

## Preprint statement

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# Amplifying Exploration of Regional Climate Risks: Clustering Future Projections on Regionally Relevant Impact Drivers Not Emission Scenarios

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## Abstract

In the upcoming decades, climate change impacts will increasingly emerge, requiring regions worldwide to obtain actionable climate information. Global Climate Models (GCMs) are often used to explore future conditions, but the variability of projections among GCMs complicates regional climate risk assessments. Often, multi-model means of climate responses to various emission scenarios are used to reduce analysis resources and uncertainties. Unfortunately, emission scenarios can only explain a small fraction of variance in the mean climate responses of local precipitation patterns and are dominated by model uncertainty and internal variability. Emission scenarios model means, therefore, lead to similar mean responses across emission scenarios. This results in inefficient use of analysis resources and a narrow view of potential climate risks in the region. Since precipitation is a key driver for many hazards like flood, drought and wildfire, local assessment of these risks using emission-based multi-model means is probably not optimal. This study proposes a method to select more impact-relevant scenarios by determining regionally relevant climatic impact drivers and grouping GCMs on their projected changes in these drivers. We quantify the effectiveness of our approach by comparing future impacts covered by emission-based scenarios with our approach, expressed as an “exploratory amplification” factor. We illustrate the method for flood risk in the Latvian Lielupe basin and find the novel method has an exploratory amplification up to a factor of eight for the mid-century. We conclude that our method significantly improves regional exploration of future impacts, enabling more informed adaptation decisions.

Keywords: regional climate risk, climate scenarios, climate uncertainty

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## 1. Introduction

In the decades of the mid-twenty-first century, the impacts of a changing climate will increasingly emerge. (Mora et al., 2013). Therefore, regions worldwide must start taking inventory of their future climate risks and have societal discussions on their adaptation efforts. Although many global risk assessments exist, translating global assessments of climate risks to a regional level remains challenging. Global impact studies can help set the agenda, but regional action requires more locally specific information (Blankespoor et al., 2023). Meanwhile, at a regional level, available resources may be limited (Measham et al., 2011) to process the large volume of climate data from large model intercomparison projects.

Even though resources are limited, there is a need to analyse multiple GCM outcomes to capture the vast variability of regional climate change features. In particular, changes in rainfall patterns – driving natural hazards like flooding (Merz et al., 2021), drought (Cook et al., 2020) and wildfires (El Garroussi et al., 2024) or crop failures (Goulart et al., 2021) – display large uncertainties that are a complicating factor in risk planning. For instance, flood impacts can vary significantly over different climate model ensembles (Rojas et al., 2013).

The combination of limited local resources combined with uncertainty in climatic impact drivers (CIDs) (Ruane et al., 2022) emphasises the need to obtain a broad picture of potential future impacts while limiting the number of scenarios needed to analyse. An often-used approach to handle projection uncertainty is to use multi-model means of emission-based scenarios used in the IPCC reports, such as a representative concentration pathway (RCP), socio-economic pathway (SSP), or Global Warming Level (GWL). Taking means allows for a robust signal of climatological trends and reduces the number of scenarios needed to analyse for policy making. In recent years, many policymakers have become accustomed to these types of scenarios. However, emission scenarios only explain about 15% of total precipitation variance in CMIP6 by the end of the century on a global level (Lehner et al., 2020) and 5-10% of European winter precipitation in CMIP5 (Hawkins & Sutton, 2011). For the mid-century, the emission scenarios can explain even lower fractions of the total variance. Reasons for lower fractions in the mid-century compared to the end of the century are due to the large inertia of the climate system and multiple modes of internal variability that complicate the detection of forced climate response for the near to medium-terms (Samset et al., 2020; Tebaldi & Friedlingstein, 2013). As a result, projected precipitation change in the various multi-model means of emission scenarios are very similar. It is hypothesised that, the impacts of these mean changes are then also similar across the emission scenarios. As a result regions could spend their limited resources on the analysis of scenarios that highlight only a very limited risk range. Their collection of scenarios has limited exploratory power. Enhancing insight into the future climate risk range can help regions better prepare for an uncertain climate future. This gives rise to the question: Are there better ways to highlight the spread of potential climate risks at the local level?

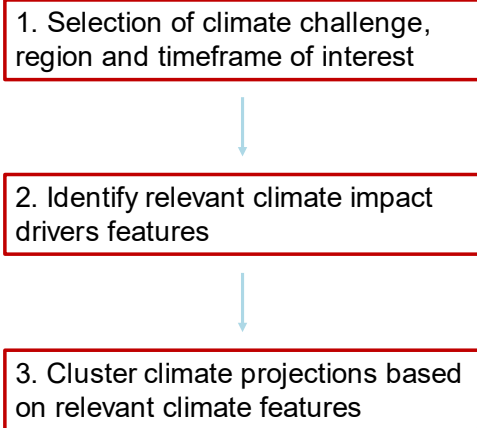
This paper presents a three-step framework to increase the exploratory power of future climate scenarios. We do this by creating ‘impact-oriented climate information’ (van den Hurk, 2022) by spanning the range of future conditions, taking into account regional uncertainty in climate change responses of locally relevant CIDs. The three-step process first identifies the climate challenge, the region and the timeframe of interest. Then, the most relevant CIDs in the region are determined. Afterwards, new impact-oriented climate scenarios are defined based on the GCM projections of the relevant climate features. To analyse the framework's effectiveness in highlighting a large range of vulnerabilities while keeping the number of scenarios low, the exploratory power of emission-based scenarios versus impact-relevant scenarios is compared.

The framework is illustrated using a riverine flood example. Flooding is one of the four key risks in Europe, and regions will need to implement measures to prevent increases in damages and number of people affected (Bednar-Friedl et al., 2022). The example covers the Lielupe basin, which spans 17.600 km<sup>2</sup> across Estonia and Latvia. The area covers 13.8% of Latvian territory and is home to about 400.000 inhabitants. Latvian authorities have identified the land area around the Lielupe river as a flood-risk area of national importance.

## 2. Methods

This section introduces the data and methods that make up the scenario selection procedure (Figure 1) to explore the future risk range with limited scenarios. First, we describe the region and the hydrological model. Second, we elaborate on the selection of the climate region and the timeframe of interest (step 1). Third, we describe the method to obtain relevant CIDs (step 2). Then, we detail how GCM projections are grouped into impact-oriented climate scenarios (step 3). Lastly, the exploratory power of impact-oriented scenarios is compared to that of emission-based model mean scenarios.

### Scenario selection procedure



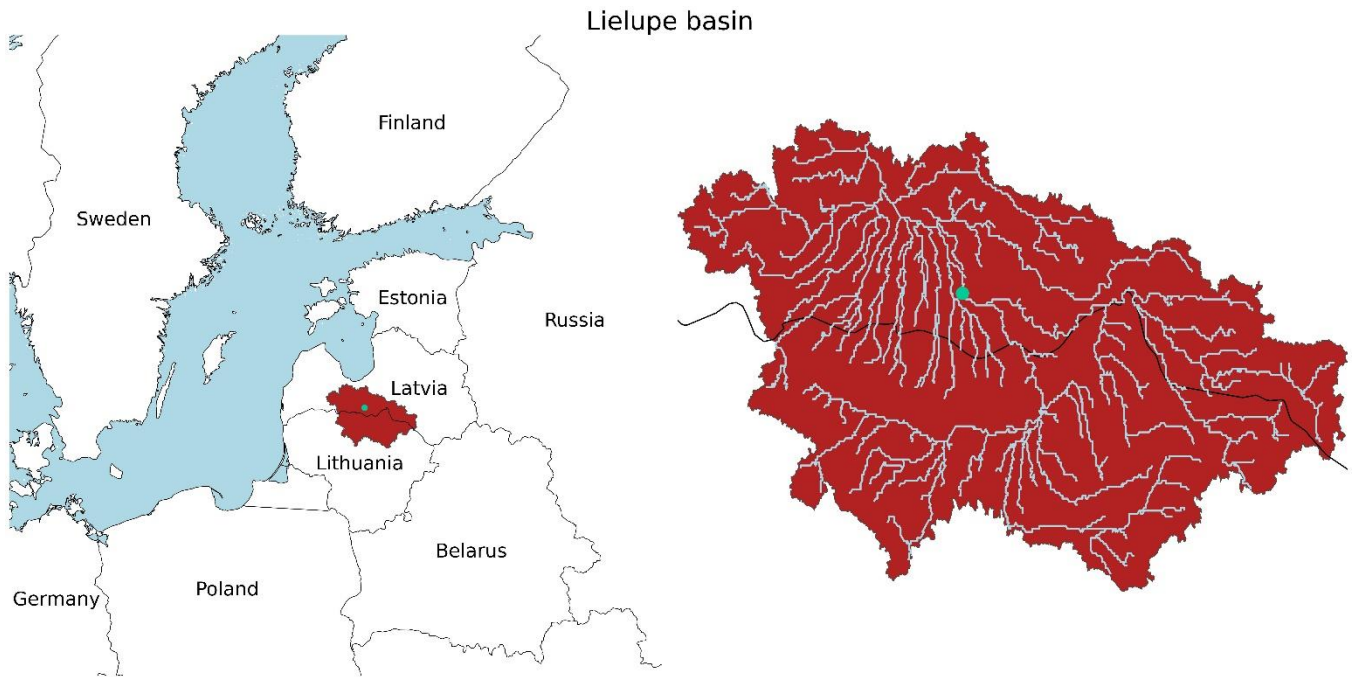
**Figure 1:** General framework used in the study to obtain impact-relevant climate scenarios. The application to the case study is detailed in the text.

#### 2.1 Study area and hydrological modelling

The area of interest, shown in Figure 2, is a basin in the Baltic States region of Europe. Although precipitation amounts in the region are higher during summer than in winter, the catchment is characterised by seasonal high flows in the spring period. However, with potential increases in mean precipitation and its variability (expressed as larger changes in the extremes compared to changes in the mean) in the summer period (see Figure B.3), this study also considers the possibility of future high flows in the summer.

The hydrological model used is the distributed hydrological model `wflow_sbm` (van Verseveld et al., 2024). This is set up using `wflow_sbm` model builder HydroMT, which combines openly available global datasets to develop first-order models for any basin in the world (Eilander et al., 2023). The used model serves as a tool to make a quick scan of the climate variables that influence high-discharge statistics the most. This study does not consider ice jams in rivers, which can be a cause of flooding in the region. The model runs on a daily timestep with a resolution of  $0.00833 \times 0.00833^\circ$  per grid cell (locally  $\sim 925 \times 515 \text{m}$ ). To validate the model, historically observed discharges are compared with those reconstructed by forcing the hydrological model with historical ERA5 reanalysis of  $0.25 \times 0.25^\circ$  (locally  $\sim 27.8 \times 15.2 \text{km}$ ) resolution (Hersbach et al., 2023) between June 1950 and June 2023. The observational data is retrieved from local authorities (Latvian Environment, Geology and Meteorology Centre) and the World Meteorological Organization Global Runoff Data Centre (GRDC). Overall, the modelled discharges have a fair correspondence with the historical record for various stations in the basin. For more details, see Appendix A.

For the impact variables, discharges at Mezotne station are taken due to its proximity to high flood-risk areas identified by local authorities. We aim to capture changes in high flows with a return period of 20, 50 and 100 years.



