CLIMATE

Activity A3.3

Background study

Site Visit and Workshop on Climate Information Management

CLIMATE Project

Developed by:

HSY

GREEN

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Executive Summary

This report is a thematic background document prepared as part of Activity A3.3 of the CLIMATE project, an Interreg Europe initiative focused on strengthening regional resilience to climate change. It is divided into two parts. Part 1 describes the uses and uncertainties of climate model data and describes the potential of citizen science to support climate data collection. Part 2 consists of policy learning guidelines and explores climate information management and the integration of climate data into decision-making.

Understanding and predicting the impacts of climate change at regional and local scales is essential for effective adaptation planning. However, uncertainties remain in how climate models simulate key variables such as temperature, precipitation, and, in particular, extreme events like heavy rainfall. Part 1 of this report explores these uncertainties, using the Helsinki Metropolitan Region and the broader Uusimaa region in Finland as a case study.

The report examines biases and variability in regional climate model outputs by comparing climate simulations with reanalysis data. Bias correction methods, such as quantile mapping, improve alignment with historical observations and reduce variability among models. Still, future projections continue to show a range of outcomes, reflecting inherent differences in model behavior.

Extreme precipitation events present a particular challenge due to their short duration, small spatial scale, and statistical rarity. A higher-resolution model is shown to capture these localized events more effectively than a coarser-resolution model, though it also reveals their scattered and unpredictable nature. This variability complicates local impact assessments, especially in small areas. Bias correction methods are also less reliable at the statistical extremes where such events occur, and projecting these into a future climate hence introduces additional uncertainty.

Finally, part 1 considers the potential of citizen science to support climate data collection. While data quality must be carefully managed, citizen observations can complement traditional monitoring, improve spatial coverage, and enhance public engagement in climate science.

Despite significant advances in climate science, integrating climate data into real-world decision-making remains a complex challenge. Part 2 of the report describes aspects of climate information management, introducing common challenges CLIMATE project territories face in integrating climate data into decision-making. The Helsinki Metropolitan Region is used as a case study to illustrate uses of climate data. Finally, part 2 introduces the A3.3 site visit and interregional workshop organised in Helsinki on the 12th of June 2025.

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PART 1

Uses of Climate Model Data and Citizen Science

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Introduction

The CLIMATE Project

The CLIMATE project, part of the Interreg Europe programme, aims to improve EU regions' environmental and socioeconomic resilience to climate change. The project brings together 10 partners from 9 countries, each bringing diverse levels of climate regulatory maturity and operational expertise to the table.

The primary objectives of the CLIMATE project include a) fostering integrated climate governance, b) improving regional policies through joint learning and experience exchanges, and c) building the capacity of public administrations to develop and implement effective climate adaptation strategies. By addressing the root causes of territorial vulnerability and promoting proactive disaster management planning, the project seeks to create a more resilient Europe.

This thematic background report is part of Activity A3.3 of the CLIMATE project. This interregional policy learning and capacity building activity aims to increase partners' operational capacity in systematising the use of weather and climate data in climate governance. This background report will facilitate the interregional process alongside a site visit and workshop organized by the Helsinki Region Environmental Services Authority (HSY) in June 2025 in Helsinki.

Thematic background

Understanding and predicting the impacts of climate change at regional and local scales is critical for informed decision-making and effective adaptation strategies. However, uncertainties remain in how climate models represent and predict specific phenomena such as changes in mean temperature and precipitation, and especially extremes like heavy rainfall events. This report aims to explore these uncertainties, focusing particularly on their implications for the Helsinki Metropolitan Region and the wider Uusimaa region in Finland.

Building on the findings of Rantanen et al. (2023), which examined projected changes in key climate parameters, this report delves deeper into the uncertainties in predictability of climate-related hazards. We evaluate how climate models can be improved to better forecast extreme weather events. Additionally, the report explores the potential of citizen science in enhancing the collection and accuracy of climate data, especially at the local scale.

By using the Helsinki Metropolitan Region as a case study, we illustrate the challenges of modeling average temperature and precipitation changes, as well as the frequency and intensity heavy rainfall. The goal of this report is to clarify where current climate models succeed, where they fall short, and what these uncertainties mean for climate risk assessment and local preparedness efforts.

List of abbreviations

- CMIP5, CMIP6: "Coupled model intercomparison project" - CMIP is a project of the World Climate Research Programme (WCRP) providing climate projections using

global climate (earth system) models to understand past, present and future climate changes. CMIP and its associated data infrastructure have become essential to the Intergovernmental Panel on Climate Change (IPCC) and other international and national climate assessments.
- Euro-CORDEX: The Coordinated Regional Climate Downscaling Experiment (CORDEX) is an initiative to use regional models to increase the spatial resolution of CMIP simulation results. Euro-CORDEX is a branch of CORDEX that concentrates on the European domain.
- ERA5: Reanalysis data combining observations and model data to provide hourly estimates of a large number of atmospheric, land and oceanic climate variables (see Section 2.2).
- SSP: "Shared Socioeconomic Pathways" are climate change scenarios of projected socioeconomic global changes, which includes pollutant emission and greenhouse gas concentration projections.
- RCP: "Representative Concentration Pathways" are climate change scenarios to project future greenhouse gas concentrations used by global climate models.

Model predictability of key variables and related extreme events

In Rantanen, et al., 2023, the analysis of the historical trends of average temperature and precipitation, and the related extremes were based on gridded observational data, which is available from FMI for the years 1961 through 2024. The analysis of future climate projections of average temperature and precipitation was based on CMIP6 global climate model data (O'Neill et al., 2016) for the SSP2-4.5 scenario (e.g., Meinshausen, et al., 2020). The future projections of extreme precipitation, on the other hand, were done using data from the HCLIM model (Medus et al., 2022, Lind et al., 2023). HCLIM was used because it has a kilometer-scale spatial resolution and it has been shown simulate extreme sub-daily precipitation more realistically than coarser models (Medus et al., 2022). In the report, uncertainties in the projected changes were reported as 90% probability intervals (see Figure 1 for an example).

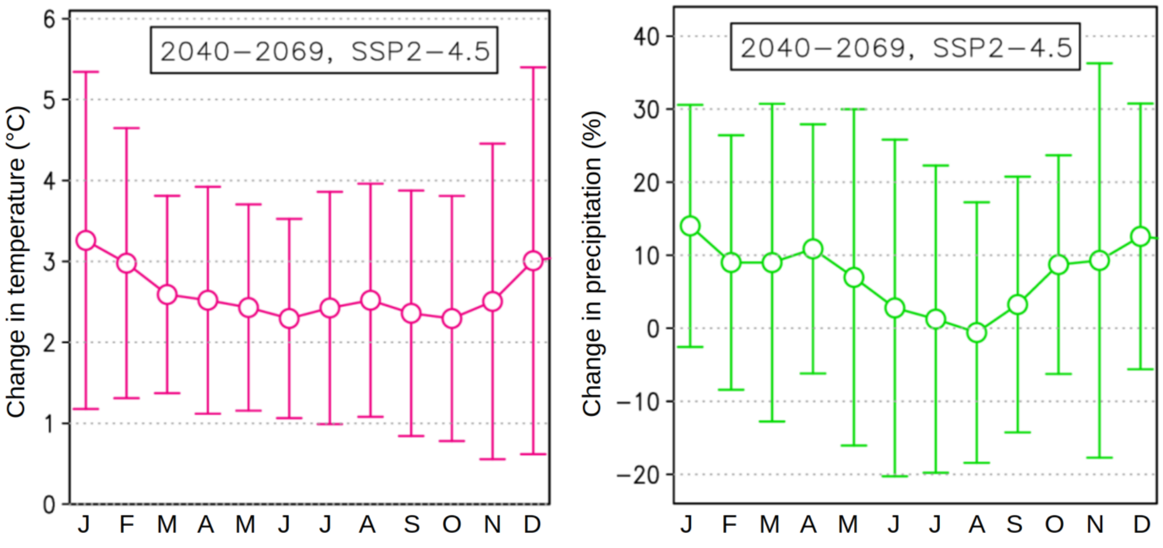

Figure 1: Projection of future change in monthly temperature and precipitation after Rantanen et al., 2023.

In this report, we will discuss in more detail the sources of uncertainties in the projected changes in average temperature and precipitation, as well as occurrence heavy precipitation in Uusimaa and HSY-region in Finland (Figure 2).

We will first demonstrate how the differences between model data (see Section 0) and model-internal variability lead to uncertainties in the climate projection for the Helsinki Metropolitan Region. To assess the skill of the models to reproduce the historical climate in the region, we compare the model results to ERA5 data for the same time period. In order to make the ERA5 data more easily comparable to the Euro-CORDEX data, the ERA5 data was interpolated to the Euro-CORDEX resolution. We will then use bias-corrected data (see Section 0) from a smaller set of models to demonstrate the effect on analysis uncertainties.

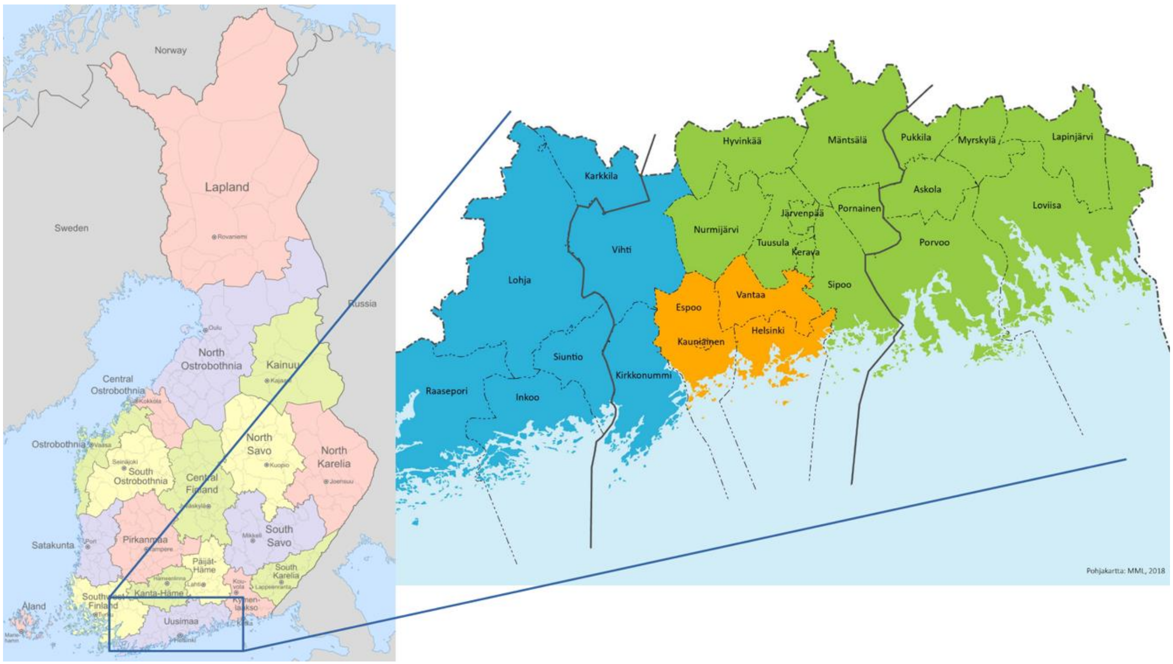

Figure 2: Map of Finland and location of the Uusimaa region. Helsinki, Vantaa, Espoo, and Kauniainen, i.e. the Helsinki Metropolitan Region , is shown with orange color in the zoomed map. Maps originally from https://en.wikipedia.org/wiki/Regions_of_Finland and https://uudenmaanliitto.fi/liiton-aluevastaavilla-on-keskeinen-rooli-maakuntakaavan-tavoitteiden-toteuttamisessa/.

Uncertainties in climate models

In science, uncertainty is a well established measure to tell how well something is known: it generally means that there is a range of possible values (an uncertainty interval) which contains the true value of the measurement. Reporting an uncertainty interval does not mean that the results are wrong – on the contrary, reporting the level of uncertainty strengthens the research results and makes them more useful, and may guide the focus of future research.

By design, climate model simulations produce projections with variabilities (e.g., diurnal, seasonal, year to year) which correspond to the natural variability of the climate. To account for this model-internal variability, model results are usually averaged over a given period of time, with 30 years being somewhat of a standard (WMO, 2020), while shorter or longer periods are also being used. However, depending on, e.g., the parameter, area of the globe, size of the region analysed, this model variability also is a source of uncertainty, both in the average values of any given time period and the projected change in a climate variable. In general, more model data (e.g., a longer time period) reduces the uncertainties due to internal model variability, but when analysing very long time periods, possible trends in the average climate have to be accounted for.

