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Special Collection:
Multi-Sector Dynamics: Advancing Complex Adaptive Human-Earth Systems Science in a World of Interconnected Risks

Key Points:

- Targeted insights into direct and cascading flood risks for multi-sectoral systems facing climate and socio-economic uncertainty
- A "plausibilistic" framework to robustly assess uncertain regional climate risks by incorporating event probabilities and storylines
- Application to the Lielupe basin highlights key risk areas and sectors, aiding risk managers in their adaptation planning

Correspondence to:
F. E. Buskop,
t.buskop@vu.nl

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Author Contributions:
Conceptualization: F. E. Buskop, F. Sperna Weiland, S. Hochrainer-Stigler, R. Šakić Trogrlić, B. J. J. M. van den Hurk
Formal analysis: F. E. Buskop
Funding acquisition: F. Sperna Weiland, B. J. J. M. van den Hurk
Investigation: F. E. Buskop
Methodology: F. E. Buskop, F. Sperna Weiland, S. Hochrainer-Stigler, B. J. J. M. van den Hurk
Project administration: F. Sperna Weiland, B. J. J. M. van den Hurk

Beyond the Floodplain: Integrating Probabilities and Storylines to Explore Regional Uncertain Direct and Cascading Climate Risks in Multi-Sectoral Systems

F. E. Buskop[1,2,3], F. Sperna Weiland[2], S. Hochrainer-Stigler[3], R. Šakić Trogrlić[3], and B. J. J. M. van den Hurk[1,2]

[1]Institute for Environmental Studies, Vrije Universiteit Amsterdam, Amsterdam, The Netherlands, [2]Deltares, Delft, The Netherlands, [3]IIASA—International Institute for Applied Systems Analysis, Laxenburg, Austria

Abstract Effective management of future regional climate risks in interconnected multi-sectoral systems is complicated by uncertainties in risk drivers within both human and natural systems. Comprehensive yet comprehensible targeted climate risk information exploring these uncertainties is essential for the strategic allocation of limited resources to vulnerable areas and sectors in the region. Yet conventional approaches struggle to provide it. This study addresses this gap by introducing an interdisciplinary framework incorporating meteorological, hydrological, and socio-economic perspectives. A "plausibilistic" flood risk assessment approach is presented which combines both climate and socio-economic storylines. Plausible climate scenario storylines are sampled based on their relevance for local impacts, allowing the assessment of conditional changes in high-impact probabilistic discharges. Plausible socio-economic storylines are integrated to asses future urban area and economic sectoral development. This information allows the projection of the impact potential in the region and its cascading socio-economic effects. An example application to the flood-prone, transboundary Lielupe basin shared by Latvia and Lithuania highlights sub-catchments and sectors consistently vulnerable across diverse, relevant, and credible set of future storylines. The framework thus equips regional risk managers with targeted and robust risk information, providing a strong knowledge base for prioritizing adaptation planning.

Plain Language Summary Planning for future regional climate risks like flooding is challenging due to climate and societal uncertainties, making it vital to consider diverse and plausible future scenarios. Our study introduces a new framework providing targeted information to help regional decision-makers prepare. We achieve this by sampling a limited yet comprehensive range of future climate ánd socio-economic conditions. By this combination, we identify areas where direct flood risks are likely to change and assess how these changes could ripple through the economy—for example, how the construction sector might face high pressure to rebuild after a severe flood event. We tested this approach in the flood-prone Lielupe river basin, shared by Latvia and Lithuania. We analyzed potential shifts in extreme flood discharges and their impacts using various scenarios of relevant future climate conditions, urban development, and economic changes. The findings reveal that flood risks can vary significantly across the region and sectors due to changes in both climate and socio-economic conditions. Importantly our framework quantifies these changes and identifies sectors and areas that face high risk levels across many scenarios. This provides regional policymakers with robust risk information to confidently prioritize areas and sectors in need of targeted adaptation strategies.

1. Introduction

As climate impacts intensify throughout the twenty-first century (IPCC, 2023), regions across the globe increasingly need targeted climate risk information to inform adaptation plans that protect vulnerable areas and sectors. Climate risk arises from the interplay between climate and human systems (Field et al., 2014; Simpson et al., 2021), requiring an understanding of future changes in both. However, significant uncertainties characterize the future trajectories of these systems. Climate risk uncertainties are driven by unknowns in emission pathways (O'Neill et al., 2017; van Vuuren et al., 2011), earth system responses to those emissions (Hawkins & Sutton, 2011; F. Lehner et al., 2020) and societal developments (O'Neill et al., 2014; Wilby & Dessai, 2010). The resulting variety of potential risk futures present a considerable challenge for policymakers tasked with prioritizing adaptation options across diverse locations and sectors. To help regional stakeholders with priority setting,

Software: F. E. Buskop
Supervision: F. Sperna Weiland, S. Hochrainer-Stigler, R. Šakić Trogrlić, B. J. J. M. van den Hurk
Validation: F. E. Buskop
Visualization: F. E. Buskop
Writing – original draft: F. E. Buskop
Writing – review & editing: F. Sperna Weiland, S. Hochrainer-Stigler, R. Šakić Trogrlić, B. J. J. M. van den Hurk

it is critical to create a comprehensive but comprehensible climate risk information package that can identify priority areas or sectors while designing effective adaptation strategies.

Within the context of uncertainty exploration and management, a promising approach is the concept of physical climate storylines. Shepherd et al. (2018) defines a storyline as physically self-consistent unfolding of the climate system, weather event, or climate event which can vary from hours to decades. Storylines have gained traction in recent literature as an approach that enhances scenario relevance and plausibility for regional climate risk assessments (Shepherd, 2019; Shepherd et al., 2018). Storylines provide a framework for partitioning and analyzing uncertainty in regional climate risks by exploring 'what if' scenarios along with their conditional explanations (Sillmann et al., 2021). By exploring multiple storylines that are conditioned on specific climate change and/or socio-economic aspects, critical impacts, vulnerabilities and risk drivers can be identified, guiding actions (Goulart et al., 2024; van den Hurk et al., 2023). While climate storylines are designed to describe a causal impact chain under specified assumed conditions, within the given set of conditions multiple realizations can be depicted. For example, the classical emission scenario framework is conditioned on narratives of global emission pathways, known as representative concentration pathways or shared socio-economic pathways (SSPs), leading to a range of climate realizations expressing uncertainty in the climate system response or internal variability in the global climate system (O'Neill et al., 2017; van Vuuren et al., 2011). Meanwhile decision support at a local or regional scale can be better informed by constraining the regional climate and socio-economic uncertainties of interest rather than by global uncertainties (Frame et al., 2018).

Although storylines can be used to explore potential climate risk futures, storyline studies have often pointed to irreducible uncertainties in the impact chain that challenge the quantitative assessment of probabilistic risk (Pfleiderer et al., 2025; Shepherd et al., 2018; Sillmann et al., 2021; van den Hurk et al., 2023). However, probabilities of extreme events are embedded into policies and legal frameworks globally, such as flood protections standards (Scussolini et al., 2016). Furthermore, likelihoods are a crucial component for investment decisions in either risk prevention, consequence reduction, or risk transfer (Linnerooth-Bayer & Hochrainer-Stigler, 2015; Mechler et al., 2014). To address this need, climate scenario storylines have recently been introduced. In contrast to often used event based storylines (Sillmann et al., 2021; van den Hurk et al., 2023; van der Wiel et al., 2021), where impacts are conditioned on a specified event, climate scenario storylines are conditioned on narratives of the regional climate responses known to be inductive for high impact events. This allows the creation of ensembles of hydrometeorological conditions for a storyline (Buskop et al., 2024; Liné et al., 2024; van der Wiel et al., 2024), providing probabilistic risk information at the regional scale, conditioned on a locally relevant climate state. Although the likelihood of the conditioned climate remains unknown, this approach, which we call "plausubilisitc," does allow mapping changes in probabilistic events within that conditioned climate. Next to emission uncertainty the resulting probability range includes the effects of both internal variability and model uncertainty, which are the main governing factors of uncertainty in regional precipitation patterns (Hawkins & Sutton, 2011; F. Lehner et al., 2020). As such, a relevant range of potential future conditions is generated that can be used in regional climate risk management and adaptation planning (Deser, 2020).

Usually, climate scenario storylines focus on representing changes in a broad set of atmospheric conditions (Liné et al., 2024; van der Wiel et al., 2024). Although this approach has merit in providing scenarios for many types of hydrometeorological events, they lack specificity of particular types of events featuring in specific societal decision contexts and associated information requirements (Kirchhoff et al., 2013), potentially foregoing required information salience (Lemos et al., 2012). To enhance the relevance of specific storylines for decision-making, recent studies have employed systematic scenario discovery methods (Bryant & Lempert, 2010). Buskop et al. (2024) introduced a method to select a focused set of, the previously introduced, climate scenario storylines from a collection of future climate projections. Their approach selects a limited but insightful set of climate scenario storylines by aggregating future climate model projections based the set of climate variables that influence impact in the region, also known as locally relevant Climatic Impact-Drivers (CIDs) (Ruane et al., 2022). This approach enhances climate risk exploration when compared to often used emission pathway based aggregation. Similarly Hadjimichael et al. (2024) use scenario discovery to find a limited and focused sample of climate storylines that represent states of the world that specifically influence determined objectives. However, a limitation of both these studies is that they only represent changes in the climate system.

Climate storyline literature has developed a variety of ways to explore climate-related uncertainties (Baldissera Pacchetti et al., 2024). However, including socio-economic dynamics and perspectives in climate storylines (as in

Alizadeh et al., 2024; Koks et al., 2023) is considered critical for comprehensive risk assessment (Dottori et al., 2018; Steinhausen et al., 2022). Yet Baulenas et al. (2023) find in their review that climate storyline studies often focus on the physical climate science aspects, the hazard. Neglecting socio-economic dynamics misses how exposure and vulnerability, and thus impacts change over time. Meanwhile, regional impacts of extreme climate events are rarely confined to the assets directly affected. As societies are increasingly interconnected, direct climate effects in one area can trigger cascading failures or disruptions through critical infrastructure, supply chains, or financial markets, leading to significant cascading risks within the same region or others (Middelanis et al., 2021; Sieg et al., 2019). It therefore becomes increasingly important in climate risk assessments to include a broader perspective that includes these, socio-economic, dimensions (Challinor et al., 2018; Higuera Roa et al., 2025; Hochrainer-Stigler et al., 2023; Levermann, 2014; Simpson et al., 2021). Integrated risk assessments, such as from the European Environment Agency (2024), are essential to inform adaptation measures in connected multi-sector systems. While cascading societal effects induced by climate hazards have been analyzed for future climate conditions (Lawrence et al., 2020; Willner et al., 2018), the effect of socio-economic changes, such as growing or shrinking economic sectors over time (Leimbach et al., 2023), on cascading effects remains largely unexplored.

This review of the climate storyline literature reveals two critical gaps that hinder actionable policy support. First, despite being recognized as crucial for climate risk assessments the integration of uncertain socio-economic dynamics and their cascading impacts remains limited. Second, storyline approaches still struggle to deliver the salient, probabilistic risk information needed for policy planning. To bridge these gaps, this study introduces a comprehensive "plausibilistic" framework. This framework applies and significantly extends the storyline selection methodology introduced by Buskop et al. (2024). While adopting their core idea of selecting climate scenario storylines based on relevant impact drivers to provide targeted conditional probabilistic hazard information, the framework extends their approach in two key ways. First, it incorporates spatially explicit information into both the climate scenario storyline selection criteria and the resulting analysis of discharge changes across a river basin, offering a geographical representation of potential impacts. Second, our framework explicitly integrates plausible socio-economic storylines alongside the climate storylines. The integration allows for the retrieval of targeted, probabilistic, and cascading climate risk information in uncertain multi-sectoral human-natural systems.

The framework focusses on flood risk as it is one of the key risks throughout Europe in a changing climate (Bednar-Friedl et al., 2022; European Environment Agency, 2024). Damages to structural assets, buildings, along these rivers are of particular concern both now and increasingly in the future (Winsemius et al., 2016). In terms of cascading effects, the framework looks at the construction sector and its connected sectors as these are crucial for rebuilding flood-impacted assets. Furthermore in many countries the construction sector in the top two of sectors with the strongest supply chain linkages (Song et al., 2006), potentially leading to system wide cascading supply chain effects after a flood.

