Integrating Probabilities and Storylines to Explore Uncertain Direct and Cascading Climate Risks in Multi-sectoral Systems: A Case of The Lielupe Basin

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Abstract

Anticipating and managing future climate risks in interconnected multi-sectoral systems is complicated by uncertainties in risk drivers in both human and natural systems. Comprehensive yet comprehensible targeted climate risk information exploring these uncertainties is relevant for e.g. strategic allocation of limited resources to the most vulnerable areas and sectors. To address these complexities, this study introduces an interdisciplinary methodology combining meteorological, hydrological, and socio-economic perspectives, tested in the flood-prone, transboundary Lielupe basin shared by Latvia and Lithuania. A 'plausibilistic' risk assessment approach is applied in which plausible climate scenario storylines are sampled on their relevance for local impacts, allowing the assessment of conditional changes in high-impact probabilistic discharges. In addition, plausible yet differently structured future urban areas and economies are sampled to project direct impact potential and its cascading socio-economic effects. By integrating both climate and socio-economic scenarios, a risk mapping can be made to highlight regions where (compounding) risk drivers may occur. Application to the Lielupe basin reveals those areas and sectors most vulnerable to climate impacts across diverse climate and socio-economic scenarios. Our comprehensive approach equips regional risk managers with targeted risk information essential for prioritising adaptation planning.

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Key Points:

- A 'plausibilistic' approach to assess uncertain regional climate risks by combining event probabilities and plausible climate storylines
- Targeted insights addressing direct and cascading risks in multi-sectoral systems facing climate and socio-economic uncertainty
- Application to the Lielupe basin highlights key risk areas and sectors, aiding risk managers in their adaptation planning

Abstract

Anticipating and managing future climate risks in interconnected multi-sectoral systems is complicated by uncertainties in risk drivers in both human and natural systems. Comprehensive yet comprehensible targeted climate risk information exploring these uncertainties is relevant for e.g. strategic allocation of limited resources to the most vulnerable areas and sectors. To address these complexities, this study introduces an interdisciplinary methodology combining meteorological, hydrological, and socio-economic perspectives, tested in the flood-prone, transboundary Lielupe basin shared by Latvia and Lithuania. A 'plausibilistic' risk assessment approach is applied in which plausible climate scenario storylines are sampled on their relevance for local impacts, allowing the assessment of conditional changes in high-impact probabilistic discharges. In addition, plausible yet differently structured future urban areas and economies are sampled to project direct impact potential and its cascading socio-economic effects. By integrating both climate and socio-economic scenarios, a risk mapping can be made to highlight regions where (compounding) risk drivers may occur. Application to the Lielupe basin reveals those areas and sectors most vulnerable to climate impacts across diverse climate and socio-economic scenarios. Our comprehensive approach equips regional risk managers with targeted risk information essential for prioritising adaptation planning.

Plain Language Summary

Understanding future climate risks, like flooding, is crucial but challenging due to uncertainties in how both the climate and human societies will evolve. It is, therefore, important to consider

a range of plausible risk futures. Our study introduces a new method to sample a limited yet comprehensive range of possible risk futures, providing targeted information to help decision-makers prepare for an uncertain future. By combining climate and socio-economic perspectives, we identify areas where direct flood risks are likely to change and assess how these changes could ripple through the economy. We tested this approach in the flood-prone Lielupe river basin, shared by Latvia and Lithuania. We analysed 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 regions and sectors, depending on the combination of climate and socio-economic conditions and resulting risk drivers. Our approach allows policymakers to find those areas and sectors most vulnerable across diverse scenarios, offering valuable insights for prioritising targeted adaptation strategies.

1 Introduction

As climate impacts intensify throughout the twenty-first century (Mora et al., 2013), regions across the globe increasingly need targeted climate risk information to inform adaptation plans that protect vulnerable areas and sectors. Unfortunately, future climate risk information is obscured by large uncertainties in future climate conditions due to 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). To assess this uncertainty and convert it into a manageable risk information package serving the design of effective adaptation strategies, a subset of plausible climate impact scenarios can be explored to inform robust decision-making (Lempert, 2013; Lempert et al., 2003) or adaptive planning approaches (Haasnoot et al., 2019).

One method to explore impact uncertainty is through physical climate storylines (Shepherd, 2019; Shepherd et al., 2018), where lessons can be learned from 'what if' scenarios and their conditional explanations (Sillmann et al., 2021). By exploring multiple storylines that incorporate climate change or socio-economic developments, one can find vulnerabilities and drivers of risks that require specific attention (Goulart et al., 2024; van den Hurk et al., 2023). One application of climate storylines is to explore plausible changes in conditional probabilities of extreme meteorological events for the selected climate storylines (Liné et al., 2024; van den Hurk, 2022; van der Wiel et al., 2024). Such probabilities (or likelihoods) are an important factor for investment decisions in either risk prevention, consequence reduction, or risk transfers (Linnerooth-Bayer & Hochrainer-Stigler, 2015; Mechler et al., 2014). However, quantitative estimates of changes in impact probabilities, which require an interdisciplinary approach, have remained elusive in current literature.

Climate scenario storylines such as those of Liné et al. (2024) take a meteorological perspective to storyline construction, aiming to cover the variability of a broad set of 'target weather variables' conditioned on a few large-scale Earth system characteristics such as the North Atlantic Oscillation (NAO) or Atlantic meridional overturning circulation (AMOC). Conversely, Van der Wiel et al. (2024) construct storylines conditioned on the direct local precipitation response while aiming to describe a large set of associated target weather variables to serve a broad group of stakeholders. Although this approach has merit in providing climate scenarios for many, such generic scenarios may lack specificity for individual decision-making contexts since information needs are not uniform throughout society (Kirchhoff et al., 2013). Information salience is one of the key requirements for decision-making (Lemos et al., 2012), requiring appropriate methods to provide such information. Climate scenario storylines targeting variables directly related to the impacts on specific stakeholders have the potential to provide effective insights into the local implications of climate change (Sillmann et al., 2021).

Additionally, climate impacts occur in an increasingly connected world where direct effects in one region or industry can cascade through to connected industries or regions (Middelanis et al., 2021; Sieg et al., 2019). As a result, systemic risk assessments are essential to inform adaptation measures that comprehensively mitigate the various risk mechanisms in multi-sector systems (Challinor et al., 2018; Hochrainer-Stigler et al., 2023; Levermann, 2014). While

indirect or cascading societal effects induced by climate hazards have been analysed for future climate conditions in several studies (Lawrence et al., 2020; Willner et al., 2018), to the best of the author's knowledge, none have sought to explore the cascading effects of climate shocks in future socio-economic scenarios, despite evidence in Leimbach et al. (2023) that economies and their compositions can change over time. Changes in sector interactions may contribute considerably to the occurrence of indirect effects of climate shocks.

To address identified limitations in the current storyline literature, we propose and test a novel multi-modal methodology designed to provide targeted, conditional probabilistic climate impact information for plausible climate and socio-economic storylines. We term this integrated approach 'plausibilistic,' as it merges probabilistic hazard information with plausible storylines. By separating impacts into direct and cascading effects, a rich and comprehensive overview can be obtained of future risks in uncertain multi-sectoral human-natural systems. Our methodology focuses on identifying locally relevant impact drivers, which guide the selection of relevant storylines from the wide range of possible climates and socio-economic projections. Within each storyline, we map regional impact drivers and illustrate where these drivers potentially compound. Furthermore, we analyse which economic sectors experience the most severe stress after a climate shock and how this changes in various conditions.

To demonstrate the utility of the presented methodology, we test it in an illustrative case. We focus 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). An exemplary case is the transboundary Lithuanian-Latvian Lielupe, where flood risk is already a prominent issue and is a core focus of the Latvian National Adaptation Plan (Ministry of Environmental Protection and Regional Development, 2019). We, therefore, apply and test the framework in a riverine flood risk case in the Lielupe basin.

2 Method

This study aims to provide a comprehensive assessment of future flood risk impacts in multi-sectoral systems by sampling from a range of projections differentiating emission scenarios, Earth system responses, internal variability, and societal development. We follow the multi-model experimental design depicted in Figure 1. The analysis starts with climate risk scoping, where the key issue of interest is defined, and the boundaries of the analysis are set (Section 2.1). Secondly, we examine how climate uncertainties influence extreme discharges across the basin (Section 2.2). This analysis starts by crafting plausible climate scenario storylines from an ensemble of Global Climate Model projections based on locally relevant Climatic Impact Drivers (CIDs) revealed by a sensitivity analysis. For each climate storyline, conditional probabilistic extreme discharges are determined using hydrological modelling and stochastic weather generation. The resulting plausibilistic storylines of extreme discharge are spatially mapped to gain insight into regional and inter-storyline differences in local flood risk.

In parallel, the propagation of direct flood impact to indirect economic repercussions is analysed in multiple projections of plausible socio-economic developments influencing exposed building asset values and relevant sectors in the region. These socio-economic projections

provide perturbations to the exposure characteristics in regional floodplains and modify economic structures and, consequently, sectoral interactions (Section 2.3). Comparing direct impacts and resulting cascading effects across scenarios illustrates how sectoral and regional stresses can potentially evolve, allowing the identification of those areas and sectors whose direct and indirect flood risks are most affected by socio-economic changes (Section 2.4).

Lastly, the plausibilistic discharge storylines and socio-economic scenarios are overlaid to identify those locations where risk drivers compound, providing a risk mapping under future conditions (Section 2.5).