In addition to the internal variability, climate projections also include other uncertainties. Many atmospheric processes cannot be resolved explicitly in climate models, as the characteristic length and/or time scales are beyond the resolution of the models. These processes are therefore parameterised in the models, which leads to uncertainties in the model results. Other reasons for parameterising processes or choosing one parameterisation over another are trade-offs in computational cost or amount of data produced. Furthermore, some atmospheric processes are still poorly confined (e.g., aerosol-cloud interaction, atmospheric chemistry), and are thus sources of model uncertainties (IPCC, 2021). To account for such uncertainties, data analysis of climate projections usually includes results of many different models (a model ensemble). The so-called spread of the models helps to understand the overall impact of the uncertainties due to different model designs and to find the most probable state of the future climate. More importantly, when using only one model to estimate the future impacts of climate change, the information about the model uncertainties is missing from the analysis and the results may deviate substantially from the result obtained by analysing an ensemble.

To obtain a reasonable climate projection in a region of the globe, especially if the region is small, uncertainties in the projections can be very large, even to the point of growing larger than the projected change. There are, however, several ways to address this conundrum. For one, the skill of each model to reproduce the historically observed climate can be assessed, and a subset of best-performing models can be selected for the analysis. Another possibility is to use observational data to perform a bias correction of the model results (see Section 0). Bias correction usually reduces the differences in historical simulations between different models substantially, and only the future climate trends remain different.

Bias correction of regional climate models

Climate model results often exhibit systematic biases, meaning that the climate produced by the models is, in comparison to observations, for example, too cold, warm, wet, or dry in a given area. Several bias correction methods have been developed to adjust climate model outputs, e.g., delta change, quantile mapping, and empirical cumulative distribution based scaling (see e.g. Maraun et al. (2010), Teutschbein and Seibert (2012), Räisänen and Räty (2013), Räty et al. (2014)). These are statistical techniques designed to adjust model outputs such that they better align with historical observations. This process enhances the realism of the data and makes it more suitable for downstream applications, such as hydrological modeling, agricultural planning, or climate impact assessments.

Bias correction methods (like quantile mapping) are generally based on the assumption that the model captures the structure of the variable reasonably well — particularly the seasonal timing and variability — even if there are systematic errors in magnitude. If a model predicts, for instance, peak precipitation in the wrong month, or misses the spring dry season entirely in Finland, then simply correcting its distribution will not fix the timing error. The goal is to adjust the distribution, mean, or extremes, rather than correct deep structural errors.

Bias correction can improve the estimation of climate extremes, such as heavy rainfall events or prolonged dry periods, which are critical for risk assessment and infrastructure planning. These extremes are often poorly captured in climate model data, but bias correction can adjust their frequency and intensity to better match observed records.

Importantly, the goal of bias correction is not to alter the climate change signal projected by the model (i.e., the relative change from a historical reference period to a future scenario), but to ensure that the baseline from which this change is measured is more accurate. Nevertheless, the magnitude of the change may be altered (Zhang et al., 2024). Generally, bias correction leads to more reliable estimates of future conditions and makes the data more useful for decision-makers who rely on precise, location-specific information.

From the perspective of bias correction, heavy precipitation poses significant methodological challenges. Generally, bias correction techniques perform well for correcting average conditions but struggle with the statistical tails of distributions where extreme events lie. Because there are fewer data points in the extreme percentiles, the correction functions for these ranges are less reliable. Moreover, in a warming climate, future model simulations may produce extreme values that go beyond the range of the historical observations used to train the bias correction models. This forces the methods to extrapolate beyond the domain where they were calibrated, which can introduce large errors. Additionally, the assumption of statistical stationarity—that the relationship between model output and observations remains consistent over time—may not hold true in a changing climate. This non-stationarity can undermine the reliability of bias correction for future extremes.

Model data

Regional climate models

For this report, we decided to base our analysis on regional Euro-CORDEX (Jacob et al., 2014) model data, which have a higher resolution than the global climate model data from the CMIP projects (11 km instead of about 1-2°). In the analysis, we used data from 16 different global - regional model combinations (Table 1). Further information on the different models used can be found, for example, from CORDEX website (CORDEX, 2025).

In assessing uncertainties related to heavy rainfall, the high-resolution (3 km x 3 km) regional HARMONIE-Climate (HCLIM, Belušić et al. (2020)) model was utilized in addition to the CORDEX models listed in Table 1. HCLIM is capable of simulating local precipitation from thunderstorms and convective clouds more accurately than models with coarser resolution (Médus et al., 2022; Lind et al., 2023).

As CORDEX and HCLIM models only simulate a sub-region of the globe, they require input from global climate models to operate correctly. These data are taken from results of the CMIP5 (Taylor et al., 2012) project which are older than the CMIP6 data used in Rantanen et al., 2023. Here we concentrate on the RCP4.5 (Moss et al., 2010) greenhouse gas scenario, which is comparable to the SSP2-4.5 scenario (Meinshausen, et al., 2020), used in the CMIP6 model simulations.

Table 1: Overview of the model combinations used in the uncertainty analysis of the Euro-CORDEX and HCLIM simulations. Columns denote global models providing boundary conditions to regional models, while rows denote regional climate models. Note that the HCLIM model (underlayed in grey) was only used for the analysis of extreme precipitation.

	CNRM-CM5	EC-Earth	HadGEM2-ES	IPSL-CM5A-MR	MPI-ESM-LR	NorESM
CCLM4	x	x	x		x	
HIRHAM5						x
RACMO22E		x	x			
RCA4	x	x	x	x	x	x
REMO2009					x	
REMO2015						x
WRF381P				x		
HCLIM		x				

ERA5 reanalysis data

To put the results of the Euro-CORDEX models into context, and to get a measure of their skill to reproduce key variables in the Uusimaa region, we compare the Euro-CORDEX results to ERA5 (Hersbach et al., 2020) reanalysis data. ERA5 is a state-of-the-art global atmospheric reanalysis dataset produced by the European Centre for Medium-Range Weather Forecasts (ECMWF). It provides hourly data on a broad range of atmospheric, land, and oceanic climate variables at a horizontal resolution of approximately 31 km, covering the period from 1950 to the present. ERA5 combines model data with observations using data assimilation techniques, offering a consistent and physically coherent representation of past weather and climate conditions.

Bias-corrected climate models

In this report we use bias corrected CORDEX model results for Finland (Table 2) which have been adjusted using the so-called quantile correction method (Lehtonen et al., 2024).

In the quantile correction method, the distribution of climate variables produced by models is adjusted such that the modeled distribution of the variable to be corrected — for example, daily mean temperatures — matches the observed distribution during a reference period (in this case, 1976–2005) after correction. After that, the same correction is applied to the modeled values of the future scenario period. The correction is carried out by comparing the percentiles of the modeled and observed distributions of the climate variable to be corrected, categorized by month. For more details, see for example Räisänen and Räty (2013), and Räty et al. (2014).

Table 2: Overview over the model combinations used in the uncertainty analysis of the bias corrected Euro-CORDEX simulations. Columns denote global models providing boundary conditions, while rows denote regional climate models.

	EC-Earth	IPSLM-CM5A-MR	MPI-EMS-LR	NorESM
CCLM4	x		x	
RACMO22E	x			
RCA4	x		x	x
REMO2015				x
WRF381P		x		

Results

Climate model data

We first perform a general analysis using EURO-CORDEX models to visualise the sources of uncertainty in climate projections and also to introduce some of the most common ways to perform such data analysis.

Temperature

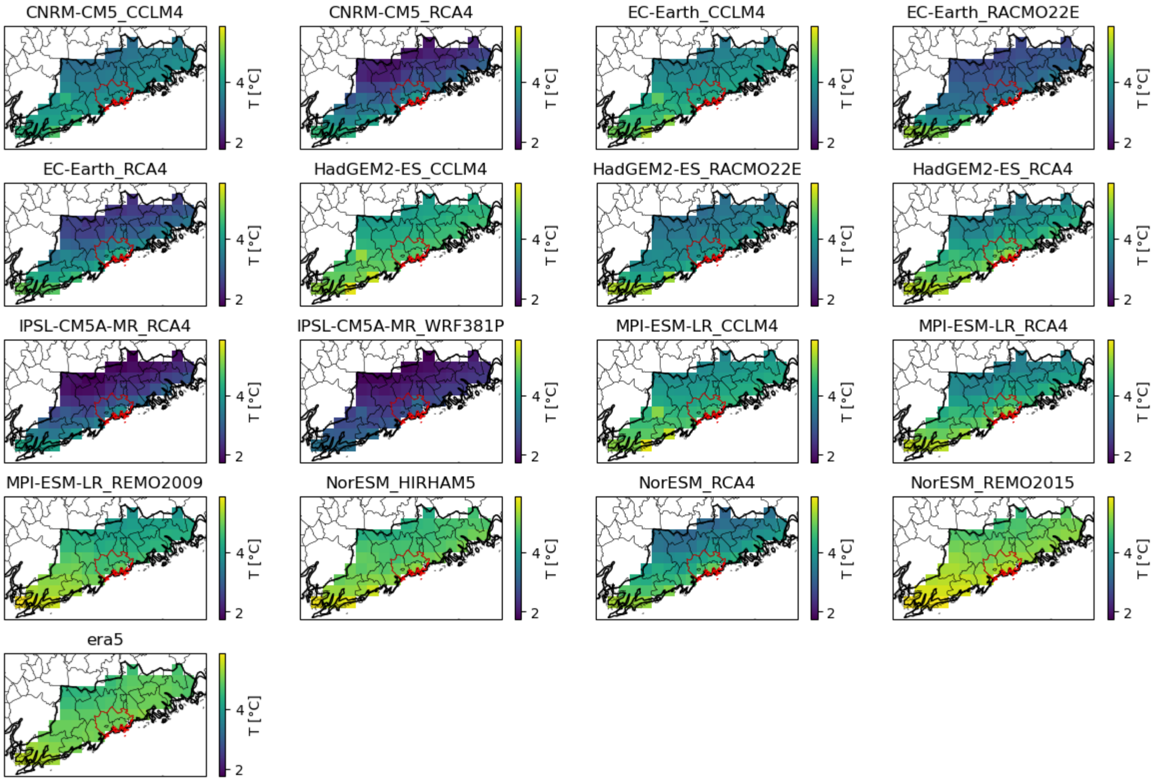

Figure 3: Yearly average temperature for the 16 Euro-CORDEX models. The interpolated ERA5 data is shown for comparison in the last panel.

The historical yearly average temperature in the Helsinki Metropolitan Region varies quite a lot between different Euro-CORDEX models. Figure 3 shows maps of yearly average temperature for the 16 model combinations used. Note that, because Euro-CORDEX data for the Helsinki Metropolitan Region only comprises of a few grid points, we here show data for the entire Uusimaa region, which the Helsinki Metropolitan Region is part of. The data shown are averages over 30 (1976-2005) model years. The time period was chosen based on availability of the model data. For comparison, the 30 year average over the same time period of the ERA5 temperature is shown in the last panel.

Figure 4 shows the model bias (e.g., the difference between each model and the ERA5 data) for the yearly average temperature of each model. Compared to the ERA5 reanalysis data, many models produce a too cool yearly average, but a few models also show a warmer yearly average.

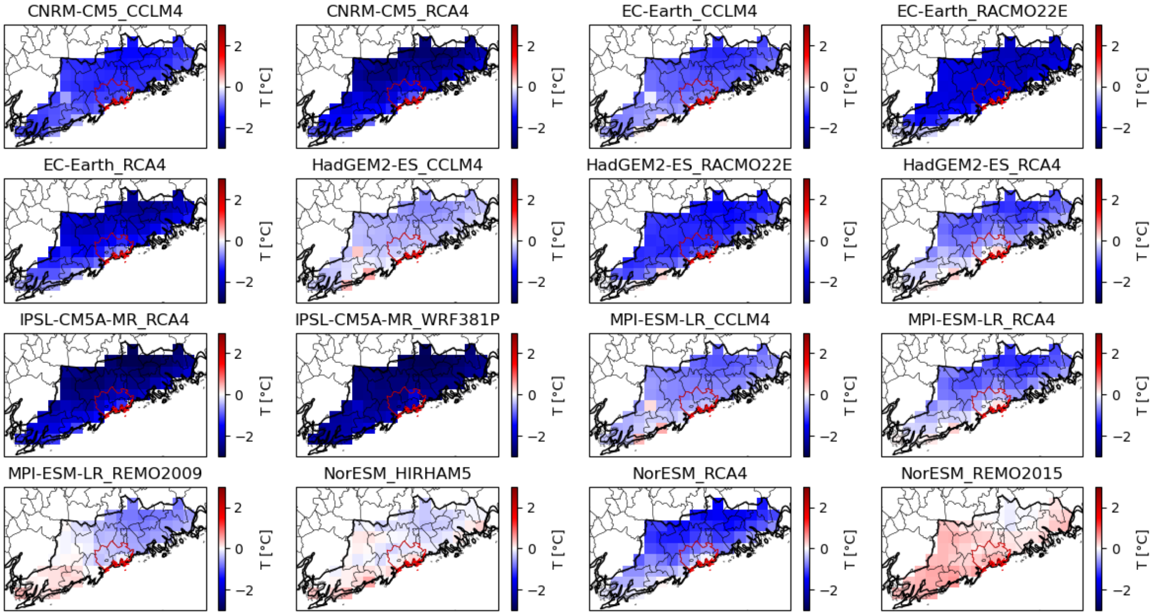

Figure 4: Euro-CORDEX model bias against ERA5 historical (1976-2005) data for the Uusimaa region. The Helsinki Metropolitan Region is marked in red.