**Figure 2:** Region of interest. The red-filled shape is the Lielupe basin, the green dot indicates the discharge station Mezotne, and light blue indicates the sea surface and the rivers. The top image shows the location in Europe and the bottom image is a more detailed image of the river network in the basin.

## 2.2 Selection of climate region and timeframe of interest

Since the Lielupe basin is small and, therefore, subject to large internal variability in the observed and modelled weather, getting a climate signal can be challenging. To retrieve a more robust signal of the climatological changes in the area, a larger region of interest has been defined to extract climate features from (See Figure 3). This region is selected by analysing monthly average precipitation and temperature in Europe with the ERA5 dataset between 1940-2024. We filtered the area on grid cells that have a correlation higher or equal to 0.60 to the grid cell at the centre of the basin. If the correlation area for temperature and precipitation differs, the smallest area is selected.

In this study, we select three timeframes of interest to explore how the scenarios develop over time and compare them to the development of the emission-based model over time. However, in other studies, a timeframe can be selected depending on the decision-maker's planning horizon. The three selected timeframes are: near-term 2021-2040, mid-century 2041-2060, and end-of-century 2081-2100. These timeframes coincide with those used in the IPCC Atlas (Gutiérrez et al., 2021).

## 2.3 Identify impact-relevant climate features

For the second step in defining impact-relevant climate scenarios, we determine the relevant CIDs for the region. We follow the exploratory modelling and analysis principle (Bankes, 1993; Bankes et al., 2013), where uncertainties are systematically sampled to find those of highest influence on the outcomes of interest. The decision-scaling method (Brown et al., 2012) is an exploratory modelling and analysis method which we will follow in this paper to find relevant CIDs. The method has been successfully used in water resource (Steinschneider, McCrary, et al., 2015) and flood studies (Spence & Brown, 2016). The method allows us to sample hydro-meteorological uncertainties of GCM projections and relate them to hydrological impacts. This method uses a stochastic weather generator based on Steinschneider and Brown (2013) to generate weather time series for current-day (baseline) and future climate conditions. Future time series are made by adjusting selected climate features in the baseline series. Using the baseline and future climate weather time series, we generate discharges using the hydrological model introduced in section 2.1 and compare discharge extremes in the future climate realisation against the extremes resulting from the baseline weather time series. From the set of preselected climate variables, we identify those CIDs that are most influential on the discharge quantities of selected return periods. Lastly, a filtering step is applied to go from influential to relevant CIDs by checking for plausibility.

### 2.3.1 GCM spread of initial variables of interest

The first step is to define potential CIDs that should be investigated and quantify the change factors in those variables. Often used climate variables in decision-scaling studies are yearly changes in average temperature, mean precipitation and the coefficient of variation (CV) of precipitation (El Garroussi et al., 2024; Fronzek et al., 2022; Ray et al., 2019; Taner et al., 2017; Steinschneider, McCrary, et al., 2015). These three variables are considered ‘core variables’ as these influence a broad array of climate-related flood processes (e.g. antecedent snowfall and melt, precipitation intensities, and soil moisture conditions). In the Lielupe basin, changing annual averages misrepresent future dynamics of extreme discharges since precipitation patterns change differently across the seasons in large parts of Europe (Gutiérrez et al., 2021). See also the specific dynamics of seasonal changes for the Lielupe basin in Figure A.3. Therefore, the study examines the impact relevance of the often used features in a seasonal manner. The seasons are defined as: winter (December-January-February), spring (March-April-May), summer (June-July-August) and autumn (September-October-November). Since temperature extremes scale similarly to temperature means (Seneviratne, et al., 2023), changes in temperature extremes relative to the mean seasonal changes are not considered.

To quantify the changes in these variables, we calculate the relative change of these seasonal features to the average value between 1940 and 2014 against the selected timeframes. The historical range of 1940-2014 has been selected since 2014 is the last year of many historical GCM simulations, and 1940 is the earliest year of ERA5 reanalysis data, later used to create future weather time series.

Using the dataset on CMIP6 climate projections from the Copernicus Climate Data Store (Copernicus Climate Change Service, 2021), grids for the region of interest are extracted for each available model and the SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5 emission experiments, each ascending in emissions (see Table D.1 for a list of used model projections). Given the relatively small contribution of emission scenarios to the total variance of precipitation response patterns across models (Hawkins & Sutton, 2011; Lehner et al., 2020) we consider the selection of four emission scenarios sufficient to capture a large set of potential futures.

From the datasets, the average monthly near-surface air temperature is obtained together with daily accumulation values for precipitation amounts. The extracted data is masked by the identified climate region in Section 2.2. The relative change of a climate feature is found by comparing the feature value of a model, emission experiment and timeframe combination to the feature value of a model’s historical run. Long-term area average seasonal temperature and precipitation sums were estimated. Then, seasonal changes in precipitation variability are defined by using the coefficient of variation (CV), which is a measure comparing the standard deviation of rainfall to the mean rainfall. The change in CV value is found by fitting a gamma distribution using shape and scale parameters of wet day (> 0.1 mm) rainfall per grid cell using the method of moments estimation. The CV value per cell is calculated by taking the inverse root of the fitted shape parameter. After finding all percentual grid cell CV changes, the changes are averaged across the basin. Method of moments estimation is chosen as this better represents extremes in the mid-latitudes (Watterson, 2005; Watterson & Dix, 2003) which is of interest in this flood study. Gamma distributions have been shown to provide good estimations of daily rainfall probability density curves and for analysing changes in precipitation extremes and distributions under changing climate conditions (Martinez-Villalobos et al., 2022; Martinez-Villalobos & Neelin, 2019; Shadmehri Toosi et al., 2020; Watterson, 2005; Watterson & Dix, 2003; Wilby & Wigley, 2002).

### 2.3.2 Future weather time series

Next, we apply a decision-scaling approach where the change factors across the GCM projections inform a stochastic weather generator (Brown et al., 2012). With stochastic weather generators, an extensive range of weather scenarios can be produced to identify climate vulnerability regimes for floods (Alcantara & Ahn, 2021; Steinschneider, Wi, et al., 2015). The approach entails a stochastic vulnerability analysis and, afterwards, performing a plausibility check using the collection of GCM projections. Using the weather generator as described by Steinschneider & Brown (2013), a baseline weather time series is made based on the historical climate. Then, this time series is adjusted for future climates. In this case, we adjust the average seasonal temperature by adding an absolute degree change factor on top of the baseline climate realisation. For precipitation changes, a quantile mapping procedure is applied where the mean and CV of the historical rainfall are adjusted to match future climate projections. Increasing the CV entails that small rainfall events will be smaller, and heavy rainfall events will be heavier. (For an example of a climate manipulation, see Figure B.4).

ERA5 reanalysis of 0.25x0.25° resolution from 1940-2014 (Hersbach et al., 2023) in the basin is used on a daily temporal resolution as input for the stochastic weather generator. The year 1940 is the earliest data available in the dataset and is chosen to be able to capture a large number of weather patterns to inform the stochastic weather generator. The year 2014 is selected to be able to compare it to historical runs of GCMs, which typically end then. Using the stochastic weather generator with historical information, a baseline synthetic weather time series of 100 years is created adhering to historical statistics. The combinations of change factors to tweak the baseline time series are determined by sampling four values for each uncertain climate feature ( $\Delta P$ ,  $\Delta CV$ ,  $\Delta T$ ) in a season. The samples span the minimum to the maximum projected changes in the region

with equal spacing. Within a season each of these values is combined with the other values, leading to  $4 \times 4 \times 4 = 64$  scenarios per season and 256 in total. Each of these scenarios alters the baseline weather time series and is run in the hydrological model to obtain discharge extremes.

### *2.3.3 Assessing changes in discharge extremes*

Discharge extremes are determined based on the annual maxima. Each annual maxima is coupled to a return period by dividing the number of years by the count of annual maxima that exceed or equal the specific annual maximum. The flows with a return period (RP) of 20, 50 and 100 years for each climate scenario are compared to the simulated extended historical climate time series. The comparison leads to a relative change from the current-day flows.

### *2.3.4 Importance and filtering of climate features*

Not all climate features considered are necessarily influential on the discharge extremes. To find the climate variables that are most influential in changes on the impact the Extra-Trees feature scoring algorithm (Geurts et al., 2006) is applied. This method links the seasonal climate features to the discharge variables. Higher scores indicate a higher importance on the outcome.

After obtaining the climate feature importance, we select the two highest-ranking CIDs per impact metric. These are used to create impact-relevant climate scenarios. However, before final selection, the CIDs are subjected to a relevancy test. Relevancy is defined as a combination of high feature importance and plausibility when compared to GCM projections. We do this by plotting an impact response surface for the season and plotting projected changes of GCMs for each available timeframe and emission experiment. The impact response surface shows the discharge change under a combination of the two CIDs. If impact changes only occur at feature combinations that are not plausible, then the variable is discarded and replaced with the next most influential CID.

### *2.4 Clustering GCM projections on relevant climate features*

To identify new impact-oriented model clusters, a k-means clustering algorithm (Likas et al., 2003) is used to cluster model projections on the  $n$  selected climate features for all impact variables (RP20, RP50, RP100) in a particular timeframe. The clustering of the models occurs in an  $n$ -dimensional space. The clustering optimises on two goals. Goal one is to keep data points within each cluster similar to each other. Goal two is to create clusters that are very different from each other. Separation of GCMs aids the selection of well-chosen scenarios that highlight the potential vulnerabilities, as discussed by Shepherd (2019). The number of clusters used is similar to the number of SSPs used (4) to compare the exploratory power of both methods with the same number of data points. The step results in groups of models that exhibit similar behaviour for the targeted CIDs and the model means of those clusters.

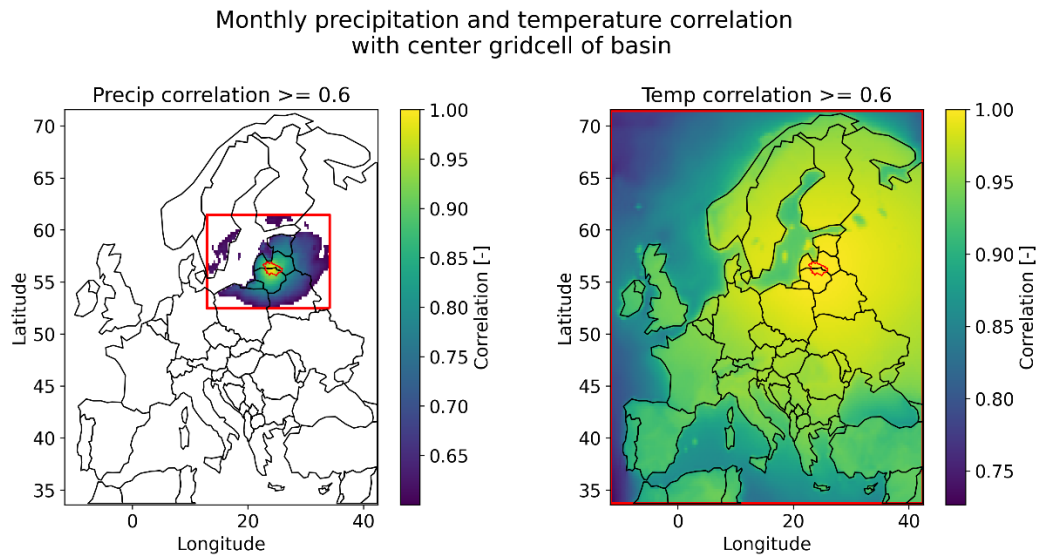
### *2.5 Comparing exploratory power*

As a final step, the exploratory power of both methods is analysed and compared. Here, we define exploratory power as the ability to represent a range of impact values. For each scenario method, the range between the lowest impact model mean and the highest impact model mean is determined. The impact value is deduced from the impact response surface for the impact of interest. The impact response surfaces are created by creating 16 new weather time series that capture the interaction between chosen CIDs per impact metric. After obtaining the flow changes on a  $4 \times 4$  grid, the grid is interpolated to identify flow changes in between grid points. Then, we compare the exploratory powers to find the exploratory amplification of the impact-oriented scenario method. A value below one means that the exploratory power is smaller than the emission-based method. A value above one means that the impact-oriented scenario method has higher exploratory power than the emission-based method.