The framework described in Section 2: (a) guides the selection of credible and relevant storylines from plausible climate and socio-economic projections, (b) spatially maps regional impact drivers within each storyline to illustrate where both socio-economic and climate trends overlap and elevate risks, (c) and identifies economic sectors that experience the most severe consequences of cascading impacts after climate induced shocks under varying conditions. While the framework maps variability in risk, its core value lies in identifying high-risk areas and sectors across credible scenarios, providing a stronger knowledge basis for the prioritization of adaptation policies. While the framework focuses on regional climate risks, it leverages globally available and openly accessible data and tools to ensure wide geographic applicability.

This paper demonstrates the framework's utility by testing it on an illustrative case. An exemplary case is the transboundary Lithuanian-Latvian Lielupe river basin, where flood risk is a prominent issue and is a core focus of the Latvian National Adaptation Plan (NAP) (Ministry of Environmental Protection and Regional Development, 2019). This case is detailed in Section 3 and results of the application of the framework to this case are presented in Section 4.

2. Framework

This study aims to provide a comprehensive assessment of future flood risk across a river basin in multi-sectoral systems by sampling from a range of future projections including global emission scenarios, regional Earth

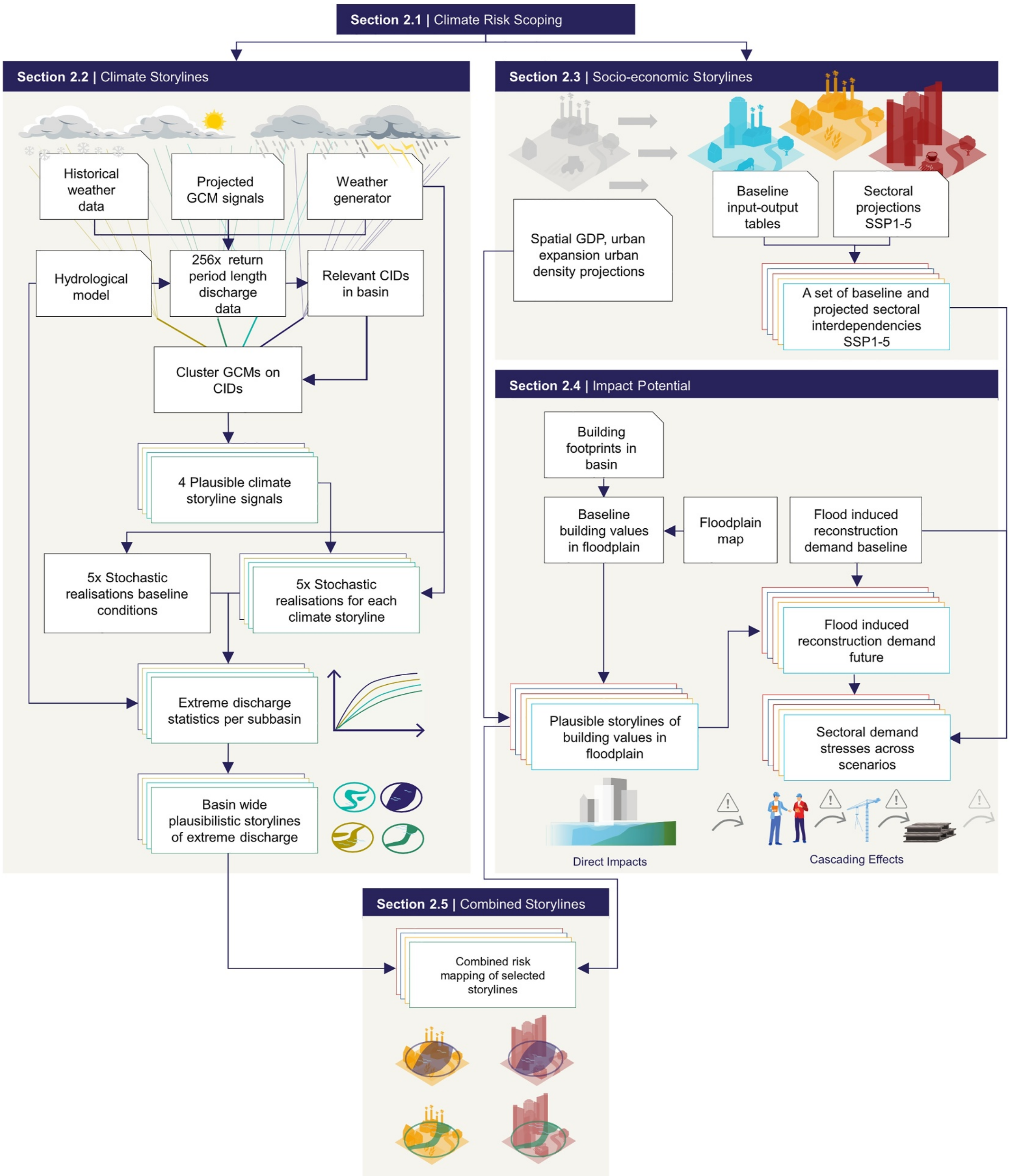

Figure 1. Framework used in the study to gain insight into uncertain future direct and cascading climate impacts. Boxes with a cut corner indicate that the data or tool is openly available. Stacked boxes refer to a set of data corresponding to the various storylines. See the respective method sections for further explanation of each step.

system responses, internal variability, and societal development. We follow the multi-model experimental design depicted in Figure 1. The figure depicts what tools and data are combined in the framework to produce credible and comprehensive climate risk storylines applicable at basin scale. These storylines feature direct impacts and cascading economic effects by integrating future socio-economic and climate data. The analysis starts with a climate risk scoping and data collection for a selected case study through the analysis of regional policy documents (Section 2.1). Second, the framework obtain plausiblistic changes in extreme discharges across the basin by creating a set of climate scenario storylines based on future projection of the CMIP6 (Eyring et al., 2016) climate model ensemble (Section 2.2).

Additionally, the propagation of direct flood impact to cascading economic effects is analyzed for multiple projections of plausible future socio-economic developments, guided by the SSP narratives (O'Neill et al., 2017).

These socio-economic projections provide regional perturbations to (a) the exposure characteristics in floodplains, (b) the size of economic sectors and, consequently trigger altered cascading effects (Section 2.3). Direct impacts and resulting cascading effects of each storyline are compared to a baseline, illustrating how sectoral and regional stresses can potentially evolve. By doing so, the framework identifies those areas and sectors most affected in a flood situation under various socio-economic changes (Section 2.4). Lastly, the climate scenario storylines and associated plausibilistic discharges and socio-economic storylines are combined to identify those locations where risk drivers converge, providing a risk mapping under future conditions (Section 2.5).

2.1. Climate Risk Scoping

The first step of our methodology is to define and scope the regional climate risk of interest. This step involves identifying the region, hazard, impacts, sectors, and time horizon of interest, which collectively influence the conclusions drawn in risk analyses. A regional and local risk assessment like this preferably relies on local or national documents and interaction with local stakeholders (Zebisch et al., 2023) to better fit the local decision context.

The framework is designed in a modular fashion to accommodate varying levels of data availability. It establishes a robust, globally applicable baseline using comprehensive global data sets, while this same structure allows for the integration of local information (i.e., local flood extend maps, planned building developments and economic sectoral trade data) to enhance and refine the risk assessment. The subsequent sections will highlight where this integration can occur. The adaptability is demonstrated in Section 3, where local data of our example case are introduced to produce a more tailored analysis.

2.2. Climate Storylines

To obtain a set of plausibilistic changes in extreme discharge relevant across the basin, this study extends the method introduced by Buskop et al. (2024). Their method distils uncertain climate projections into decision-relevant climate scenario storylines by clustering projection on locally relevant climatic-impact drivers. The approach is extended by incorporating spatially explicit information into both the climate scenario storyline selection criteria and the resulting analysis of discharge changes across the basin.

2.2.1. Relevant Climatic Impact Drivers in the Basin

To find which Climatic Impact-Drivers (CIDs) are locally relevant, a scenario discovery process is applied to find which climate variables or combinations of variables influence extreme discharges in the region most. These relationships are inferred by stress testing the basin for many different climate futures. To achieve this, the framework: (a) develops atmospheric forcing time series under various, CID adjusted, climate conditions, (b) simulates discharge extremes in each climate condition using a calibrated hydrological model, (c) relates CIDs to extreme discharges and find their relevance.

In step 1 there are two requirements. First, meaningful hydrological modeling of discharge extremes requires high resolution, forcing time series of daily temperature and precipitation. Second, comparing the influence of CIDs on discharge extremes requires a consistent sequence of events across alternative forcing runs. These two requirements are currently unavailable in the available General Circulation Model (GCM) time series. Therefore, an openly accessible implementation of the stochastic weather generator by Steinschneider and Brown (2013) is used as it can generate multivariate and spatial weather time series that accurately match historical climate patterns and provides functionality to make adjustments for alternative climate states. Alternative climatological forcing conditions are created by modifying the baseline time series by adjusting the following seasonal CIDs: mean temperature (ΔT), mean rainfall (ΔP) and the coefficient of variation (ΔCV) of that rainfall. The CV captures the changes in rainfall variability. Lowering the coefficient implies smaller variability of the rainfall distribution leading to a larger concentration of rainfall events centered around the mean. Changes in variability of temperature are not considered as changes in local temperature extremes generally scale well with changes in the local mean temperature (Seneviratne et al., 2023).

Step 1 uses historical ERA5 reanalysis data (Hersbach et al., 2023) to create a synthetic baseline time series of temperature and precipitation in the region, with a length equal to the extreme discharge return period of interest. Next, projected changes are extracted in CIDs from the collection of CMIP6 models (Eyring et al., 2016). These model projections are available at the Copernicus Climate Data Store (Copernicus Climate Change Service, 2021), for the full list of models and projections used see Appendix A. Change signals are collected for the mid-century, as defined in the IPCC atlas, 2041–2060 (Gutiérrez et al., 2021). Then the minimum and maximum projection are identified across the model and projection set for each CID and uniformly sample scenarios between these ranges. Using the stochastic weather generator a total of 256 alternative climate states are created by adjusting the created synthetic baseline timeseries according to the sampled CIDs change scenarios.

In step 2 the comprehensive set of alternative weather time series from step 1 is used and provided to the open source hydrological model Wflow_sbm (van Verseveld et al., 2024) which is configured for local conditions using complementary model builder HydroMT (Eilander et al., 2023). Discharges are simulated for each of the 256 sampled climate conditions and the resulting return period extremes are compared against the baseline run.

In step 3, the changes in discharge extremes identified for each climate condition and associated CID adjustment in step 2 are used to determine the relevance of each CID. To create climate scenarios that are relevant across the basin, it is necessary to know which combination of CIDs changes flood risk at a variety of locations. This information is retrieved from observed discharge extremes collected at multiple observation stations spread throughout the basin. For each of these stations, the two most influential CIDs that alter extreme discharge are determined using the Extra Trees feature scoring algorithm (Geurts et al., 2006). After removing duplicates this results in a list of CIDs that influence flood risk basin wide.

2.2.2. Climate Scenario Storylines and Their Plausibilistic Extreme Discharges

The framework clusters the set of CMIP6 GCMs into four distinctive clusters based on the projected changes for each relevant CID. These four clusters form the basis for the climate scenario storylines. A number of four storylines optimizes the trade-off between comprehensively covering internal variability and model uncertainty, and maintaining a robust climate signal. A larger number of clusters would capture more of the detailed model variations and internal variability but at risk of obscuring the signal attributable to climate change. Conversely, fewer than four clusters limits the representation of plausible futures, and therefore limits the representation of future impacts. Furthermore the number of four clusters is small enough to be manageable for stakeholder engagement and the analysis process yet large enough to capture structurally different climate futures.

For each GCM cluster the multi-model seasonal average climate change signal is calculated for the sampled CIDs (ΔT, ΔP, ΔCV). These change signals are used to generate storyline specific stochastic weather time series from the baseline time series. Since weather generators are subject to sampling uncertainty (Alodah & Seidou, 2020), five alternative realizations, equal to the length of the return period of interest, have been created and used as input to the hydrological model. For each realization of a climate scenario storyline, the fractional change in return period discharge of interest relative to the control baseline is calculated. These change values are averaged across realizations to obtain the discharge change for each storyline used in further analysis.

Basin-wide probabilistic discharge changes are calculated and mapped for each climate storyline using the HydroSheds classification of sub-catchments (B. Lehner & Grill, 2013). The resulting map provides a spatial representation of hazard intensity changes, revealing potential differences across catchments. We call these changes to extreme discharge events "plausibilistic."