The difference between various models (and the ERA5 data) becomes even more pronounced when looking at shorter time windows (e.g., seasons or months). A practical way to illustrate this is to visualise the spread of the data in the form of a histogram. Figure 5 shows histograms of average summer temperatures for the historical period (1976-2005) for each of the Euro-CORDEX models for the Helsinki Metropolitan Region (outlined in red in Figure 4): Each bar in the histogram spans a temperature interval in the horizontal direction (i.e., marks a minimum and maximum average summer temperature). The height of the bar shows how many summers had an average summer temperature within that range. Especially for the summer, these histograms clearly show that there is a most common average summer temperature with lower and higher temperatures occurring as well, but less often. The median of all average summer temperatures (a value for which half of the average summer temperatures are smaller and half are larger) can be interpreted as the most likely average summer temperature for this model. In Figure 5, the 30 year median for each model is show as vertical dashed black line. The histogram of the ERA5 data is reproduced in each panel for comparison, and the median of average summer temperature for ERA5 is shown as vertical solid black line. As can be seen in Figure 5, each model produces a different histogram (the different panels in the figure), with a different width, a different shape, and a different median. The spread of each histogram is the result of the model internal variability and the natural climate variability for the Euro-CORDEX models and ERA5, respectively. The difference in medians is due to the other sources of uncertainty, as outlined in Section 0.

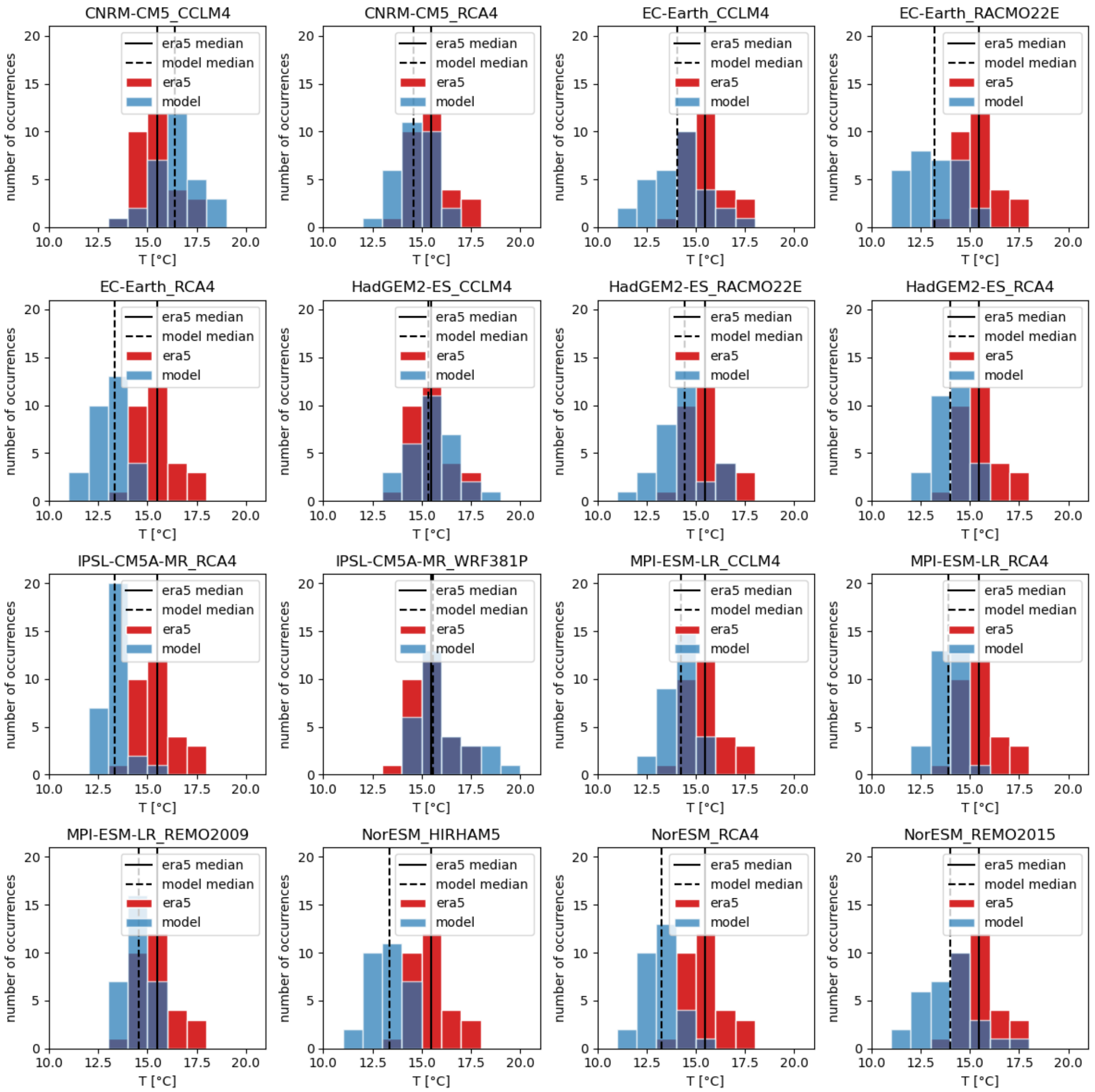

Figure 5: 30 year distribution of average summer (JJA) temperature of 16 Euro-CORDEX models for the Helsinki Metropolitan Region (blue). For comparison, the results for the same period for ERA5 are shown in red in each panel.

Similar to the histograms for the average summer temperature, histograms can also be produced for the other seasons (not shown). For each of the seasons, the model medians can then be accumulated into new histograms to show the distribution of model medians for each season and how they compare to to the median of ERA5 data for the same season. This is shown in Figure 6: The blue bars show how the most likely (median) average temperature is distributed for each season. The vertical dashed black line is the median of all model medians, and the vertical solid black line shows the median of the ERA5 data for the same season. As can be seen, the Euro-CORDEX models in general produce too cold average temperatures for the Helsinki Metropolitan Region. This could already be anticipated from the map plots in Figure 4, but Figure 6 shows that this is the case for all seasons, not just the yearly average. Note that the histograms have much more arbitrary shapes compared to the histograms in Figure 5. This is both because there are less data points (only 16 models for Figure 6 compared to 30 years for Figure 5) and because the underlying cause of the variability is different (see Section 0).

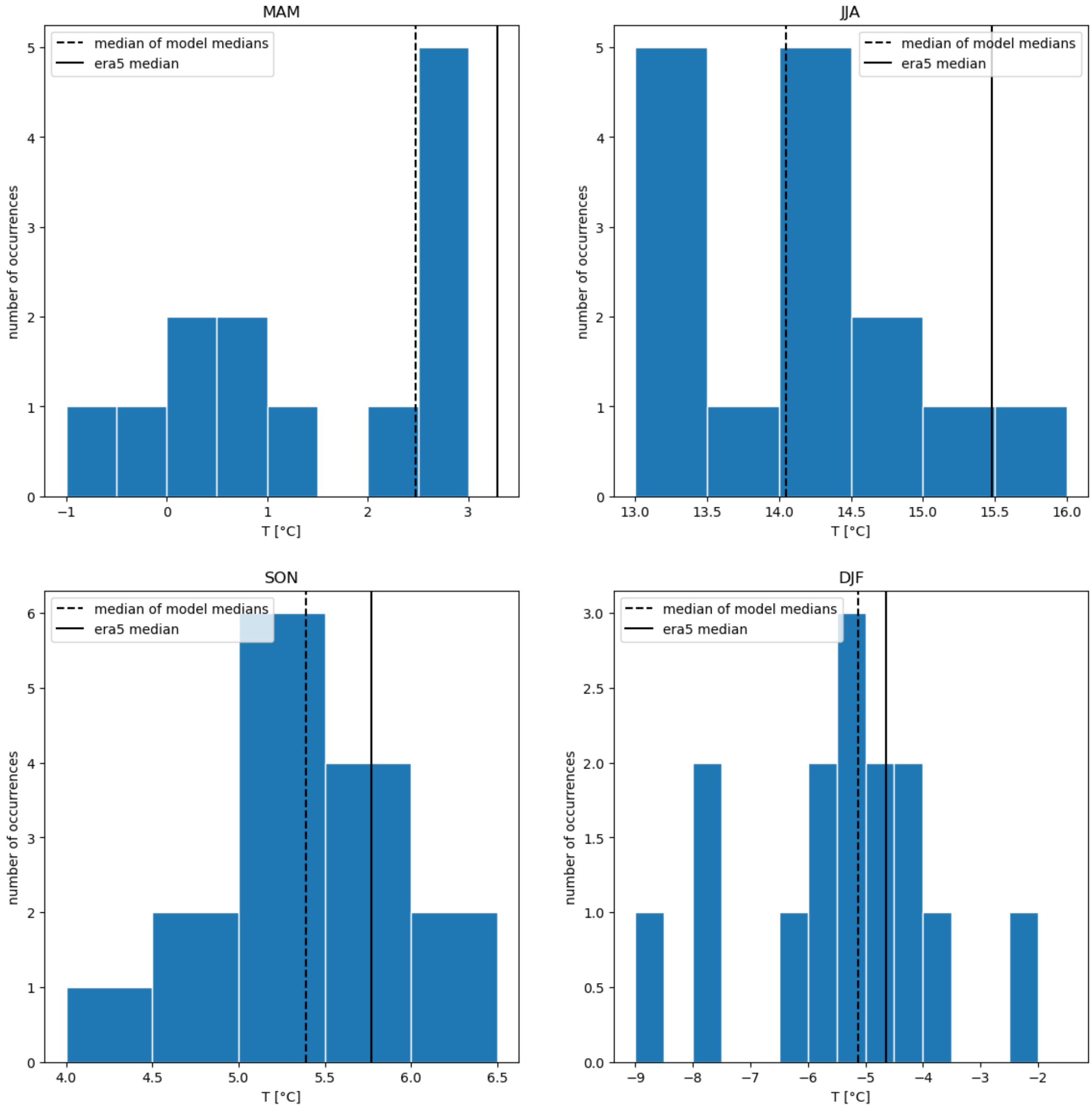

Figure 6: Distribution of the model medians of seasonal average temperature for the historical period (1976-2005). Black dashed lines denote the median of the model medians, and the black solid line shows the median of the ERA5 data for comparison.

When analysing the change in a climate variable, the sources of uncertainty outlined above have to be taken into account. To this end, analysis results usually show a range into which the change in a variable most likely falls, with the most likely change marked separately. Here, in correspondence with Rantanen et al., 2023, we analysed the change in monthly average temperature between the historical period (1976-2005) and the middle of the century (2041-2070) for the Helsinki Metropolitan Region (Figure 7). The figure shows the 30 year median average monthly temperature for each model separately (colored lines) and the median of the medians as solid black line and black circles. The top left panel shows the results for the historical period, while the top right panel shows the mid-century values. For comparison, a black dashed line showing the ERA5 median is also shown in the top left panel.

