (26% compared to 8%). This is usually found near to the denser higher flood-risk urban-agriculture mosaic, presumably further away from water.

Agricultural mosaics that feature dominance of agriculture and relevant proportions of both forest and urban areas are categorised by their level of agricultural dominance and intensity of nitrogen fertilisation input. The “**high-input agricultural mosaic**” class is land dominated by agriculture (57%) with smaller portions of forest (11%) and urban (25%) areas characterised by high levels of nitrogen fertilisation (152 kg N/ha). There is also relatively high flood risk (0.34) and low fulfilment of SOC potential (0.39). In comparison, the “**agricultural mosaic**” class has a greater dominance of agricultural regions (72%), with small areas of forest (16.2%) and intermediate levels of nitrogen input (101 kg N/ha) and

corresponding higher SOC fulfilment (56%). The high-input agricultural mosaic is found in small patches across Europe usually near to larger cities. Whereas the agricultural mosaic is more widespread and covers many less-populated areas across Europe.

In a similar vein, the “**high intensity agriculture**” class has near total dominance of agricultural land (87%), also with high nitrogen input (142 kg N/ha) and intermediate fulfilment of SOC potential (46%). This class is widespread throughout Europe, with particularly large areas in France, Romania, Northern Germany and Poland. Given its widespread coverage and modest SOC fulfilment, this class could be target for agricultural interventions.

The two tiers of mountainous class are separated by the extremity of their topography and proportion of forest cover. The “**high mountain partially forested**” class represent high elevation (1617 m above sea level) and sloping (22.6°) areas with partial forest cover (37%), found in mountainous areas all across Europe. This is typically bordered by the less extreme “**mountainous forest**” class also with high elevation (907 m), slope (14.8 °) and majority forested area (48%).

Northern European forested areas characterised by cold and dry climates, particularly in Scandinavia and parts of the Baltics, are separated into three categories based on forest proportion, elevation, level of cold and projected future heatwaves. The “**cold-dry lowland forest**” class refers to areas with a high proportion of forest (60%) in cold regions at low elevation (155 m) and high projected incidence of future heatwaves (8.5 days per year). Furthermore, the “**cold-dry heatwave-prone forest**” class represents partially forested (55%) areas, characterised by cold temperatures and little human presence and a high(er) projected incidence of future heatwaves (9.6 per year). Finally, the “**mid-elevation cold forest**” class is partially forested (42%) cold areas at intermediate average elevation (658 m) with the highest projected incidence of future heatwaves (10.2 per year).

The different archetypes show mixed relevance for mitigation and adaptation purposes, with many archetypes acting collectively to represent a type of region rather than a type of intervention space. This likely reflects the same pattern in the majority context-leaning input variables compared to a few risk and mitigation related inputs.

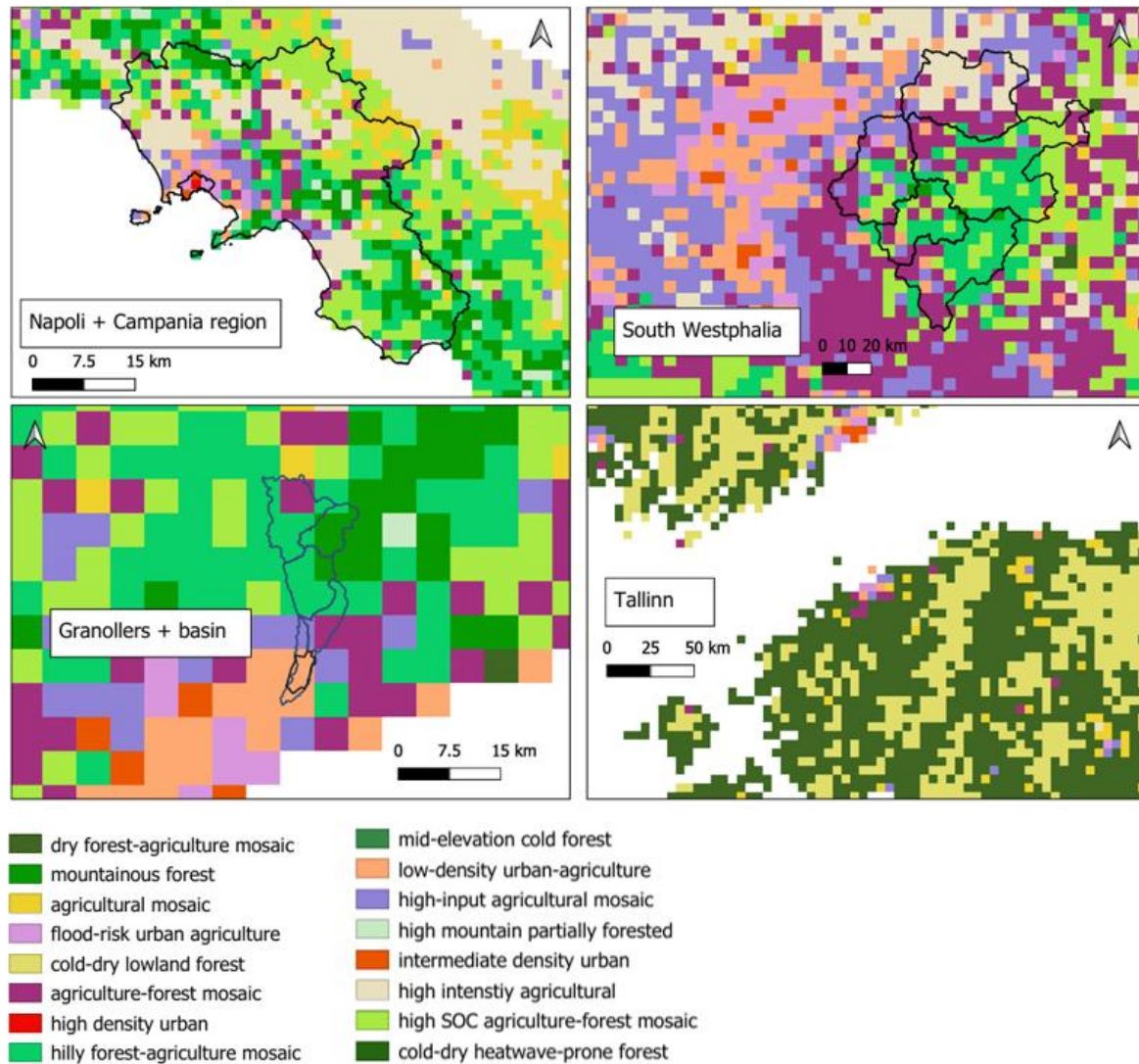


Figure 6: Archetypes per Demonstrator

Visualisation of Archetypes per Demonstrator show clear differences between the modelled regions, presenting a basis for varied climate mitigation pathways (Fig.6).