2.3. Socio-Economic Storylines

Flood risk in the region emerges from a combination of direct risks (damage to exposed assets) and cascading risks (via the propagation of flood impacts on production and demand of connected economic sectors affected by the flood event). For direct risks, the framework explores sub-catchment level future values of building exposure (Section 2.31). To explore economic cascading effects, perturbations are applied to regional economic networks by changing future sectoral production and consumption volumes and their interdependencies (Section 2.3.2). Shared Socio-economic Pathways (SSP) framework (O'Neill et al., 2014, 2017) are used to guide calculations for the regional economic and exposure development. Multiple SSPs are used to explore the uncertainty range in regional socio-economic trends. By using the SSP framework the framework can use and combine output from studies that are based on the SSPs in a way that projected variables are consistent with each other, an integral part of storylines (Shepherd et al., 2018). To reflect our localized application, we refer to these SSP-inspired scenarios as "regional economic storylines." We argue in Section 2.5 how the framework combine these socio-economic storylines with the created climate storylines.

2.3.1. Asset Development in the Region

To assess changes in direct impacts, the change in building value exposure over time is determined as it is a key driver of risk. Direct impacts are modulated by altering each sub-catchment's total area occupied by building footprints and the cost of rebuilding a structure. These changes in exposed asset values are calculated using three global data sets of downscaled spatial projections at a 1 km resolution: urban density (Gao & Pesaresi, 2021a) and urban expansion (Chen et al., 2020) to represent physical asset development, and Gross Domestic Product (GDP) growth (T. Wang & Sun, 2022) to represent increasing asset value accumulation. Because GDP is a measure of the size of the national economy by aggregating all monetary value of nationally produced goods and services in a year, it provides a good proxy for the increasing value of physical assets. These data sets disaggregate national-level GDP, population, and urbanization based on current population and GDP distributions, where built-up areas experience larger projected changes than rural areas. By multiplying the GDP growth with urban density change and urban expansion in a sub-catchment, the asset value change factor is obtained that is used to project the asset values in the floodplains between the baseline year and year of interest (see Section 2.4.1). Local data of future development plans could be used to further inform building exposure maps.

2.3.2. Scaling Sectors and Their Interdependencies

Cascading effects in the economic system are influenced by how individual sectors develop and how sectors interact. Changes in cascading effects are assumed to be related to socio-economic trends in GDP and the contribution of individual sectors to that GDP. These factors allow one to analyze changing national economic structure, sectoral dependencies and, consequently, cascading impacts of flood events.

Input-output tables, introduced by Leontief (1936), are a common way for government statistical agencies to collect and describe the relationships between sectors within a country and sectors abroad by documenting the monetary value of the flow of goods between sectors. These tables thus describe how much each sector supplies to (output) and consumes from (input) other sectors. Using these tables, ripple effects from one sector to another can be tracked. In climate impact science, input-output tables have been used in a variety of studies covering the cascading effects of supply losses after flooding (Sieg et al., 2019), accounting of environmental footprints, including global trade (Tukker et al., 2016), and post-disaster dynamics in the economy (Koks & Thissen, 2016; Middelanis et al., 2021).

To obtain sectoral interactions and production quantities for the future, the framework projects national input-output tables using socio-economic trends and sectoral shifts depicted in the SSPs. When using openly available input-output tables from either the national statistics office or global databases such as EORA (Lenzen et al., 2013) there will be more industry categories in the table than those available in Leimbach et al.'s (2023) economic sector projections. A such, one first aggregates detailed sectors to the larger categories available in the projections. The projection calculation starts by scaling the gross value added to projected GDP levels in the target year, from Dellink et al. (2017), and allocating the GDP among the large sector categories proportional to the projected contributions found by Leimbach et al.'s (2023). Then the value added of the larger categories are disaggregated back to detailed sectors using today's production ratios within the large categories, and subsequentially one calculates the input requirement of each sector using the current relationship between a sector's inputs and its value added. Additionally final demands are scaled according to GDP growth.

To address potential imbalances between domestic supply and demand, arising from unequal sector growth, the framework implements an import and export mechanism. This ensures that all future demand and supply are properly accounted for, a key requirement in input-output analysis (Miller & Blair, 2009). When domestic sector production cannot meet increased demand, additional imports are introduced distributed among domestic sectors according to current-day usage shares. Conversely, when local production exceeds demand, imports of each sector are reduced, to a minimum of zero. Any surplus production is converted into exports. The end results are input-output projections per regional economic storyline suitable for analyzing the cascading effects of flood events. See Appendix B for detailed explanations and formulas describing the calculations.

2.4. Impact Potential

2.4.1. Exposed Assets in the Floodplain

Direct flood impact potential is estimated by evaluating asset values exposed within sub-catchment floodplains. To avoid resource-intensive hydraulic flood modeling, a pragmatic approach was employed. We argue that a preliminary assessment of high risk areas can effectively be achieved by analyzing the current day floodplain extent which occurs at lower probability (longer return period) than the event analyzed. These flood extent maps may be obtained from local authorities to match the decision making context or, alternatively from global high resolution data sets (such as Dottori et al. (2022) or Ward et al. (2020)) The resulting flood extend is used to identify exposed buildings. When combined with future changes in extreme discharge at the return period of interest (described in Section 2.2), a first order risk assessment can be provided (Section 2.5) from which priorities can be set for further investigation, potentially requiring a detailed hydraulic flood modeling study for high risk sub-catchments.

Present-day monetary exposure values in the floodplains are estimated using empirical estimates of reconstruction costs per unit area as identified by Huizinga et al. (2016). The reconstruction costs per building are specific to its use class. Using OpenStreetMap (OSM) (Haklay & Weber, 2008), flooded building footprints are obtained and assigned a use class. First, all footprints are classified as residential, refine them using the 50×50 m LUISA land use data set (Pigaiani & Batista e Silva, 2021) and refine further with OSM land use and amenity information (see Appendix C Table C1 and C2 for the classifications). Lastly, the total footprint areas are calculated and multiplied by the reconstruction costs per unit area to obtain exposed asset values in the floodplain. Content losses are not considered since our focus is on the construction sector and how flood induced reconstruction demand puts stress on the national economy (also see the case description in Section 2.1).

To incorporate socio-economic trends in the assessment, current exposure values per sub-catchment are adjusted to future values. The framework incorporates urban growth and property value growth by multiplying current exposure in the sub-catchment with their projected change factor, as described in Section 2.3.1.

2.4.2. Cascading Effects

A relevant cascading impact of flood risk is the pressure on sectors to substitute what was lost. If these sectors are overwhelmed by the extent of the event and the resulting increased demand, this can lead to enhanced and prolonged impacts (Hallegatte et al., 2024). To highlight potential reconstruction issues in the recovery phase, this study analyses cascading sectoral pressures directly after a flooding event in the baseline year and the various regional economic storylines. We use the term "stress" to indicate demand pressures due to the event relative to the pre-event demand for a sector. Sectors are ranked by their post-event demand stresses in baseline conditions, and the framework explores how these stresses develop across socio-economic storylines.

Economic input-output tables are used to explore sectoral demand change effects throughout the economy (Miller & Blair, 2009). The monetary interconnections between sectors recorded in these tables, available through national statistics offices and online databases such as the EORA database (Lenzen et al., 2013), are manipulated to show economy wide effects of a demand shock in the construction sector after a flood. The framework implements this manipulation by calculating the Leontief inverse matrix (Leontief, 1936), which formulates the economy-wide input requirements for each sector to produce one output unit of the sector. This formulation allows one to trace cascading demand effects from a flood induced demand in one sector through to all of its direct and indirect suppliers in the supply chain. For a formulaic representation of the demand changes, see Appendix D.

To assess stress across the economy the above Leontief inverse is multiplied with a flood induced reconstruction demand to construction sector. This results in absolute demand changes for the construction sector and its entire supply chain. Instead of absolute demand increases in each sector, relative demand increases are explored as they signal stresses on the sectors. Those sectors that need to upscale production most are likely to become bottlenecks and hamper the post-disaster recovery process.

To compare baseline conditions with future scenarios, the analysis is performed for the base year and all socio-economic storylines in the defined year of interest using associated input-output tables (described in Section 2.3.2) and the growth of asset values in the floodplain (see Section 2.4.1). The set of input-output tables

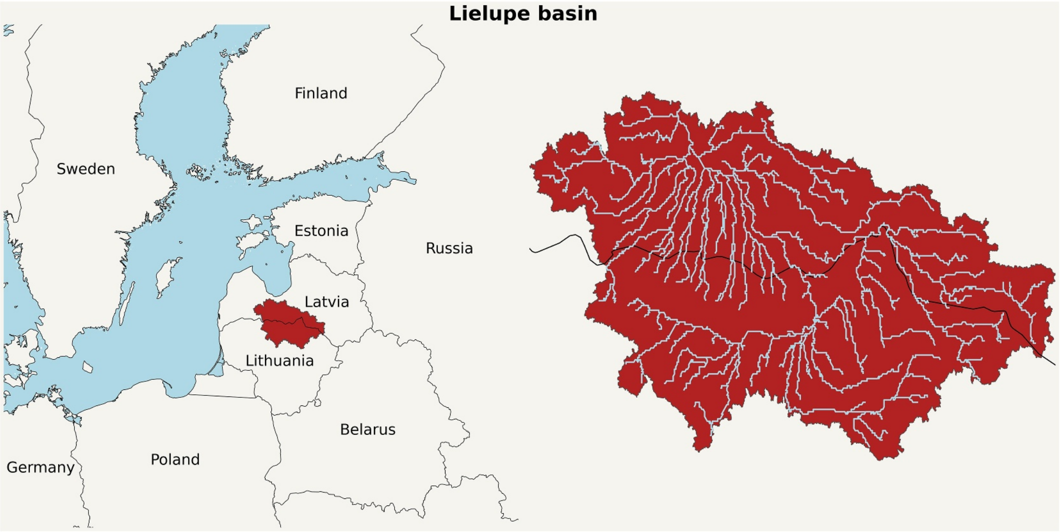

Figure 2. Region of interest. The left image shows the location in Europe, and the right image is a more detailed image of the river network in the basin. The red-filled shape is the Lielupe basin, and light blue indicates the sea surface and the rivers.

provides estimates of sectoral interactions and the relative size of sectors in the regional economy. The asset value growth in the floodplain is used to compare how a single unit of loss today is expected to grow in the future.

2.5. Combined Storylines

The identified climate scenario storylines with associated plausibilistic extreme discharges (Section 2.2.2) and socio-economic storylines of exposure to direct impacts (Section 2.4.2) are combined into climate impact storylines to find those regions most vulnerable to future climate impacts. Sub-catchments where both the exposure and extreme discharge increase, are assigned the highest risk level. A comprehensive overview of potential future risks can be made by making combinations of the plausibilistic discharge changes in climate scenario storylines with socio-economic storylines.

Whereas global and continental scale risk assessments often couple RCPs and SSPs, we choose to explore mutually independent variation of climate and socio-economic storylines for this regional study. For global and continental-scale risk assessments, coupling between climate and socio-economic drivers is intuitive since a specific global emissions level can only occur when there is a specific global socio-economic development (van Vuuren et al., 2014). However, local socio-economic developments driven by local policies and economic conditions can diverge substantially from global trends governing climate change processes. In addition, our scenario framework is not designed to scale with global greenhouse gas emissions in order to account for regional impact drivers (see the introduction). Therefore, the framework allows regional climate and socio-economic conditions to vary independently.

To avoid an overwhelming set of climate impact storylines, the methodology uses the reductionistic scenario-axis technique (van 't Klooster & van Asselt, 2006), spanning climate uncertainty on one axis and socio-economic uncertainty on the other. The two most divergent climate scenario storylines are combined with the two most contrasting socio-economic storylines, to highlight the spread in outcomes.