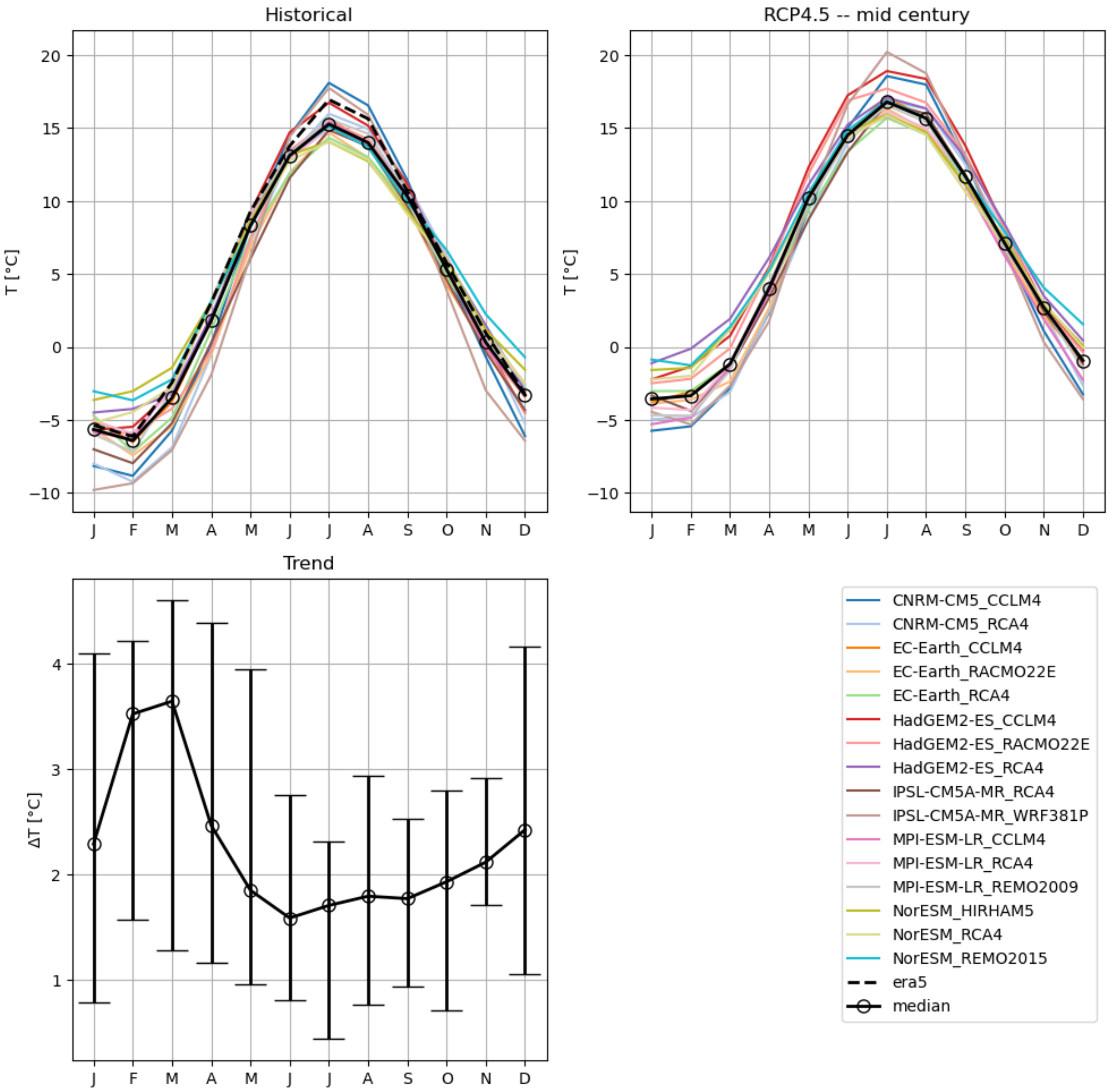

Figure 7: Medians of monthly average temperature in the Helsinki Metropolitan Region. Individual models are shown as coloured curves, and the model median is shown as black curve. Upper left: historical period (1976-2005), upper right: mid-century, lower left: projected change (error bars denote the 90% probability interval).

The bottom left panel of Figure 7 shows the projected change of the monthly average temperature. Similar to the procedure in Rantanen et al., the change was calculated separately for each model (i.e., the median for the historical period was subtracted from the median of the mid-century period model by model). From the so-obtained results, a most likely value of change was calculated as the median of the model-specific changes (marked as solid black line and black circles). The range of likely change, i.e, the uncertainty interval, was calculated as the interval between the 5th and 95th percentile (i.e., 90% of all model values lie within that interval) of the same model-specific changes. This range of likely change is shown as error bars in Figure 7. Both internal variability of each model and variability between models contribute to the with of the range of likely change for each month.

As can be seen from Figure 7, the uncertainty in the average temperature change is particularly large in the winter and spring months. However, all months show a warming, and the most likely amount of average temperature increase lies between 1.6°C in June and 3.6°C in March.

Precipitation

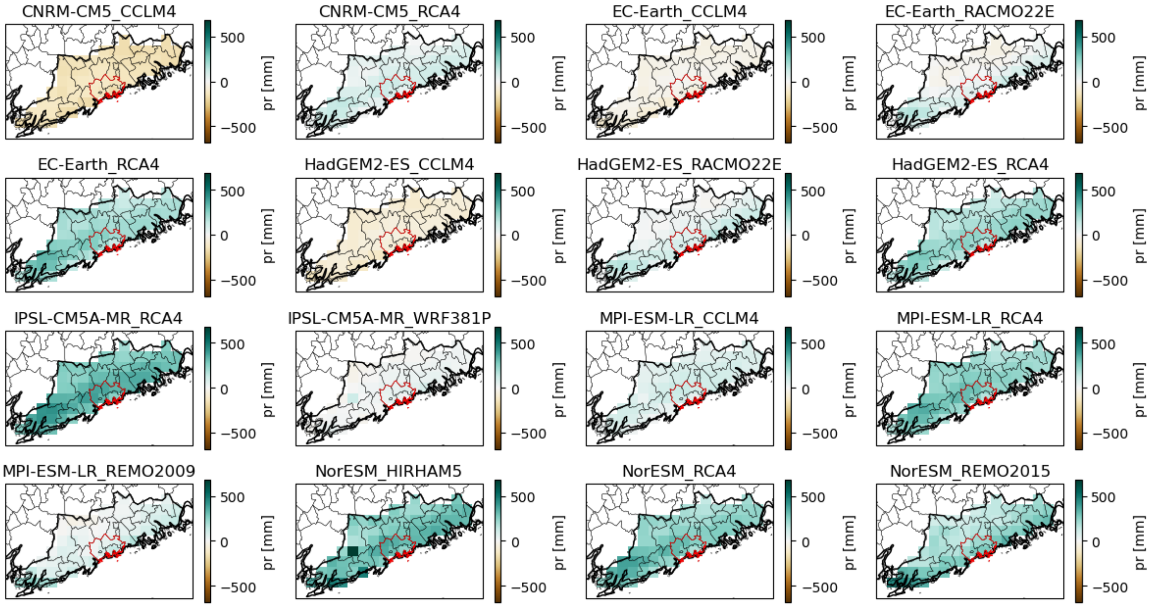

Figure 8: Difference in annual mean precipitation between CORDEX models and ERA5. The data shown are averages over 30 (1976-2005) model years.

The observed annual precipitation in Finland varies between approximately 400 and 700 millimeters. The least rainfall occurs in Lapland, while the highest amounts typically fall in the inland areas of southern Finland and in eastern Finland, in Kainuu and North Karelia (Jokinen et al., 2021). The driest period in Finland is during the spring months, with precipitation increasing toward summer, usually peaking in July and August. In autumn, precipitation gradually begins to decrease again, although the number of rainy days tends to be higher in autumn and winter. Summer has the fewest rainy days per month, but the daily precipitation amounts are highest during summer showers.

Precipitation was analysed in the same manner as average temperature (Section 0). Figure 8 shows the model biases for the different models used (see Table 1) compared to the ERA5 data of the same period (1976-2005) and region. As with average yearly temperatures, some global and regional climate models tend to simulate conditions that are too wet or too dry, which can significantly affect projections of precipitation (Figure 8). We omit here the seasonal analysis which was performed for the average temperature values (Section 0), as a general picture of seasonal biases can also be obtained from the analysis of the change in monthly precipitation.

Figure 9 shows the main results of the analyis of change in monthly precipitation in the Helsinki Metropolitan Region. Like in Section 0, changes are analysed between the historical period (1976-2005, top left panel) and the middle of the century (2041-2070, top right panel). The two top panels show the 30 year median values for each of the Euro-CORDEX models (coloured lines), as well as the median of these model medians (solid black line with black circles). In the top left panel, the ERA5 median is also shown as black dashed line for comparison. The bottom left panel of Figure 9 shows the projected change in monthly precipitation, where the solid black line with black circles denotes the most likely amount of change, while the error bars denote the interval which contains 90% of all model projections.

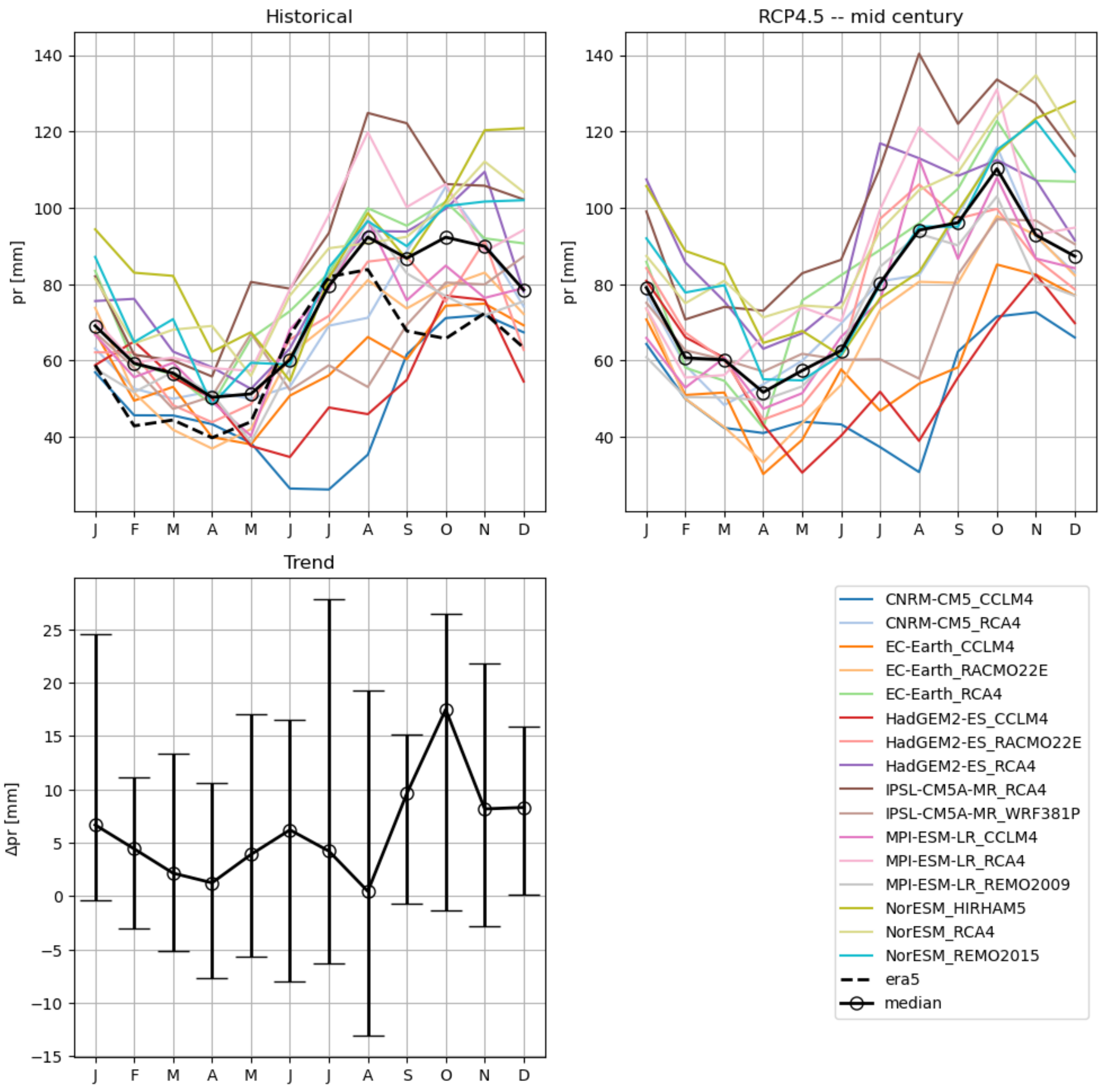

Figure 9: Medians of monthly average precipitation in the Helsinki Metropolitan Region. Individual models are shown as coloured curves, and the model median is shown as black curve. Upper left: historical period (1976-2005), upper right: mid-century, lower left: projected change (error bars denote the 90% probability interval).

Comparing the coloured lines (individual model medians) to the black dashed line (ERA5) in the top left panel of Figure 9, it is quite apparent that not all models capture the seasonal precipitation cycle accurately—some may misrepresent the timing or intensity of seasonal precipitation patterns. Therefore, careful evaluation of model performance against observed data, (in this case ERA5), and consideration of model spread are critical in choosing appropriate models for analysis of projected precipitation changes. Failing to do so may lead to biased results or misinformed decision-making. Nevertheless, when comparing the historical model best estimate (median of model medians), the yearly cycle in monthly precipitation follows observations (ERA5) quite well. The models are, however, in general too wet.

When selecting suitable climate models for Finland, or any other region, it is crucial to consider the country's seasonal variability in precipitation. Finland experiences distinct differences between seasons, such as snowfall-dominated winters and convective rainfall in the summer (Figure 9). Therefore, model evaluation should include not only annual precipitation totals (Figure 8) but also a careful assessment of how well models capture seasonal characteristics (Figure 9). One important step is to evaluate the model's ability to simulate precipitation separately for each season—winter, spring, summer, and autumn. This involves examining whether the model reproduces not only the correct amount of precipitation in each season but also the timing of seasonal peaks.

Extreme precipitation

Extreme precipitation events, such as intense summer thunderstorms, tend to be short-lived and very localized. Because extreme events are, by nature, rare and highly variable, statistical robustness is key to reduce uncertainty. Figure 10 illustrates the local character of extreme precipitation for the example of the CNRM_CM5-RCA4 model. The figure visualises for each grid box within the Uusimaa region the number of days where total precipitation falls within a given range: the topmost and leftmost panel shows the smallest analysed amounts of 20-25mm of daily total precipitation. This range increases, panel by panel, in 5mm increments towards the right and in 20mm increments towards the bottom.