The north of South Westphalia (SWF) is a mixture of high intensity agriculture, phasing into low SOC agricultural forest mosaic, with smaller areas of high-input agricultural mosaic. The southern 2/3 of SWF is mostly high SOC agricultural-forest mosaic and hilly forest-agriculture mosaic, with small areas of mountainous forest. There are also individual pixels of low-density urban-agriculture representing several cities and towns throughout the region.

The city of Napoli is a mixture of high and medium density urban at the coast, surrounded by high flood-risk urban agriculture, low-density urban agriculture and high-input agricultural mosaic. The wider Campania region is a mixture of high intensity agriculture and various forest and agricultural mosaics, along with mountainous and forested archetypes around Mount Vesuvius.

The city of Tallinn is archetyped as low-density urban agriculture and a mixture of high-input and high-flood-risk agricultural mosaics and agricultural forest mosaic, surrounded by heatwave-prone dry forest agricultural mosaic.

The city of Granollers is similarly archetyped as low-density urban agriculture with nearby high input agriculture and agriculture-forest mosaic, while the river basin is a mixture of hilly forest-agriculture mosaic and mountainous forest.

The archetypes apply best to the larger SWF and Napoli regions, whereas the resolution of pixels seems unable to fully parse Tallinn and Granollers from surrounding agricultural land.

6.2. Level of similarity identified compared to KNOWING demonstrators SWF for proof-of-concept

The level of similarity to SWF across Europe varies considerably depending on the type of indicators used. For example, across socio-economic variables, most differences range between 0.5 to 0.7, making it hard to identify especially different or similar regions to SWF across those three variables. For the biophysical drivers, the most similar regions appear largely constrained by elevation, reflecting the hilly forest nature of parts of SWF. Furthermore, land use structural similarity is greatest in proximity to SWF, such as in Western Germany, parts of the Netherlands, and Belgium that combine different agricultural and forest mosaics at high density. For mitigation and adaptation similarity, there is a wider spatial variety of somewhat similar regions. Based on the distribution, similarity here likely driven primarily by potential SOC values.

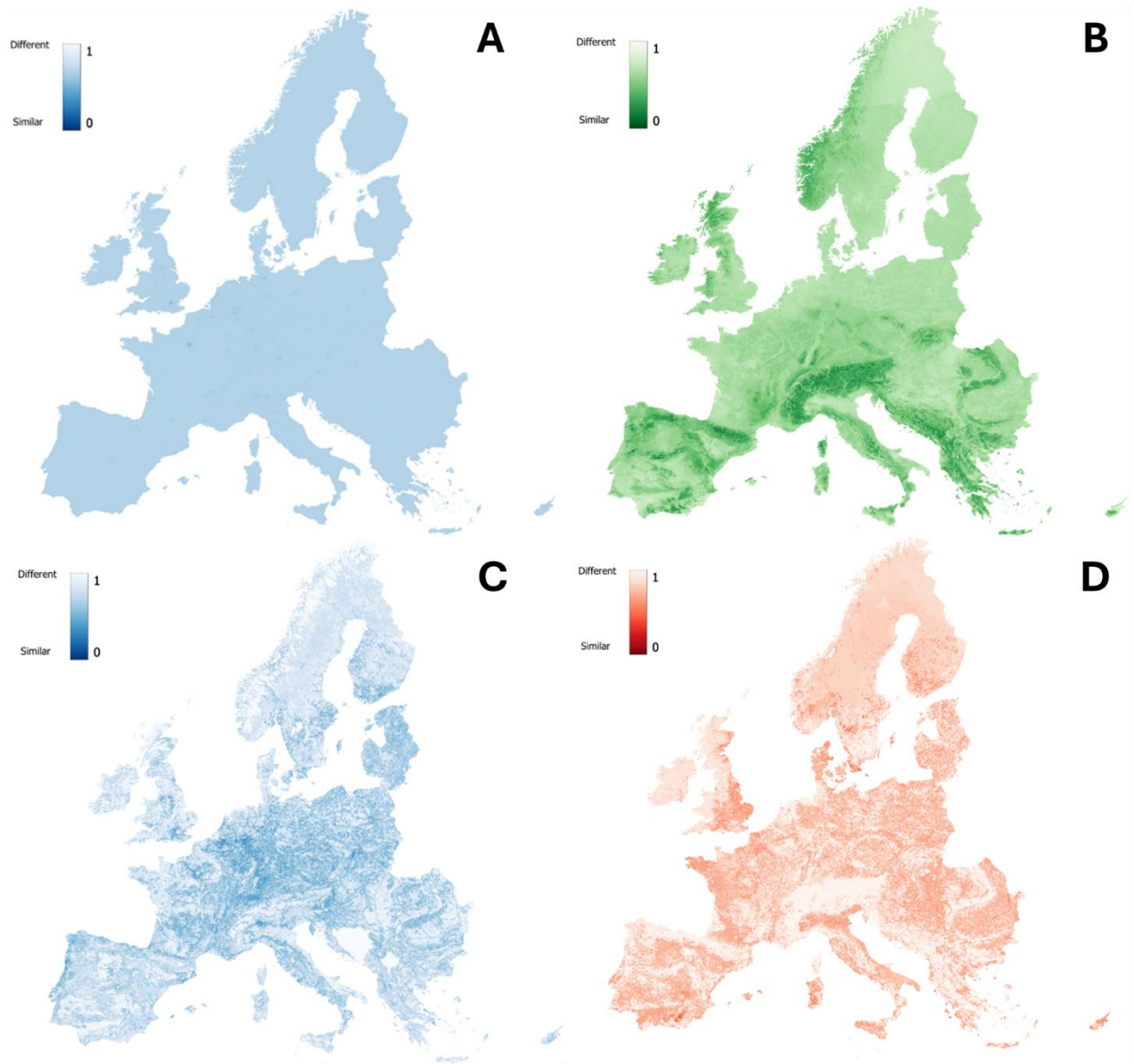


Figure 7: Mapping of the 4 indices calculated in the similarity analysis namely (A) the socioeconomic context, (B) the biophysical variables, (C) the land system variables and (D) Future mitigation (with sequestration) and Adaptation