## **3. Results**

### *3.1 Climate region of interest*

Following the steps described in section 2.2, we find the correlation areas for both precipitation and temperature as shown in in Figure 3. The correlated area of precipitation is smaller than that of temperature, and, therefore, the climate region of interest is defined as the non-white area describing the correlated precipitation area. Also, a clear non-correlation is seen in areas above water, even within the bounding box encompassing the correlated region.



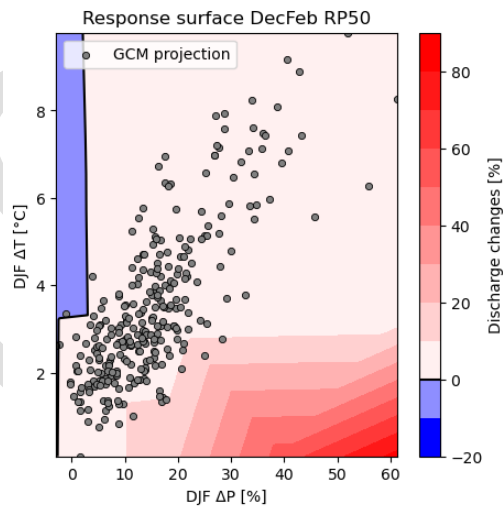
**Figure 3:** Correlation of monthly averaged precipitation (top) and temperature (bottom) time series of each grid cell when compared to the time series of the grid cell at the centre of the Lielupe basin. The heatmap shows the correlation value. The red square indicates the rectangular boundary of the region where the correlation condition is met, and the red shape indicates the boundary of the Lielupe basin. Country borders are shown in black.

### 3.2 Identify relevant climate features

After following the steps described in the methods, Table 1 shows varying importance of climate features across return periods. For 100-year discharge, changes in the CV of precipitation during the spring season are most influential. High-scoring features in this season are expected since current-day high flows occur in spring. At a 50-year return period, mean precipitation and temperature changes in winter and mean precipitation in summer are important variables. In general, we find that high discharges occur when high rainfall amounts fall on saturated soil. At a 100-year discharge, the soil is already saturated before a large rainfall event (see Figure C.1 and Figure C.2), whereas for the other return period events, the soil is not pre-saturated, making average rainfall a more important factor of importance (see Figure C.3 and Figure C.4). Since current-day high-intensity rainfall occurs in summer but soil saturation is at its lowest, added average rainfall can greatly increase discharges. Next to this mechanism, we find that winter temperatures can also lead to high discharges when large quantities of snow start to melt at once. By a combination of low temperature change and increased mean precipitation in winter, more snow can accumulate during precipitation events and melt at once later in time, causing high river discharge. With increasing temperatures, more precipitation falls as rain, resulting in more uniform, and lower peak, discharges (see Figure C.5). For 50-year discharges to be governed by this mechanism, mean precipitation needs to increase while temperatures should not increase much (See Figure 4).

**Table 1:** Climate feature importance table on the impact indicators. The seasonal climate features are indicated for December-January-February (DJF), March-April-May (MAM), June-July-August (JJA), and September-October-November (SON). For each season, the influence of changes in average precipitation ( $\Delta P$ ), coefficient of variation ( $\Delta CV$ ) of that precipitation, and temperature ( $\Delta T$ ) on high discharges are shown. The discharges with a return period (RP) of 20, 50 and 100 years are shown. Higher values indicate higher importance of that feature. Features indicated with a "\*" are used in the grouping of GCMs.

		Impact Metrics			
		<i>RP20</i>	<i>RP50</i>	<i>RP100</i>	
Climate Features	<i>DJF</i>	$\Delta P$	0.12	0.18	0.02
		$\Delta CV$	0.03	0.03	0.00
		$\Delta T$	0.14	0.24	0.00
	<i>MAM</i>	$\Delta P$	0.05	0.08*	0.07*
		$\Delta CV$	0.00	0.05	0.83*
		$\Delta T$	0.01	0.01	0.07
	<i>JJA</i>	$\Delta P$	0.30*	0.24*	0.00
		$\Delta CV$	0.05	0.06	0.00
		$\Delta T$	0.03	0.03	0.00
	<i>SON</i>	$\Delta P$	0.18*	0.05	0.00
		$\Delta CV$	0.08	0.03	0.00
		$\Delta T$	0.01	0.01	0.00



**Figure 4:** Impact response surface plot showing the effect of change in average temperature during December-January-February (DJF  $\Delta T$ ) and average precipitation changes during the same months (DJF  $\Delta P$ ) on percentual changes of the 50-year return period discharge (indicated by the blue to red background hue). Each point represents a GCM model projection in the set that covers the 2021-2040, 2041-2060 and 2081-2100 periods in SSP126, SSP245, SSP370 and SSP585.

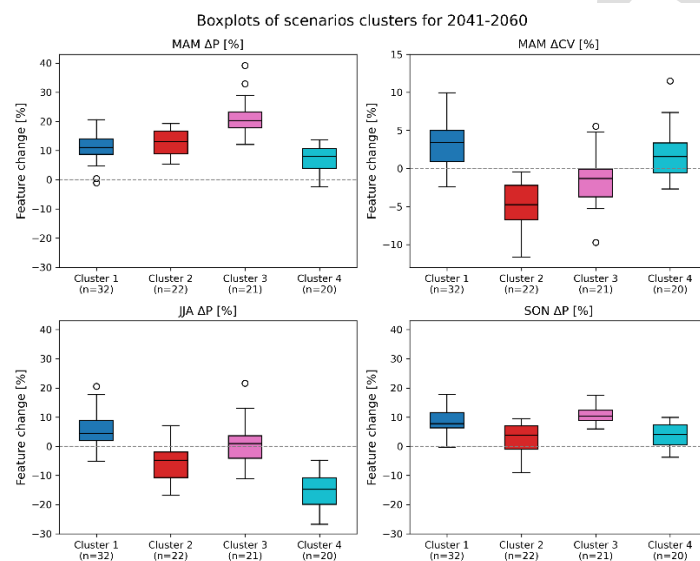
After analysing the two highest-scoring climate features per impact metric for plausibility, we find that 50-year discharge increases due to winter temperature changes are not plausible. None of the GCMs project conditions in which discharges change much (see Figure 4). Although the CIDs are influential, it is not considered relevant to the study area. For RP50, the two most relevant climate features are, therefore, mean changes in spring and summer precipitation. For RP20, autumn and summer precipitation means are most relevant. For RP100 we select CV changes in Spring. Since temperatures and mean precipitation



score equally high, we additionally choose mean spring precipitation since it is already in the set of relevant climate features and keeps complexity for clustering lower.

### 3.3 Clustering GCM projections on relevant climate features

Per timeframe, we clustered the set of GCM projections on the four most relevant climate features we found in the previous section. Here, we further examine the four-dimensional clusters created for the mid-century timeframe. For the mid-century, the four groups can be characterised by the boxplots in Figure 5. The boxplots show the median and spread of each cluster for the relevant climate features. Group one has a high change in rainfall variability during the spring period. As one of the main drivers for RP100 flows, this causes the flood risk to increase. The other precipitation impact drivers also increase, causing this group to have increased flows for all return periods. Group two projects decreases in the CV value in spring – lowering the RP100 flood risk. Group three is characterised by large changes in spring average rainfall, preconditioning wet soils and, therefore, increasing the 50-year flood discharge in spring. However, the model group’s CV value in spring decreases and, therefore, lowers RP100 flows. Group four stands out by the decreases in summer rainfall limiting RP50 flow changes and decreasing RP20 flows.



**Figure 5:** Boxplots clusters per relevant climate feature. Each window represents an impact-relevant climate feature, and within each window, the spread of that feature in the clusters is represented on the vertical axis. The titles represent seasonal March-April-May (MAM), June-July-August (JJA), and September-October-November (SON). For selected seasons, precipitation ( $\Delta P$ ) and coefficient of variation ( $\Delta CV$ ) of that precipitation are shown. The cluster number is given on the horizontal axis together with the number of projections in that cluster. The black lines within the boxes represent the cluster median for that variable.

Variations in the clusters are thought to result from uncertainties in physical processes across climate models. Precipitation in Latvia is mainly governed by incoming westerly winds transporting moist air from the Atlantic Ocean. In winter, the North Atlantic Oscillation (NAO) is a dominant factor bringing in precipitation (Jaagus et al., 2010; Klavins & Rodinov, 2010; Rutgersson et al., 2015). The NAO north-south position is also important (Rutgersson et al., 2015), although the pattern weakens in spring and only picks up again in autumn. In the transition seasons, meridional circulation patterns, such as the Scandinavian blocking pattern, are a large determinant of precipitation amounts (Klavins & Rodinov, 2010). However, large uncertainties exist in changes of the strength of the NAO, the position of the NAO and blocking frequencies across models due to different weights given to different physical processes and potentially missing dynamical processes (Doblas-Reyes et al., 2023; Douville et al., 2023; Lee et al., 2023; Ranasinghe et al., 2023). One such mechanism is the interaction between the Atlantic Meridional Overturning Circulation and the atmosphere, which in turn influences precipitation patterns in Europe (Börgel et al., 2022, 2023).

In general, a strong NAO causes the jet stream to extend more towards eastern Europe and brings more precipitation; a shift of the westerlies northward also brings more moist air, while a southward shift brings more cold and dry air from the polar region. More blocking over the region results in moist air from the ocean being blocked and, therefore, less precipitation in the area. High increases in average precipitation can, therefore, mean two things. One is that there is less frequent blocking and, therefore, more uniform precipitation coming from a strengthened NAO and in a more northward position over Latvia. Or, the

blocking frequencies increase due to a weakening of the NAO, and when it does rain, it pours heavily. Lower increases in average precipitation can indicate a weakening of the NAO or NAO position that is more southward, bringing in less moist air. An increase in blocking can also keep the moist westerlies out, resulting in lower average precipitation. The various clusters can have a combination of these precipitation drivers to a varying degree of change. However, the complex interaction of smaller drivers cannot be excluded from the overall resulting changes.