3. Example Case and Local Data

The framework starts by scoping the problem (Section 2.1). For our example case the analysis is informed by the Latvian NAP (Ministry of Environmental Protection and Regional Development, 2019) and river basin management plans (Latvijas Vides, ģeoloģijas un meteoroloģijas centrs, 2023). These documents are intended to support regional planning in the upcoming decade. Therefore, information about potential risk developments during the mid-21st century is of particular interest. The NAP voices concerns about flooding along rivers in the country. One such flood area is the transboundary Lielupe Basin (Figure 2). The Latvian-Lithuanian basin covers 17.600 km^2 and houses around 400,000 people. Local authorities have identified parts of the basin as a flood zone

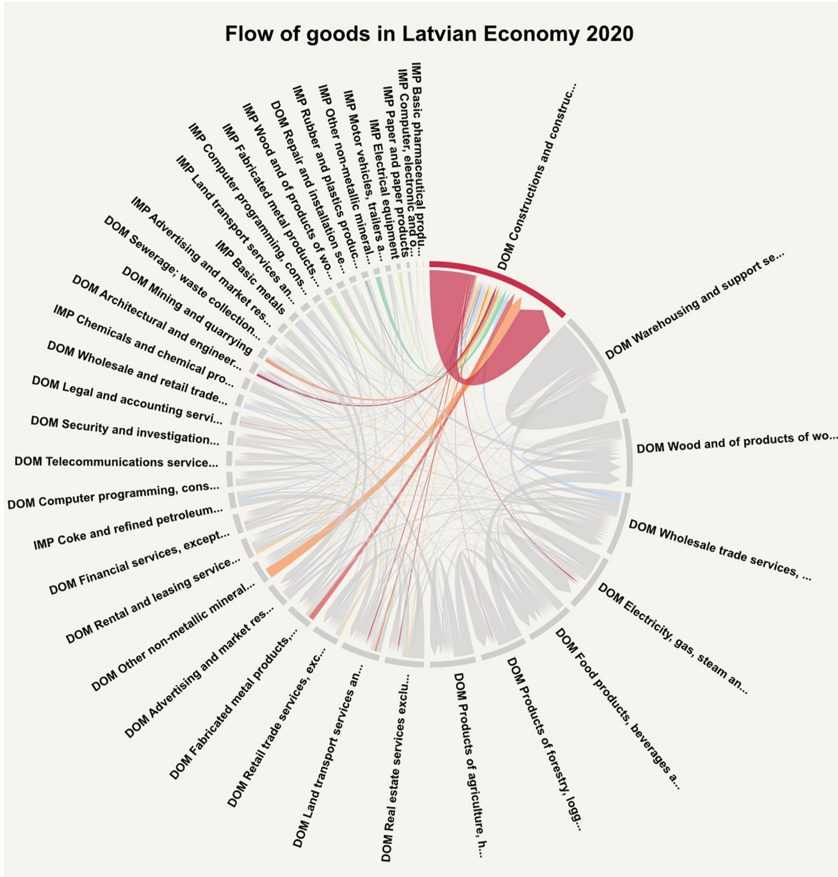

Figure 3. Sectoral interdependencies of the 40 largest sectors in Latvia represented by intermediate sectoral consumption and production of goods in euro. Sectors are sorted on the cumulative flow of goods between sectors from large to small in a clockwise position. Arrows indicate the flow direction of goods where products from one sector are used in another. The studied construction sector and its direct supplier and customer streams are highlighted in color. Underlying data is obtained from the Latvian statistics portal (Central Statistical Bureau of Latvia, 2023). "DOM" indicates domestic sectors, while "IMP" represents imported products, distinguishing between locally produced and imported sectoral impacts.

of national importance, and therefore, information on current and near-future flood risk is highly valuable. Especially the 1/100-year return period flooding is of interest, as events of this intensity cause significant impacts in the region (Latvijas Vides, ģeoloģijas un meteoroloģijas centrs, 2023). Both the NAP and river basin management plan are particularly concerned about losses to constructed assets, in our case buildings, along rivers. Consequently, this study will provide the evolution of risk to these assets.

Direct flood impacts on buildings have the potential to affect economic sectors outside of the flooded area. To illustrate the potential of cascading effects, Figure 3 shows the flow of goods between sectors in Latvia, as recorded in the economic input output table provided by the Central Statistical Bureau of Latvia (2023), revealing intersectoral dependencies. The construction sector and its direct suppliers and consumers in the economy comprises Latvia's largest producer and consumer of goods and depends on many domestic and foreign sectors. The sector and its dependencies are highlighted in Figure 3. This local data is used over globally available data (Lenzen et al., 2013) in our analysis steps described in Sections 2.3.1 and 2.4.2.

Figure 4 shows various pathways of GDP development (Dellink et al., 2017) and sectoral contributions (Leimbach et al., 2023) for the Latvian region under various SSPs. Here the construction sector is part of the "manufacturing" aggregate. In Section 2.3.2 we describe how we disaggregate the aggregate sector projections in Figure 4 to detailed information. Note that the manufacturing sector becomes a smaller part of the national economy in favor of the services sector.

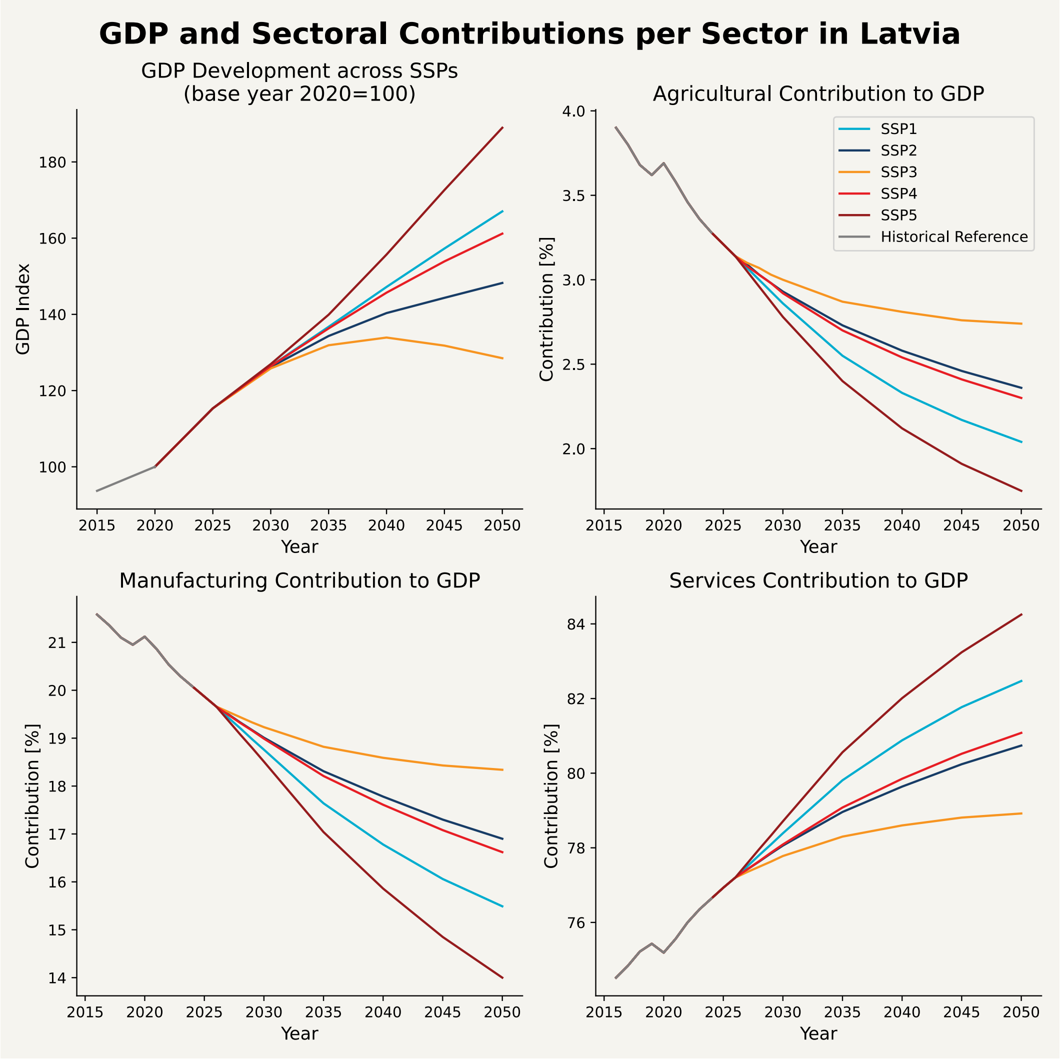

Figure 4. Gross Domestic Product (GDP) development and sectoral contributions. Top left panel: GDP development index across various global shared socio-economic pathways (SSPs) (100 = GDP in base year 2020). Other panels show changes in the composition of the Latvian economy. Each plot shows the change in the contribution of a specific aggregate sector to Latvian GDP. Data obtained through the IIASA SSP Extensions Explorer (Andrijevic et al., 2024) and IIASA SSP Scenario Explorer (https://data.ece.iiasa.ac.at/ssp).

Another local data integration is that of floodplain extent identification for each sub-catchment. We used 50-m resolution historical flood extent maps created by local authorities (Aplinkos apsaugos agentūra, 2022; Latvijas Videsģeoloģijas un meteoroloģijas centrs, 2019). Maps from local authorities are used over harmonized European or global data sets (e.g., Dottori et al. (2022) or Ward et al. (2020)) as these data set have low agreement with the used local maps. In the global and European data sets water reaches locations that are inaccessible in reality leading to misrepresented areas at risk. We attribute this low agreement with local data sets to the fact that the Lielupe basin contains levees and weirs to control floods. These structures are likely to be too small to be picked up by coarse large-scale flood modeling efforts. The flood extent for the highest available return period under current climate conditions is used. Since the basin covers two countries with different flood risk assessment procedures, we had to spatially merge the 200-year return period flood map for Latvia and the 1,000-year return period map for Lithuania into a regional product.

4. Results

4.1. Future Discharge Changes

By analyzing changes in the 1/100-year return period discharge across 8 basin stations using the 256 samples of future climate weather time series (method Section 2.2.1), Six unique CIDs are found that have a major impact on extreme discharge. Included are the average rainfall in winter, spring and summer, causing soil saturation to rise, leading to higher runoff volumes. Additionally, changes in the CV of precipitation in spring and summer are found to be important. Increases in CV correspond to more intense rainfall patterns, intensifying floods. Lastly, temperature in winter is a driver for extreme discharge change due to the influence on snow accumulation and melt. While sudden snowmelt is a large driver of floods in present-day climate conditions, this effect decreases when average temperatures rise and snow volume is reduced. Appendix A Figure A2 shows effects of the individual drivers on discharges across stations.

GCM projections are clustered into four independent climate scenario storylines based on the associated regional response of the six selected CIDs (see Section 2.2.2). For each cluster, the average change signal is calculated the each seasonal CIDs, not just the selected six CIDs. Figure 5 shows the change signals in the selected climate scenario storylines for seasonal precipitation, temperature, and precipitation CV. Larger changes in rainfall roughly coincide with larger temperature changes. Climate scenario storylines 1, 2, and 4 show similar trends with increasing monthly precipitation except in the summer months, where there is limited change. In contrast, storyline 3 shows less pronounced precipitation changes except for the winter months, with increased precipitation, and summer months, which show a drying trend. For the CV values, we can see a large variability of potential changes in the full set of GCM projections.

Figure 5 also shows changes in the 100-year return period extreme discharge across the basin for the different climate scenario storylines. Storyline 1 has the largest changes in the region. This is expected as the storyline is projected to have the most exacerbating changes of relevant CIDs, such as high increases in precipitation amounts during the winter and spring and increased rainfall variability in summer. Climate storylines 2 and 4 are similar to storyline 1 but with smaller changes. In climate storyline 3, many regions experience a decrease in extreme discharge. This reduction is tied to a combination of CIDs, rainfall decrease in summer and high winter temperatures, favoring lower flood peaks. Drying in the summer desaturates soils, with relatively limited recharge in the remaining months and low snow accumulation due to high temperatures. In general, a similar spatial pattern can be seen across the climate storylines, where the west of the basin is expected to have lower peak discharges in all climate storylines. These locations have smaller streams that are particularly sensitive to snow melt-induced extreme discharges. Since all climate storylines indicate a temperature increase, extreme snow melt occurs less frequently and less intensely.

4.2. The Effects of Socio-Economic Trends on Exposure

Following the steps outlined in Section 2.3.1 and 2.4.1, the basin aggregated asset value in the Latvian section of the floodplains is shown in Figure 6 for each socio-economic storyline. These aggregate values will be used when analyzing the cascading effects in the Latvian economy in Section 4.3. A similar calculation could be made for the Lithuanian section, however we focus our analysis to Latvia as indicated in our case description. The other panels show the spatial distribution of asset values across the basin for selected socio-economic storylines. An overall increase in building asset reconstruction value is found, especially in the regional economic storyline inspired by SSP5, where values rise to about 375% compared to the original. Also notable is the doubling of floodplain asset values compared to GDP in SSP5, indicating an increased value accumulation in floodplains compared to the 2020 baseline. The largest collection of assets in the floodplain continues to coincide with present-day urban centers for both Latvia and Lithuania. These urban centers also develop faster than the surrounding rural areas.