As can be seen from Figure 10, according to the CNRM_CM5-RCA4 model, precipitation events of up to 25mm are still fairly common, with up to 72 days during 30 years in each of the pictured grid boxes (which means more than two days per year on average). However, as the daily total precipitation amount increases, the number of days on which such amounts are experienced, decreases rapidly. Starting from 40-45mm, not every grid box shows at least one such day in a 30 year period. Starting from about 60mm upwards, there are only a few days on which Uusimaa region (all grid points combined) experiences such precipitation amounts. As precipitation events become this rare, statistical analysis also becomes more and more unreliable. This is clearly visible, for instance, comparing the panels showing precipitation amounts of 80-85mm and 85-90mm, where the number of grid boxes experiencing one day of the respective precipitation amount increases from 3 to 5, while after that, the number decreases again to 4.

The spatial resolution of regional climate models plays a critical role in how well they capture localized extreme precipitation events. The CNRM-CM5_RCA4 model (Figure 10), with its coarser spatial resolution, tends to smooth out small-scale variability and may underrepresent the intensity and frequency of highly localized extreme rainfall. In contrast, the high-resolution HCLIM model (Figure 11) demonstrates an improved ability to simulate localized extreme precipitation

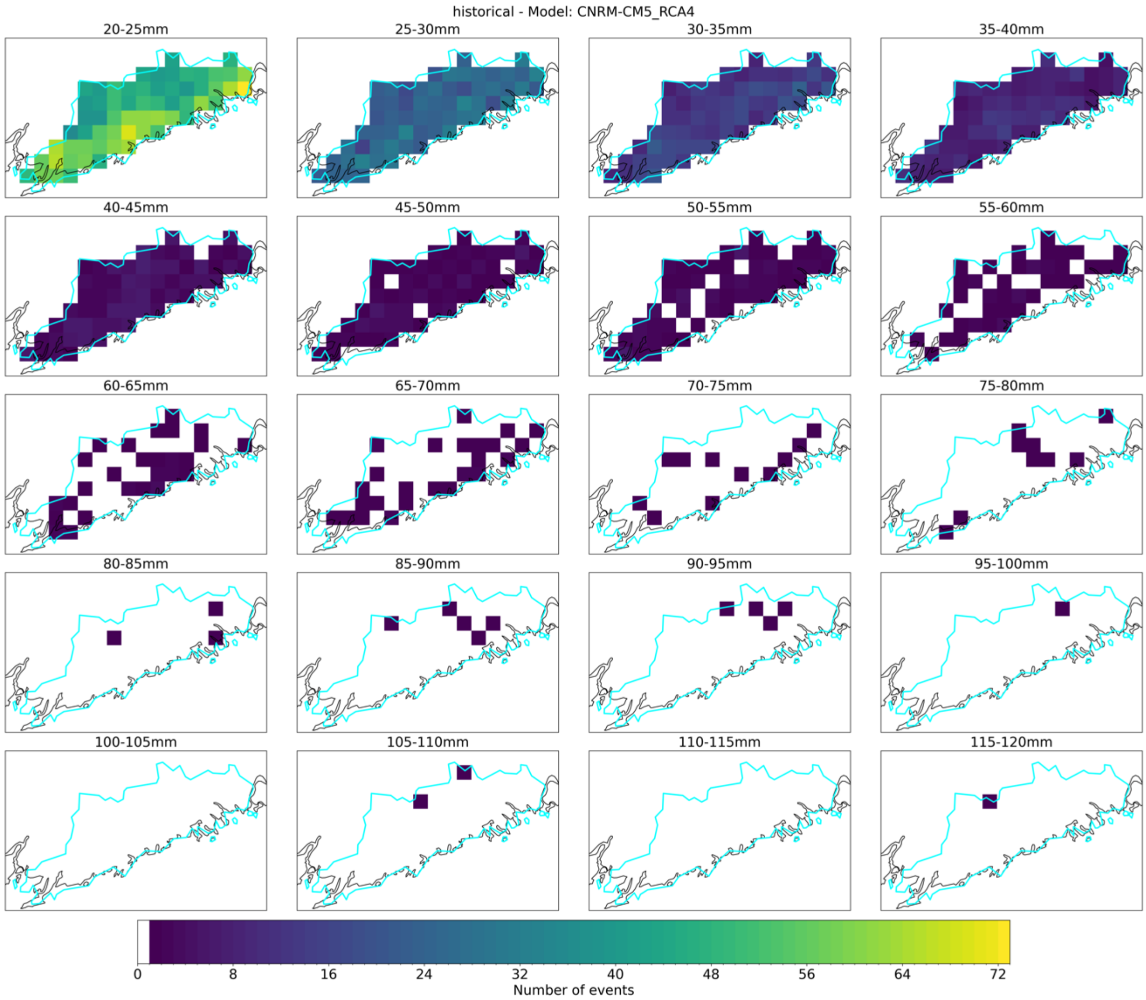

Figure 10: The number and location of extreme precipitation events when a given precipitation threshold is exceeded in Uusimaa region during 30-year period, 1976-2005, based on CORDEX model CNRM-CM5_RCA4. Notice random locations of extreme precipitation events.

This enhanced resolution allows for the identification of isolated hotspots of intense precipitation that are often missed or diffused in coarser models. These localized extremes can be critical in impact assessments, particularly in urban or complex terrain settings where hydrological responses are highly sensitive to the spatial distribution of rainfall. However, higher resolution also reveals the inherently small-scale and scattered nature of such extremes, reinforcing the point that their occurrence and location is often random and difficult to generalize.

These two figures underscore a key challenge in regional climate change impact assessments: the inherently sporadic and localized nature of extreme precipitation events which introduces considerable uncertainty when analyzing small geographic areas. A single high-impact event may dominate local statistics, especially when using relatively short time series. Furthermore, rare extremes may not be adequately captured by all model configurations or observation networks, leading to underestimation or overestimation of potential impacts.

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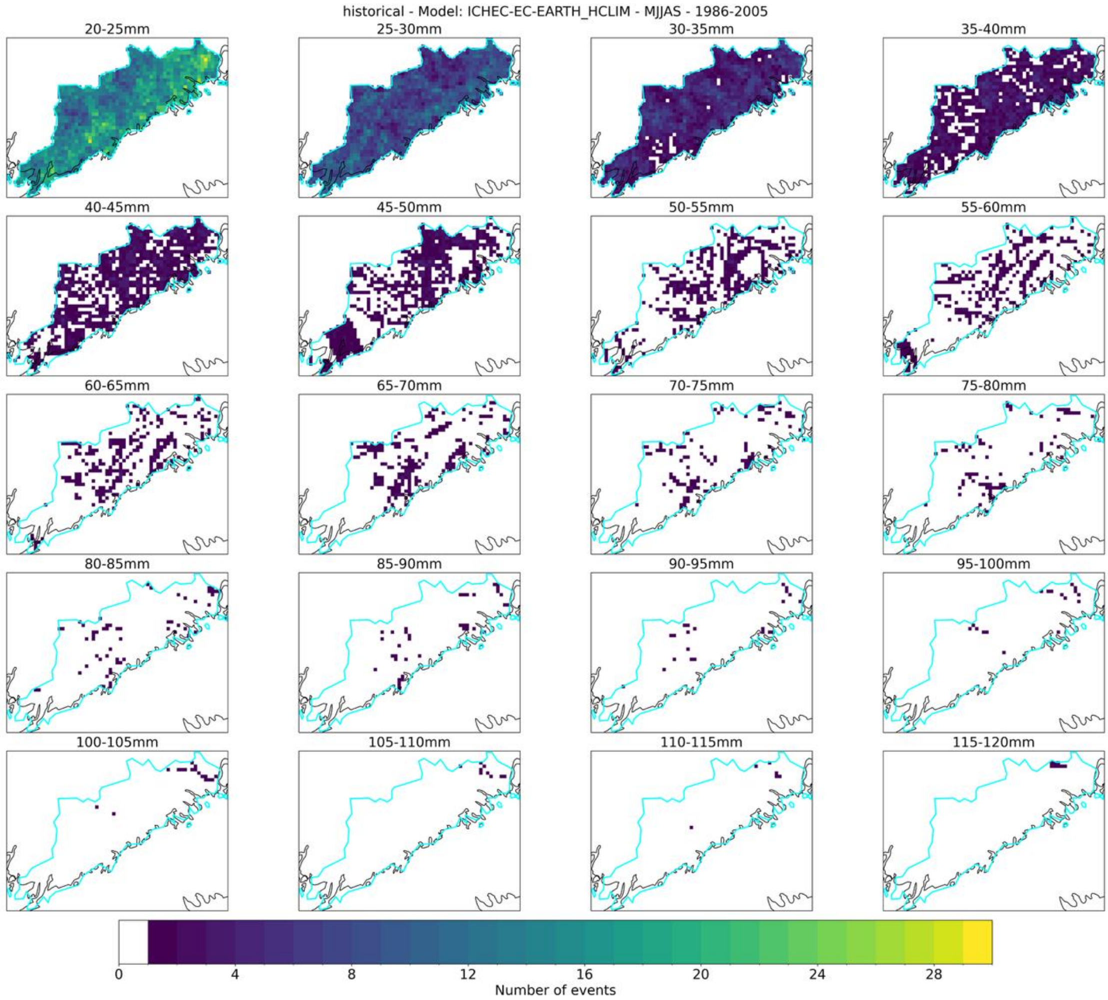

Figure 11: The number and location of extreme precipitation events when a given precipitation threshold is exceeded in Uusimaa region during warm season from May to September in historical 20-year period, 1986-2005, based on HCLIM model. Notice random locations of extreme precipitation events.

Therefore, when assessing climate risks related to extreme precipitation—such as flash flooding or urban drainage overload—analysts must account for this spatial and temporal variability. Relying solely on long-term averages or coarse spatial resolutions may obscure localized vulnerabilities. Ensemble modeling (CORDEX models) and high-resolution simulations (HCLIM model) can help reduce this uncertainty, but some level of unpredictability will always remain due to the stochastic nature of these events.

Because heavy precipitation events are rare and highly variable, there are fewer observed instances from which to draw robust conclusions, and any statistical estimates—such as return periods, trends, or bias correction—are associated with high levels of uncertainty. The limited number of extreme precipitation events makes it inherently difficult to analyze long-term changes with confidence, particularly in smaller regions where such events are even rarer. To reduce this uncertainty, it can be more effective to consider a larger spatial area and then scale the results to represent smaller regions. This is demonstrated in Figure 12, where the total number of extreme daily precipitation events was first calculated as a sum across the entire Uusimaa region and historical period. This total was then divided by the number of grid points in the region and the length of the time period (amount of days in 30 years). This provides a measure of how likely it is, on average, at a single grid point for such an event to occur. This can then be translated into a probability of an extreme event to occur in a small area (e.g. Helsinki Metropolitan Region), even if such an event has only occurred outside of the area in the reference data.

This means that, in principle, the uncertainty in extreme precipitation event occurrence predictions in small areas can be reduced if the area of analysis is chosen as big as possible. However, this way of analysing extreme precipitation also comes with caveats, as it assumes implicitly that the patterns of extreme precipitation do not vary across the extended region of analysis. For southern Finland, and Uusimaa in particular, this assumption is reasonably good as long as ocean tiles are not included in the analysis.

Figure 12 shows the number of occurring extreme events as cumulative sum for increasing event intensity. This means that each curve increases from the count of least intense events (left) to the most intense events (right). This way of visualisation was chosen, because the number of occurrences change drastically from smalles to largest intensity. Showing cumulative curves pronounces high intensity events more, and makes comparision between different models easier.

As can be seen in Figure 12, the probabilities for extreme events to occur varies greatly between different models, with ERA5 data being at the lower end of extreme event occurrence. This result emphasises that model biases can affect analysis results of extreme events very much, as critical threshold values of precipitation (i.e., where pluvial flooding starts to cause damage or harm) are strongly dependent on location and cannot easily be adjusted to reflect modelled distributions of extreme precipitation.