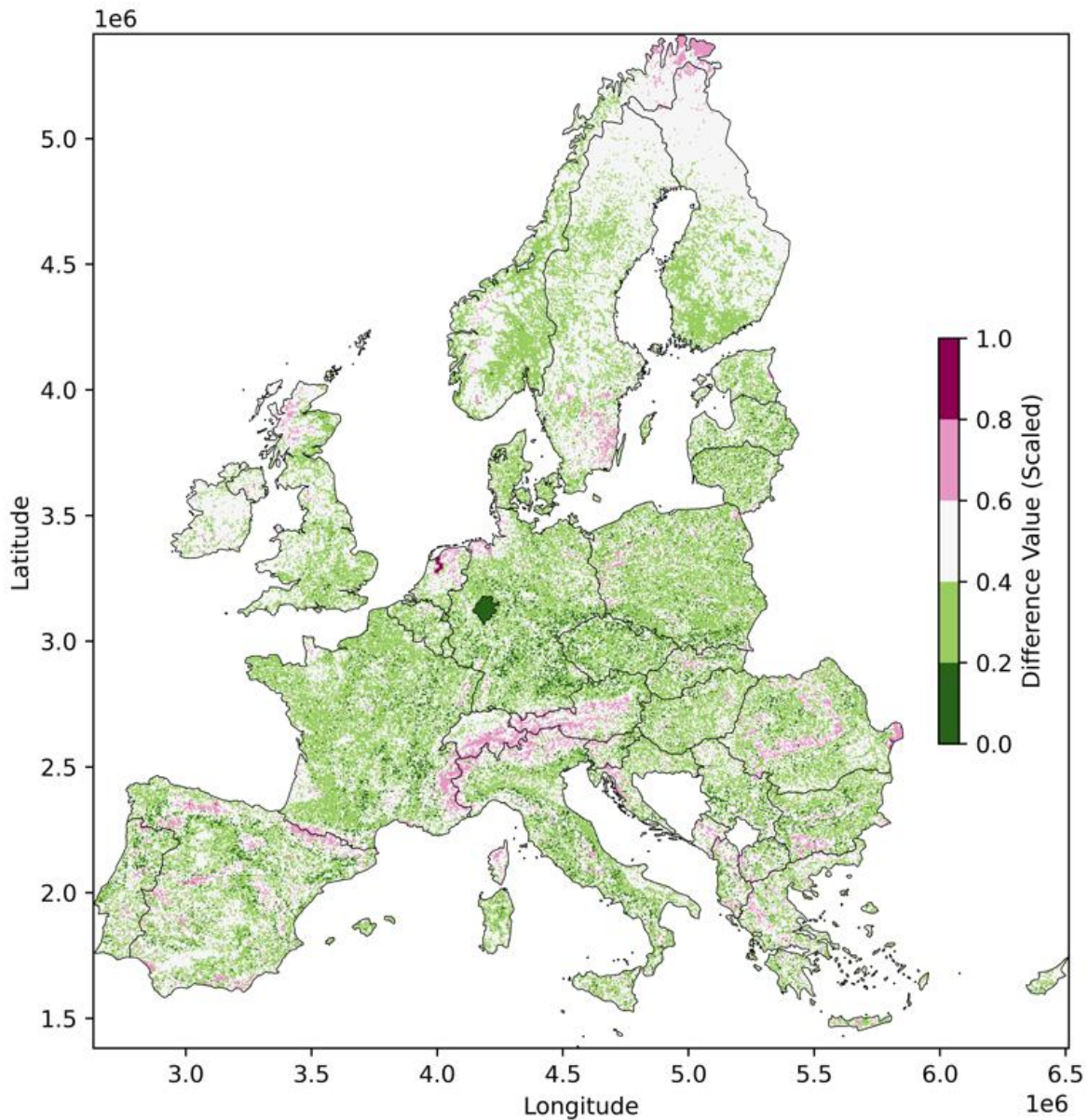


Figure 8: Map of composite similarity analysis across the 4 previous indices, with the reference region SWF outlined in black with green fill.

The composite similarity analysis combining all 4 of the previous indices highlights areas that are overall most similar to SWF. Areas most similar to SWF include: South-East Germany; South-East France; Czechia; Northern Austria; South-Eastern Poland; A small hotpot in Eastern Slovenia; Western Serbia. Consequently, these areas should be the starting point for transferring the mitigation pathways found in SWF within KNOWING. This would include potentially increased afforestation with climate adapted species as tested in T2.3. It is important to note that due to the averaging of variables for SWF to produce difference from all other cells, even values within SWF are not equal to zero. Therefore, the lack of large patches of similar area do not limit the transferability to exact those pixels but rather the general (larger) area where high similarity is found.

7. Discussion

7.1. Uses of the archetype framework

The 16 archetypes obtained in the typology analysis show very contrasted regions in Europe with particularly different gradients of land use structure and climate hazards targeted in KNOWING (i.e., river flooding, heatwave) that largely drive the definition of archetypes. Urban archetypes encompass mostly ‘high density urban’ and ‘intermediate density urban’. Typically, although this does not appear explicitly in the analysis, we could imagine that the ‘high density urban’ would be at risk of experiencing urban heat island effect whilst ‘intermediate density urban’ would be less prone to that particularly due to higher level of vegetation observable with the NDVI indicator. Such effect could be for instance quantified with the use of the Palm4U model in Tallinn in the frame of T3.2. A large scale mapping of the risk of urban heat island or an assessment specifically for all cities could be integrated in our archetype analysis to more precisely identify locations where adaptation measures with urban green space, air conditioning or improved building conditions (e.g., upgraded building insulation) would be needed.