4.3. Cascading Effects

Using the methods described in Sections 2.3.2 and 2.4.2 we find that under various socio-economic storylines, the Latvian economy experiences different levels of sectoral stresses when confronted with a spike in construction demand, as seen in Figure 7. Sectors closely related to construction are under the highest stress in the baseline, and in most of these sectors, stresses rise as asset values in the floodplains increase. At the same time, stresses are compounded by the projected shrinking of manufacturing sectors across all SSP-inspired regional economic

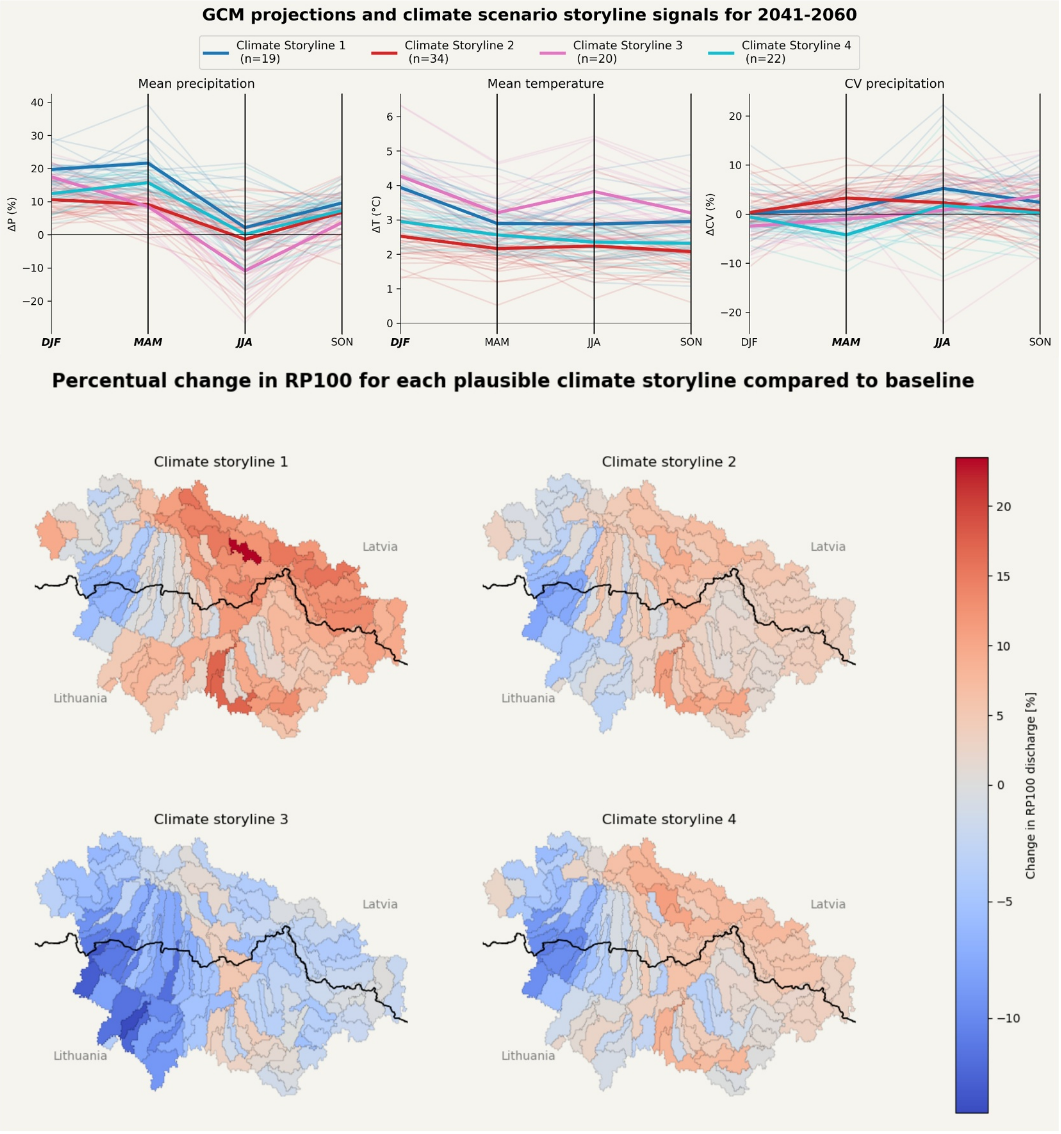

Figure 5. The top panel shows seasonal patterns of mean precipitation, temperature, and precipitation variability for the CMIP6 ensemble of model projections and four derived climate scenario storylines to assess ranges in regional discharge response to global warming. Thick colored lines represent the storyline's mean projections. Thin lines represent individual model projections color-coded according to the storyline cluster. In the legend, "$n = \#$" signifies the number of General Circulation Models assigned to the cluster. The bottom panel shows the change in 1/100-year probability discharge across the sub-catchments in the basin for each climate storyline.

storylines (Leimbach et al., 2023), leading to higher construction demand shocks and fewer resources to meet them. Stresses in the construction sector can rise from about 12% extra workload in the 2020 baseline situation to 36% in SSP5. Many other sectors can expect a doubling of their stress levels in SSP5 compared to levels in 2020. Koks and Thissen (2016) assume a production absorption capacity of 10% relative to the pre-disaster production levels for industries. Using 10% as a stress threshold, our findings show that when the region is confronted with a 2020 €500 mln. equivalent reconstruction demand shock, sectors can cross the stress threshold for some regional economic storylines, meaning the increased demand cannot be absorbed. Socio-economic developments can thus be a key driver in defining whether sectors will be overwhelmed and unable to meet additional demands induced by floods.

Rankings of sectors according to their stress levels, while relatively robust for domestic construction and closely related sectors, can shift over the various socio-economic storylines. For example, domestic architectural services

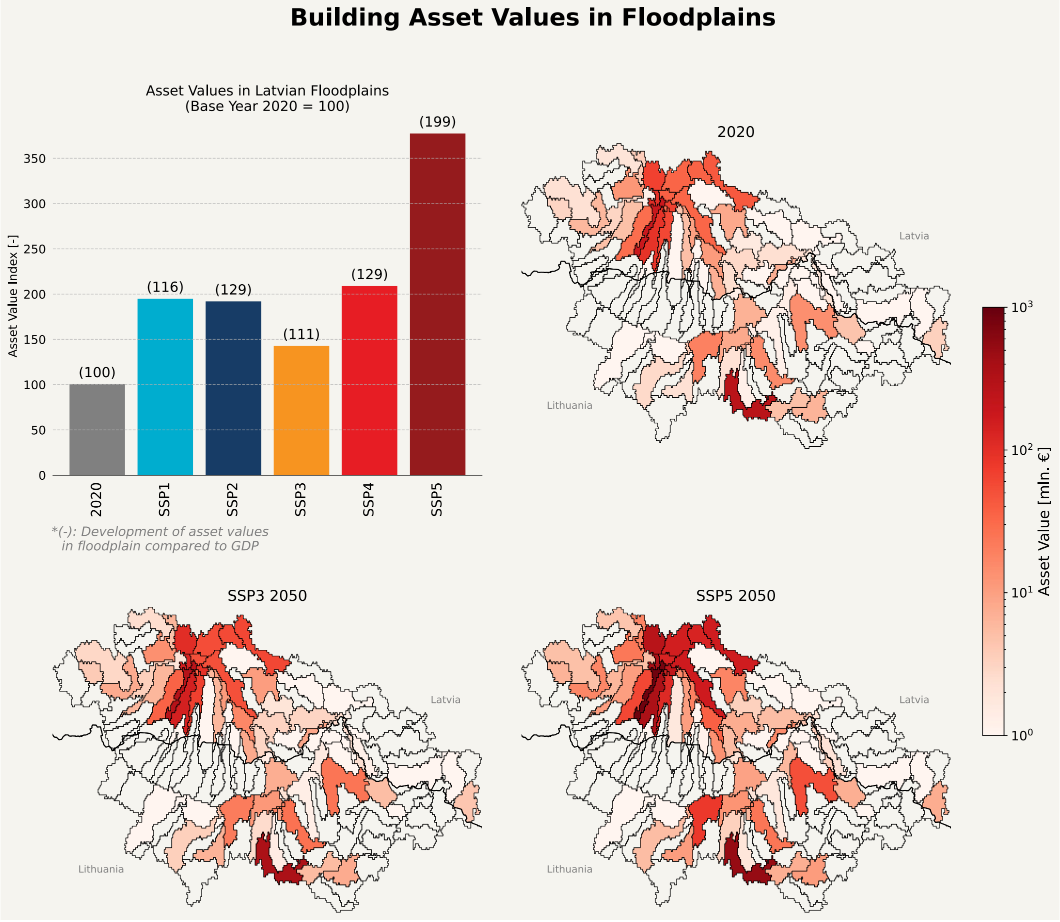

Figure 6. Building asset values in floodplain across shared socio-economic pathways (SSPs) relative to base year 2020. The top left shows the development of accumulated values in Latvia compared to the base year. In brackets, the asset values in the floodplain are compared to the national Gross Domestic Product in the SSP-inspired regional economic storyline. The remaining plots show the spatial development of building asset value for the 2020 baseline and the most divergent future socio-economic storylines for 2050.

experience increased stress, while imports by the same sector show decreased stress. As more service work is performed domestically, the demand and stresses shift from import sectors to domestic ones. Meanwhile, the stress ranking of construction imports decreases because this sector has grown significantly compared to its domestic counterpart; as more processes are offshored, import sectors become increasingly capable of handling the demand shock and absorbing increased demands.

4.4. Combined Storylines

Following Section 2.5, Figure 8 combines the most divergent socio-economic and climate storylines to detect patterns of overlapping risk drivers. The underlying data are already shown in Figures 5 and 6. Noticeably, across storylines both different and in intensity varying high-risk sub-catchments emerge. The storyline with the highest risk levels is a combination of Climate 1 and SSP 5. Compared to the baseline, asset values are increasingly situated in the floodplains due to high urban development, while the wetting of climate scenario storyline 1 causes more antecedent soil moisture, leading to increased discharges and higher overall flood risk. The lowest risk storyline is the combination of Climate 3 and SSP 3. In this case, the floodplain has low urban development, leading to lower losses when an event occurs than in SSP 5. Meanwhile, extreme discharges mainly decrease throughout the region due to reduced antecedent soil moisture and snowpack volumes. Although there is significant variability across storylines, sub-catchments can be identified that persistently face relatively high-risk levels.

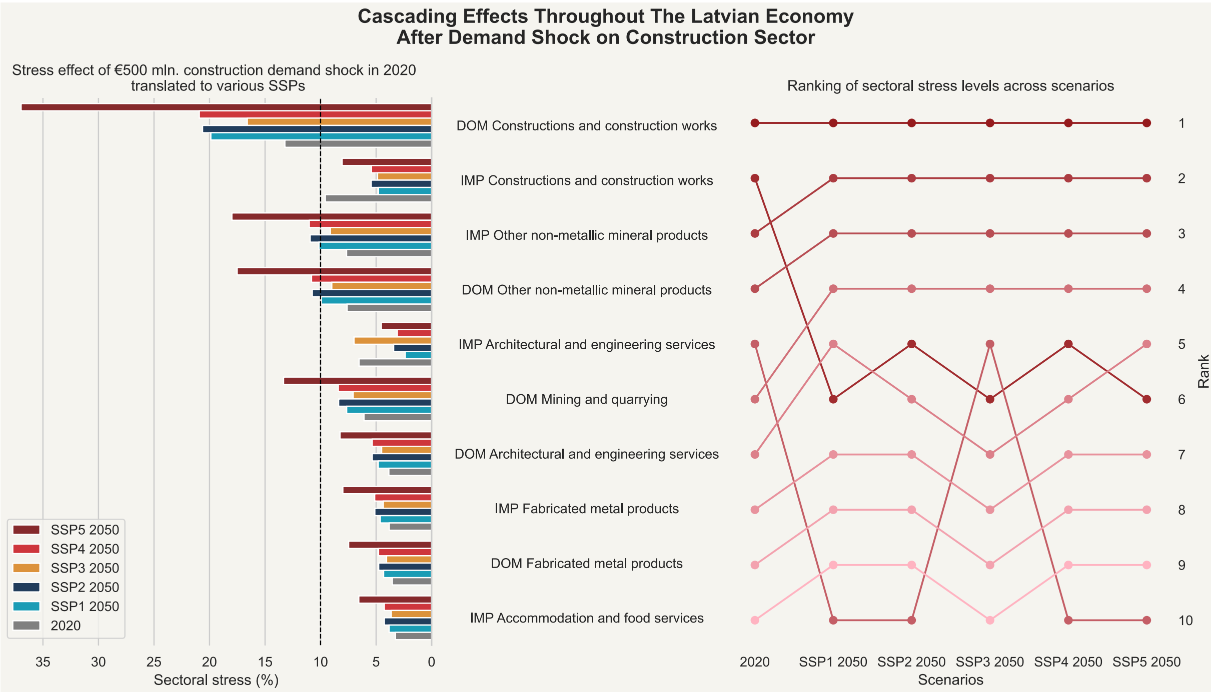

Figure 7. Sectoral stress levels in response to a €500 million (in 2020 and projected for each shared socio-economic pathway) construction demand shock across different socio-economic storylines, displayed as a bar chart (left) and a rank plot (right). The bar chart illustrates the percentual stress levels across socio-economic storylines in various sectors due to the shock. The rank plot ranks sectors by stress level across socio-economic storylines, with the vertical position of each line indicating each sector's rank, with the sector under the most stress at the top. Each line is color-coded from most stress (dark red) to least stress (light red) according to 2020 ranks. "DOM" indicates domestic sectors, while "IMP" represents imported products, highlighting the distinction between locally produced and imported sectoral impacts.