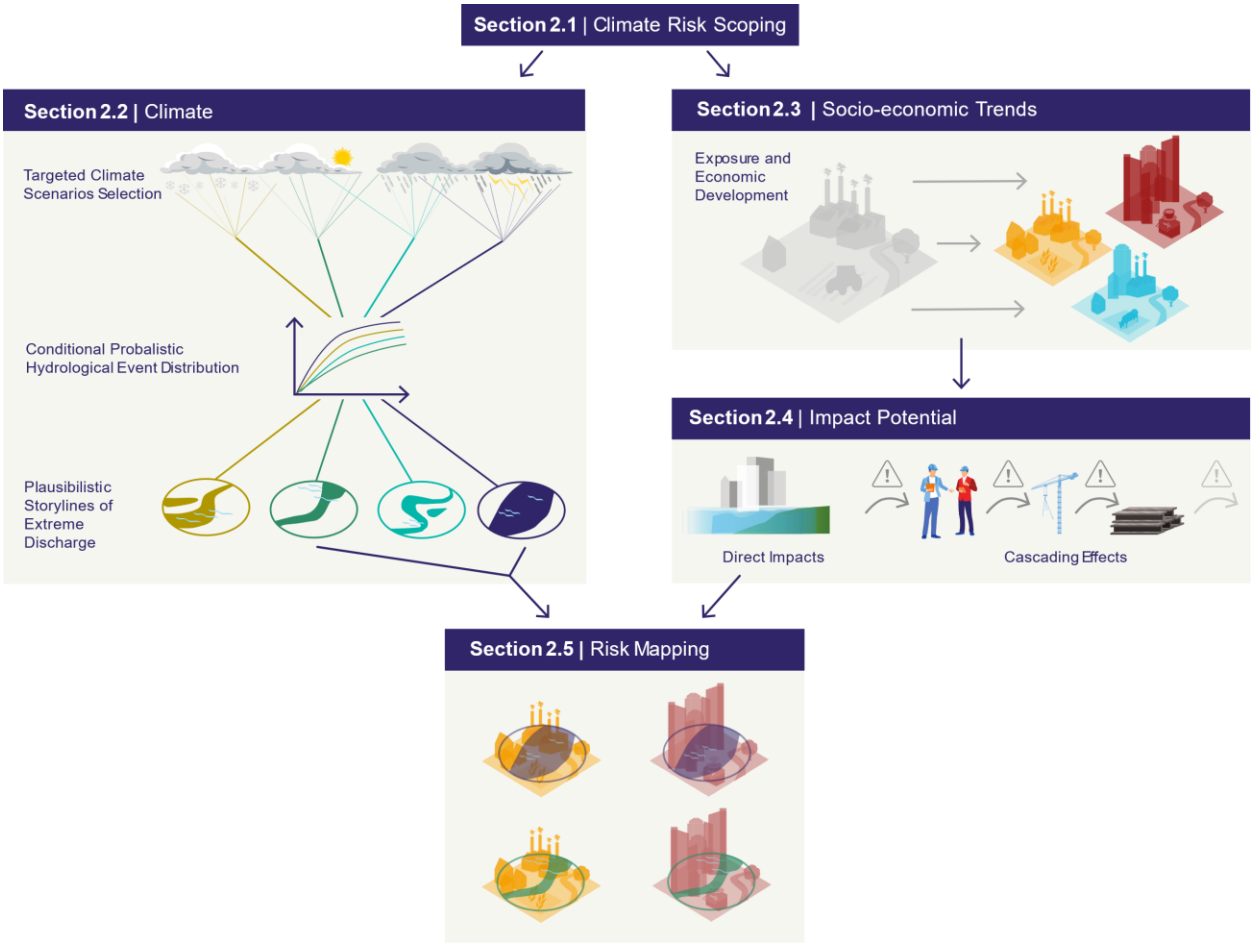

***Figure 1**: Methodology used in the study to gain insight into future climate impacts for the specified climate challenge.*

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 type, impacts, sectors, and time horizon, which collectively influence the conclusions drawn in risk analysis. Points of departure for our analysis are the Latvian National Adaptation Plan (NAP) (Ministry of Environmental Protection and Regional Development, 2019) and river basin management plans (Latvijas Vides, ģeoloģijas un

147 meteorologijas centrs, 2023). These documents are intended to support regional planning in
148 the upcoming decade, and as such, information about potential risk developments during the
149 mid-century is of particular interest.

150 The NAP voices concerns about flooding along rivers in the country. One such flood area is the
151 transboundary Lielupe Basin (Figure 2). The Latvian-Lithuanian basin covers 17.600km² and
152 houses around 400.000 people. Local authorities have identified parts of the basin as a current-
153 day flood zone of national importance, and therefore, information on near-future flood risk is
154 highly valuable. Especially the 1/100-year return period flooding is of interest, as events of this
155 intensity cause significant impacts in the region. Both the NAP and river basin management
156 plan are particularly concerned regarding losses to constructed assets, in our case buildings,
157 along rivers. Consequently, this study will aim to provide risk developments regarding these
158 assets.

159 These direct flood impacts on buildings have the potential to affect economic sectors outside of
160 the flood area. To illustrate the potential of cascading effects, Figure 3 shows the flow of goods
161 between sectors for the region, revealing intersectoral dependencies. The construction sector
162 and its direct to suppliers and consumers in the economy are particularly highlighted, because
163 it is Latvia's largest producer and consumer of goods and depends on many domestic and
164 foreign sectors, and has a large importance in the national economy. It is arguably an important
165 sector in rebuilding flood-impacted assets, so it is relevant to investigate the direct and indirect
166 effects around this sector.

167 In summary, this study will analyse plausibilistic climate impact storylines for the 1/100-year
168 return period flood event, its direct impact on building assets and the cascading effects in the
169 Latvian economy for the mid-century.

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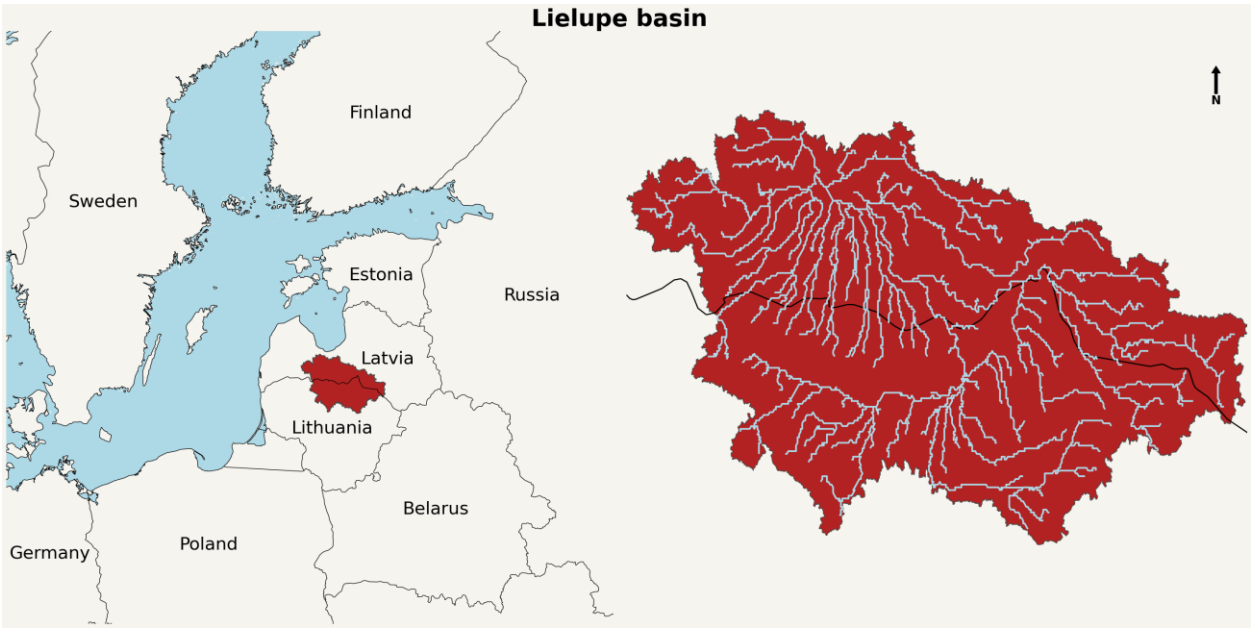

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***Figure 2**: Region of interest. The left image shows the location in Europe, and the right image is a more detailed image of the river network in the basin. The red-filled shape is the Lielupe basin, and light blue indicates the sea surface and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