Some archetypes capture different types of forest-based archetypes namely ‘Cold-dry heatwave prone forest’, ‘mid-elevation cold forest’, ‘Mountainous forest’ with different associated climate hazards. ‘Cold-dry heatwave prone forest’ would typically corresponds to large patches of forest in Northern Europe that have experienced increased episodes of forest fires risks in the previous years. For instance in 2018, large patches of forest dominated by managed *Pinus sylvestris* belonging to this archetype experienced the most severe wildfire season recorded in modern history in Sweden (Kelly et al. 2024). ‘Mountainous forest’ represent large patches of forest in high elevation areas where soil carbon is at its equilibrium and with lower sequestration potential. These areas should be maintained from major human direct and indirect disruptions in order to maintain the current carbon stocks. ‘Cold-dry lowland forest’, ‘Mid-elevation cold forest’ and ‘High mountain partially forested’ represent intermediate types with lower vulnerability to forest fire and lower intensive production from lowland to high altitude.

Agricultural land uses are a major descriptor of nine of the groups. Intensity in inputs is largely explaining the emergence of ‘High intensity agricultural’ and ‘High input agricultural mosaic’ areas in which large scale production of cereals and livestock occur and where mitigation measures around increase diversity in crop (e.g., crop rotations or intercropping) and reduction in livestock density would be interesting measures to reduce emissions and increase adaptation to global changes while maintaining the production purpose of such archetypes. ‘Agricultural mosaic’ present similar characteristics with lower potential for carbon sequestration and production with lower intensity.

Other archetypes are mixture of land uses that would call for solutions at the cross road of sectors. Typically ‘Dry forest agriculture’, ‘Agriculture forest mosaic’, ‘hilly forest agriculture mosaic’ and ‘high SOC agriculture forest mosaics’ are mixture of agriculture and forest. ‘Agriculture-forest mosaic’ and ‘High SOC agriculture forest mosaic’ are typical landscape dominated by agriculture with a bit of forestry

where forest in agricultural landscape delivers services in terms of biodiversity and natural pest control allowing for more resilient production facing climate change. The High SOC in the second type call for measures like reduced to no tillage that prevent the depletion from carbon stock over time with increasing temperature. The forest dominated types ‘Dry forest-agriculture mosaic’ and ‘Hilly forest-agriculture mosaic’ are zones of lower intensity of agricultural production with high forest coverage where mostly livestock activities may remain. Those areas could be considered as priority areas for increased afforestation as the land is suitable for forest production and potential for higher C sequestration exist as long as they do not undermine other function provided by the area such as cultural ecosystem services. Finally, two types of combine agriculture and urban areas namely ‘Flood-risk urban agriculture’ and low-density urban agriculture. The first archetype is particularly characterized by its large risk of river flooding and in which adaptation measures should be strongly recommended to decrease exposure of population. Particularly, the maintenance and development of flood plain and agricultural management practices increasing water infiltration would be appropriate.

7.2. Transferability of results from KNOWING in other regions

The similarity analysis performed allowed the identification of some small areas where the pathways of adaptation and mitigation designed in SWF would be also suitable and effective in Europe. Those areas are particularly close to SWF showing that the pathways designed could be transferred in adjacent areas and the project would benefit from contacting neighbourhood regions where similar socioeconomic, biophysical and land and climate hazards are similar. For instance, in Bavaria which is very similar to the conditions found in SWF, optimized landscape management programs are tested to improve climate change mitigation and adaptation in forests using approaches similar as the ones from T3.4 (Caicoya et al. 2023). The results from KNOWING on T3.4 and the backcasting scenarios could help identify scenarios that would be of relevance for more climate smart management of forest in Bavaria.

This similarity analysis could be used more largely by other projects to identify Follower regions before the start of the project that would have roughly similar conditions as Demonstrator regions. In the frame of KNOWING several followers are involved where existing initiatives regarding climate change mitigation and adaptation exists locally and who consider that results from KNOWING demonstrators are of interest for them. However, the choice of Follower regions was made beforehand and the characteristics of these regions may differ to the one from the Demonstrators. For example, Lauenburg region is the Follower region of SWF and is considered ‘relatively similar’ (light green in Fig. 8) but we would have had higher similarity and then transferability potential with a follower region in southeast Germany, northern Czech republic or South of Poland to ensure greater relevance of designed pathways. We acknowledge that this is also due to the fact that the region boundaries defined in the system may actually contain different types of land systems as seen in Fig. 6, meaning the transferability of solutions could be applied to sub-sections of Demonstrator or Follower regions.

The question of how similar regions need to be to enable the transferability of pathways is key to determining the detail required to capture those similarities between regions. If the goal is to find broadly similar areas that could be approached with information from the KNOWING project to enter into a dialogue, then the level of detail required would be lower – perhaps at the region level to capture broad similarities. However, if the goal is direct transferability, where the transferability analysis would be used to prescribe interventions directly, then sub-setting regions into their composite parts for different interventions would be necessary. On one hand, given the idiosyncrasies of local places, the direct transferability of interventions might be too much of a reach and thus a more generalised similarity might be better suited. Moreover, this would alleviate data availability concerns discussed in the following section. However, on the other hand, the value proposition of directly prescribed interventions is likely greater and may therefore be worth certain omissions.

7.3. Current limitations and further developments

Some limitations to the ability of gearing adaptation and mitigation measures appear with the current state of the proof of concept in terms of i) choice of variables, ii) data coverage and spatial resolution, iii) typology stability.