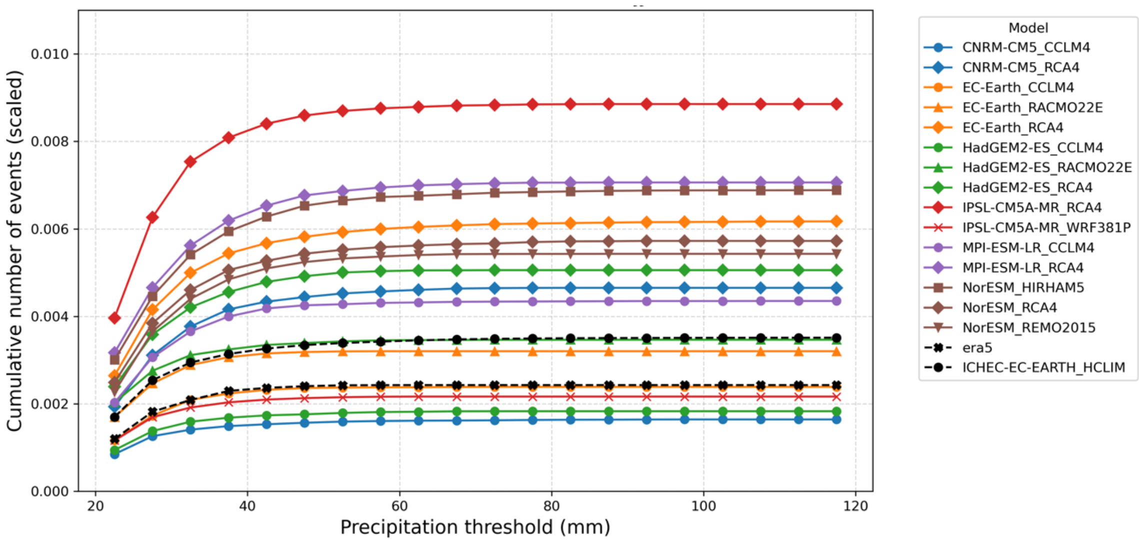

Figure 12: Cumulative number of extreme extreme precipitation events in the Uusimaa region in different CORDEX models as well as HCLIM model during warm season from May to September in historical period 1986-2005. The number of events has been averaged over the region and time period because the number of grid points vary between CORDEX models, ERA5 and HCLIM.

Bias-corrected model data

Average temperature and precipitation

Average monthly temperature and montly precipitation amount in the Helsinki Metropolitan Region (historical, mid-century, and change) are shown in Figure 13 and Figure 14, respectively. The figures were produced in the same manner as Figure 7 and Figure 9, respectively, but using the bias-corrected models listed in Table 2.

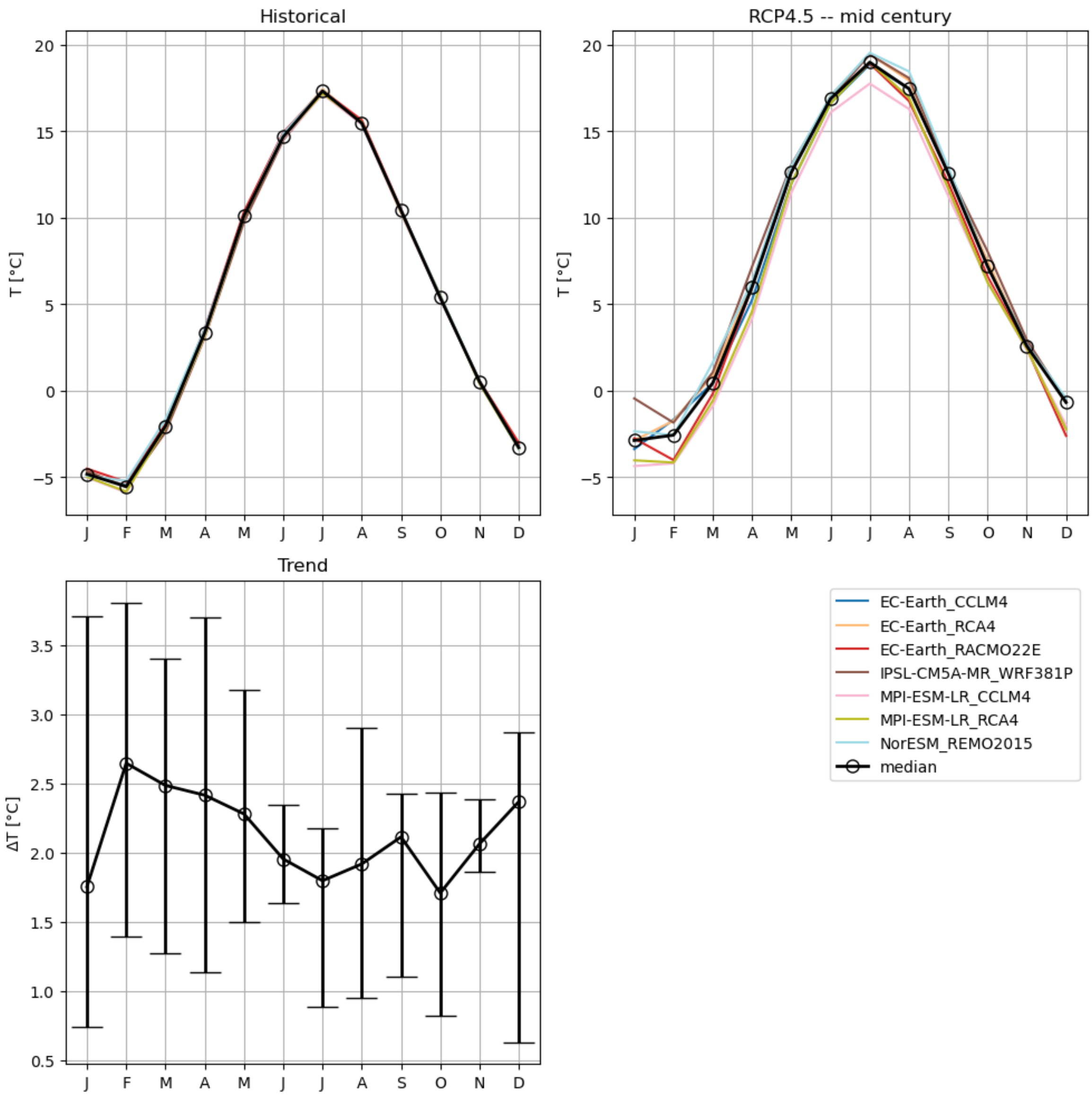

Figure 13: Medians of monthly average temperature in the Helsinki Metropolitan Region for bias-corrected models. Individual models are shown as coloured curves, and the model median is shown as black curve. Upper left: historical period (1976-2005), upper right: mid-century, lower left: projected change (error bars denote the 90% probability interval).

It is evident that the spread between different climate models in the historical period (top left panel) is notably reduced when comparing bias corrected model data (Figure 13 and Figure 14) against model data (Figure 7 and Figure 9). This outcome reflects the core function of quantile mapping, which is to align each model's historical distribution with observed temperature and precipitation statistics over a reference period. As a result, differences among models—stemming from individual biases in simulating the frequency or intensity of precipitation—are corrected, leading to increased agreement and consistency across models during the historical baseline.

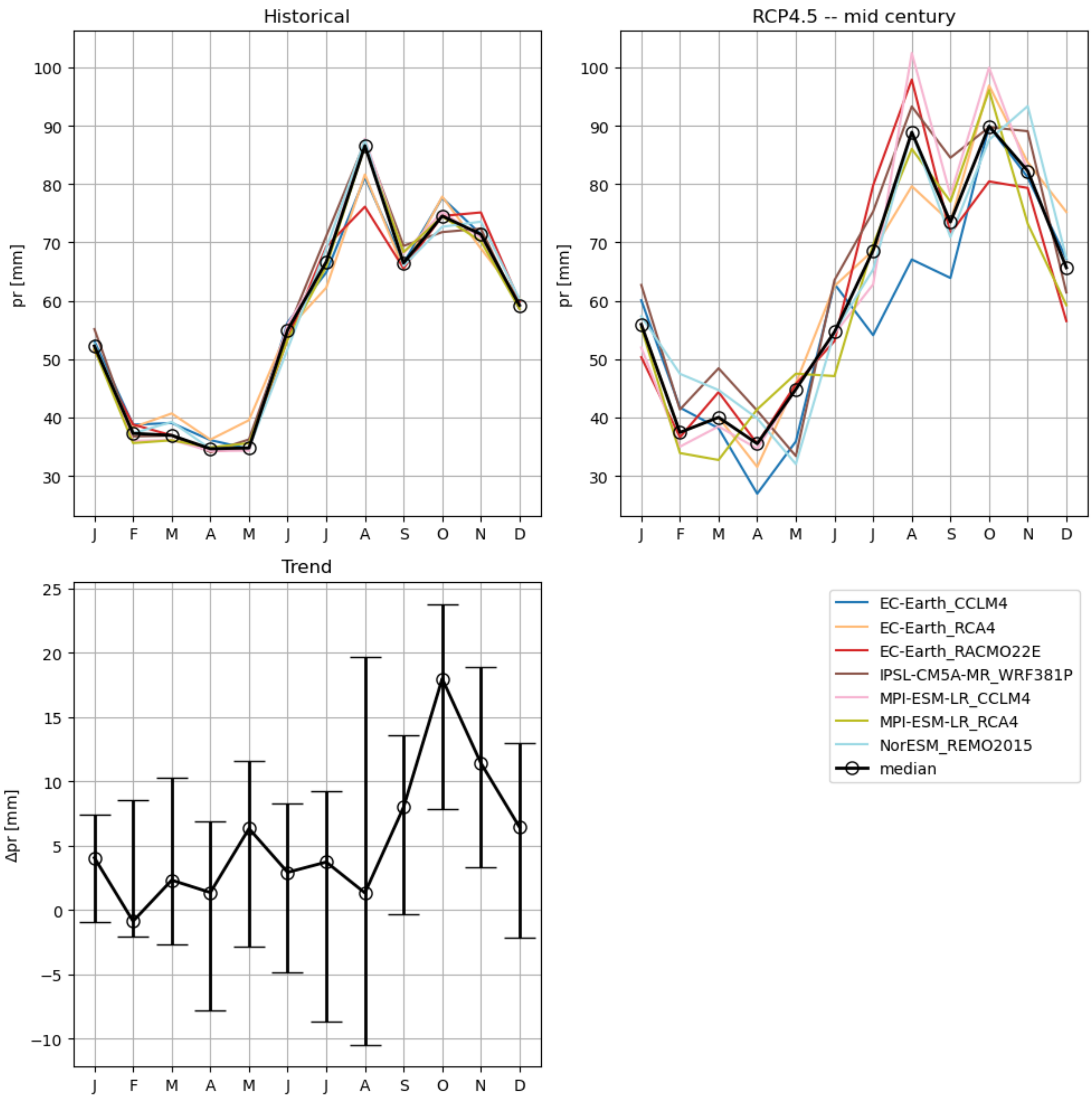

Figure 14: Medians of monthly average precipitation in the Helsinki Metropolitan Region in the bias-corrected models. Individual models are shown as coloured curves, and the model median is shown as black curve. Upper left: historical period (1976-2005), upper right: mid-century, lower left: projected change (error bars denote the 90% probability interval).

The future period (top right panel) shows a wider spread between models after bias correction (Figure 13 and Figure 14) compared to the historical period. The spread is, however much smaller than for the model data (Figure 7 and Figure 9). This increased divergence is a desirable and expected result: the quantile mapping method should adjust future values to match observed distributions while retaining each model's internally projected climate change signal (Räisänen and Räty, 2013, Räty et al., 2014).

Consequently, the differences in future projections reflect genuine differences in how models simulate climate change, rather than artifacts of bias correction.

Extreme precipitation

Figure 15 and Figure 16 present cumulative exceedance curves for daily precipitation events across a range of threshold values (20–120 mm) for the historical and mid-century period, respectively. The figures are based on bias-corrected outputs from the regional climate model (RCM) combinations listed in Table 2. Each curve illustrates the cumulative number of events exceeding a given precipitation threshold, providing insight into the frequency and intensity of extreme rainfall events as simulated by different models (see also Section 0).

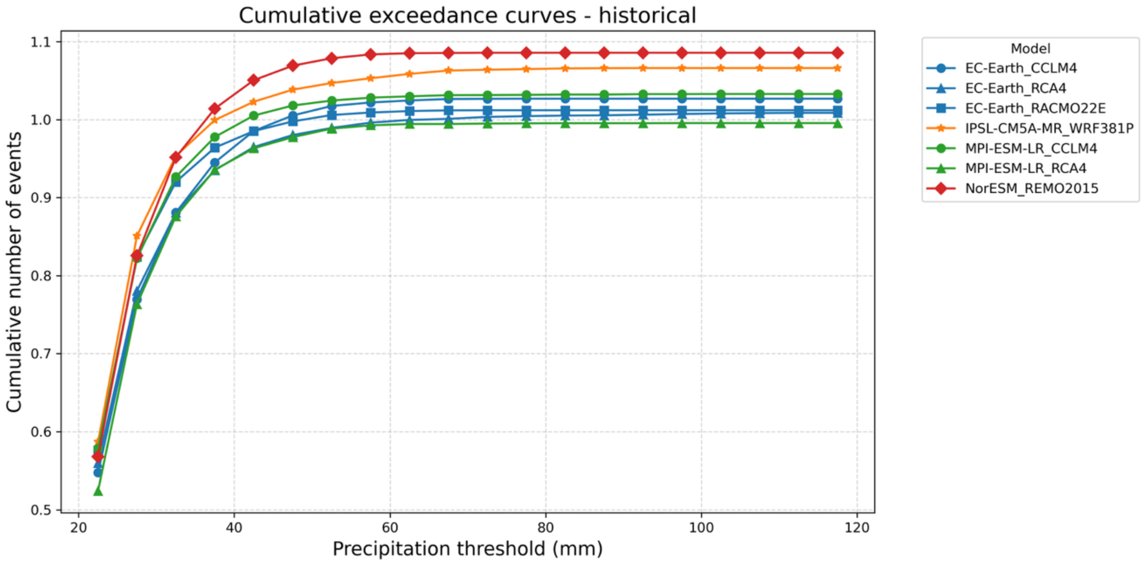

Figure 15: Cumulative number of extreme precipitation events averaged over the Uusimaa region and 30 years (1976-2005) in different bias-corrected CORDEX models (coloured lines).