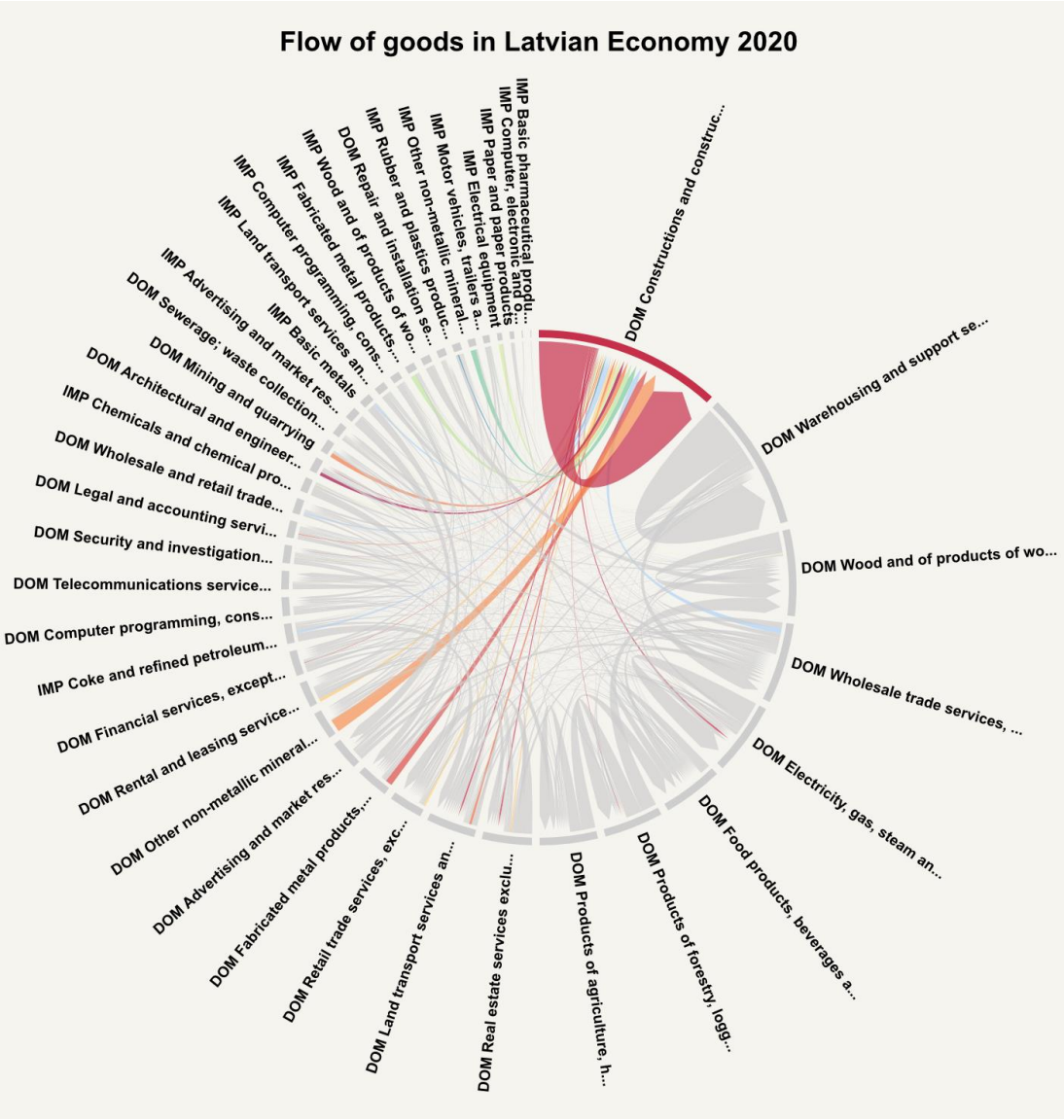


***Figure 3**: Sectoral interdependencies of the 40 largest sectors in Latvia based on the sum of intermediate sectoral consumption and production of goods in euro. Sectors are sorted on flow sums from large to small in a clockwise position. Arrows indicate the direction of goods. The studied construction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

2.2 Plausibilistic storylines of extreme discharge

Analysing how extreme discharges change in the basin is a key component of mapping future risks. However, these extremes are dependent on uncertain future climate conditions. For the

Lielupe case, we specified a sub-selection of plausible mid-century climate scenario storylines, and calculated changes in the conditional probabilistic 1/100 return period discharge for each storyline relative to the current baseline.

To obtain this information, this study replicates and extends the method introduced by Buskop et al. (2024). This method creates a set of four climate scenario storylines by clustering GCM projections based on modelled changes in locally relevant CIDs, instead of clustering by emission scenario. Projections of local precipitation patterns are primarily governed by internal variability and model uncertainty (Hawkins & Sutton, 2011; F. Lehner et al., 2020), and aggregation by emission scenario leaves hardly any meaningful scenario variability for exploring regional climate risks. As such, a relevant range of potential future conditions combines the effects of internal variability, model uncertainty, and emission pathways to be used in regional disaster risk management and adaptation planning (Deser, 2020).

2.2.1 Relevant Climatic Impact Drivers in the Basin

To develop climate scenario storylines that allow us to explore a range of plausible extreme discharge changes in the basin, we use the method detailed by Buskop et al. (2024). The method starts by identifying CIDs that significantly influence flood risk in the region. Using these CIDs, flood-relevant climate scenario storylines can be constructed (section 2.2.2). Relevant CID identification requires the development of atmospheric forcing time series under various climate conditions, a calibrated hydrological model to capture resulting discharge extremes, and a feature scoring step that identifies those CIDs that influence extreme discharges most.

Meaningful hydrological modelling of discharge extremes requires high resolution, forcing time series of daily temperature and precipitation. At the same time, 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 GCM time series. To this end, a stochastic weather generator based on Steinschneider and Brown (2013) is used. ERA5 data (Hersbach et al., 2023) informs the weather generator to create a 100-year-long synthetic baseline time series of temperature and precipitation in the region. Alternative climatological forcing conditions are created by modifying the baseline time series seasonal mean temperature (ΔT), mean rainfall (ΔP) and the coefficient of variation (ΔCV) of that rainfall. These changes are informed by CMIP6 GCM projections available at the Copernicus Climate Data Store (Copernicus Climate Change Service, 2021), also see Appendix A. Change signals for the mid-century as defined in the IPCC atlas, 2041-2060 (Gutiérrez et al., 2021), are retrieved across four seasons: winter (December-January-February), spring (March-April-May), summer (June-July-August) and autumn (September-October-November). The hydrological model Wflow_sbm (van Verseveld et al., 2024) is configured using model builder HydroMT (Eilander et al., 2023). Using the alternative forcing time series and the hydrological model, discharge extremes are calculated for each climate condition. The Extra Trees feature scoring algorithm (Geurts et al., 2006) is applied to link simulated changes in extreme discharge to associated changes in CIDs, identifying the most influential CIDs in determining these discharge variations.

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. For this, we extended the approach of Buskop et al. (2024) from a single-point location analysis of discharge change to a spatial, basin-wide application. Discharge changes are collected at observation stations, where the hydrological model fairly replicates historical discharge (KGE => 0.5). For each of these stations, the two most influential CIDs that alter extreme discharge are determined as described by Buskop et al. (2024). This results in a list of CIDs that influence flood risk across the basin. After removing duplicates from the list, we cluster the GCMs into four clusters based on the projected changes for each CID in the list.

2.2.2 Climate scenario storylines and their conditional probabilistic extreme discharges

Each GCM cluster is transformed into climate scenario storylines by calculating the cluster's multi-model average climate change signal for the sampled climate variables (ΔT, ΔP, ΔCV) in each season. The four distinct climate storylines are then used to discover future discharge changes across the basin. For each constructed climate storyline, new 100-year-long stochastic weather time series are created. This is done by modifying the baseline time series by each climate storyline's precipitation and temperature change signals. Since weather generators are subject to sampling uncertainty (Alodah & Seidou, 2020), five alternative realisations have been created and used as forcing to the hydrological model. For each realisation of a climate storyline, the fractional change in the 1/100-year return period discharge relative to the control baseline is calculated. These change values are averaged across realisations to obtain the discharge change in the storylines to be used in further analysis.

For each climate storyline, basin-wide probabilistic discharge changes are calculated and mapped using the HydroSheds classification of sub-catchments (B. Lehner & Grill, 2013). The resulting map provides a spatial representation of hazard intensity changes per hydrological run, revealing potential differences across catchments. We call this set of discharge event changes 'plausibilistic storylines of extreme discharge' that span a range of GCM projections and resulting impacts.

2.3 Socio-economic trends

Socio-economic changes in a region significantly contribute to changes in overall climate risk (Dottori et al., 2018; Steinhausen et al., 2022) as they alter regional exposure and vulnerability and should be included in regional climate risk assessments. For direct risks, we explore how exposure and, therefore, the impact potential in each sub-catchment develops into the future. Specifically, this study focuses on building exposure values (Section 2.31). For cascading effects throughout the economic network, we construct perturbed regional economic networks by changing future sectoral production and consumption volumes and their interdependencies (Section 2.3.2). Both developments in the exposure and economic network are guided by the Shared Socio-economic Pathways (SSP) framework (O'Neill et al., 2014, 2017). Multiple SSPs are used to explore the uncertainty range in regional socio-economic trends. By using the SSP framework we can combine studies that are based on the SSPs in a way that projected variables

are consistent with each other. To reflect our localised application, we further refer to these SSP-inspired scenarios as 'regional economic futures'.

2.3.1 Asset development in the region

To assess changes in direct impacts, we explore the change in building value exposure over time 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. We calculate these changes in exposed asset values in the regions by using global datasets of downscaled spatial projections of GDP growth (Wang & Sun, 2022), urban density (Gao & Pesaresi, 2021), and urban expansion (Chen et al., 2020) at 1 km spatial resolution. These datasets disaggregate national-level Gross Domestic Product (GDP), population, and urbanisation based on current population and GDP distributions, where built-up areas aggregate a larger fraction of the projected changes than countryside areas. By multiplying the GDP growth with urban density change and urban expansion in a sub-catchment, we obtain the asset value change factor that is used to project the asset values in the floodplains between the 2020 baseline and 2050 (see Section 2.4.1).

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 us to analyse changing national economic structure, sectoral dependencies and, consequently, cascading impacts of flood events. National GDP projections under various global SSP scenarios exist for some time (Dellink et al., 2017) and have been used before to downscale GDP projections (Wang & Sun, 2022). However, a decomposition into sectoral contributions has only been introduced recently by Leimbach et al. (2023). Figure 4 shows various pathways of GDP development and sectoral contributions.

To obtain new sectoral interactions and production quantities in 2050, we project national input-output tables for each economic scenario. 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 and consumes from other sectors. Using these tables, ripple effects from one sector to another can be tracked. In climate science, input-output tables have been used in a variety of studies covering the indirect 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).

We project national input-output tables using socio-economic trends and sectoral shifts depicted in the SSPs. Starting with the 2020 Latvian input-output table containing 64 NACE sectors, we aggregate these into three NACE3 sectors (Agriculture, Manufacturing, and Services) to align with Leimbach et al.'s (2023) projections. The NACE nomenclature is a

standardised system in the European Union to classify and aggregate economic activities (Eurostat, 2008). The projection calculation starts by scaling the 2020 national value added to 2050 GDP levels and allocating it to sectors proportional to projected contributions shown in Figure 4. We then disaggregate back to NACE64 sectors using 2020 ratios, calculate required input goods, and scale final demands with GDP growth.