By adopting an explicitly spatial approach for capturing archetype regions with similar socioeconomic, biophysical, land system descriptors, and mitigation and adaptation contexts, we bind ourselves to the existence of spatial datasets that represent the spatial variability in these contexts which may limit the depth of analysis of each of these categories. A major limitation is the fact that we do not represent the current policies at stake in the different regions and their ability to ease the adoption of certain mitigation and adaptation measures within sector. For instance, we have identified an archetype ‘Flood-risk urban agriculture’ where both agricultural and urban land are at risk of experiencing increasing flooding in the future. This is an important information in order to make recommendations on reducing the exposure of the population with measures such as flood plains or zoning plans. However, our current framework does not explicitly state whether those are already in place or not. Additionally, our framework does not provide information on whether or not policy incentives exist to favour the adoption of measures to reduce exposure for instance techniques that would increase the water infiltration in agricultural land. The framework rather acts as a way of identifying where mitigation and adaptation measures could be desirable and effective but does not say where they are in place or where there are already measures in place to facilitate their implementation. Recent development in some large scale mapping of mitigation and adaptation measures (e.g., wind turbines (Bessin et al. 2025)) could allow better integration of the existing level of measure adoption. Large scale mapping of policies is rather scarce but zooming in specific case studies would allow to bring in more local documents on plan and general interests for the development of adaptation and mitigation measures. The framework could also use behavioural data to identify areas where changes are perceived more desirable by the local populations. This dataset is produced in KNOWING in the frame of WP1 using the coping typology for some EU countries. Finally,

the framework could integrate additional climate hazards, such as coastal flooding—whose dataset was not obtained in time for the deliverable—and forest fires, which impact mitigation and adaptation pathways.

The current proof-of-concept for transferability makes an explicit choice in terms of data coverage and resolution with the adoption of i) a European focus and ii) a 5 x 5 km resolution. In terms of focus, the transferability is 'limited' to European level as it is assumed that a global level the number of areas that present similar biophysical conditions are rather limited to few temperate and Mediterranean areas including North America & parts of south America, Central and East Asia. While in North America, the socioeconomic context is largely similar in terms of energy demand and GDP per capita, the socioeconomic context in South America, central and east Asia largely differs from the one in Europe which prevent the ability to transfer mitigation and adaptation measures in these areas. Indeed, the calibration and validation of our model does not extend to these areas which would lead to major estimation errors. This is the reason why the project explicitly seeks for areas in Europe where the potential for transferability is deemed greater. In terms of resolution, the current results present findings at a 5 x 5 km resolution which helps identify regions of broad similarity to our demonstrator regions. The resolution could be coarser (e.g., Municipalities/Local administrative units; NUTS3 level) which would allow for more data sources to be included in the framework. However, this would lead to simplification of the pattern of spatial variability, as for instance NUTS3 regions can cover very different areas including large forested areas and large cities whose mitigation and adaptation measures would be very different. In a similar way the framework could use higher resolution datasets but some information is not available at 1 km resolution which would then lead to more simplification in terms of information to be included. Finally, more datasets could be included in the current proof-of-concepts for instance covering per sector information regarding GDP, energy consumption, labour. These datasets would lead to more precise recommendations per sector but would considerably increase the number of types. We recommend to include this information in a later stage to split up the different archetypes. To conclude on data coverage and resolution, this deliverable makes an explicit choice to minimize trade-offs between higher coverage but coarse resolution and lower transferability potential and finer resolution with lesser spatial and variable coverage but higher transferability potential.

The current typology of archetypes has led to 16 types in Europe. The exact number of archetypes should not be seen as an exact science but rather as a way of heuristically understanding the diversity in situation across Europe and climate hazard faced by regions. While the number is aligned with similar typologies, we could eventually gain further information by splitting existing group for more targeted recommendations. As an example, the current 'High dense urban areas' probably cover some diversity in terms of building height, transport regime that would then lead to different mitigation and adaptation measures in terms of reduction of traffic or reduction of urban heat island effect.

Collectively, the current set of limitations highlight the potential value of adopting a multi-step or tiered approach to transferability. In this approach, an initial broad similarity assessment could be conducted at a coarse resolution to capture the widest possible range of variables and thus similarity dimensions.

Once potential regions of transferability have been identified, a subsequent targeted high-resolution analysis could be carried out, combining existing datasets with data sources only available locally to prescribe interventions directly.

8. Conclusions

The backcasting approach employed in KNOWING provides a structured methodology for defining long-term sustainability goals and developing strategic pathways to achieve them. By integrating system dynamics (SD) models, built based on sector models, this approach allows for a comprehensive evaluation of policy interventions, ensuring that mitigation and adaptation strategies are both effective and suitable over time. Unlike traditional forecasting, which extends current trends into the future, backcasting starts with a defined vision and works backward to identify necessary steps, highlighting the importance of proactive decision-making in climate change resilience, agricultural, forest and urban land use planning, improved coastal management.

A key contribution of the KNOWING project is the development of structured pathways that account for the interdependencies between various sectors and domains. These pathways provide a framework for implementing interventions, with possible changes over time to curb trajectories, and ensuring long-term sustainability. Policy optimization is possible with this SD model approach, where a large range of scenarios can be tested to determine the most effective pathways. This approach not only facilitates comparison between different pathways but also enables continuous refinement based on policy optimization with stakeholders' inputs.

We illustrated the general concept of backcasting and transferability by analysing similarities in terms of socioeconomic and biophysical context, key system variable and adaptation and mitigation potential via sequestration within the European context. In doing so, we managed to identify 16 archetype of regions where similar recommendations in terms of mitigation and adaptation pathways could be made. It also allowed us to identify several regions, under the set of variables tested, similar to South Westphalia one of KNOWING demonstrator region namely in southeast of Germany (i.e., Bavaria), North of Czech Republic and south of Poland.

Despite its strengths, the approach has limitations, particularly concerning data integration, resolution and policy representation. The framework identifies where mitigation and adaptation measures are needed but does not account for existing policies or local socio-political dynamics that could influence implementation. Additionally, while spatial typologies provide valuable insights, the granularity of data can impact transferability and precision. Future enhancements could integrate additional data on biophysical and socioeconomic context, more climate hazards, behavioural data and policy mapping to refine adaptation and mitigation strategies further. In T3.5, we explore the potential to which pathways would have to be realised in archetypical regions to reach some target in terms of mitigation of GHG emissions.