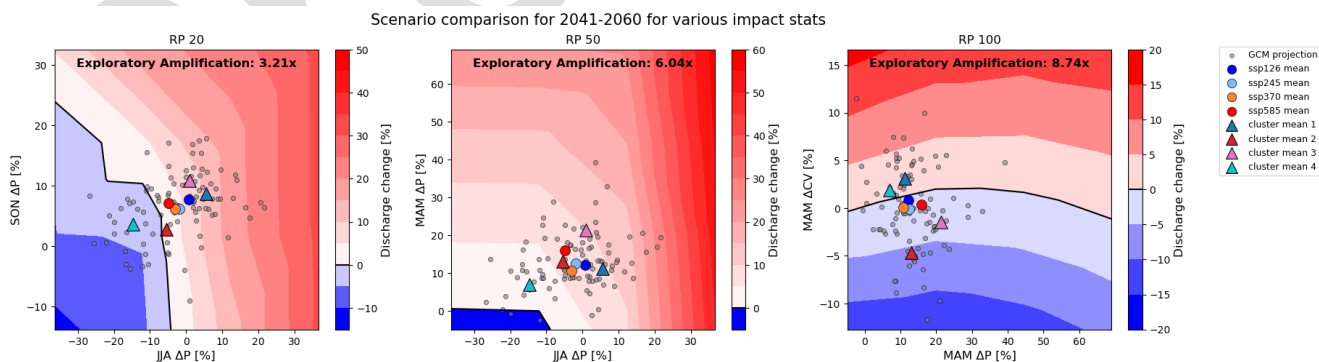
### 3.4 Comparing exploratory power

Using the new groups of GCMs, we analyse the exploratory power of the impact-oriented cluster means and emission-based model means for the mid-century. In Figure 6, both emission-based means and impact-oriented cluster means are plotted on an impact response surface. Overall, the exploratory amplification increases for all return periods. For the 20-year return period, the exploratory amplification is the smallest, with 3.2 times the exploratory power of emission-based means, whereas the return period of 100 years has the largest amplification factor of 8.7. This can be partly explained by the fact that the climate feature governing the 100-year return period has a very clear importance. For the 20- and 50-year return period, the relevancy is more spread out across the initial set of climate features and is, therefore, tougher to get a clear signal from the two most relevant features.

Table 2 shows the development of the projections for RP50 over the various timeframes. Noticeable in the table is that the exploratory amplification factor decreases when considering timeframes further into the future. One reason is that over time the climate response due to emissions becomes clearer over time as the inertia of the climate system is overcome and the role of internal variability becomes smaller (Samset et al., 2020; Tebaldi & Friedlingstein, 2013). Therefore, the emission-based model means start to diverge over time, and the explored impact will, therefore, increase. It must be noted that the explored impact range of impact-oriented model means is still 2.7x that of emissions-based model means.

**Table 2:** Exploratory amplification numbers of the impact relevant cluster means versus emission-based model means for the different impact metrics and timeframes.

		Timeframe		
		2021-2040	2041-2060	2081-2100
Impact metric	RP20	4.82	3.21	2.65
	RP50	7.68	6.04	6.57
	RP100	9.4	8.74	5.94



**Figure 6:** Impact response for the 2041-2060 timeframe for the different impact variables of interest and their top two climate features of importance. Where the axis labels represent seasonal changes for March-April-May (MAM), June-July-August (JJA), and September-October-November (SON). For selected seasons, the changes in average precipitation ( $\Delta P$ ) and coefficient of variation ( $\Delta CV$ ) of that precipitation are shown. The background hue indicates the discharge increase 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 impact-oriented model means of the different clusters. The exploratory amplification for each return period is given below each plot.

## 4. Discussion

In this paper, we introduced a procedure to enhance the exploratory power of future climate scenarios by grouping projections based on locally relevant climatic impact drivers instead of emission-based model means. A comprehensive exploration of the future risk range is needed to aid decisions today to adapt to an uncertain climate future tomorrow. We illustrated the procedure's effectiveness by applying the framework to a riverine flood study for the Lielupe basin in Latvia. For the mid-century, the explored impact range can increase by a factor of 3.2 to 8.7. Also, the different scenario clusters reveal that the high discharge with a 20 and 100-year return probability can either increase or decrease depending on particular climate response features. This largely depends on uncertainties in the response of large-scale earth system processes, such as the NAO, blocking patterns, and AMOC to increasing greenhouse gas concentrations (Börgel et al., 2022; Doblas-Reyes et al., 2023; Douville et al., 2023; Lee et al., 2023; Ranasinghe et al., 2023). Our approach enables an evaluation of the effectiveness of potential adaptation measures across a range of plausible scenarios.

### 4.1 Impact driver-based clustering and earth system process clustering

In this study, we substantiate uncertainties in climatic impact drivers with uncertainties in earth system processes under a changing climate. In climate literature, there is a body of work on physically consistent storylines (Shepherd et al., 2018; Zappa & Shepherd, 2017) where the behaviour of large-scale physical processes such as tropical and polar amplification, polar vortex strength or AMOC stability of different GCMs are isolated to highlight the spread of future climate conditions (Bulgin et al., 2023; Zappa & Shepherd, 2017). The Dutch climate scenarios take such an approach where regionally relevant circulation patterns and their uncertain response to a warming climate are used to highlight the envelope of climate uncertainty (van den Hurk, 2022; van der Wiel et al., 2024). These types of scenarios allow a variety of domains to work with a consistent set of scenarios, which enhances cooperation across stakeholders due to common basis.

However, these storylines are often created considering earth system processes that explain a large fraction of variability of set 'target variables'. These target variables may not reflect all sector-specific dominant impact features and thus prove to be sub-optimally. To create storylines that fit these needs, substantial knowledge is required about the relationship between locally relevant climatic impact drivers and large-scale climate processes. This includes understanding rare but (possibly significant) combinations of earth system interactions determining local impact. Disentangling many processes in separate scenarios leads to an unfeasible number of scenarios, overrunning the decision-maker's capacity.

Our method does not identify specific earth system processes driving local variability but does acknowledge their existence and contribution to uncertainty in the CIDs. System knowledge from local users on which CIDs are most relevant for local impacts is helpful to optimize a scenario framework also without detailed a priori knowledge on key driving large-scale earth system processes. This system knowledge is often available through local stakeholders (New et al., 2023)

In summary, physical storylines have their merits in providing a solid scientific basis of uncertainties and how they affect future climate. Tailoring these storylines to local conditions enhances their specificity and applicability for sectoral planning.

### 4.2 Framework opportunities and limitations

Although this study illustrates a riverine flood study, the proposed procedure is generic and can be implemented for any river basin of interest, provided the availability of adequate climate data and a hydrological modelling capability. The framework itself is flexible and can be adjusted to incorporate regional models, alternative risk metrics, and climate features of interest. This increases the framework's applicability to the local scale and trust in the outcomes. This study used a data and modelling-intensive method to find relevant CIDs. However, one can also directly identify these climate features using local knowledge and extract the CID values from GCM projections. The framework can be extended to other hazards where emission-based model means do not necessarily have a large exploratory power for future impacts. Since the climate response of rainfall is uncertain in many areas of the world (Douville et al., 2023), particularly for mid-century conditions with little contrast between multi-model mean responses to different emission scenarios (Hawkins & Sutton, 2011; Lehner et al., 2020), most water-driven hazards (not only floods, but also droughts or fire weather conditions) are good candidates. The proposed methodology allows for a multi-hazard scenario selection, but relevant CIDs for all hazards and fitting impact metrics should be considered and included in the process.

A few limitations apply to the framework. The procedure does not explicitly distinguish between internal variability and forced climate response. The combination of these highlights the total range of future risks. The forced response can be isolated

by the application of SMILEs, designed to separate internal variability and the forced climate response (Maher et al., 2021). Furthermore, the study only used changes in CIDs using GCM runs driven by SSP scenarios. The socio-economic dimension of these scenarios (O'Neill et al., 2017) is not explicitly sampled in our approach. Considering risk to be a combination of hazard, exposure, vulnerability (Field et al., 2014), and response (Simpson et al., 2021), expansion of the framework representing relevant socio-economic impact drivers may improve the assessment of changes in regional risk profiles.

The choice of climate variables to define the relevant CIDs in this study is partly restricted by the capabilities of the weather generator and computational resources, which limited the number of alternative realisations of time series from the weather generator. Due to sampling uncertainty in stochastic weather generators (Alodah & Seidou, 2020) the resulting return probabilities of given intensities may depend on the number of time series samples. This affects the assessment of the impact range amplification achieved by our methodology.

This study uses CMIP6 model outcomes without any selection or screening. However, not all models are suitable for every analysis and every region, and there are many ways to assess this (Raju & Kumar, 2020). The proposed framework allows for filtering input models when the filter specifications are defined. Higher resolution results may be achieved by using slightly older, but bias corrected CMIP5 based CORDEX data (Giorgi & Gutowski, 2015) or once available CMIP6-based CORDEX data. These data may be more suitable for regional analysis.

## 5. Conclusion

Future climate projections across global climate models show a large range of potential futures due to internal variability and varying model representations of physical processes and their response to emissions. Taking multi-model means of the emission scenarios, one loses vital information on the potential risk indicated by individual models. Separating models into multiple clusters can help gain insight into a broad range of climate risks that occur due to various underlying earth system processes. Here, we presented and illustrated a framework where locally relevant climatic impact drivers are used to cluster projections, and this allows us to explore up to eight times the impact range when compared to using multi-model means of emission scenarios. Not only is the range extended, but we also found that risk can increase or decrease depending on the selected cluster. The framework helps the analysis of future impacts while aggregating a large sample of model projections into an affordable set of scenarios to explore. Overall, the framework allows for an enhanced exploration of future climate risks to aid adaptation decision-making.

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## Data availability statement

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>. 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 <https://doi.org/10.5281/zenodo.11638284>