To address imbalances between growing and shrinking sectors, we implement a balancing mechanism within the input-output framework. When domestic sectors cannot meet increased demand, we introduce additional imports distributed according to current-day usage shares. Conversely, when local production exceeds demand, we reduce imports according to usage shares with a minimum of zero imports. We convert the surplus production into exports. This balancing process ensures that sectoral inputs and outputs align. The end results are input-output projections per regional economic future suitable for analysing the cascading effects of flood events. See Appendix B for detailed explanations and formulas describing the calculations.

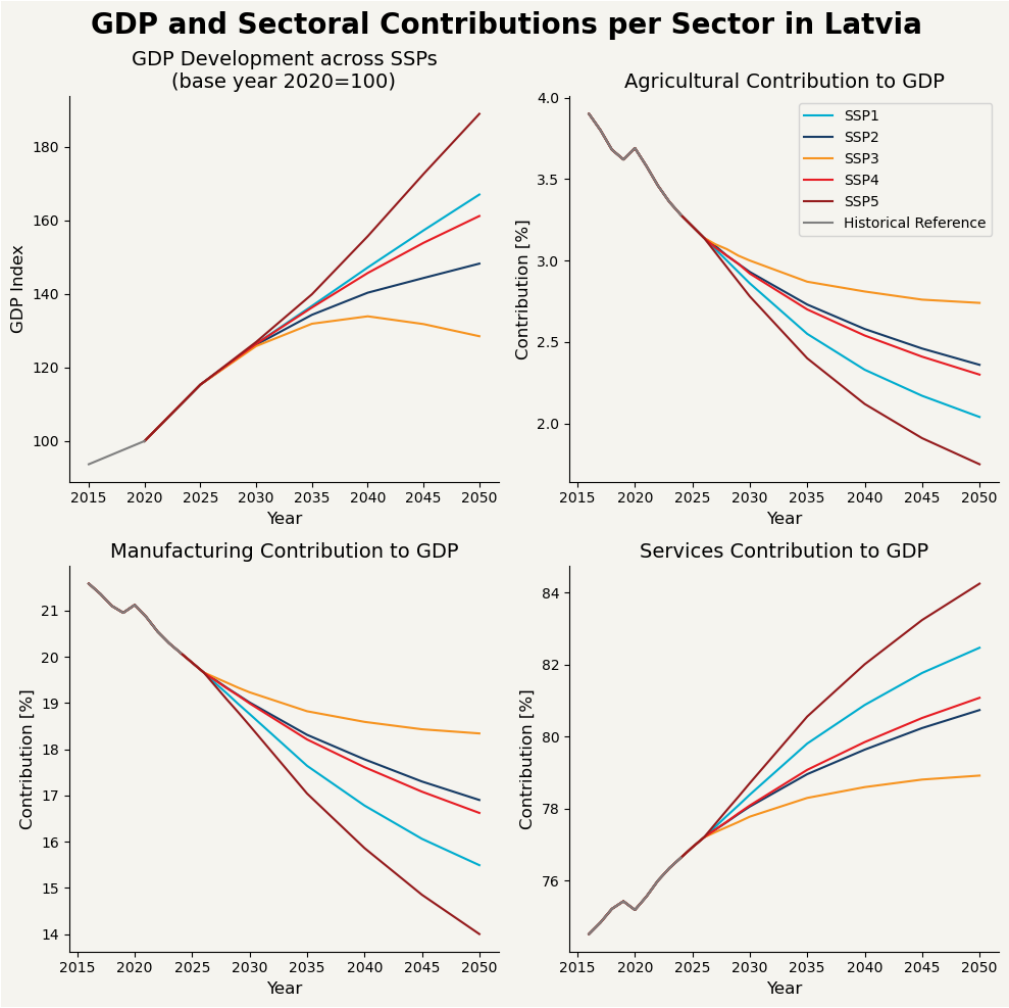


***Figure 4**: GDP development and sectoral contributions. Top left panel: GDP development index across various global SSPs (100 = GDP in base year 2020). Other panels show changes in the composition of the Latvian economy. Each plot shows the change in the contribution of a specific sector to Latvian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

2.4 Impact potential

2.4.1 Exposed assets in the floodplain

Direct flood impact potential is estimated by evaluating asset values within the floodplains. To identify the floodplain for each sub-catchment, we use 50-meter resolution historical flood extent maps created by local authorities. The flood extent for the highest available return period under current climate conditions is used. Since the basin covers two countries, we had to harmonise the 200-year return period flood map for Latvia and the 1000-year return period map for Lithuania to a regional product. This leads to better agreement with local maps than utilising harmonised European or global datasets for multiple low-probability return periods (e.g. Dottori et al. (2022) or Aqueduct (Ward et al., 2020)), which may let water reach locations that are inaccessible in reality leading to misrepresented areas at risk. We attribute this low agreement 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 modelling efforts.

Current-day exposure values in the floodplains are estimated using empirical estimates of reconstruction costs per square meter identified by Huizinga et al. (2016). The reconstruction costs need to be defined per building and its use class, since each use class has a different associated cost. Using OpenStreetMap (OSM) (Haklay & Weber, 2008), flooded building footprints are obtained and assigned a use class. First, we classify all footprints as residential, refine them using the 50x50m LUISA land use dataset (Pigaiani & Batista e Silva, 2021) and refine further with OSM land use and amenity information (see Appendix C Table C.1 and C.2 for the classifications). Lastly, the total footprint areas are calculated and multiplied by the reconstruction costs per square meter to obtain exposed asset values in the floodplain. Content losses are not considered since our focus is on reconstruction.

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

2.4.2 Indirect effects

A relevant indirect 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 an applied shock for the 2020 baseline and the various regional economic futures. We use 'stress' to indicate demand pressures due to the event relative to the pre-event

demand for a sector. Sectors are ranked by their demand stresses in 2020 conditions, and we explore how these stresses develop across scenarios.

Input-output tables are used to explore sectoral demand change effects throughout the economy (Miller & Blair, 2009). The monetary interconnections between sectors in these tables are manipulated to show economy wide effects of a demand shock in the construction sector after a flood. We implemented 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, including cascading demand effects from suppliers. For a formulaic representation of the demand changes, see Appendix D.

We find stresses across the Latvian economy by applying an arbitrary demand on the construction sector resulting from direct losses. Using the Leontief inverse, we find how much pressure occurs in the construction sector and its supply chain. Instead of absolute demand increases, relative demand increases are explored as they signal stresses on the sectors. Those sectors that need to upscale production most are particularly vulnerable to indirect flood impacts.

To compare baseline conditions with future scenarios, we perform the analysis for the base year 2020 and all regional economic futures in 2050 using associated input-output tables (see Section 2.3.2) and the growth of asset values in the floodplain (see Section 2.4.1). The set of input-output tables 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 in 2020 is expected to grow in the future.

2.5 Compounding Impact Drivers

The identified plausibilistic extreme discharge storylines and socio-economic developments can be integrated to find those regions most vulnerable to future climate impacts. Using the exposure to direct impacts and discharge change for each sub-catchment, a climate risk mapping can be performed. Sub-catchments, where both impact potential and extreme discharge increases, are highest are assigned the highest risk level. A comprehensive overview of potential future risks can be made by making combinations of the plausibilistic discharge storylines with socio-economic developments.

Whereas global and continental scale risk assessments often couple RCPs and SSPs, we choose to let climate and socio-economic scenarios vary independently of each other for this regional study. For large-scale risk assessments, coupling 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 can diverge substantially from global trends governing climate change processes, driven by local policies and economic conditions. In addition, our scenario framework does not scale with global greenhouse gas emissions (also read Section 2.2). Therefore, we allow regional climate and socio-economic conditions to vary independently.

As the complete combinatory set of storylines might overwhelm the decision-maker, we use the scenario-axis technique (van 't Klooster & van Asselt, 2006). We define climate uncertainty on one axis and socio-economic uncertainty on the other. Two climate storylines are integrated with two socio-economic scenarios. On each axis, the two most divergent scenarios are chosen to highlight the spread in outcomes.