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10. Annex

10.1. Large maps indices for SWF

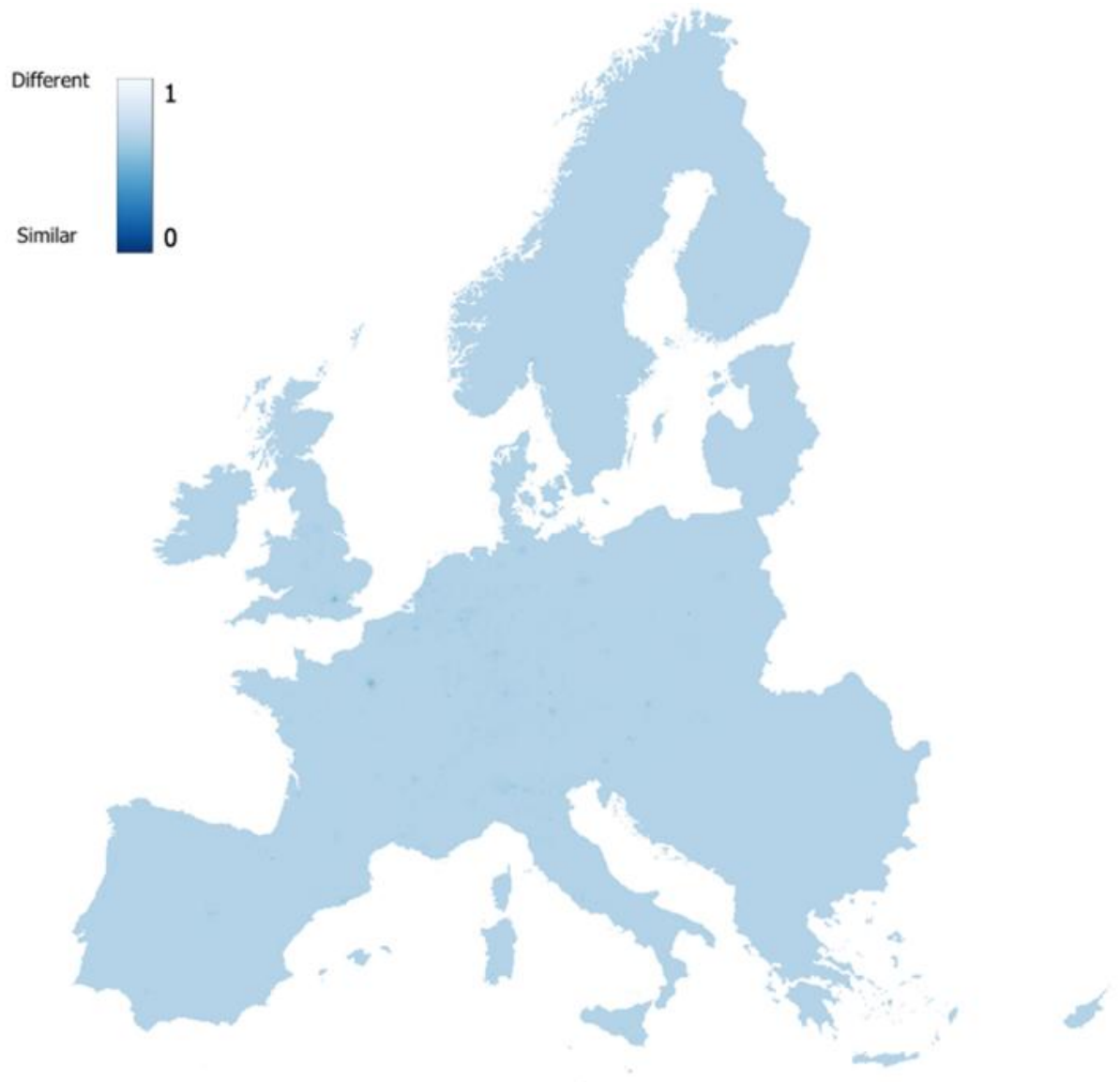


Figure : socio-economic differences from SWF. Data used: economic density; electricity demand; and population.