5. Discussion

5.1. From Risk Variability to Robust Priorities Using Integrated Storylines

Results highlight the importance of using multiple climate storylines to robustly assess future discharge extremes. Flood patterns vary significantly across storylines; while some indicate 10% regional reductions in the 100 year return period discharge, others indicate increases up to 20%. The storylines also reveal spatial heterogeneity: in some storylines and regions flood preconditions such as snow accumulation are reduced, whereas other preconditions (such as higher soil moisture volume due to increased rainfall) are amplified. Projected socio-economic changes can further amplify these climate risks. As exposed reconstruction values in the Latvian basin almost quadruple in SSP5 compared to the 2020 baseline, sectors are confronted with heightened flood-induced demand shocks related to reconstruction. Simultaneously, a trend of declining domestic manufacturing capacity doubles or triples most sectoral stresses relative to the 2020 baseline. In some storylines, the demand shock exceeds absorptive capacity of sectors, amplifying and prolonging indirect impacts (Hallegatte et al., 2024). Furthermore, increased dependency on imports due to the offshoring of the manufacturing sectors may create new vulnerabilities to foreign supply disruptions (Ercin et al., 2021). Conversely, this may lead to enhanced regional resilience through import diversification (Willner et al., 2018).

The main value of the frameworks, beyond the risk quantification, lies in enhancing confidence in risk priorities for decision-makers confronted with uncertainty. As Walker et al. (2013) argue, the objective is not to predict what will happen, but the objective is to guide actions that are likely to be beneficial in the future. The framework addresses this by creating a set of plausible and consistent storylines (Shepherd et al., 2018) based on well-established climate model ensembles (Eyring et al., 2016) and socio-economic narratives of the future (O'Neill et al., 2017). Furthermore, the integration of socio-economic, climate and cascading impact perspectives deepens the risk understanding, crucial for effective decision-making (Simpson et al., 2021). In our framework application, the approach reveals robust risk patterns across all storylines for specific sectors and regions (Figures 7 and 8), highlighting high confidence in their vulnerability. Ultimately, by building confidence in risk

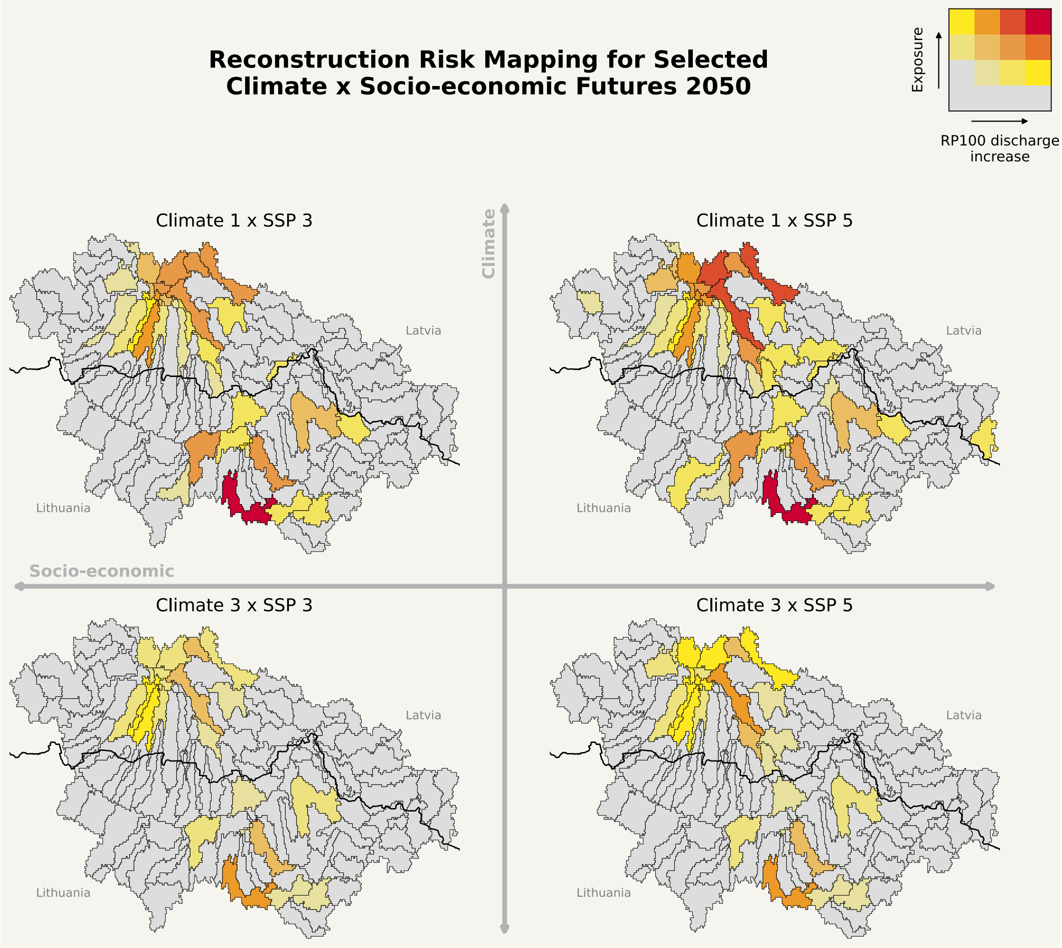

Figure 8. Spatial reconstruction risk mapping for 2050 under selected storylines highlighting potential regional climate and socio-economic developments. Each map highlights hazard changes and exposure levels using a bivariate color map, providing a measure of overlapping risk drivers.

priorities our framework improves the propensity to act, helping to overcome decision paralysis (Hallegatte, 2014) regarding where to act first.

This methodology is designed to create a diverse yet analytically affordable set of risk scenarios. To do so, certain choices were made that limited the exploration space in favor of robustness in the risk signal. While our storyline selection method displays a range of impact scenarios with higher regional representativity than emission-scenario based GCM clustering (Buskop et al., 2024), it reduces the explored impact range relative to the full ensemble of model outputs. Similarly, averaging discharge change results across multiple stochastic weather realizations reduced the variability in outcomes. Both steps involved a trade-off between achieving robust, high-confidence projections of likely outcomes and preserving detail about the less likely, but potentially critical risk scenarios. Other aggregation choices could have been made (Kwakkel et al., 2016; McPhail et al., 2018), and this warrants further discussion.

5.2. Global Projections for the Local Context

Our methodology uses freely available global data and tools, making it flexible to apply to a diverse set of regions for which climate risks need to be mapped. For example, we included Lithuania in the spatial mapping results to show the flexibility of the framework across countries. Our methodology for selecting climate scenario storylines could also be applied to other hazards by changing the CIDs of interest, such as those relevant to drought impacts. Additionally, the projected macro-economic input-output tables provide versatility to analyze cascading effects arising from impacts in a variety of sectors. For instance, a preliminary analysis for this study also addressed agricultural impacts and cascading disruptions within the region. However, for Latvia these were minor compared to the (in)direct impacts on the reconstruction sector and have therefore not been considered in detail.

The geographical and sectoral flexibility comes with its limitations. Although the risk scoping was guided by (gray) literature specifically targeting regional issues, the used socio-economic projections are derived from downscaled global data sets. Consequently, these projections may not fully capture local socio-economic developments, as global studies do not capture regional nuances and policies (Blankespoor et al., 2023). Therefore, the accuracy of risk information from our methodology should be verified with regional stakeholders and adjusted if needed.

This study could benefit from localizing the global SSPs (Alizadeh et al., 2022; Reimann et al., 2021) to incorporate policies influencing sectoral changes or add spatial detail to urban developments. Adding local socio-economic information could further specify direct and cascading impacts on specific income groups or businesses and/or sectors, as demonstrated by Bachner et al. (2024). Additionally, expertise on local hazard profiles could refine climate scenario storylines selection by assigning higher weights to CIDs relevant to known high-risk areas, steering clustering of climate projections. Furthermore, hazard estimation could benefit from spatial flood modeling using local hydrodynamic models.

5.3. Socio-Economic and Climate Developments for Impact Attribution

In climate science, attribution often refers to how anthropogenic emissions change the likelihood of extreme meteorological events (Shepherd, 2016; Stott et al., 2016; van Oldenborgh et al., 2021). However, extreme meteorological events themselves are not always sufficient to lead to high (societal) impacts. These can also occur from coinciding moderate events (van der Wiel et al., 2020), and flood impacts are often enhanced due to socio-economic risk drivers (Merz et al., 2021; Steinhausen et al., 2022; Winsemius et al., 2016). Therefore, impact-focused attribution can help to better understand and quantify risk drivers' contribution to future climate risks (Mengel et al., 2021). Under particular conditions socio-economic developments, rather than climate changes, are the main risk drivers (Barnes et al., 2023). Identifying the "differences that make a difference" enables risk managers to take targeted actions on the most impactful risk drivers within their control.

Our applied methodology aligns well with an impact attribution framework but is not fully comprehensive. While it analyzed how socio-economic changes and a changing climate drive risk, it is not able to quantify their comparative effects in the absence of detailed flood modeling. Future studies could extend our model chain to include flood maps under climate change, enabling risk attribution to specific drivers.

5.4. System Boundaries and Their Effects

As with many studies, the problem scoping and system boundary definition can significantly influence outcomes and recommendations. Our research confined the problem boundary to Latvia and specifically focused on the adverse stress effects. Expanding the scope to incorporate cross border dynamics, using a similar economic input-output method could highlight positive spillover effects across the border as production is shifted to unaffected areas (Middelanis et al., 2022). At the same time construction sectors of neighboring countries can be called upon to lower domestic sectoral stresses. Even within Latvia, positive effects can occur. The disaster event might act as an "opportunity tipping point" (Haasnoot et al., 2019), opening a window of opportunity to increase adaptation efforts and "build back better," as seen in New York after Hurricane Sandy (Rosenzweig & Solecki, 2014). Reconstruction efforts may also boost the local economy. The labor-intensive construction work might lower unemployment in the aftermath of business destruction while at the same time having a positive effect on GDP (Vagliasindi & Gorgulu, 2021). However, further extending the system boundary to include macro-level trends in the region, such as an aging population which limits the upscaling of production, can further modulate risks and adaptation opportunities. We, therefore, reiterate that setting the objectives and system boundary remains an important factor in the climate risk analysis.

6. Conclusion

Our ability to manage future climate risks is partly determined by our ability to anticipate these risks. This requires handling a diversity of possible future developments in both human and natural systems. This in turn is aided by a comprehensive but comprehensible package of targeted climate and socio-economic risk information to allow for informed adaptation decision-making. To this end, we introduced a novel multi-modal methodology targeting flood risk assessment that explores "plausibilistic" future climate risks by sampling a range of plausible socio-economic and climate storylines with associated conditional discharge probabilities. By combining meteorological, hydrological, and socio-economic perspectives, this approach comprehensively captures the influence of future changes on both direct impacts and cascading effects in connected multi-sectoral systems.