3 Results

3.1 Future discharge changes

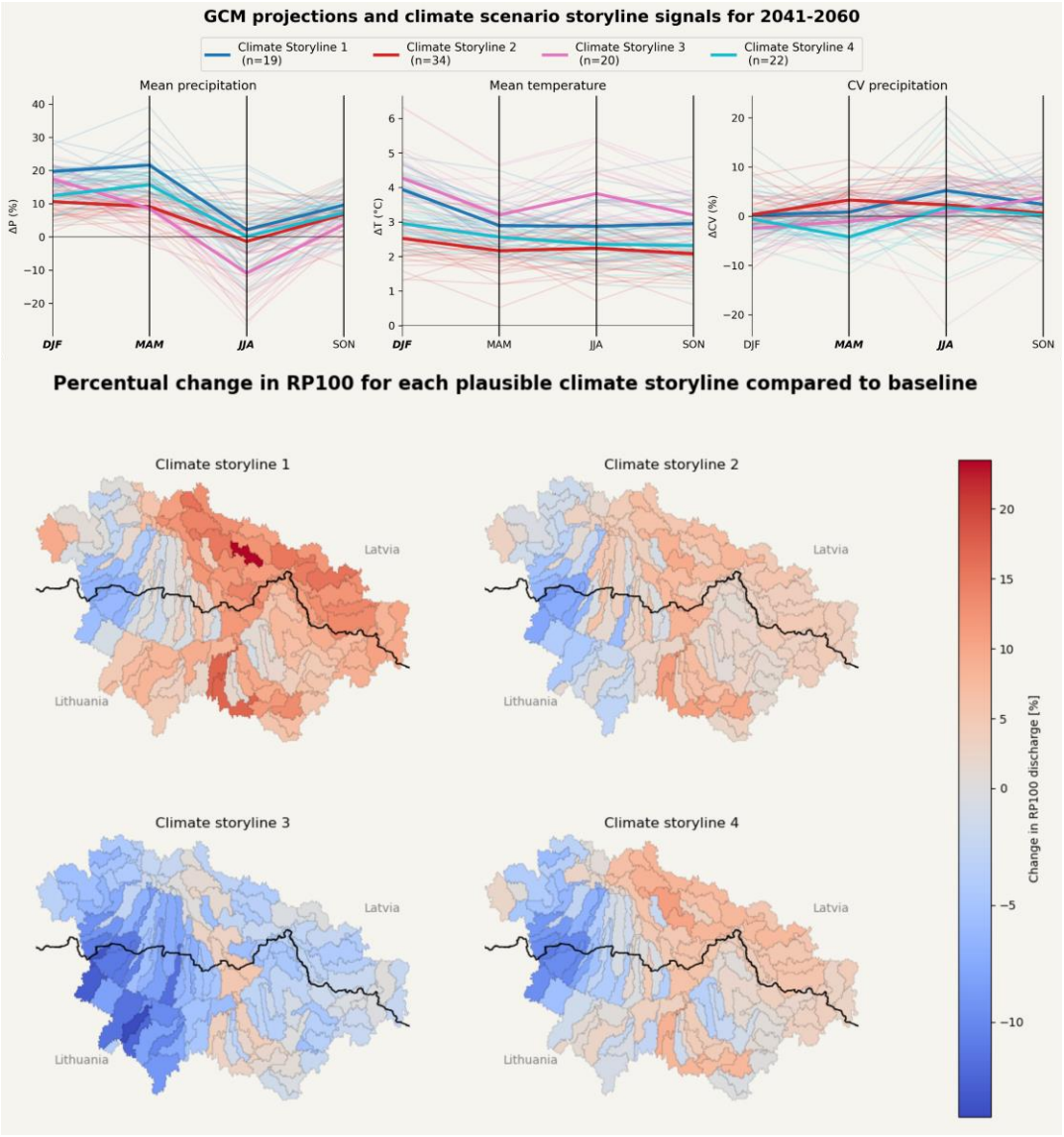
After generating various weather time series of future climate scenarios and analysing the resulting conditional 1/100-year return period discharge changes across CIDs, we find six unique CIDs most relevant for the eight selected stations in the basin. Three of these are the average rainfall in winter, spring and summer, causing soil saturation to rise, leading to higher runoffs. Additionally, changes in the coefficient of variation (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 of discharge change due to the influence on snow accumulation and melt. While sudden snowmelt is currently a large driver of floods, this effect decreases when average temperatures rise and snow volume is reduced. See Appendix A Figure A.2 for the effects of the individual drivers on discharges across stations.

GCM projections are clustered into four climate scenario storylines based on the associated regional response of the six selected CIDs. For each cluster, the multi-model average climate signal for the seasonal climate indicators is calculated. Figure 5 plots the storyline signals for seasonal precipitation, temperature, and precipitation CV changes. 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 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 signals.

Figure 5 also shows changes in the 100-year return period extreme discharge for the different climate storylines across the basin. 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, favouring 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

435 extreme discharges. Since all climate storylines indicate a temperature increase, extreme snow
436 melt occurs less frequently and less intensely.

437



438

439 ***Figure 5****: The* top panel *shows seasonal patterns of mean precipitation, temperature and precipitation variability*
440 *for four climate scenario storylines derived to assess ranges in regional discharge response to global warming.*
441 *Thick coloured lines represent the storyline's mean projections. Thin lines represent individual model projections*
442 *colour-coded according to the storyline cluster. In the legend, 'n=#' signifies the number of GCMs assigned to the*
443 *cluster. The b*ottom panel *shows the change in 1/100-year probability discharge across the sub-catchments in the*
444 *basin for each climate storyline.*

445 **3.2 socio-economic trends on exposure**

446 The basin aggregated asset value in Latvian floodplains is shown in Figure 6 for each socio-
447 economic scenario, together with a spatial distribution of asset values across the basin for

selected divergent scenarios. An overall increase in building asset reconstruction value is found, especially in the regional economic future inspired by SSP5, where values rise to about 375% compared to the original. Also notable is the doubling of floodplain asset values compared to GPD 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 centres. These urban centres also develop faster than the surrounding rural areas.

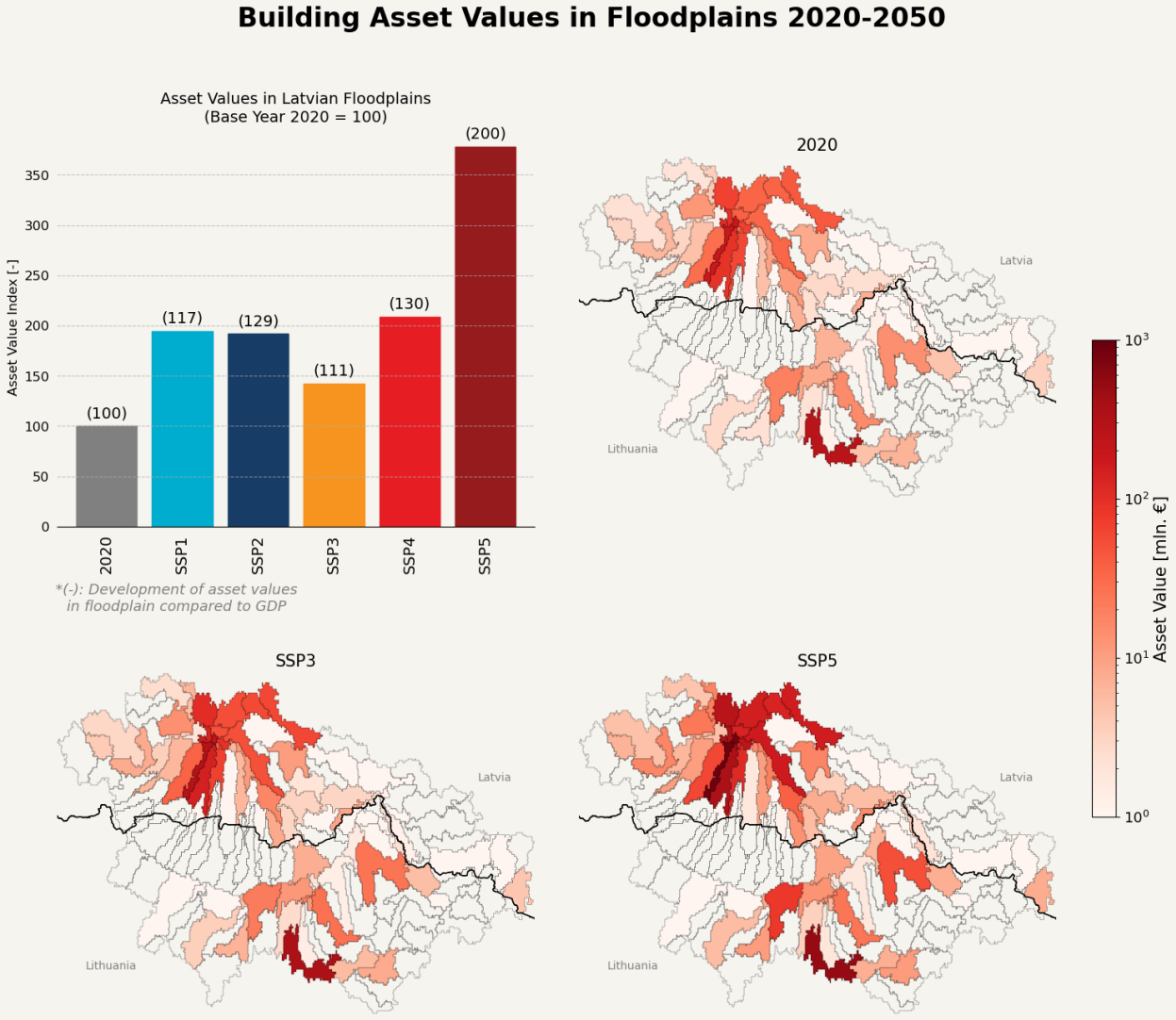


***Figure 6**: Building asset values in floodplain across SSPs relative to base year 2020. The top left shows the development of accumulated values in Latvia compared to the base year. In brackets, the asset values in the floodplain are compared to the national GDP in the SSP-inspired regional economic future. The remaining plots show the spatial development of building asset value for the 2020 baseline and the most divergent future socio-economic scenarios.*

3.3 Cascading effects

For the various economic scenarios, the Latvian economy experiences varying sectoral stresses when confronted with a spike in construction demand, as seen in Figure 7. Stress is defined here as the flood-induced demand compared to the pre-event demand. 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 in Leimbach et al. (2023) projected shrinking of manufacturing sectors across all SSP-inspired regional economic futures, 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. In their analysis, Koks & 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 tipping point for some regional economic futures, 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 those sectors under the most stress also shift. For example, domestic architectural services experience increased stress, while imports by the same sector decrease in 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 more capable of handling the demand shock, increasing the capabilities of absorbing increased demands.