Comparing Figure 15 to Figure 12, it is very apparent that the bias correction decreases the spread in models (and thereby the uncertainty) also for the counts in extreme precipitation events. However, some differences between the models remain. In the historical simulation (Figure 15), the cumulative number of exceedance events plateaus for thresholds above 60 mm. Notably, the NorESM_REMO2015 and IPSL-CM5A-MR_WRF381P models simulate the highest frequencies of heavy precipitation events, whereas the MPI-ESM-LR_RCA4 and EC-Earth_CCLM4 models yield comparatively lower frequencies.

Under the RCP4.5 scenario (Figure 16), all models exhibit an increase in the cumulative number of exceedance events relative to the historical baseline. For the IPSL-CM5A-MR_WRF381P and MPI-ESM-LR_CCLM4 models the increase is most evident. While all models show some increase, the magnitude of change varies, highlighting the inter-model uncertainty in projecting future extreme precipitation events even after bias correction.

Overall, the figures demonstrate a consistent upward shift in precipitation extremes across all models under RCP4.5, emphasizing the importance of considering ensemble approaches to account for model spread. These findings underscore the projected intensification of heavy rainfall events in future climate scenarios, with implications for urban flood risk and infrastructure resilience in the Helsinki Metropolitan Region.

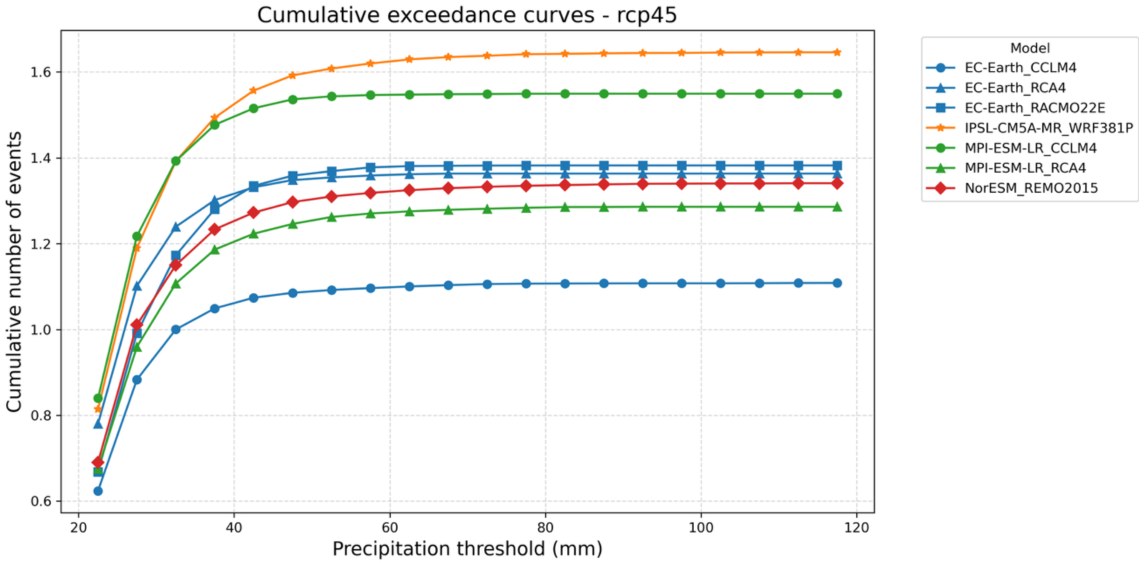

Figure 16: Cumulative number of extreme precipitation events averaged over the Uusimaa region and 30 years (mid century) in different bias-corrected CORDEX models (coloured lines).

Extreme precipitation values, by their nature, are rare and highly variable, which makes them particularly sensitive to sampling limitations and methodological assumptions. When these extremes are further processed through bias adjustment techniques they are influenced not only by the climate model output but also by the quality and representativeness of the reference observational data. Small errors, inconsistencies, or gaps in the observational record can significantly affect how extremes are adjusted, potentially amplifying or dampening their apparent frequency or intensity (Berg et al., 2024).

As a result, extreme precipitation indicators can carry substantial uncertainty, especially in small regions with sparse observational coverage or short reference periods. If not carefully evaluated, this uncertainty may lead to overconfidence in the projected magnitude or frequency of future extremes, which could misguide risk assessments and adaptation planning (Berg et al., 2024). For this reason, extreme precipitation values must always be interpreted with caution, and their limitations clearly communicated, particularly when used for decision-making in climate-sensitive sectors.

How citizen science can support climate data collection

Literature review

Citizen science refers to the practice of public participation and collaboration in scientific research. Citizen science involves volunteers collaborating with professional scientists to conduct research and generate knowledge (Lee et al., 2020). It involves non-professional scientists, or so-called "citizen scientists," who voluntarily contribute their time, effort, and resources to help collect data, analyse results, and even co-author scientific papers. Citizen science in research promotes large-scale data collection allowing citizens to contribute valuable data to scientific studies. This collaborative approach not only enhances the scope and scale of research but also fosters a greater public understanding and appreciation of science. In addition, it can often save a lot of resources (e.g. travelling funds) as research teams or scientists may not have to make field trips nor collect samplings from numerous different areas depending on the scope of the study.

A similar, sometimes cross-referenced, term Community Based Monitoring (CBM) also exploits non-scientists in research. While both citizen science and CBM refers to the participation of non-professionals in scientific research, typically through data collection, observation, or analysis, they should not be confused with each other. Compared to CBM, citizen science is often initiated by the invitation of academic or governmental institutions and usually designed and led by scientists operating at regional or global scales, with participants contributing under structured protocols. In contrast, CBM is a locally driven process, often initiated and controlled by the communities itself, particularly Indigenous or rural communities, with the goal of addressing locally relevant environmental or resource management concerns. CBM frequently integrates Indigenous knowledge, local knowledge or traditional ecological knowledge and emphasizes community ownership of both the process and the data. While both citizen science and CBM engage the public in knowledge production, their motivations, power structures, and knowledge systems differ. Citizen science tends to prioritize scientific outcomes, whereas CBM often emphasizes traditional and local ways of knowing, meaningful collaboration, empowering marginalised groups, and localised decision-making.

Citizen science projects can cover a wide range of fields, including environmental monitoring, astronomy, biology, and more. Citizen science can complement traditional research methods and contribute to understanding broad geographic patterns (Dickinson et al., 2010). For example, citizen science offers unique benefits for ecology by enabling large-scale studies and access to private lands (Dickinson et al., 2010). Furthermore, the integration of machine learning with citizen science has shown promise, particularly in biodiversity projects for species identification (Lotfian et al., 2021).

However, citizen science faces challenges, including data quality concerns and limited impact on policy-making (Lee et al., 2020). Risks include potential compromises to scientific principles (Funke, 2017), intentional mockery or mistakes to sabotage the results or misuse of the platform. To prevent intentional sabotage in citizen science projects, it's essential to implement several strategies. Establishing robust verification processes is crucial, as it allows for cross-checking data submitted by participants against professional observations or using statistical techniques to identify anomalies. Providing clear instructions and training to participants ensures they understand how to collect and submit data accurately, which helps maintain the integrity of the project. Also, fostering a sense of community and shared purpose among participants can discourage disruptive behavior. When people feel connected to the project's goals, they are more likely to contribute positively. Regular monitoring of submissions and providing feedback to participants can help identify and correct mistakes early on, further reducing the likelihood of intentional errors. Despite these challenges, citizen science presents opportunities for advancing scientific knowledge, increasing public engagement, and addressing global environmental issues (Lee et al., 2020; Funke, 2017). Future developments may focus on enhancing the partnership between citizen science and artificial intelligence to maximize benefits while mitigating risks (Lotfian et al., 2021).

One notable example of citizen science in action is a study conducted by Meinander et al. (2023) in Finland, which focused on the atmospheric transport of dust. In this study, the Finnish Meteorological Institute's SILAM model was used to predict the dust deposition five days before the dust storm. During the event period, Finland was experiencing cloudy weather, thus the satellite data was insufficient to provide detailed information about the atmosphere and the dust deposition. Instead, researchers relied on samples collected by citizens to compare against computer model calculations which were made beforehand. The location data and analytical results from citizen-collected samples were crucial in verifying the model calculations. Based on the samples, researchers discovered that the properties of the dust varied across different regions of southern Finland, with some areas having redder dust and others more yellowish. The results from citizen's observations showed that the prediction by the model was correct and therefore the study not only demonstrated the accuracy of computer models in predicting atmospheric phenomena but also showed the power of citizen science as well as provided researchers with valuable insights into how to improve sample collection and handling in future studies.

Another interesting example of citizen science is the iSCAPE project (iScape, 2024), which addressed the problem of reducing air pollution by focusing on the use of "Passive Control Systems" in urban spaces, policy intervention, and behavioural changes of citizens lifestyles. Real-world physical interventions and projections were applied to selected cities. Cities were selected based on future climate change scenarios and for their representation of different cultures and lifestyles across Europe. The project's approach was to transform the city becomes into a living lab, deploying a network of air quality and meteorological sensors (stationary and mobile). The benefits of these interventions were evaluated from a neighbourhood and city-wide scale – ranging from quantification of pollutant concentration to exposure. The project even developed its own device (Smart Citizen Kit), which measures a range of different meteorological and air quality parameters. The device is affordable and can be registered to a centralised database, where users can see and compare their measurements.

Citizen science projects like the ones presented highlight the significant contributions that non-professional scientists can make to research. By involving the public in data collection and analysis, scientists can gather more extensive and diverse datasets, leading to more robust and comprehensive findings. Additionally, these projects help to demystify scientific processes and engage the public in meaningful ways, ultimately promoting a more scientifically literate society. By engaging the public in scientific endeavours, these projects not only enhance research but also promote scientific literacy and community involvement. The main challenges in citizen science are the need to keep the participants motivated and to ensure measurement and data quality. Both problems can be tackled by involving and informing participants regularly about all outcomes of the project.

Conclusion

This report focuses on understanding estimated climate change at regional and local scales. It emphasizes the persistent uncertainties in how climate models represent and project key phenomena, i.e., average temperature, precipitation, and extreme events such as heavy rainfall. To illustrate these challenges, the Helsinki Metropolitan Region and the wider Uusimaa region in Finland are used as a case study.

There are still considerable uncertainties in how climate models simulate regional and local climate. These arise from multiple sources, including internal model variability, the need to approximate complex atmospheric processes, and fundamental structural differences between models. Expressing results as uncertainty intervals strengthens the analysis by acknowledging the range of possible outcomes rather than relying on single projections.

The report also shows that climate models can exhibit considerable bias and spread. Analysis using regional model data reveals that different models produce varying results for the same historical period (1976–2005), especially when compared with reanalysis datasets. In general in the Uusimaa region, many models tend to simulate colder and wetter conditions than observed, and not all models reproduce seasonal cycles accurately. This discrepancy becomes more pronounced when examining shorter timeframes like months or seasons.

To improve reliability, bias correction methods—such as quantile mapping—are applied to align model outputs with observed historical data. This process effectively reduces spread and improves consistency between models for past climate conditions. However, in future climate projections, differences between models re-emerge. This increased variability is not a flaw but a reflection of legitimate differences in how models simulate the future climate, offering a more realistic range of outcomes rather than simply adjusting past errors.

Modelling extreme precipitation events presents particular challenges. These events are highly localized, short-lived, and statistically rare, which makes them difficult to represent both physically and statistically. Bias correction techniques are less reliable at the extremes of data distributions, where fewer data points exist. Extrapolating these methods into a warmer future climate introduces further uncertainty, especially as the assumption that statistical relationships remain unchanged over time may no longer hold.

As a result, estimates of extreme precipitation—particularly for small areas—should be interpreted with caution. While analyzing larger spatial areas can help reduce some uncertainty, significant differences between models remain, even after correction. This underlines the persistent unpredictability of local extreme events.

Finally, the report highlights the potential of citizen science as a complementary tool for climate data collection. Public participation can broaden data coverage, support scientific research, and increase awareness and engagement. Although ensuring data quality is a challenge, it can be addressed through verification methods, clear instructions, and fostering a sense of community among participants.

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CLIMATE

PART 2

Policy Learning Guidelines

GREEN

Climate information management

Despite significant advances in climate science, integrating climate data into real-world decision-making remains a complex challenge. One key barrier is the mismatch between the timescales and formats of scientific data and the practical needs of policymakers, who often operate on shorter planning horizons and require actionable insights rather than raw data. Additionally, institutional capacity constraints – such as limited technical expertise or resources – can hinder the effective use of climate information. A recent Frontiers in Climate article (Lempert et al. 2024) emphasizes that uncertainty in climate projections, while scientifically valid, is often misunderstood or underappreciated by decision-makers, leading to hesitation or inaction. To address these challenges, the article advocates for broader adoption of Decision Making under Deep Uncertainty (DMDU) approaches, which help navigate complexity and support robust, flexible planning in the face of uncertain futures.