Application of this framework in the transboundary Latvian Lithuanian Lielupe river basin illustrated the necessity of this integrated approach. The 100-year return period discharge extreme deviates between −10% and +20% and is highly dependent on the climate scenario storyline and sub catchment. However at the same time socio-economic developments can amplify direct impacts by up to 375% and double or triple sectoral stress levels. This underscores the fact that neglecting either climate or socio-economic risk drivers yields an incomplete picture of future risks as both amplify or attenuate (cascading) impacts. While quantification of these changes is crucial, the primary value of the framework lies in the selection process of a credible set of risk futures. By systematically mapping risk variability across storylines and sub-catchments based on plausible climate and socio-economic storyline the framework can turn uncertainty into insight. By revealing persistent high risk sub-catchments and sectors across storylines, regional decision makers can identify risk priorities with greater confidence allowing for more strategic adaptation planning.

Our plausibilistic climate impact storylines framework advances integrated climate risk assessments by embracing the complexity inherent to uncertain human and natural systems by exploring plausible developments of relevant risk drivers in both domains. While this requires risk managers to navigate complexity, the framework reduces the complexity into a small set of credible, relevant and diverse set of risk storylines leading to more comprehensive and valuable insights for adaptation planning. Because the framework leverages open data and tools, regions worldwide can apply the framework to gain critical insights into those areas and sectors most in need of adaptation strategies.

Appendix A: Obtaining Relevant Climate Impact Drivers

See Table A1 and Figures A1 and A2.

Table A1
Table of Used Models and Shared Socio-Economic Pathways (SSPs) in the 2041–2060 Timeframe

Model name	SSP1-2.6	SSP2-4.5	SSP3-7.0	SSP5-8.5
ACCESS-CM2	✓	✓	✓	✓
BCC-CSM2-MR	✓	✓	✓	✓
CanESM5	✓			✓
CESM2	✓	✓	✓	✓
CESM2-WACCM			✓	✓
CMCC-CM2-SR5		✓	✓	✓
CMCC-ESM2	✓	✓		✓
CNRM-CM6-1	✓	✓	✓	✓
CNRM-CM6-1-HR	✓			✓
CNRM-ESM2-1	✓	✓	✓	✓
EC-Earth3-AerChem			✓	
EC-Earth3-CC		✓		✓
FGOALS-g3	✓	✓	✓	✓
GFDL-ESM4	✓	✓	✓	✓
HadGEM3-GC31-LL	✓	✓		✓
HadGEM3-GC31-MM	✓			✓
IITM-ESM	✓	✓	✓	✓
INM-CM4-8	✓	✓	✓	✓

Table A1
Continued

Model name	SSP1-2.6	SSP2-4.5	SSP3-7.0	SSP5-8.5
INM-CM5-0	✓	✓	✓	✓
IPSL-CM5A2-INCA	✓		✓	
IPSL-CM6A-LR	✓	✓	✓	✓
KACE-1.0-G	✓	✓	✓	✓
KIOST-ESM	✓	✓		
MIROC-ES2L	✓	✓	✓	✓
MIROC6	✓	✓	✓	✓
MPI-ESM1-2-LR	✓	✓	✓	✓
MRI-ESM2-0	✓	✓	✓	✓
NESM3		✓		✓
NorESM2-MM	✓	✓	✓	✓
TAI-ESM1				✓
Count	24	23	21	27

Note. Model data extracted from Copernicus Data Store (Copernicus Climate Change Service, 2021).

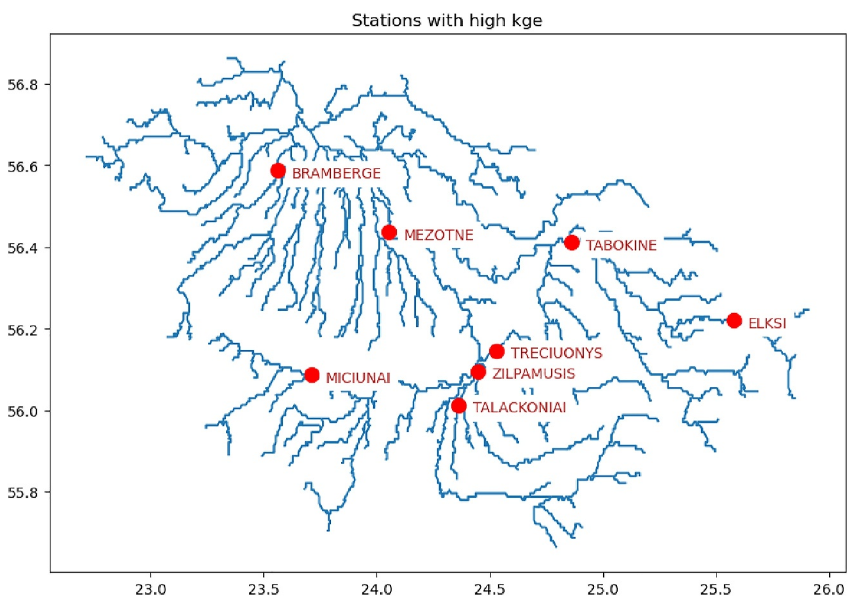

Figure A1. A map of the Lielupe basin rivers (in blue) with stations in red with Kling-Gupta Efficiency ≥0.5 and thus considered in the Climatic Impact-Driver clustering. The names of the stations are annotated in red.

Appendix B: Projecting Input-Output Tables

This appendix details the projection process of national input-output tables according to socio-economic trends and sectoral shifts in shared socio-economic pathways (SSPs). First, the baseline year national input-output table was retrieved and detailed sectors data are aggregated to those sectors available in Leimbach et al. (2023): Agriculture, Manufacturing and Services. Contribution ratios of sectors within each broad group are kept as is, since more granular sectoral change information is not available.

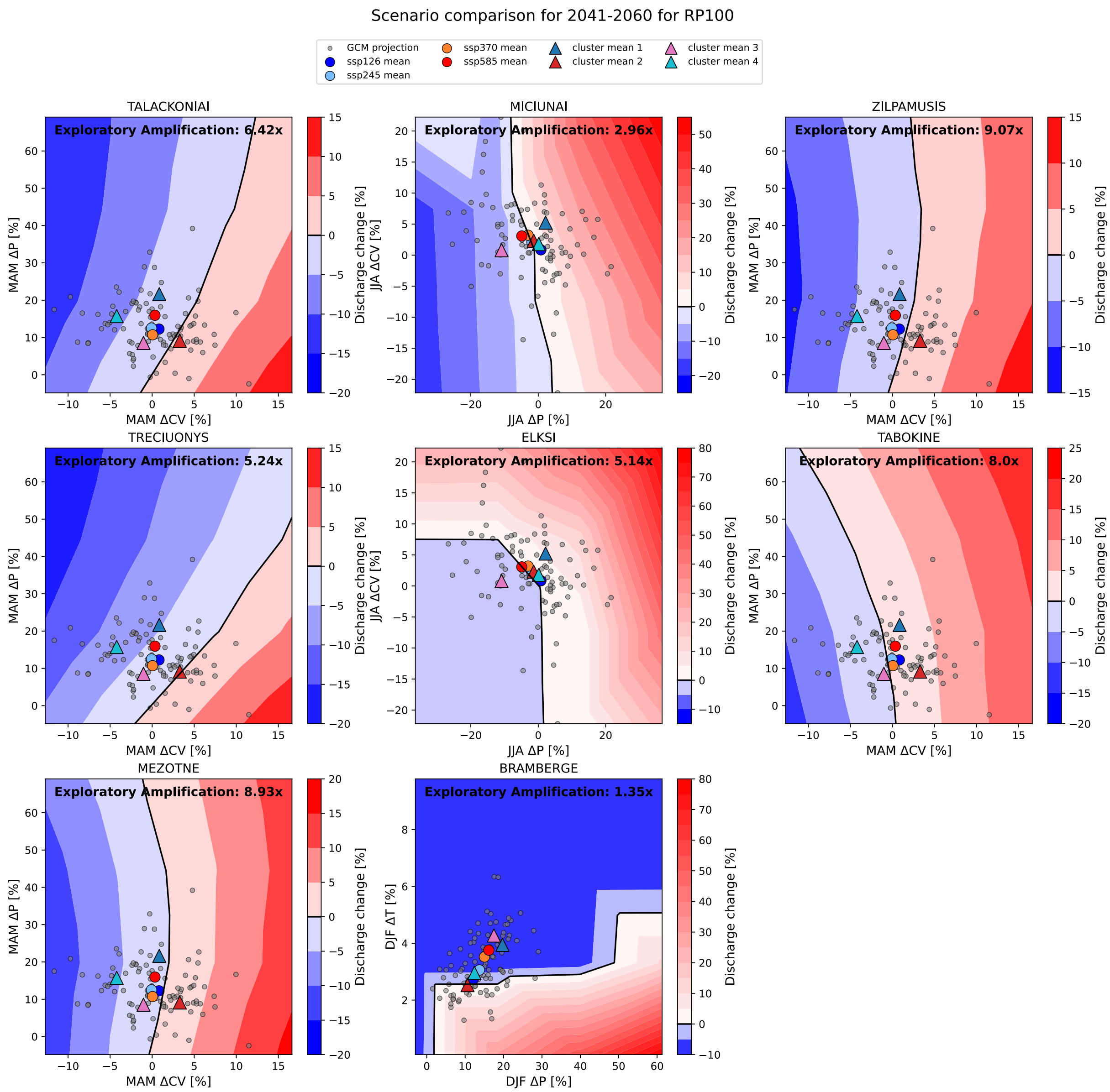

Figure A2. Impact response for the 2041–2060 timeframe for various stations in the basin and their top two climate features of importance. The axis labels represent seasonal changes for December-January-February (DJF), March-April-May (MAM), June-July-August (JJA), and September-October-November (SON). For selected seasons, the changes in average temperature (ΔT), average precipitation (ΔP) and coefficient of variation (ΔCV) of that precipitation are shown. The background hue indicates the discharge change for that return period at any combination of the selected climate features. Each gray point represents an individual General Circulation Model model projection for SSP126, SSP245, SSP370, and SSP585. The colored circles represent the shared socio-economic pathway model means, and colored triangles represent the model means of the different clusters. The exploratory amplification for each station is provided.

The projection process starts by multiplying the base year national value added by the projected gross domestic product (GDP) growth in the year of interest. Next, the value added is allocated among the three aggregate sectors according to the projection, providing an estimate of each sector's size in the year of interest for an SSP.

$$\mathrm{VA}_{s,\mathrm{SSP}}^{\mathrm{future}} = \alpha_{s,\mathrm{SSP}}^{\mathrm{future}} * \mathrm{VA}^{\mathrm{basline}} * g_{\mathrm{SSP}}^{\mathrm{future}}$$

where:

$\mathrm{VA}_{s,\mathrm{SSP}}^{\mathrm{future}}$: projected value added of NACE3 sector s in 2050 for an SSP scenario.

$\alpha_{s,\mathrm{SSP}}^{\mathrm{future}}$: projected sectoral contribution share of an aggregated sector group s in the year of interest for an SSP scenario.

$\mathrm{VA}^{\mathrm{baseline}}$: total value added in the economy in the base year.

$g_{\mathrm{SSP}}^{\mathrm{future}}$: growth value of GDP in the year of interest for an SSP scenario.

To maintain a detailed sectoral analysis, the value added of each broad sector group is disaggregated to the original sector detail using baseline value-added contributions ratios within the aggregate sector. This proportional allocation assumes that internal distribution within a broad sector groups does not change from the base year. Using the updated value added for each sector, the required input goods from the detailed sectors are calculated based on the baseline ratio of input units per unit of value added.

$$\mathrm{VA}_{i,\mathrm{SSP}}^{\mathrm{future}} = \mathrm{VA}_{s,\mathrm{SSP}}^{\mathrm{future}} * \frac{\mathrm{VA}_i^{\mathrm{baseline}}}{\mathrm{VA}_s^{\mathrm{baseline}}}$$

where:

$\mathrm{VA}_{i,\mathrm{SSP}}^{\mathrm{future}}$: projected value added of detailed sector i in 2050 for an SSP scenario.

$\mathrm{VA}_{s,\mathrm{SSP}}^{\mathrm{future}}$: projected value added of an aggregated sector group s in 2050 for an SSP scenario.

$\mathrm{VA}_i^{\mathrm{baseline}}$: value added of detailed sector i in 2020.

$\mathrm{VA}_s^{\mathrm{baseline}}$: value added of broad sector group s in 2020.

$$\mathrm{Input}_{i\leftarrow j,\mathrm{SSP}}^{\mathrm{future}} = \mathrm{VA}_{i,\mathrm{SSP}}^{\mathrm{future}} * \frac{\mathrm{Input}_{i\leftarrow j}^{\mathrm{baseline}}}{\mathrm{VA}_i^{\mathrm{baseline}}}$$

Where:

$\mathrm{Input}_{i\leftarrow j,\mathrm{SSP}}^{\mathrm{future}}$: input required from sector j for sector i in the target year for an SSP scenario.