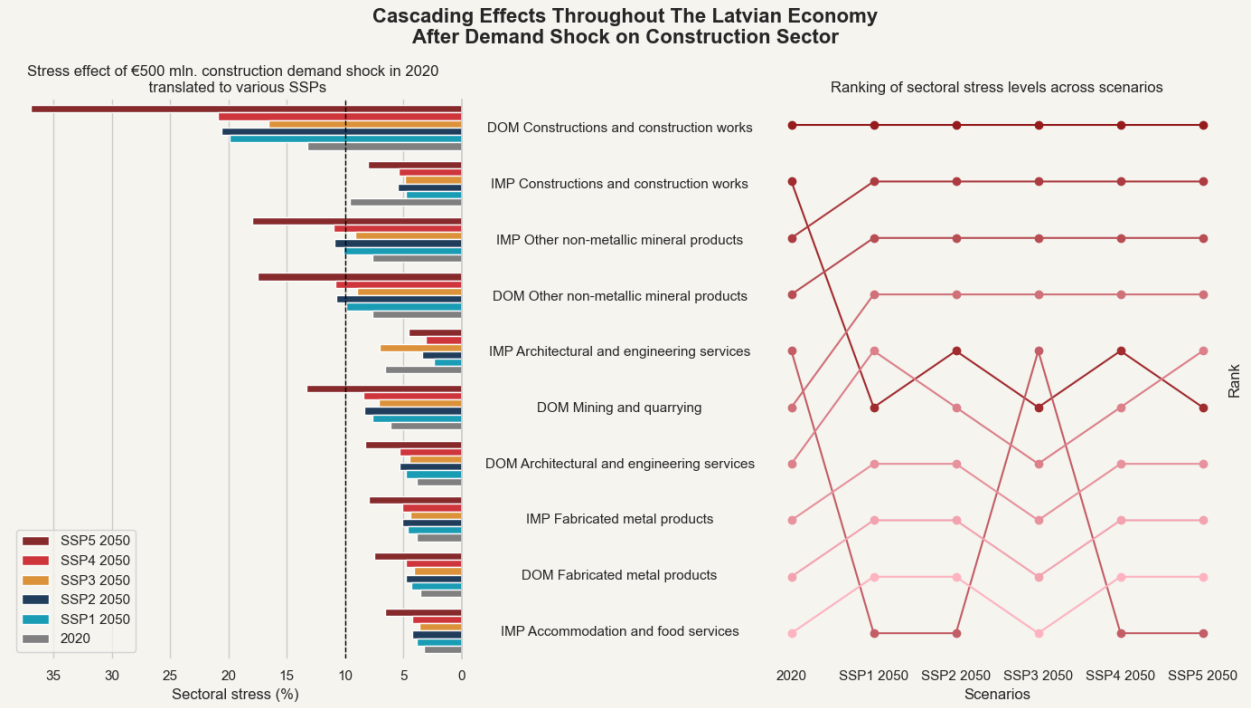


Figure 7: *Sectoral stress levels in response to a €500 million (in 2020 and projected for each SSP) construction demand shock across different scenarios, displayed as a bar chart (left) and a bump plot (right). The bar chart illustrates the percentual stress levels across scenarios in various sectors due to the shock. The bump plot ranks sectors by stress level across scenarios, 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 colour-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.*

3.4 Compounding effects

Figure 8 integrates the most divergent socio-economic and climate storylines to detect patterns of compounding risk drivers. The underlying data are already shown in Figures 5 and 6. Noticeably, entirely new high-risk areas emerge alongside risk intensification in already high-risk sub-catchments. The scenario with the highest risk levels is a combination of Climate 1 and SSP 5. More asset values are situated in the floodplains due to high urban development, while the wetting of the climate causes more antecedent soil moisture, leading to increased discharges. The lowest risk scenario is the combination of Climate 3 and SSP 3. In this case, the floodplain has low urban development, leading to fewer losses when an event occurs. Meanwhile, extreme discharges mainly decrease throughout the region due to reduced antecedent soil moisture and snowpack volumes. Although there is significant variability across scenarios, sub-catchments that always face relatively high-risk levels can be identified.

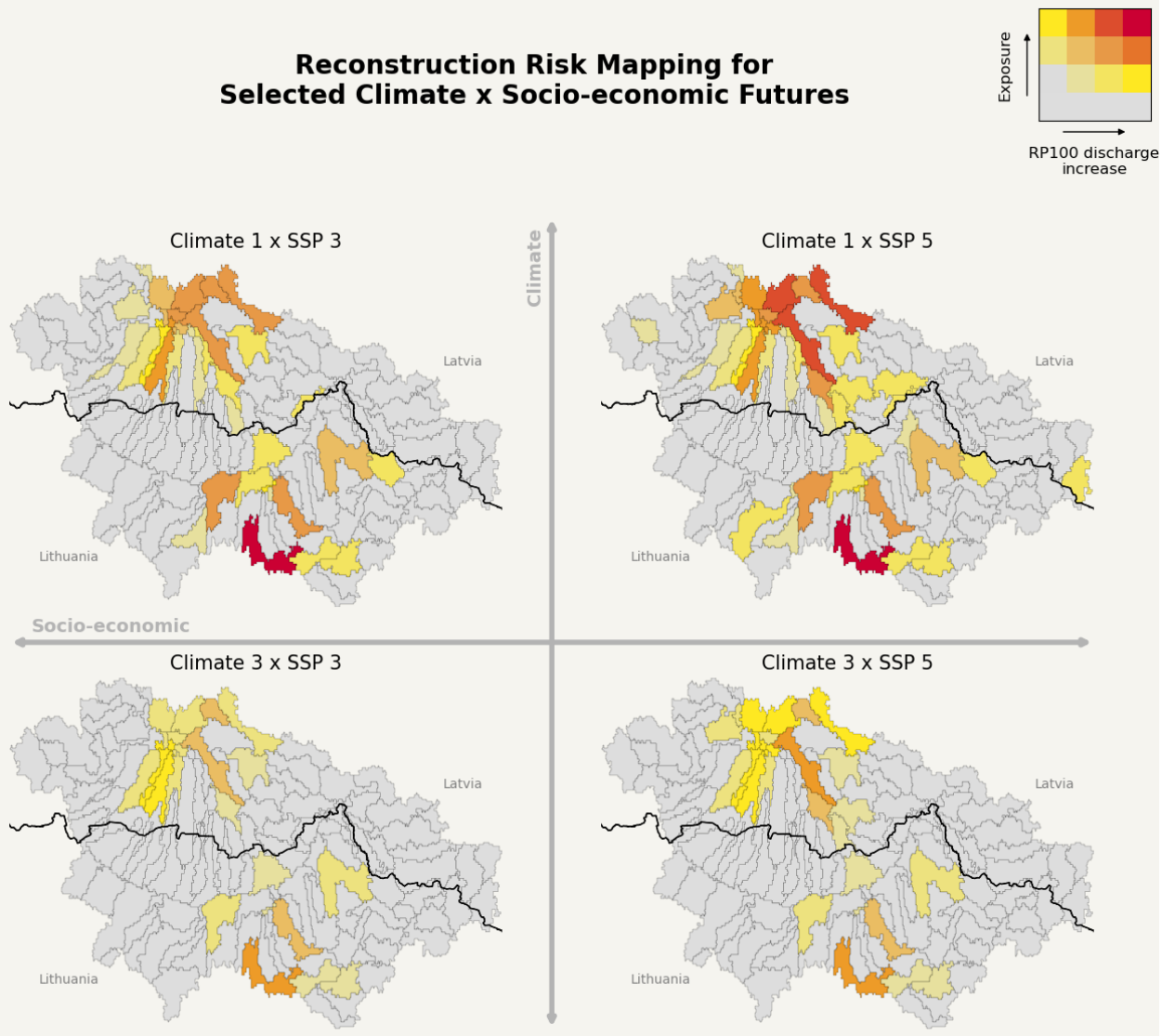


Figure 8: *Spatial reconstruction risk mapping under selected storylines highlighting potential regional climate and socio-economic developments. Each map highlights hazard changes and exposure levels using a bivariate colour map, providing a measure of compounding risk drivers.*

4 Discussion

4.1 The consequences of uncertainties and the importance of exploration

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 1-in-100 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 melt are dampened, whereas other preconditions (such as soil moisture volume) are amplified.

519 Projected socio-economic changes can further compound these risks. As exposed asset values
520 in the Latvian basin almost quadruple compared to the 2020 baseline, sectors are confronted
521 with heightened flood-induced demand shocks related to reconstruction. Simultaneously, a
522 trend of declining domestic manufacturing capacity doubles or triples most sectoral stresses
523 relative to the 2020 baseline. In some scenarios, the demand shock exceeds sectors their
524 absorptive capacity, amplifying and prolonging indirect impacts (Hallegatte et al., 2024).
525 Furthermore, increased dependency on imports due to the offshoring of the manufacturing
526 sectors may create new vulnerabilities to foreign supply disruptions (Ercin et al., 2021).
527 Conversely, this may lead to enhanced regional resilience through import diversification
528 (Willner et al., 2018).

529 This methodology is designed to create a diverse yet analytically affordable set of risk scenarios.
530 To do so, certain choices were made that limited the uncertainty exploration. While our climate
531 storylines selection method enhances impact exploration compared to emission scenario-based
532 clustering of GCM projections (Buskop et al., 2024), it reduces the explored impact range
533 relative to the full ensemble of model outputs. Similarly, averaging discharge change results
534 across multiple stochastic weather realizations reduced the variability in outcomes. Both steps
535 involved a trade-off between sampling robustness and exploration. Other aggregation choices
536 could have been made and is a topic of further discussion in the literature.

537 **4.2 Global projections for the local context**

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

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

553 This study could benefit from localising the global SSPs (Alizadeh et al., 2022; Reimann et al.,
554 2021) to incorporate policies influencing sectoral changes or add spatial detail to urban
555 developments. Adding local socio-economic information could further specify direct and
556 indirect impacts on specific income groups or businesses and/or sectors, as demonstrated in
557 Bachner et al. (2024). Additionally, with regards to the hazards, local expertise could refine
558 climate scenario selection by assigning higher weights to CIDs relevant to known high-risk

areas, steering clustering of climate projections. Hazard estimation could benefit from spatial flood modelling using local hydrodynamic models.

4.3 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 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 we analysed how socio-economic changes and how a changing climate drive risk, we were not able to quantify their comparative effects in the absence of detailed flood modelling. Future studies could extend our model chain to include flood maps under climate change, enabling risk attribution to specific drivers.