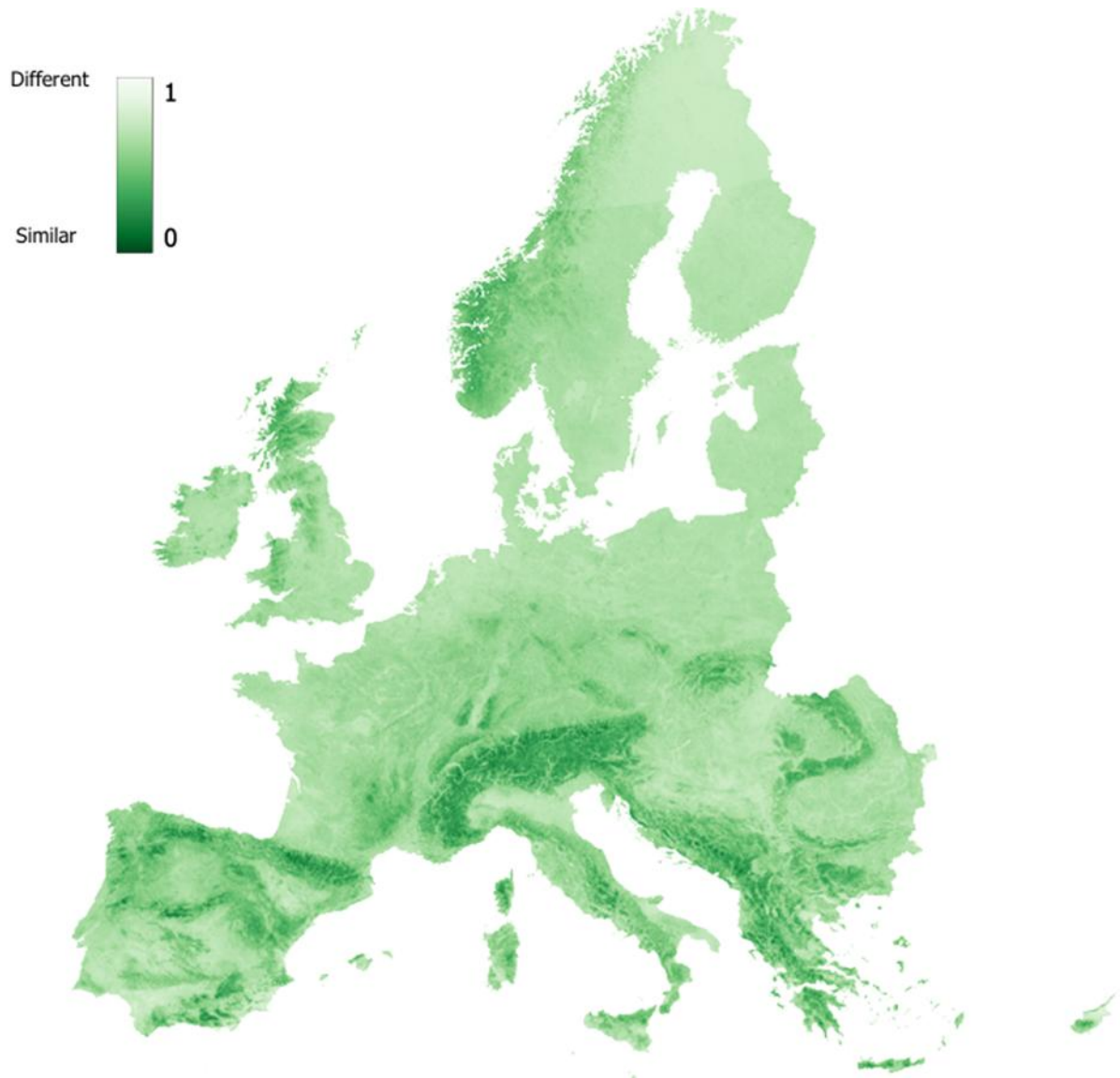


Figure : Biophysical differences from SWF. Data used: annual precipitation and temperature; topography (elevation and slope); and NDVI.

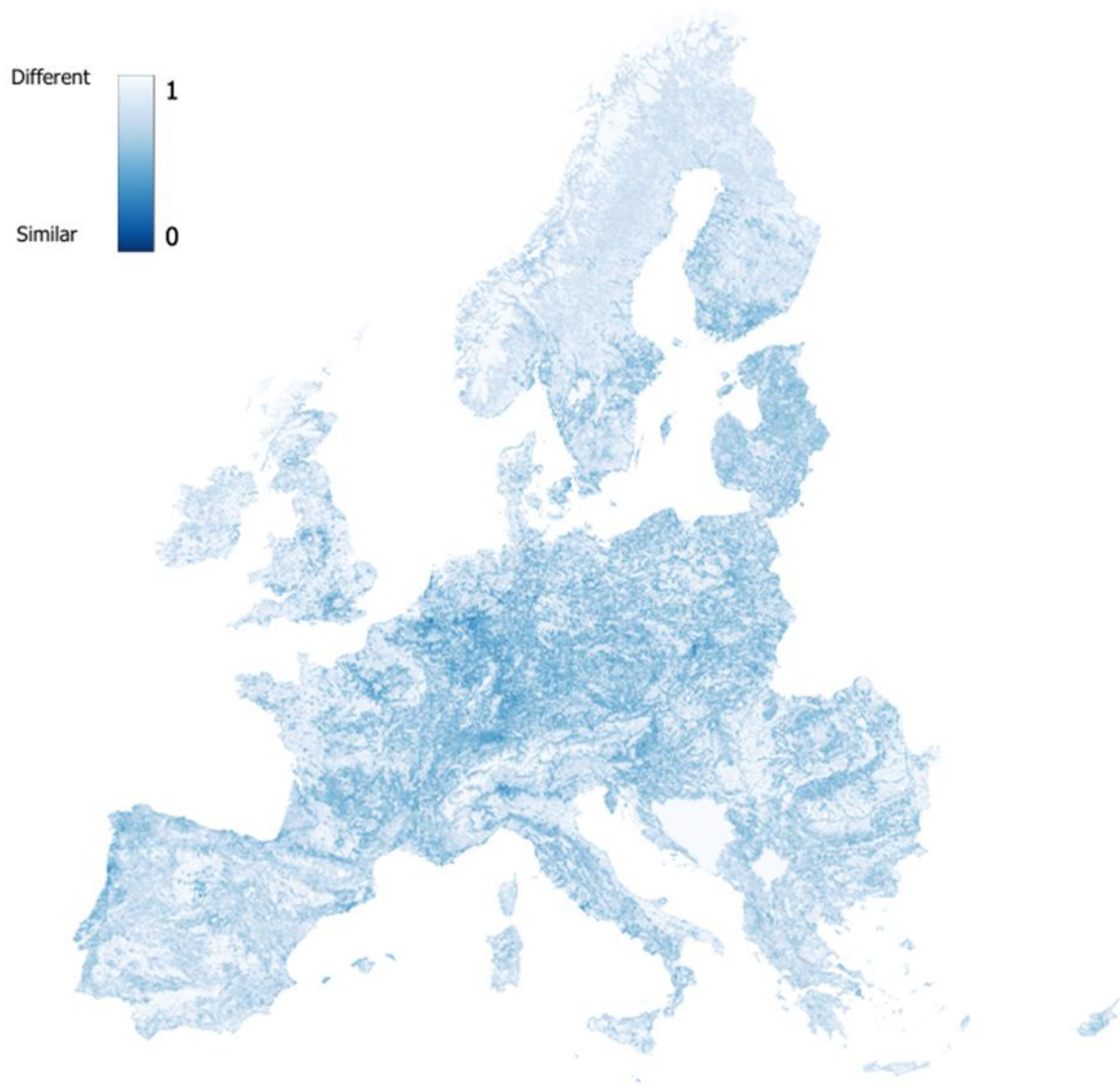


Figure : Land-use structural differences from SWF. Data used: proportion of urban, forest, agriculture; and road density.