$\mathrm{Input}_{i\leftarrow j}^{\mathrm{baseline}}$: input required from sector j for sector i in the baseline year.

$\mathrm{VA}_{i,\mathrm{SSP}}^{\mathrm{future}}$: projected value added of sector i in target year for an SSP scenario.

$\mathrm{VA}_i^{\mathrm{baseline}}$: value added of sector i in baseline year.

Meanwhile, the final demands for each sector's output, sectoral goods not used as intermediate inputs for other sectors (such as household consumption or government spending), are scaled with overall national GDP increases to anticipate increases in consumption patterns.

$$\mathrm{FD}_{i,\mathrm{SSP}}^{\mathrm{future}} = \mathrm{FD}_i^{\mathrm{baseline}} * g_{\mathrm{SSP}}^{\mathrm{future}}$$

where:

$\mathrm{FD}_{i,\mathrm{SSP}}^{\mathrm{future}}$: final demand for sector i in the target year for an SSP scenario.

$\mathrm{FD}_i^{\mathrm{baseline}}$: final demand for sector i in the baseline year.

$g_{\mathrm{SSP}}^{\mathrm{future}}$: growth value of GDP in the target year for an SSP scenario.

These calculations may cause growing sectors to demand inputs from shrinking domestic sectors, which may be unable to meet those demands. Conversely, some sectors may produce more than local demand requires. This creates an imbalance between a sector's inputs and outputs. However, a fundamental notion in the IO framework is that each sector's inputs and outputs must balance. This balance ensures that all produced goods are allocated and input goods are sourced appropriately in the accounting. To balance the table we introduce additional imports and exports for the mentioned cases.

$$X_i^{\text{future}} = \text{VA}_{i,\text{SSP}}^{\text{future}} + \sum_j \text{Input}_{i\leftarrow j,\text{SSP}}^{\text{future}}$$

where:

X_i^{future}: total output of sector i.

$\text{Input}_{ij,\text{SSP}}^{\text{future}}$: input required from sector j for sector i in the target year for an SSP scenario.

$\text{VA}_{i,\text{SSP}}^{\text{future}}$: projected value added of sector i in the target year for an SSP scenario.

$$D_{i,\text{SSP}}^{\text{future}} = \text{FD}_{i,\text{SSP}}^{\text{future}} + \sum_j \text{Input}_{j\leftarrow i,\text{SSP}}^{\text{future}}$$

where:

$D_{i,\text{SSP}}^{\text{future}}$: total demand of sector i.

$\text{FD}_{i,\text{SSP}}^{\text{future}}$: final demand for sector i in the target year for an SSP scenario.

$\text{Input}_{ij,\text{SSP}}^{\text{future}}$: input required by sector j from sector i in the target year for an SSP scenario.

In the calculus, the need for exports or imports is determined by subtracting the total inputs into a sector from the total output needed from that sector. The resulting value of extra imports or exports needed are distributed according to usage shares, sectors using most of a sector's outputs, import most. If local production exceeds local consumption, imports of domestic sectors that require the specific local goods are reduced to zero, and the remaining goods are added to a producing sector's final demand as exports. This process ensures that projected inputs and outputs are in balance.

$$\text{NP}_{i,\text{SSP}}^{\text{future}} = X_{i,\text{SSP}}^{\text{future}} - D_{i,\text{SSP}}^{\text{future}}$$

where:

$\text{NP}_{i,\text{SSP}}^{\text{future}}$: net production sector i in the target year for an SSP scenario.

X_i^{future}: total output of sector i in the target year for an SSP scenario.

D_i^{future}: total demand of sector i in the target year for an SSP scenario.

$$\text{Input}'^{\text{future}}_{j\leftarrow i_{\text{imp}},\text{SSP}} = \text{Max}\left(\text{Input}^{\text{future}}_{j\leftarrow i_{\text{imp}},\text{SSP}} + \text{NP}^{\text{future}}_{i,\text{SSP}} * \frac{\text{Input}^{\text{future}}_{j\leftarrow i_{\text{dom}},\text{SSP}}}{X^{\text{future}}_{i,\text{SSP}}};\ 0\right)$$

where:

$\text{Input}'^{\text{future}}_{j\leftarrow i_{\text{imp}},\text{SSP}}$: Adjusted imports by sector j from sector i in the target year under the SSP scenario. $\text{Input}^{\text{future}}_{j\leftarrow i_{\text{imp}},\text{SSP}}$ = Original projected imports by sector j from sector i in the target year under the SSP scenario. $\text{NP}_{i,\text{SSP}}^{\text{future}}$: net production sector i in the target year for an SSP scenario.

$\text{Input}^{\text{future}}_{j\leftarrow i_{\text{dom}},\text{SSP}}$: Total inputs required by sector j from domestic sector i in the target year under the SSP scenario.

$$\text{Input}'^{\text{future}}_{j\leftarrow i_{\text{dom}},\text{SSP}} = \text{Input}^{\text{future}}_{j\leftarrow i_{\text{dom}},\text{SSP}} + \text{Input}^{\text{future}}_{j\leftarrow i_{\text{imp}},\text{SSP}} - \text{Input}'^{\text{future}}_{j\leftarrow i_{\text{imp}},\text{SSP}}$$

where:

$\text{Input}'^{\text{future}}_{j\leftarrow i_{\text{dom}},\text{SSP}}$: Adjusted domestic inputs from sector i to sector j in the target year under the SSP scenario.

$\text{Input}^{\text{future}}_{j\leftarrow i_{\text{dom}},\text{SSP}}$: Original projected domestic inputs from domestic sector i to sector j in the target year under the SSP scenario.

$\text{Input}^{\text{future}}_{j\leftarrow i_{\text{imp}},\text{SSP}}$ = Original projected imports by sector j from sector i in the target year under the SSP scenario.

$\text{Input}'^{\text{future}}_{j\leftarrow i_{\text{imp}},\text{SSP}}$: Adjusted imports by sector j from sector i in the target year under the SSP scenario.

$$D'^{\text{future}}_{i,\text{SSP}} = \text{FD}^{\text{future}}_{i,\text{SSP}} + \sum_j \text{Input}'^{\text{future}}_{j\leftarrow i,\text{SSP}}$$

where:

$D'^{\text{future}}_{i,\text{SSP}}$: Adjusted total demand of sector i.

$\text{FD}^{\text{future}}_{i,\text{SSP}}$: final demand for sector i in the target year for an SSP scenario.

$\text{Input}'^{\text{future}}_{j\leftarrow i,\text{SSP}}$: Adjusted input required by sector j from sector i in the target year for an SSP scenario.

$$X'^{\text{future}}_{i} = \text{VA}^{\text{future}}_{i,\text{SSP}} + \sum_j \text{Input}'^{\text{future}}_{i\leftarrow j,\text{SSP}}$$

where:

X'^{future}_{i}: Adjusted total output of sector i.

$\text{Input}'^{\text{future}}_{i\leftarrow j,\text{SSP}}$: Adjusted input required by sector i from sector j in the target year for an SSP scenario.

$\text{VA}^{\text{future}}_{i,\text{SSP}}$: projected value added of sector i in the target year for an SSP scenario.

$$\text{NP}'^{\text{future}}_{i,\text{SSP}} = X'^{\text{future}}_{i,\text{SSP}} - D'^{\text{future}}_{i,\text{SSP}}$$

where:

$\text{NP}'^{\text{future}}_{i,\text{SSP}}$: adjusted net production sector i in the target year for an SSP scenario.

X'^{future}_{i}: adjusted total output of sector i in the target year for an SSP scenario.

D'^{future}_{i}: adjusted total demand of sector i in the target year for an SSP scenario.

$$\text{Input}''^{\text{future}}_{i\leftarrow i_{\text{imp}},\text{SSP}} = \text{Input}'^{\text{future}}_{i\leftarrow i_{\text{imp}},\text{SSP}} - \text{NP}'^{\text{future}}_{i,\text{SSP}}$$

where:

$\text{Input}''^{\text{future}}_{i\leftarrow i_{\text{imp}},\text{SSP}}$: Further adjusted imports by sector i from sector i in the target year under the SSP scenario.

$\text{Input}'^{\text{future}}_{i\leftarrow i_{\text{imp}},\text{SSP}}$: Adjusted imports by sector i from sector i in the target year under the SSP scenario.

$\text{NP}'^{\text{future}}_{i,\text{SSP}}$: adjusted net production sector i in the target year for an SSP scenario.

$$\text{if } \text{Input}''^{\text{future}}_{i\leftarrow i_{\text{imp}} i,\text{SSP}} < 0\,\mathbf{:}$$

$$\text{FD}'^{\text{future}}_{i,\text{SSP}} = \text{FD}^{\text{future}}_{i,\text{SSP}} + \left(-\ \text{Input}''^{\text{future}}_{i\leftarrow i_{\text{imp}},\text{SSP}}\right)$$

$$\text{Input}''^{\text{future}}_{i\leftarrow i_{\text{imp}},\text{SSP}} = 0$$

where:

$\text{Input}''^{\text{future}}_{i\leftarrow i_{\text{imp}},\text{SSP}}$: Further adjusted imports by sector i from sector i in the target year under the SSP scenario.

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$FD'^{future}_{i,SSP}$: Adjusted final demand for sector i in the target year for an SSP scenario.

$FD^{future}_{i,SSP}$: Original final demand for sector i in the target year for an SSP scenario.

Appendix C: Building Classification

See Table C1 and C2.

Table C1
Aggregation of Land Use Classes

Sector	LUISA land use class
Forestry	Agro-forestry areas
	Broad-leaved forest
	Coniferous forest
	Mixed forest
Agriculture	Non irrigated arable land
	Permanently irrigated land
	Rice fields
	Vineyards
	Fruit trees and berry plantations
	Olive groves
	Pastures
	Annual crops associated with permanent crops
	Complex cultivation patterns
	Land principally occupied by agriculture

Table C2
Classification of Building Footprints Based on OpenStreetMap (OSM) and LUISA Data

Assigned footprint class	LUISA	OSM landuse	OSM amenities
Industrial	Industrial or commercial units	Industrial	Industrial
	Road and rail networks and associated land	Construction	Construction
	Major stations	Military	Military
	Port areas	Quarry	Quarry
	Airport areas	Railway	Railway
	Airport terminals	Barn	Barn
	Mineral extraction sites	Greenhouse	Greenhouse
	Dump sites	Hangar	Hangar
	Construction sites	Garages	Garages
Commercial		Church	Church
		Commercial	Commercial
		Hospital	Hospital
		Hotel	Hotel
		Retail	Retail
		School	School
		Service	Service
		Synagogue	Synagogue
		University	University

Table C2
Continued

Assigned footprint class	LUISA	OSM landuse	OSM amenities
		Supermarket	Supermarket
		Office	Office
		Mosque	Mosque
		Kindergarten	Kindergarten
		Social_facility	Social_facility

Appendix D: Demand Change Through the Leontief Inverse

Additional demand pressures on the national construction sector and its supply chain are derived from the direct structural losses. Cascading demand changes are found by multiplying the demand increase in the construction sector equal to the reconstruction costs with the Leontief inverse. The Leontief inverse, represented by $(\text{I-A})^{-1}$, is created using the national input-output tables. The input-output table is the basis for developing the technical coefficient matrix A. This matrix formulates the direct input requirements for producing one output unit in each sector. Each element a_{ij} in matrix A represents the input of sector i to sector j, divided by the total output of j. Using this matrix, we can use the following equation to find the demand changes across the economy.

$$\Delta \boldsymbol{x} = (\boldsymbol{I} - \boldsymbol{A})^{-1} \Delta \boldsymbol{f}$$

where:

Δx: vector of total output change for each sector.

I: identity matrix. A: technical coefficient matrix.

Δf: vector with demand change of each sector.

Data Availability Statement

The CMIP6 data can be freely obtained through Copernicus Climate Change Service (2021). The historical ERA5 data is obtained from Hersbach et al. (2023). The open-source hydrological model Wflow version v1.0.0 is available on Zenodo (van Verseveld et al., 2025) development versions are accessible on https://github.com/Deltares/Wflow.jl. The projected socio-economic data can be found in the following data repositories (Chen et al., 2019; Gao & Pesaresi, 2021b; Leimbach et al., 2022; X. Wang et al., 2022). Implementation of the used weather generator can be found at https://github.com/Deltares-research/weathergenr. Analysis code and data used in this study is published at Zenodo (Buskop, 2024).

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