4.4 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 intra-regional effects, using a similar economic input-output method could highlight positive spillover effects as production is shifted to unaffected areas (Middelanis et al., 2022). 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 labour-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 ageing population, 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.

5 Conclusion

Our ability to manage future climate risks is partly determined by our ability to anticipate these risks. A task which needs to handle uncertainties in both human and natural systems. This requires a comprehensive but comprehensible package of targeted climate 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 developments and climate storylines with associated conditional discharge probabilities. By integrating meteorological, hydrological, and socio-economic perspectives, this approach captures the influence of future changes on both direct impacts and cascading effects in connected multi-sectoral systems.

We used this methodology to examine the changes in and effects of discharge extremes in the transboundary Latvian-Lithuanian Lielupe river basin. As expected, our findings reveal significant spatial heterogeneity of future discharge extremes within the basin and across climate scenario storylines as locally relevant CIDs are amplified or dampened depending on the sampled climate conditions. As a result, the 100-year return period discharge extreme can deviate -10% to +20% from the baseline depending on the scenario and region. In parallel, projected asset development in the floodplains and sectoral growth rates indicate an intensification of impact. Absolute direct impacts can increase by up to 375%, and most sectoral stress levels double or triple compared to the baseline. These findings highlight substantial variability in impacts across scenarios, regions and sectors because of developments of (spatially compounding) risk drivers in the region.

This study underscores the importance of a systems perspective to climate risks as both climatological uncertainties and socio-economic drivers can amplify or attenuate (cascading) impacts. Our interdisciplinary methodology allows for the identification of particularly vulnerable regions and sectors across diverse scenarios, offering valuable insights for robust adaptation planning. By exploring the uncertainty space of risk-inducing trends, key risk areas and sectors are identified that call for further study. Through our plausibilistic climate impact storylines, the exploration and understanding of complex risks can be significantly enhanced. This approach provides comprehensive and targeted regional climate risk information, which is essential for prioritising adaptation strategies.

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Open Research

The CMIP6 data can be freely obtained through https://cds.climate.copernicus.eu/cdsapp#!/dataset/projections-cmip6. The historical ERA5 data is obtained from https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-pressure-levels. The open-source hydrological model Wflow is accessible here https://deltares.github.io/Wflow.jl/. The projected socio-economic data can be found by

following the citations in the text. Implementation of the used weather generator can be found at https://github.com/Deltares-research/weathergen. Analysis code and data used in this study is published at Zenodo (https://zenodo.org/records/14445553?token=eyJhbGciOiJIUzUxMiJ9.eyJpZCI6IjlmZWZhNDAwLWViYjAtNDM4YS1hMDlkLTNlZWI2ZGY4MjNmOCIsImRhdGEiOnt9LCJyYW5kb20iOiI4YmZhMzRmOWI3ZGE2MjRkZWViMDUxOTNjMTA0YWFmNCJ9.WxH5ejVC-TrvHwc7BkiN8_L8EjN-1q5_yjlIQjpYedjg0xa7aRmczzmoHQeS4lf4HBfQ91SVXZv7MtBmDfIELQ) and on Github (https://github.com/TBuskop/spatial_and_sectoral_climate_impacts)

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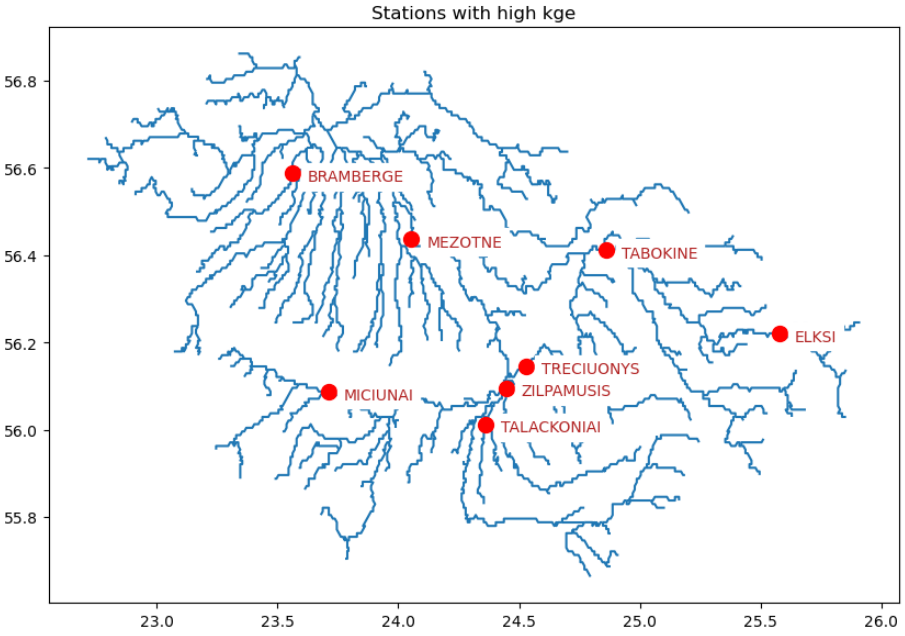
927 Appendix A: Obtaining Relevant Climate Impact Drivers

928 ***Table A.1****: Table of used models and SSPs in the 2041-2060 timeframe. Model data extracted from Copernicus Data*
929 *Store (Copernicus Climate Change Service, 2021)*

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	✓	✓	✓	✓
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



930

931 ***Figure A.1****: A map of the Lielupe basin rivers (in blue) with stations in red with Kling-Gupta Efficiency >= 0.5 and*
932 *thus considered in the Climatic Impact driver clustering. The names of the stations are annotated in red.*

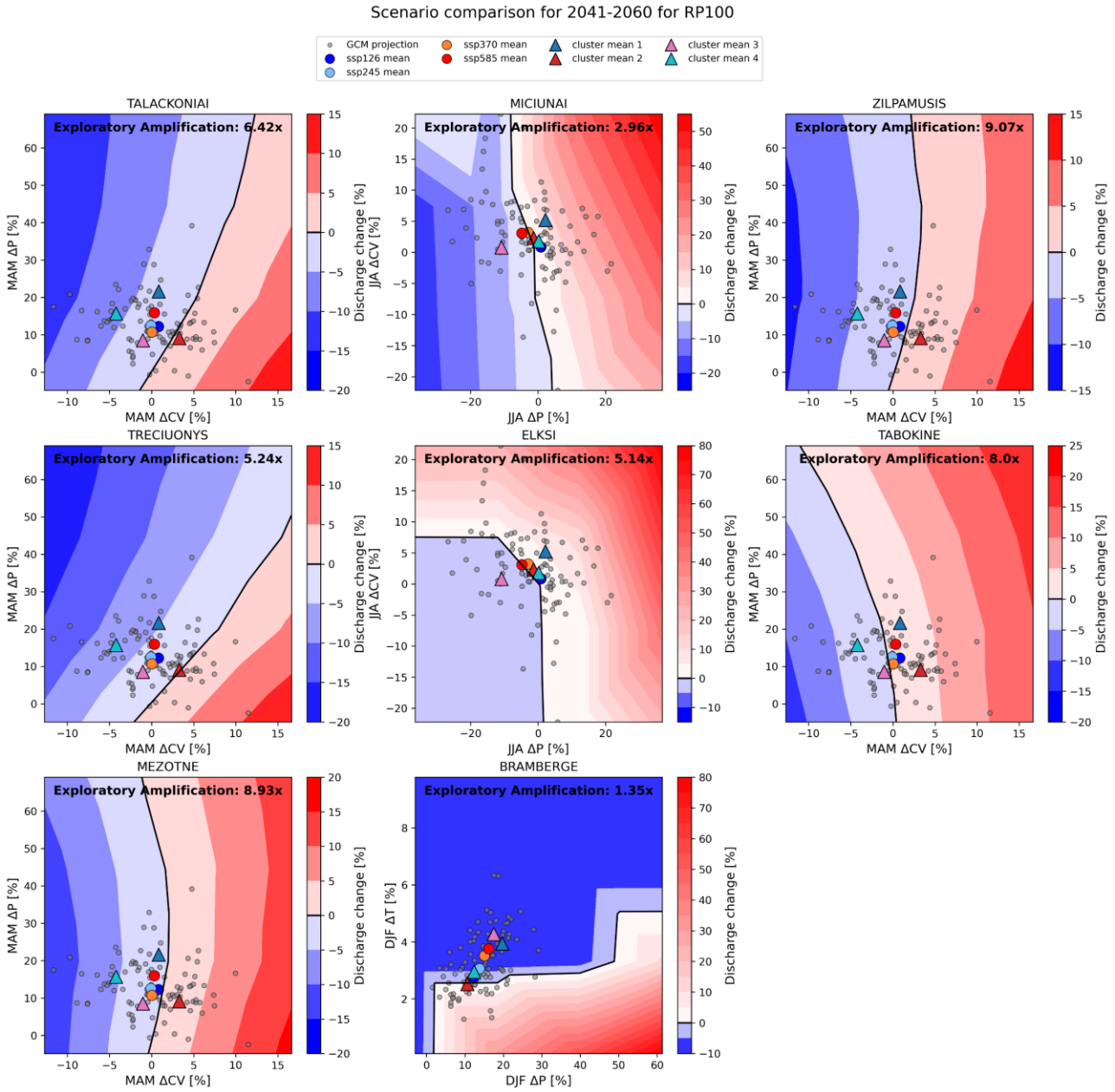


***Figure A.2**: Impact response for the 2041-2060 timeframe for various stations in the basin and their top two climate features of importance. The axis labels represent seasonal changes for December-January-February (DJF), March-April-May (MAM), June-July-August (JJA), and September-October-November (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 grey point represents an individual GCM model projection for SSP126, SSP245, SSP370 and SSP585. The coloured circles represent the SSP model means, and coloured triangles represent the model means of the different clusters. The exploratory amplification for each station is provided.*

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 SSPs. First, the 2020 national input-output table was retrieved from the Latvian statistics portal. This table includes 64 sectors corresponding to the NACE64 nomenclature used in the European Union (Eurostat, 2008). Since the projections in Leimbach et al. (2023) only cover the aggregate NACE3 sectors, the NACE64 sectors are aggregated into the NACE3 sectors: Agriculture, Manufacturing and Services. Contribution ratios of sectors within each NACE3 group are kept as is, since more granular sectoral change information in not available.