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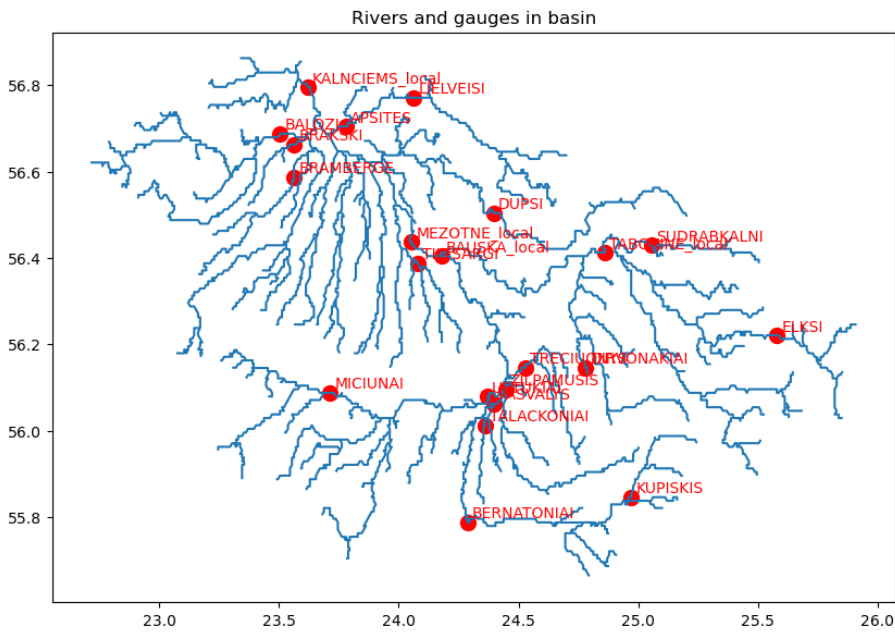
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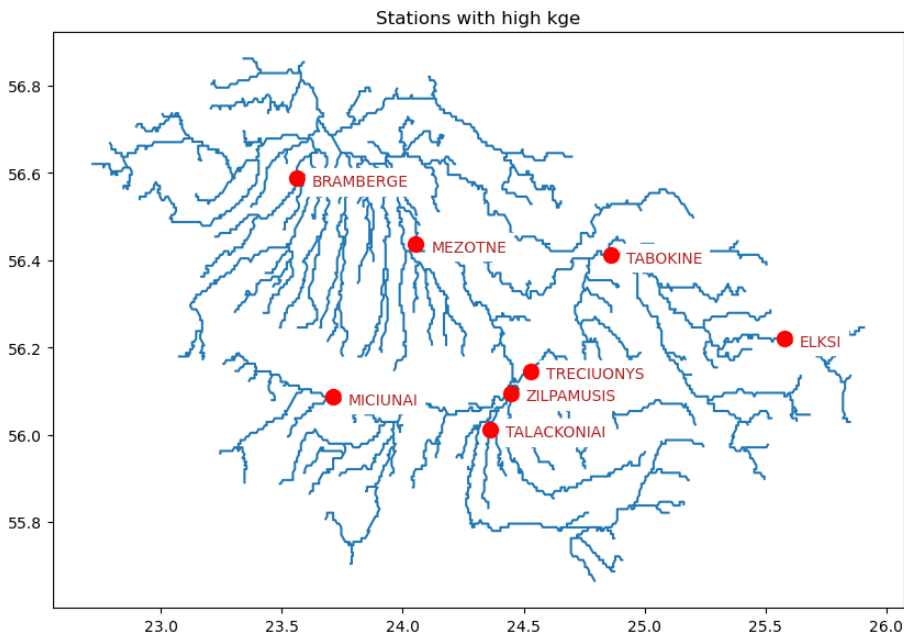
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Pre-print

## Appendix A: Hydrological Validation



**Figure A.1:** A map of the Lielupe basin rivers (in blue) with Initial stations in the basin that are used to validate the hydrological model indicated by red dots annotated with their name.



**Figure A.2:** A map of the Lielupe basin rivers (in blue) with stations in red with high enough Kling-Gupta Efficiency ( $\geq 0.5$ ) to consider. The names of the stations are annotated in red.

Modelled and observed flows at stations

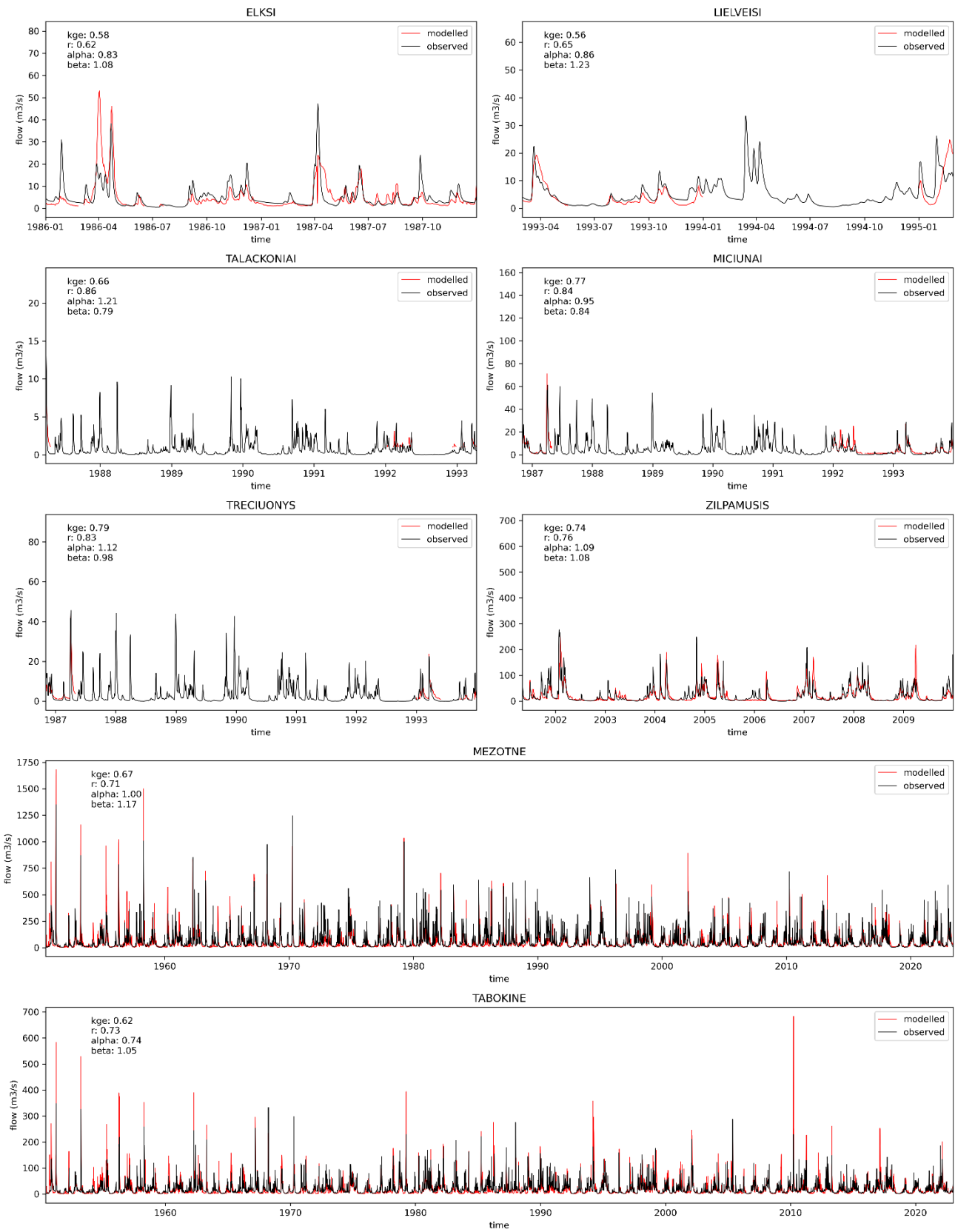
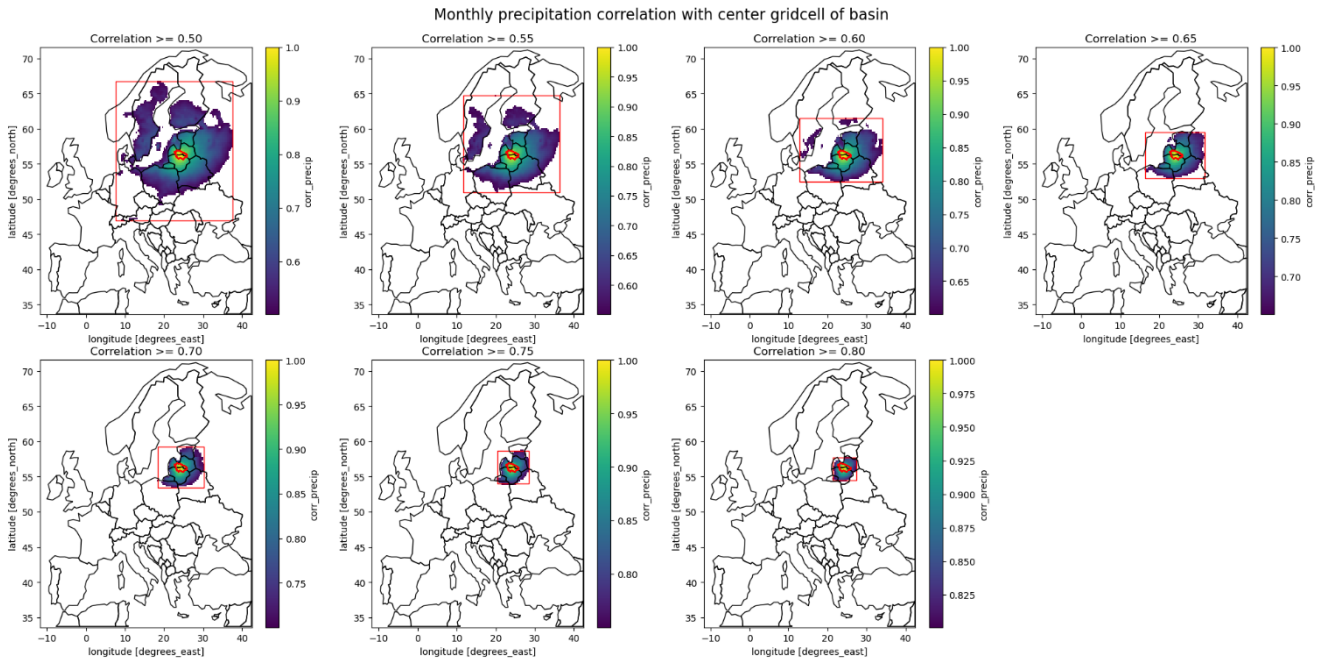
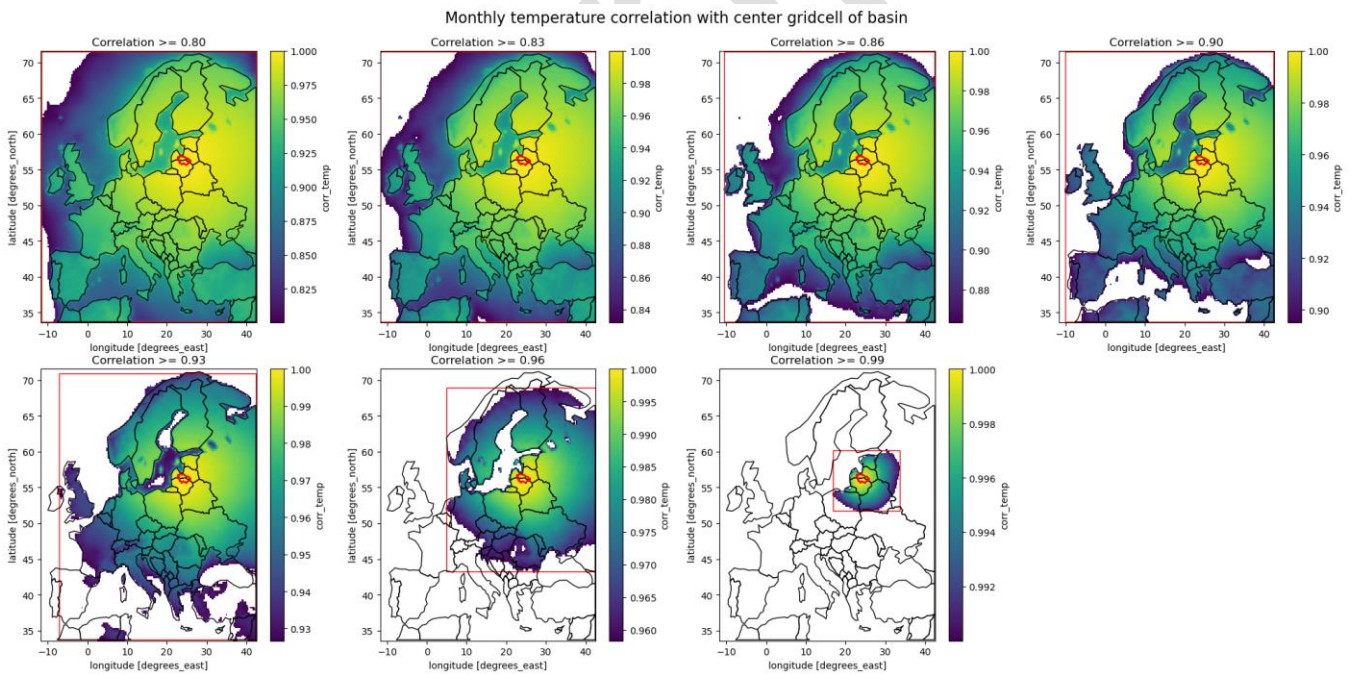