The role of Sustainable Energy and Climate Action Plans (SECAPs) in local adaptation planning

A crucial role in climate change adaptation planning on the municipal level in Europe is played by the Covenant of Mayors for Climate and Energy (CoM) – Europe. CoM is a European initiative (part of a global CoM) that brings together thousands of local and regional authorities voluntarily committed to implementing EU climate and energy objectives. Adaptation is one of the three core pillars of the Covenant, alongside mitigation and access to sustainable energy. Municipalities commit to increasing resilience and preparing for the adverse impacts of climate change as part of their Sustainable Energy and Climate Action Plans (SECAPs).

As of recent data, over 11,000 municipalities across Europe have joined the Covenant of Mayors for Climate and Energy, collectively representing around 341 million citizens. This makes it the largest initiative of its kind, demonstrating widespread local commitment to achieving the EU's climate and energy goals through coordinated action planning and implementation at the municipal level.

Local authorities participating in the CoM commit to submitting a Sustainable Energy and Climate Action Plan (SECAP) within two years of joining. The SECAP outlines both mitigation targets and adaptation goals, grounded in a Baseline Emission Inventory and a Risk and Vulnerability Assessment (RVA). Within the Covenant framework, the RVA identifies key climate hazards and vulnerable sectors, and may also assess adaptive capacity and at-risk population groups. This analysis supports evidence-based planning and prioritization of adaptation measures.

To develop a Sustainable Energy and Climate Action Plan (SECAP), municipalities participating in the Covenant of Mayors are required to use a range of climate and energy-related data. This includes:

- **Baseline Emission Inventory (BEI)**: Data on greenhouse gas emissions and energy consumption across key sectors such as buildings, transport, and municipal operations.
- **Risk and Vulnerability Assessment (RVA)**: Climate hazard data (e.g. floods, heatwaves), exposure and sensitivity of local assets and populations, and indicators of adaptive capacity.

- **Monitoring and Evaluation Data**: Information to track progress on mitigation and adaptation targets over time.
- **Optional Adaptation Scoreboard**: Qualitative and quantitative indicators to assess the effectiveness of adaptation actions.

These data sources support evidence-based planning and ensure that SECAPs are tailored to local conditions and risks. The data is typically sourced from national meteorological services, local monitoring systems, EU databases (e.g. Copernicus), and stakeholder consultations.

Integrating climate data into decision-making in the CLIMATE project regions

The CLIMATE project regions battle with many shared institutional vulnerabilities in their climate change adaptation governance. The final report on the project's activity A1.1 *Joint identification of the environmental and socioeconomic factors of CLIMATE territories' vulnerability to climate hazards, vis-à-vis partners' climate adaptation policies and natural & built environment territorial regulations* outlines common challenges the regions face in building their climate resilience and adaptive capacity. The following is an overview of the climate data related challenges and areas of intervention presented in the report.

Most CLIMATE partners identify shortcomings in their area's emergency preparedness, inter-agency coordination, and long-term adaptation planning, often linked with inadequate resources and knowledge dissemination. Even though each region's specific situation may vary (for example, one might face more flooding and another more wildfire), the underlying drivers are the same, varying from weak infrastructure to water scarcity and planning gaps. Without proactive measures to address these common issues, climate impacts will significantly worsen in the coming decades. Shared intervention priorities include

- Climate-resilient infrastructure
- Disaster preparedness and emergency response
- Ecosystem restoration and nature-based solutions
- Social equity in climate adaptation
- Institutional capacity-building and coordination

Regarding the use of climate data in decision-making, some CLIMATE partners identify the need for more advanced climate and weather monitoring systems, whereas others recognize limitations in the integration of climate data into planning and implementation processes.

The need for more advanced real-time climate monitoring in the form of meteorological and hydrological monitoring networks is rooted in the need to track flood risks, heatwaves and sea-level rise, in particular. These monitoring systems and networks would also enhance the building and effective utilization of early warning mechanisms.

While climate data and scenarios are often available for use, they are not always systematically used in policy decisions or emergency response strategies. It is not sufficient to merely make a climate risk assessment, but it must also be integrated into planning, decision-making and implementation processes.

In order to promote the use of climate data in decision-making, the data should be as standardized as possible, allowing datasets to be compared meaningfully. This enhances the integration of data and makes monitoring efforts easier. Climate data standardization should ideally be done in cooperation between local, regional and national authorities.

The report on activity A1.1 concludes that to enhance knowledge management and territorial resilience, CLIMATE project regions should focus on strengthening real-time climate monitoring, improving the accessibility and usability of climate risk data, and ensuring that assessment tools are systematically embedded into planning and policy frameworks.

Case example: Integrating climate data into decision-making in the Helsinki Metropolitan Region

The role of Sustainable Energy and Climate Action Plans (SECAPs)

All the cities of the Helsinki Metropolitan Region (Espoo, Helsinki, Kauniainen, Vantaa) have joined the Covenant of Mayors for Climate and Energy. For example, in its Sustainable Energy and Climate Action Plan (SECAP) approved in 2021, the City of Helsinki describes using the Global Covenant of Mayors monitoring list of possible harmful effects caused by natural phenomena as the basis for their risk factor identification and risk analysis. The Plan lists 23 different analysis materials that had been published at the time in the Helsinki Metropolitan Region concerning climate change adaptation, climate risk, and vulnerability. This demonstrates how using data and scientific information as the basis of adaptation planning has been a goal of the cities in the area. However, effectively integrating this information into practical decision-making remains a challenging task.

Regional cooperation

The cities of the Helsinki Metropolitan Region have formed the Helsinki Region Environmental Services Authority (HSY) to provide municipal water supply and waste management services, as well as information on the area and the environment. HSY has long acted as a promoter and coordinator of cooperation between the four cities in the region regarding the subject of climate change adaptation. The Helsinki Metropolitan Area Climate Change Adaptation Strategy was developed already in 2012 and it included policies for the period 2012-2020. The aim of the policies was to advance metropolitan area's adaptation to climate change and reduce vulnerability to extreme weather events. The strategy focused especially on enhancing the adaptation of built and urban environment to the changing climate. As all the cities in the region joined the Covenant of Mayors for Climate and Energy, the need for a metropolitan-wide adaptation strategy subsided.

HSY has developed adaptation indicators for the Helsinki Metropolitan Region in cooperation with the cities of the region to understand the need for adaptation and the effectiveness of adaptation measures. These indicators were subdivided according to the European Environment Agency (EEA) into hazard/weather, exposure, adaptability and vulnerability composite indicators. The EEA classification also includes a fifth category, i.e. indicators of sensitivity or vulnerability, but these have not yet been specifically defined for the Helsinki Metropolitan Region.

The current regional indicators include change in average temperature, number of hot days, annual rainfall, heavy precipitation, snow sum, days the temperature crossed zero degrees Celsius (especially slippery), number of inhabitants in sea flood risk areas (flood frequency 20, 50, 100 and 250 years), buildings in sea flood risk areas (flood frequency 100 years), number of buildings in inland flood risk areas (flood frequency 20, 50, 100 and 250 years), impermeable areas and vegetation cover in the region, combined sewerage network overflows, number of green roofs, and vulnerability to heat. There is ongoing discussion about the need to update and develop these indicators further. HSY coordinates the work of a regional climate change adaptation expert group where the continued development of the regional adaptation indicators can be achieved together.

In addition to compiling data in the form of indicators, HSY has commissioned reports on the realised and predicted effects of climate change on the region. The Finnish Meteorological Institute produced a report in 2023 examining the most recent information of climate change and some of its impacts in the Helsinki Metropolitan Region based on the IPCC 5th Assessment Report and its greenhouse gas (RCP) scenarios (Rantanen et al., 2023).

HSY has also been using the accumulated knowledge on the regional effects of climate change to plan and implement communications and advisory services aimed at city residents and housing companies. HSY is currently formulating new adaptation advice and communication services as part of the services provided by its Climate Info team (e.g. advice on energy efficiency and renewables).

HSY is also leading a national project 'TALVI' (Housing Companies in a Changing Climate) that promotes the adaptation of housing companies to climate change by producing tools for managing and repairing properties to be climate resilient. In the project, current tools available to housing companies are reviewed, their usability is analyzed, and suggestions for improvements and enhancements are made to create better instructions and more user-friendly products. The products developed in the project are tested in practical situations. The outcome is a set of recommendations and models of management tools for housing companies. The TALVI project is implemented with the support of the European Regional Development Fund (ERDF).

One prevalent form of regional cooperation on the subject of adaptation is joint projects that are usually partly externally funded. An ongoing example is the project VALUE (or 'ARVO' in Finnish): Valuation and strengthening of urban green spaces in landscape planning in cities. This project brings together all of the cities of the Helsinki Metropolitan Region alongside Aalto University and Green Building Council Finland to develop and strengthen the green structure in densely built cities to promote climate change preparedness and adaptation. One of the main expected outputs is a planning tool for green structure, 'green area factor for districts', suitable for assessing the quantity and quality of ecosystem services and biodiversity. The active participation of Aalto University in the project brings a significant science-based approach to the practical tools and assessments of the project. The VALUE project is implemented with the support of the European Regional Development Fund (ERDF).

Current developments

The cities are increasingly incorporating climate data and information systems into their adaptation planning, though the extent and sophistication of use vary. The following presents some examples of measures that the cities have taken where data is used to inform adaptation-related planning and action.

Several cities have developed digital monitoring platforms to track the implementation of adaptation measures and support regular reporting. These systems help embed climate considerations into urban planning and decision-making processes. Flood risk areas have been identified, and stormwater programmes are in place, with some cities using GIS tools to map stormwater infrastructure and problem areas.

In land use planning, green infrastructure is guided by zoning tools such as green efficiency metrics and vegetation coverage requirements (for example the Green factor). Modelling and scenario-based planning are also emerging as important tools. Urban heat island effects and stormwater flood risks are being modelled to inform future preparedness strategies. In building design, Helsinki has committed to begin using future climate data (2050 weather scenarios) to simulate indoor conditions and guide cooling solutions in new building projects.

While systematic monitoring of adaptation measures is still developing in some areas, there is growing recognition of the need for more comprehensive data on the costs, effectiveness, and resource needs of adaptation actions, particularly in relation to heat preparedness. Overall, while practices vary, there is a clear trend toward more data-informed and proactive climate adaptation planning across the region.

A3.3 Site visit and interregional workshop on climate information management

The CLIMATE project's policy learning and capacity-building activities, comprising six workshops and two site visits, further enrich the exchange of experiences among partners that has begun during the joint studies conducted in the project's early semesters.

Activity A3.3 of the CLIMATE project is an interregional policy learning and capacity building activity that aims to increase partners' operational capacity in systematising the use of weather and climate data in climate governance. It consists of three parts facilitating the interregional process:

1) This background report
2) A site visit to the Finnish Meteorological Institute in Helsinki on 12 June 2025
3) An interregional workshop on climate information management in Helsinki on 12 June 2025

The report is provided, and the site visit and workshop organised, by the Helsinki Region Environmental Services Authority (HSY). After the site visit and workshop, HSY will compile a summary report that consolidates the results of the site visit and the workshop, including the proposed solutions, interregional insights, guidelines, and future visions.

A3.3 Site visit and workshop on Thursday, 12th June 2025: Indicative agenda	
09:00 – 11:00	**A3.3 Site visit to the Finnish Meteorological Institute** The Finnish Meteorological Institute is the government agency responsible for collecting and disseminating climate and weather data and forecasts in Finland. The Institute functions as an impartial research and service organization, specializing in a wide range of atmospheric science activities. We will hear about the work done at the Institute and especially in the Weather and Climate Change Impact Research Unit.
11:00 – 13:00	**Lunch, networking and possible travel between locations**
13:00 – 16:30	**A3.3 interregional workshop on climate information management** Sparring in small groups to identify e.g. - key regional actors and their roles - existing processes for incorporating data into regional plans and operations - entry points, barriers and delays in the flow of climate information - related coordination mechanisms - interactions between long-term adaptation strategies and short-term emergency management

The goals of the workshop are to

- facilitate peer and interregional learning
- increase participants' awareness about how to increase operational capacity in systematising the use of climate and weather data in climate governance
- identify concrete actions and roles that partners and stakeholders can take to support implementation
- explore potential pathways for embedding climate data into decision-making systems in a way that is both systematic and anticipatory

A more detailed agenda of the site visit and workshop will be provided closer to the date. This will be accompanied with a small pre-assignment for the participants of the workshop. In general, participants will benefit from preparing with some background information on how climate data is integrated into decision-making in one's region or country; identifying if there are some good practices, challenges or gaps in knowledge that would be beneficial to share in the workshop.

Acknowledgements

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