The projection process starts by multiplying the 2020 national value added by the projected GDP growth in 2050, shown in Figure 4 of the main text. Next, the value added is allocated among the three aggregate sectors according to the 2050 projection, providing an estimate of each sector's size in 2050 for an SSP.

$$VA_{s,SSP}^{2050} = \alpha_{s,SSP}^{2050} * VA^{2020} * g_{SSP}^{2050}$$

Where:

$VA_{s,SSP}^{2050}$: projected value added of NACE3 sector *s* in 2050 for an SSP scenario

$\alpha_{s,SSP}^{2050}$: projected sectoral contribution share of NACE3 sector *s* in 2050 for an SSP scenario

VA^{2020}: total value added in the economy in 2020

g_{SSP}^{2050}: growth value of GDP in 2050 for an SSP scenario

To maintain a detailed sectoral analysis, the value added of each NACE3 sector is disaggregated to the original NACE64 sectors using 2020 value-added contributions ratios within the aggregate sector. This proportional allocation assumes that internal distribution within a NACE3 sector does not change from the base year. Using the updated value added for each sector, the required input goods from the NACE64 sectors are calculated based on the 2020 ratio of input units per unit of value added.

$$VA_{i,SSP}^{2050} = VA_{s,SSP}^{2050} * \frac{VA_i^{2020}}{VA_s^{2020}}$$

Where:

$VA_{i,SSP}^{2050}$: projected value added of NACE64 sector *i* in 2050 for an SSP scenario

$VA_{s,SSP}^{2050}$: projected value added of NACE3 sector *s* in 2050 for an SSP scenario

VA_i^{2020}: value added of NACE64 sector *i* in 2020

VA_s^{2020}: value added of NACE3 sector *s* in 2020

$$Input_{i\leftarrow j,SSP}^{2050} = VA_{i,SSP}^{2050} * \frac{Input_{i\leftarrow j}^{2020}}{VA_i^{2020}}$$

Where:

$Input_{i\leftarrow j,SSP}^{2050}$: input required from sector *j* for sector *i* in 2050 for an SSP scenario

$Input_{i\leftarrow j}^{2020}$: input required from sector *j* for sector *i* in 2020

$VA_{i,SSP}^{2050}$: projected value added of NACE64 sector *i* in 2050 for an SSP scenario

VA_{i}^{2020}: value added of NACE64 sector *i* in 2020

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.

$$FD_{i,SSP}^{2050} = FD_{i}^{2020} * g_{SSP}^{2050}$$

Where:

$FD_{i,SSP}^{2050}$: final demand for sector *i* in 2050 for an SSP scenario

FD_{i}^{2020}: final demand for sector *i* in 2020

g_{SSP}^{2050}: growth value of GDP in 2050 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.

$$X_{i}^{2050} = VA_{i,SSP}^{2050} + \sum_{j} Input_{i\leftarrow j,SSP}^{2050}$$

Where:

X_{i}^{2050}: total output of sector *i*

$Input_{ij,SSP}^{2050}$: input required from sector *j* for sector *i* in 2050 for an SSP scenario

$VA_{i,SSP}^{2050}$: projected value added of sector *i* in 2050 for an SSP scenario

$$D_{i,SSP}^{2050} = FD_{i,SSP}^{2050} + \sum_{j} Input_{j\leftarrow i,SSP}^{2050}$$

Where:

$D_{i,SSP}^{2050}$: total demand of sector *i*

$FD_{i,SSP}^{2050}$: final demand for sector i in 2050 for an SSP scenario

$Input_{ij,SSP}^{2050}$: input required by sector *j* from sector *i* in 2050 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

1005 sector's outputs, import most. If local production exceeds local consumption, imports of
1006 domestic sectors that require the specific local goods are reduced to zero, and the remaining
1007 goods are added to a producing sector's final demand as exports. This process ensures that
1008 projected inputs and outputs are in balance.

$$NP_{i,SSP}^{2050} = X_{i,SSP}^{2050} - D_{i,SSP}^{2050}$$

1009 Where:

1010 $NP_{i,SSP}^{2050}$: net production sector *i* in 2050 for an SSP scenario

1011 X_i^{2050}: total output of sector *i* in 2050 for an SSP scenario

1012 D_i^{2050}: total demand of sector *i* in 2050 for an SSP scenario

1013

$$Input'^{2050}_{j\leftarrow i_{imp},SSP} = Max(Input^{2050}_{j\leftarrow i_{imp},SSP} + NP^{2050}_{i,SSP} * \frac{Input^{2050}_{j\leftarrow i_{dom},SSP}}{X^{2050}_{i,SSP}};\ 0)$$

1014 Where:

1015 $Input'^{2050}_{j\leftarrow i_{imp},SSP}$: Adjusted imports by sector *j* from sector *i* in 2050 under the SSP scenario.

1016 $Input^{2050}_{j\leftarrow i_{imp},SSP}$= Original projected imports by sector *j* from sector *i* in 2050 under the SSP scenario.

1017 $NP_{i,SSP}^{2050}$: net production sector *i* in 2050 for an SSP scenario

1018 $Input^{2050}_{j\leftarrow i_{dom},SSP}$: Total inputs required by sector *j* from domestic sector *i* in 2050 under the SSP scenario

1019

$$Input'^{2050}_{j\leftarrow i_{dom},SSP} = Input^{2050}_{j\leftarrow i_{dom},SSP} + Input^{2050}_{j\leftarrow i_{imp},SSP} - Input'^{2050}_{j\leftarrow i_{imp},SSP}$$

1020

1021 Where:

1022 $Input'^{2050}_{j\leftarrow i_{dom},SSP}$: Adjusted domestic inputs from sector *i* to sector *j* in 2050 under the SSP scenario

1023 $Input^{2050}_{j\leftarrow i_{dom},SSP}$: Original projected domestic inputs from domestic sector *i* to sector *j* in 2050 under the
1024 SSP scenario

1025 $Input^{2050}_{j\leftarrow i_{imp},SSP}$= Original projected imports by sector *j* from sector *i* in 2050 under the SSP scenario.

1026 $Input'^{2050}_{j\leftarrow i_{imp},SSP}$: Adjusted imports by sector *j* from sector *i* in 2050 under the SSP scenario.

1027

1028

$$D'^{2050}_{i,SSP} = FD^{2050}_{i,SSP} + \sum_j Input'^{2050}_{j\leftarrow i,SSP}$$

1029 Where:

1030 $D'^{2050}_{i,SSP}$: Adjusted total demand of sector *i*

1031 $FD_{i,SSP}^{2050}$: final demand for sector i in 2050 for an SSP scenario

1032 $Input'^{2050}_{j\leftarrow i,SSP}$: Adjusted input required by sector *j* from sector *i* in 2050 for an SSP scenario

$$X'^{2050}_{i} = VA^{2050}_{i,SSP} + \sum_{j} Input'^{2050}_{i \leftarrow j,SSP}$$

Where:

X'^{2050}_{i}: Adjusted total output of sector *i*

$Input'^{2050}_{i \leftarrow j,SSP}$: Adjusted input required by sector *j* from sector *i* in 2050 for an SSP scenario

$VA^{2050}_{i,SSP}$: projected value added of sector *i* in 2050 for an SSP scenario

$$NP'^{2050}_{i,SSP} = X'^{2050}_{i,SSP} - D'^{2050}_{i,SSP}$$

Where:

$NP'^{2050}_{i,SSP}$: adjusted net production sector *i* in 2050 for an SSP scenario

X'^{2050}_{i}: adjusted total output of sector *i* in 2050 for an SSP scenario

D'^{2050}_{i}: adjusted total demand of sector *i* in 2050 for an SSP scenario

$$Input''^{2050}_{i \leftarrow i_{imp},SSP} = Input'^{2050}_{i \leftarrow i_{imp},SSP} - NP'^{2050}_{i,SSP}$$

Where:

$Input''^{2050}_{i \leftarrow i_{imp},SSP}$: Further adjusted imports by sector *j* from sector *i* in 2050 under the SSP scenario

$Input'^{2050}_{i \leftarrow i_{imp},SSP}$: Adjusted imports by sector *j* from sector *i* in 2050 under the SSP scenario.

$NP'^{2050}_{i,SSP}$: adjusted net production sector *i* in 2050 for an SSP scenario

$if\ Input''^{2050}_{i \leftarrow i_{imp}i,SSP} < 0$:

$$FD'^{2050}_{i,SSP} = FD^{2050}_{i,SSP} + (-Input''^{2050}_{i \leftarrow i_{imp},SSP})$$

$$Input''^{2050}_{i \leftarrow i_{imp},SSP} = 0$$

Where:

$Input''^{2050}_{i \leftarrow i_{imp},SSP}$: Further adjusted imports by sector *j* from sector *i* in 2050 under the SSP scenario

$FD'^{2050}_{i,SSP}$: Adjusted final demand for sector *i* in 2050 for an SSP scenario

$FD^{2050}_{i,SSP}$: Original final demand for sector *i* in 2050 for an SSP scenario

Appendix C: Building Classification

***Table C.1**: 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 C.2**: classification of building footprints based on 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
		supermarket	supermarket
		office	office
		mosque	mosque
		kindergarten	kindergarten
		social_facility	social_facility

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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 $(I\text{-}A)^{-1}$, 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