Figure A.3: Available time period of historical flows versus modelled flow. Simulated flows from June 1950 to June 2023

## Appendix B: Weathergenerator



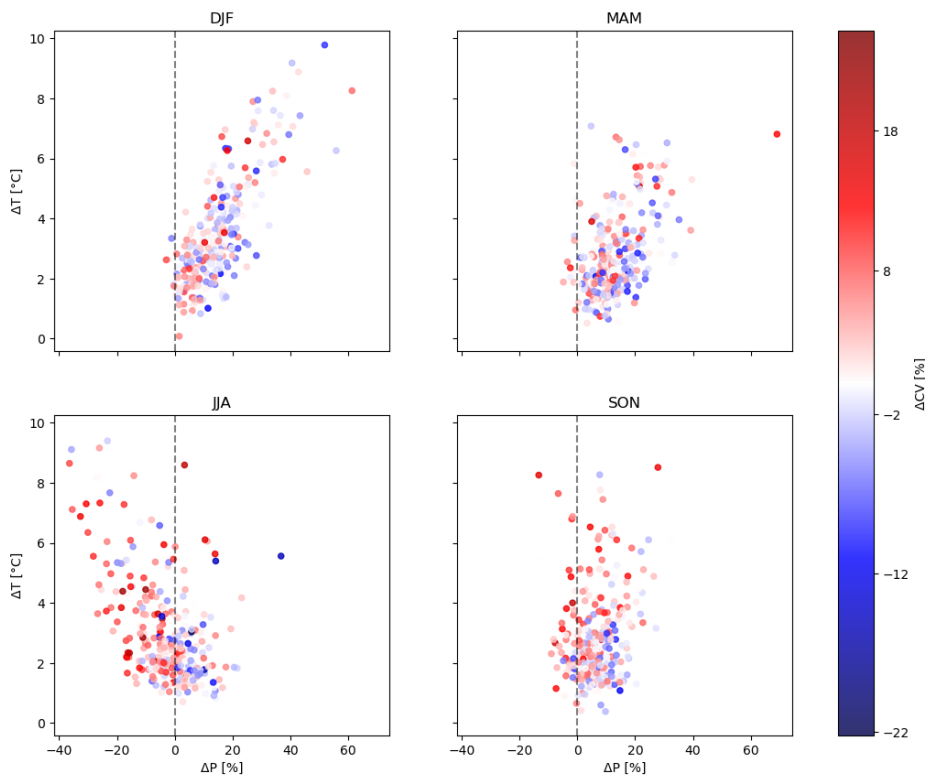
**Figure B.1:** Correlation of monthly averaged precipitation time series of each grid cell when compared to the time series of the grid cell at the centre of the Lielupe basin. The heatmap shows the correlation value. The red square indicates the boundary of the region where the correlation condition is met, and the red shape indicates the boundary of the Lielupe basin. Country borders are shown in black.



**Figure B.2** Correlation of monthly averaged temperature time series of each grid cell when compared to the temperature time series of the grid cell at the centre of the Lielupe basin. The heatmap shows the value of correlation value. The red square indicates the boundary of the region where the correlation condition is met, and the red shape indicates the boundary of the Lielupe basin. Country borders are shown in black.



Seasonal precipitation, temperature and variability change in region



**Figure B.3:** Extracted climate information in the specified region. Each dot represents an SSP, timeframe, model, and ensemble combination.

**Table B.1:** Seasonal ranges for selected climate features

season	$\Delta T$		$\Delta P$		$\Delta CV$	
	min	max	min	max	min	max
DJF	0.1	9.8	-3.0	61.3	-11.2	16.8
MAM	0.5	7.1	-4.8	69.1	-12.7	16.6
JJA	0.7	9.4	-36.4	36.7	-22.2	22.2
SON	0.4	8.5	-13.8	32.6	-11.5	25.2

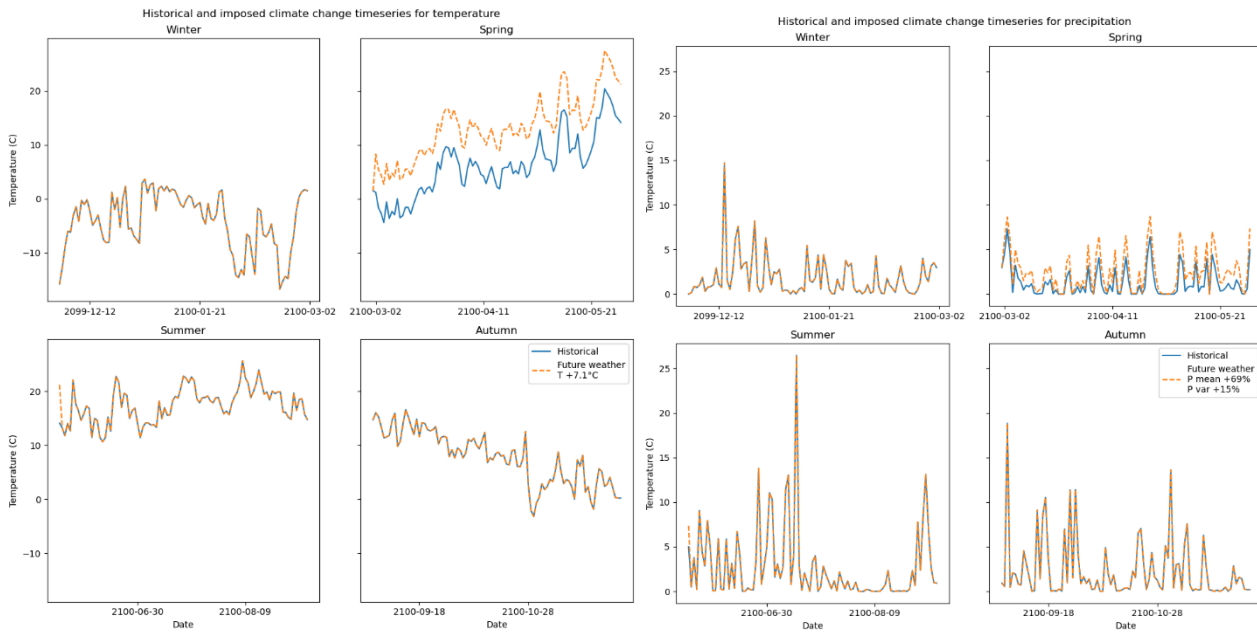


Figure B.4: Adjusted weather time series for a single scenario where spring temperature, precipitation mean and coefficient of variance (CV) are adjusted.

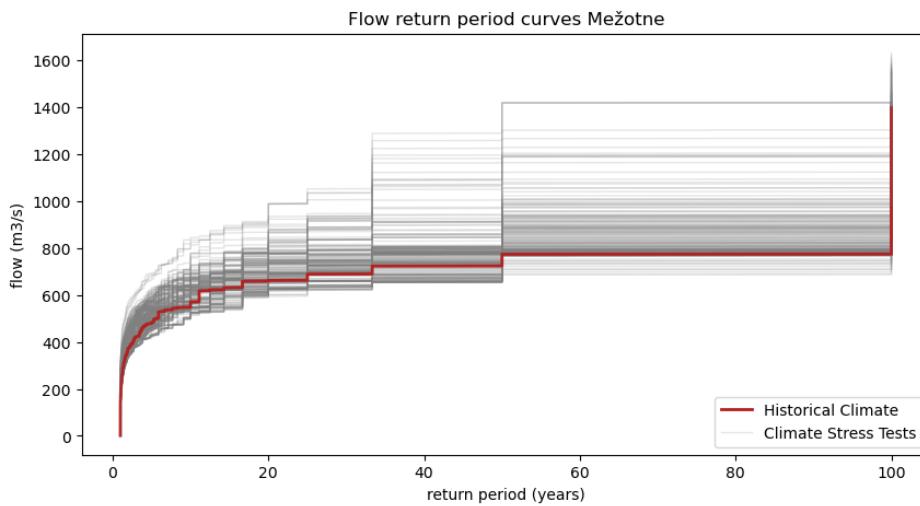
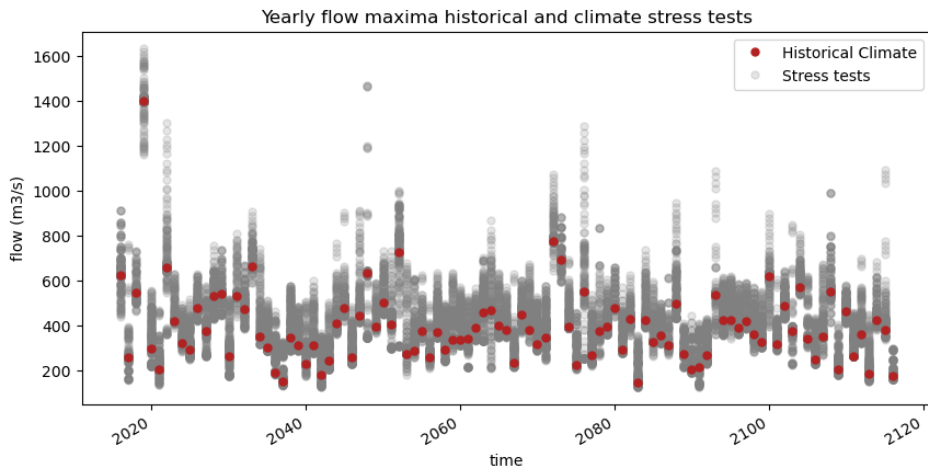
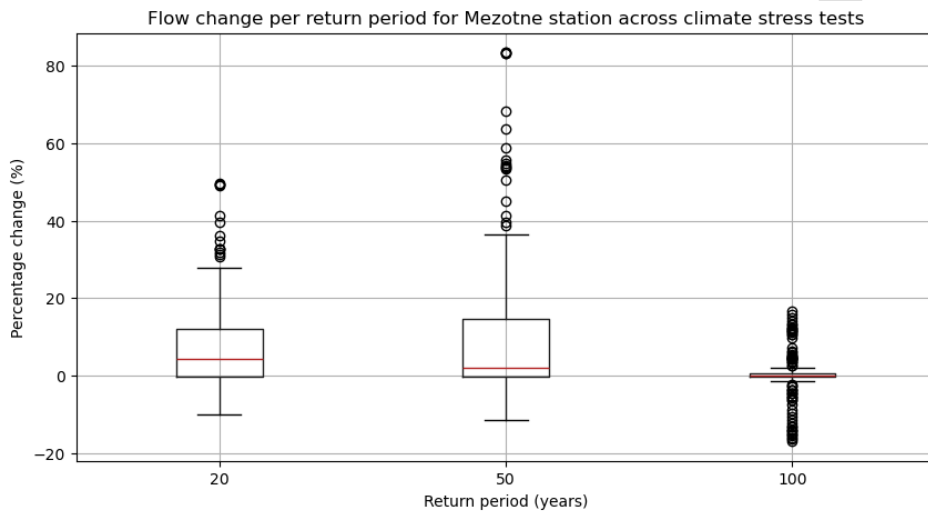


Figure B.5: Flow return periods for the historical climate realisation and 256 climate scenarios.