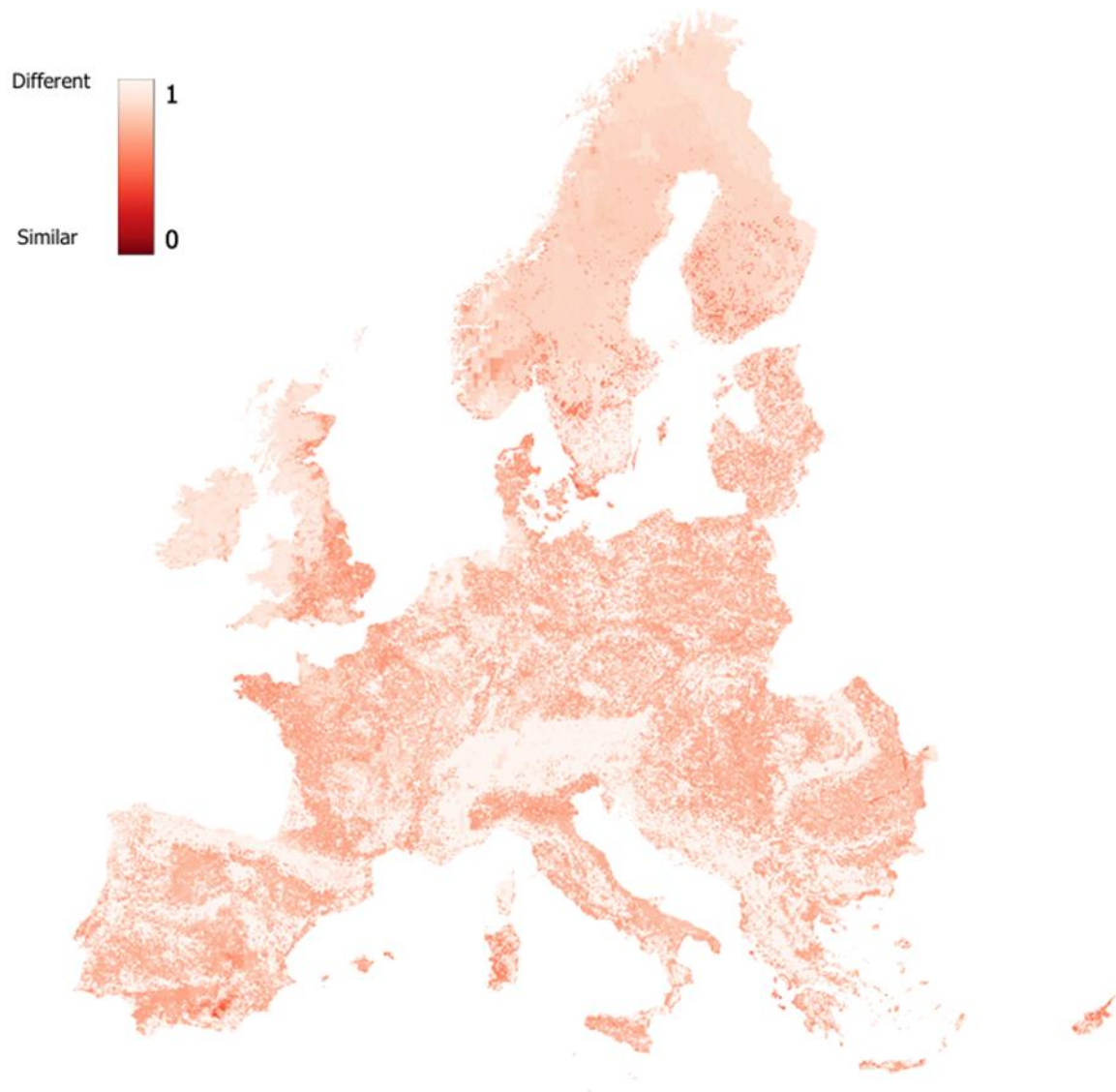


Figure : Mitigation and adaptation differences from SWF. Data used: Projected heatwaves in 2050; River flood risk; SOC potential.

10.2. Land cover proportion calculation

Table showing the categorisation of CORINE land cover classes into Urban, Agricultural, Forest and Other.

Urban = Grey; Agriculture = Orange; Forest = Green; Other = Blue

Class	Land cover
1	Continuous urban fabric
2	Discontinuous urban fabric
3	Industrial or commercial units
4	Road and rail networks and associated land
5	Port areas
6	Airports
7	Mineral extraction sites
8	Dump sites
9	Construction sites
10	Green urban areas
11	Sport and leisure facilities
12	Non irrigated arable land
13	Permanently irrigated land
14	Rice fields
15	Vineyards
16	Fruit trees and berry plantations
17	Olive groves
18	Pastures
19	Annual crops associated with permanent crops
20	Complex cultivation patterns
21	Land principally occupied by agriculture with significant areas of natural vegetation
22	Agro forestry areas
23	Broad leaved forest
24	Coniferous forest
25	Mixed forest
26	Natural grasslands
27	Moors and heathland
28	Sclerophyllous vegetation
29	Transitional woodland shrub
30	Beaches dunes sands
31	Bare rocks
32	Sparsely vegetated areas
33	Burnt areas
34	Glaciers and perpetual snow
35	Inland marshes
36	Peat bogs
37	Salt marshes
38	Salines
39	Intertidal flats
40	Water courses

- 41 Water bodies
- 42 Coastal lagoons
- 43 Estuaries
- 44 Sea and ocean
- 45 NODATA

10.3. Archetype PCA results

PCA results used for the archetype analysis

Variables	PC1	PC2	PC3
annual_precipitation	-0.142	0.331	-0.219
annual_temperature	0.314	0.016	-0.369
econ_dens	0.206	0.402	0.279
electricity_demand_clipped	0.129	0.261	0.190
elevation	-0.287	0.311	-0.193
grazing	-0.144	0.189	-0.179
heatwaves_2050	-0.259	-0.132	0.458
ndvi_01072020	0.022	0.151	-0.257
nitrogen	0.267	-0.092	-0.151
population	0.199	0.364	0.272
prop_agriculture	0.378	-0.218	-0.252
prop_forest	-0.275	0.030	0.153
prop_urban	0.299	0.332	0.226
river_flood_risk	0.064	-0.043	0.047
roaddensity	0.305	0.189	-0.006
slope	-0.232	0.385	-0.336
SOC_potential	-0.287	0.060	-0.081