**Figure B.6:** The yearly flow maxima of seasonal stress tests show the historical climate. The yearly maxima is in red, and the range of stress test maxima is in grey.



**Figure B.7:** Boxplot of stress test outcomes for the return periods of interest.

## Appendix C: Explaining hydrological response to changing climate variables

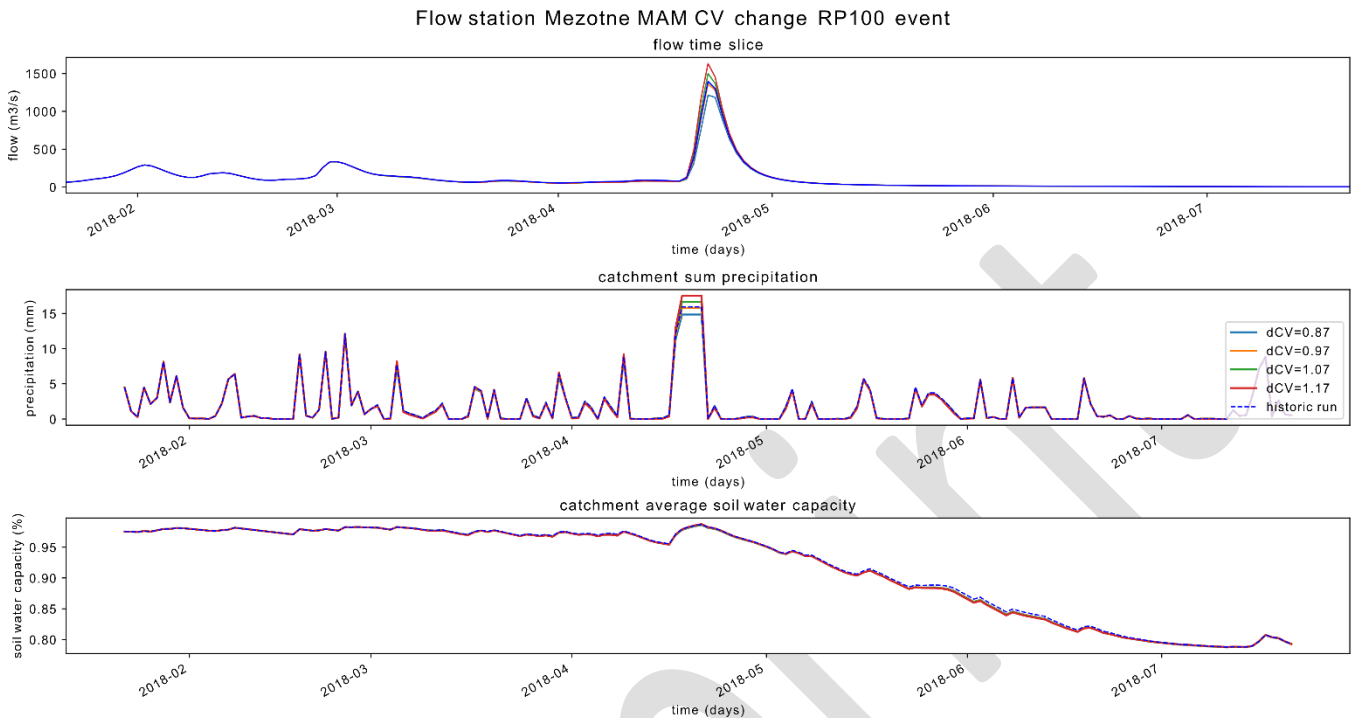


Figure C.1 100-year return period flow event under changing rainfall variability in the spring season.

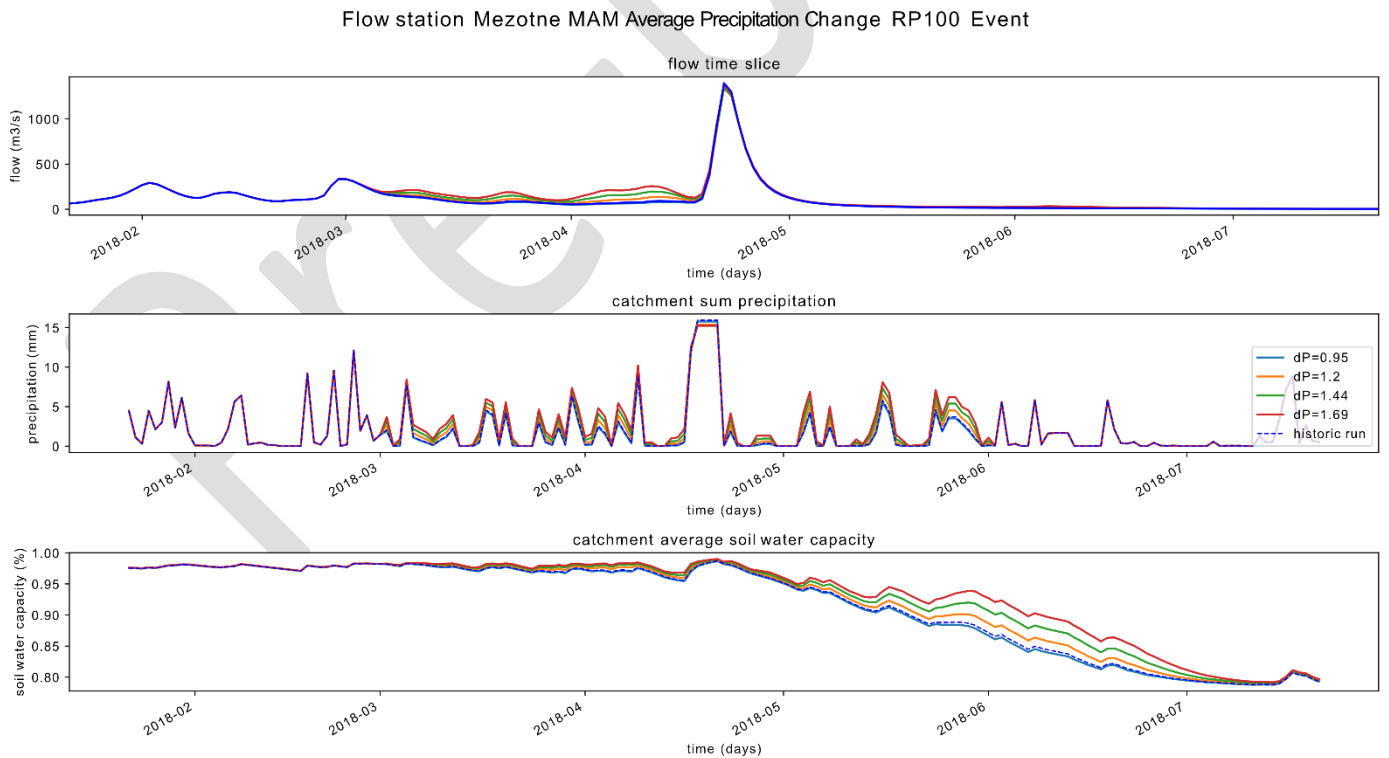


Figure C.2 100-year return period flow event under changing average rainfall in the spring season.

Flow station Mezotne MAM change average precipitation for RP50 event

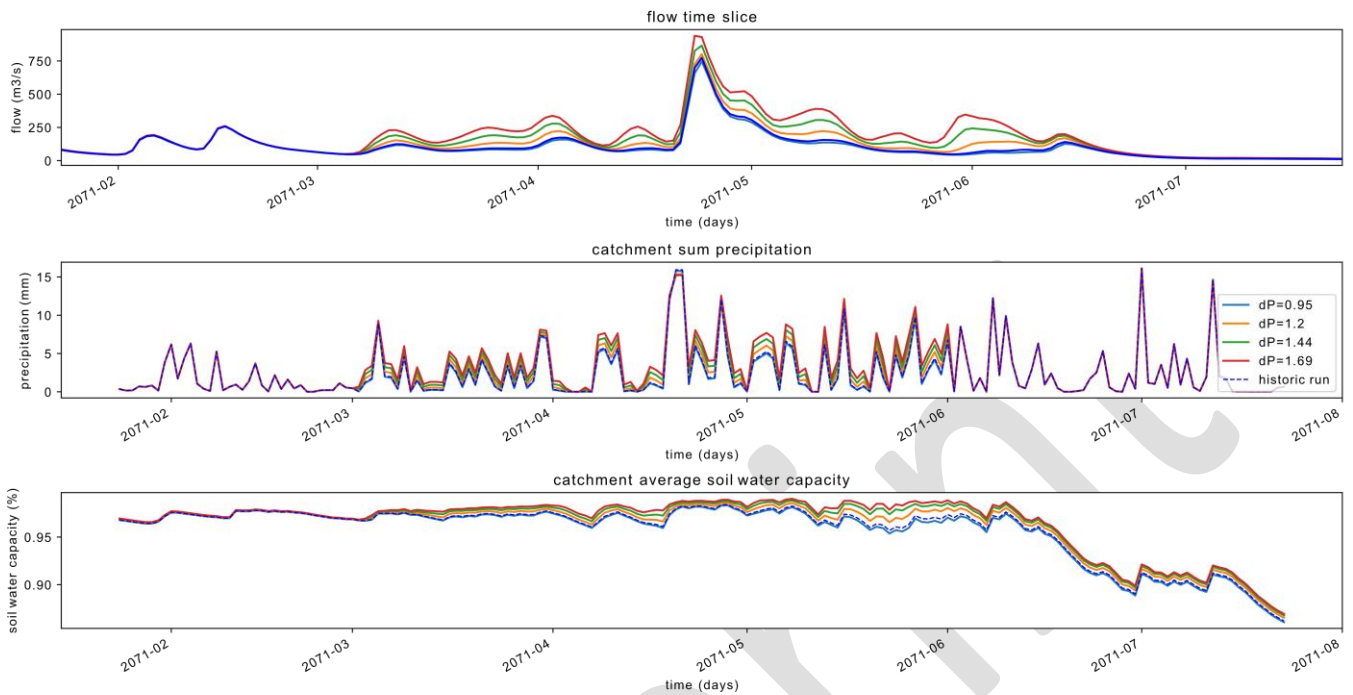


Figure C.3 50-year return period flow event under changing average rainfall in the spring season.

Flow station Mezotne SON change in average precipitation on RP20 flow

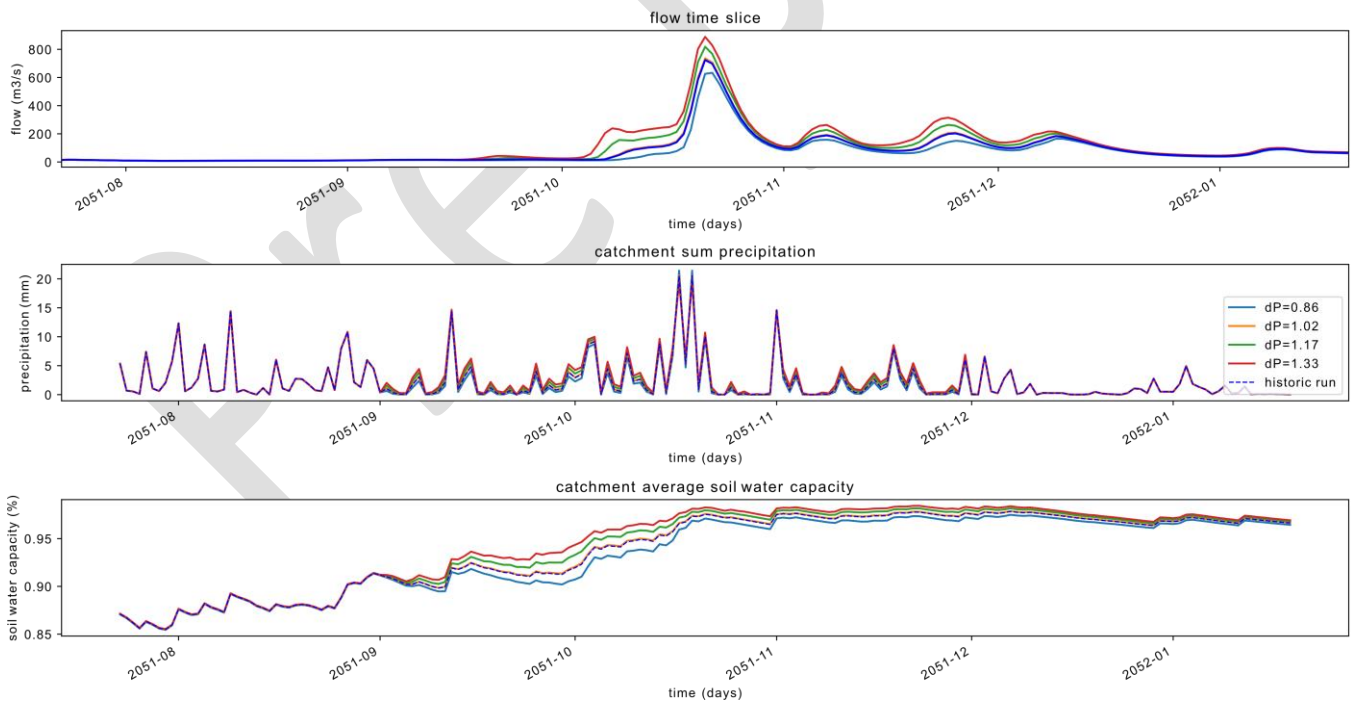


Figure C.4 20-year return period flow event under changing average rainfall in the autumn season.

Flow station Mezotne at high precipitation and varying temperatures

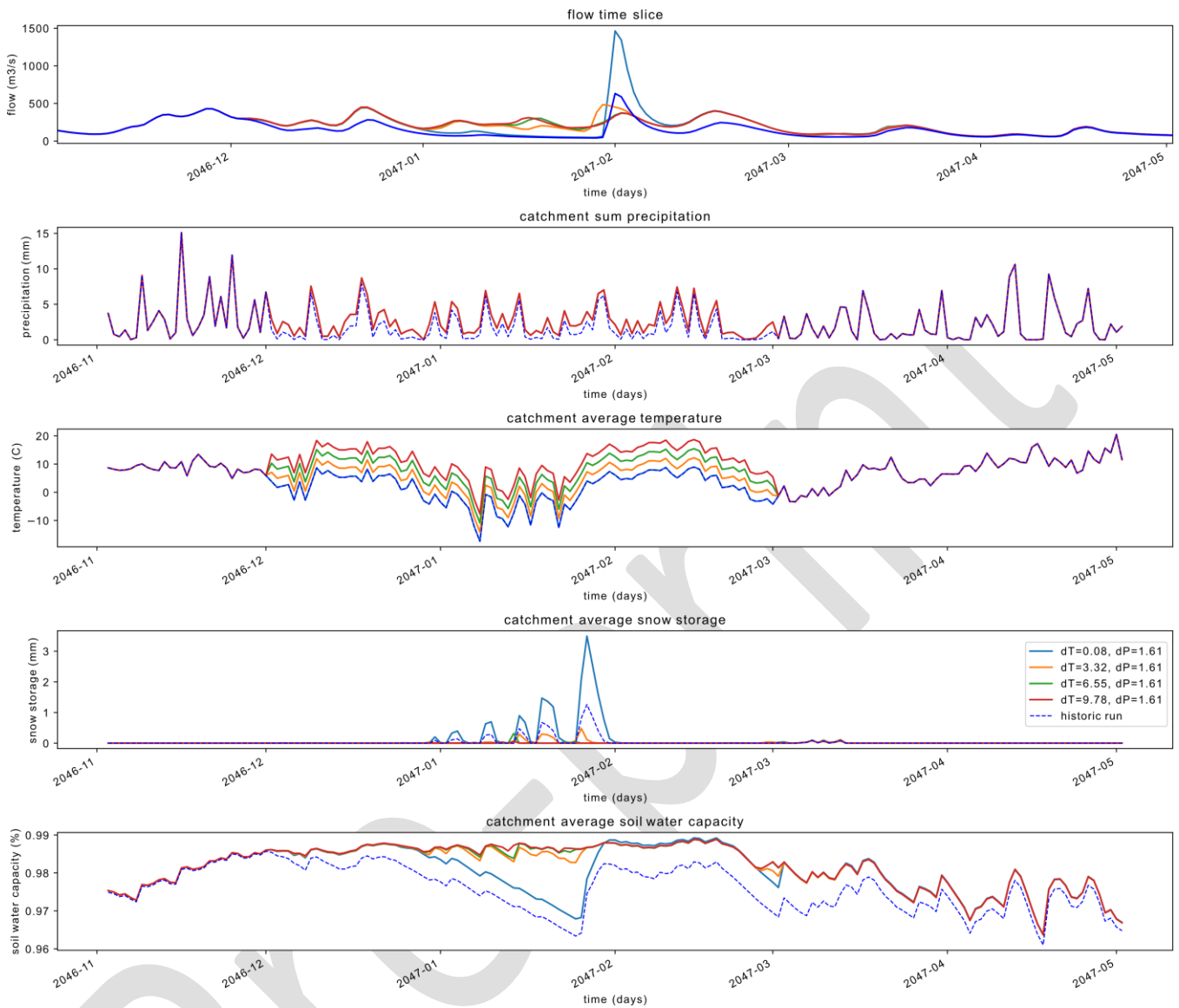
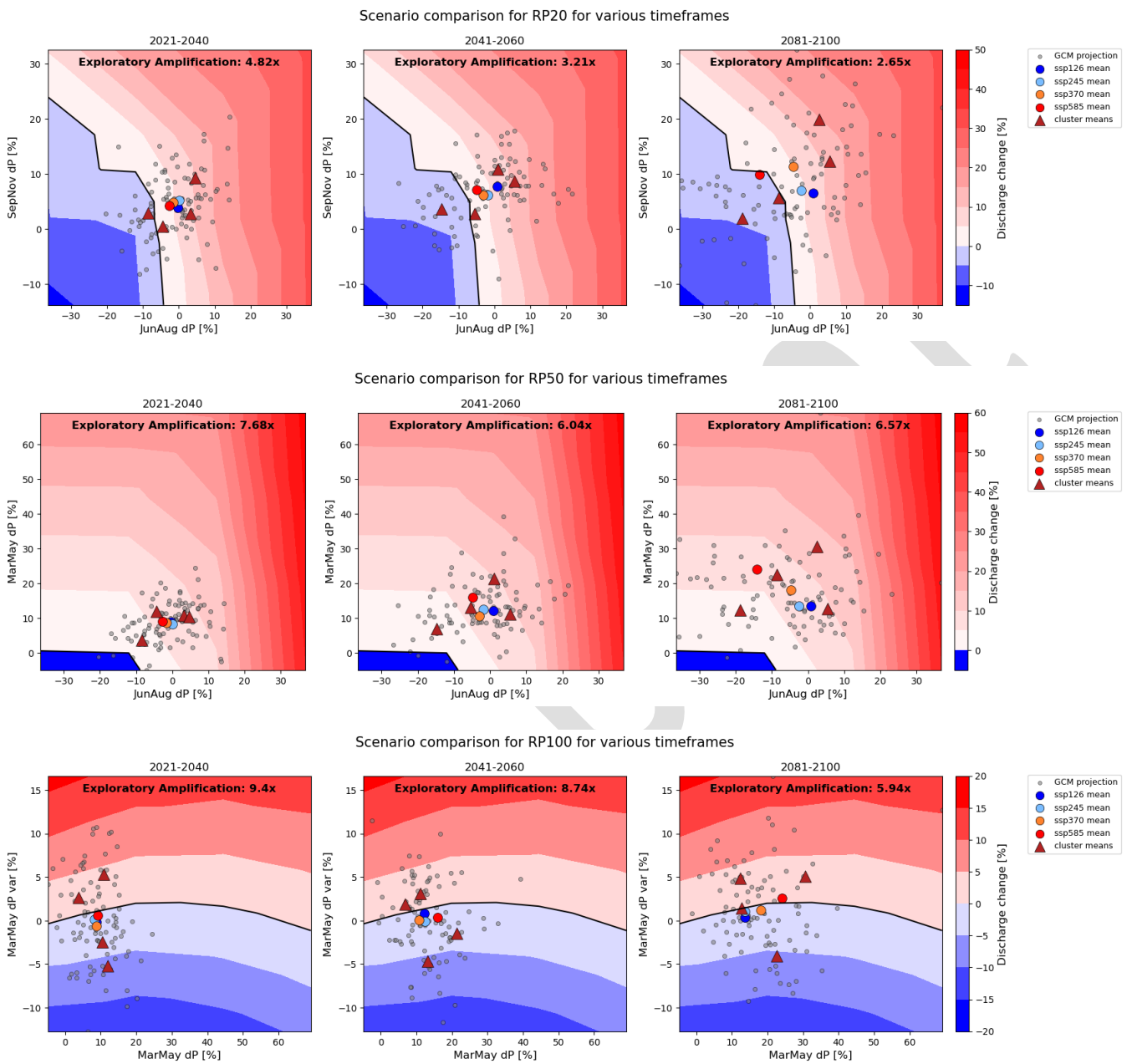


Figure C.5 Discharge change due to snowmelt under changing winter conditions.

## Appendix D: Exploratory power for each RP and timeframe



**Figure D.1:** Response plots relating the impact relevant climate features to the three impact metrics (flow change for 100, 50, 20-year return period discharge) in different timeframes.

**Table D.1:** Table of used models and SSPs in the 2021-2040, 2041-2060, and 2081-2100 timeframes

<b>Model Name</b>	<b>SSP1-2.6</b>	<b>SSP2-4.5</b>	<b>SSP3-7.0</b>	<b>SSP5-8.5</b>
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				✓
<b>Count</b>	<b>24</b>	<b>23</b>	<b>21</b>	<b>27</b>