Uncertainty Quantification of Climate Change Projections

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11.1 Introduction

The importance of uncertainty in climate change projections and its communication to stakeholders is well recognised by the IPCC as can be seen from the assessment reports. Uncertainty in regional climate change projections further cascades to uncertainties in impacts (hydrology, agriculture, etc.), and it gives a hard time to the decision makers to come up with necessary adaptation measures, as the adaptation plans and corresponding costs can significantly be affected due to these uncertainties. Hence, there are efforts by the scientific community to reduce uncertainty in climate change projections to the extent possible.

With regard to the communication of uncertainty to stakeholders, the IPCC AR6, similar to AR5, uses a “calibrated language” in various statements published in the reports. The 2 terms that are used to communicate uncertainty in the IPCC reports are “confidence” and “likelihood”. IPCC uses a rather detailed methodology to assess and communicate uncertainty as can be seen in Figure 11.1 taken from the AR6 WG-I report.

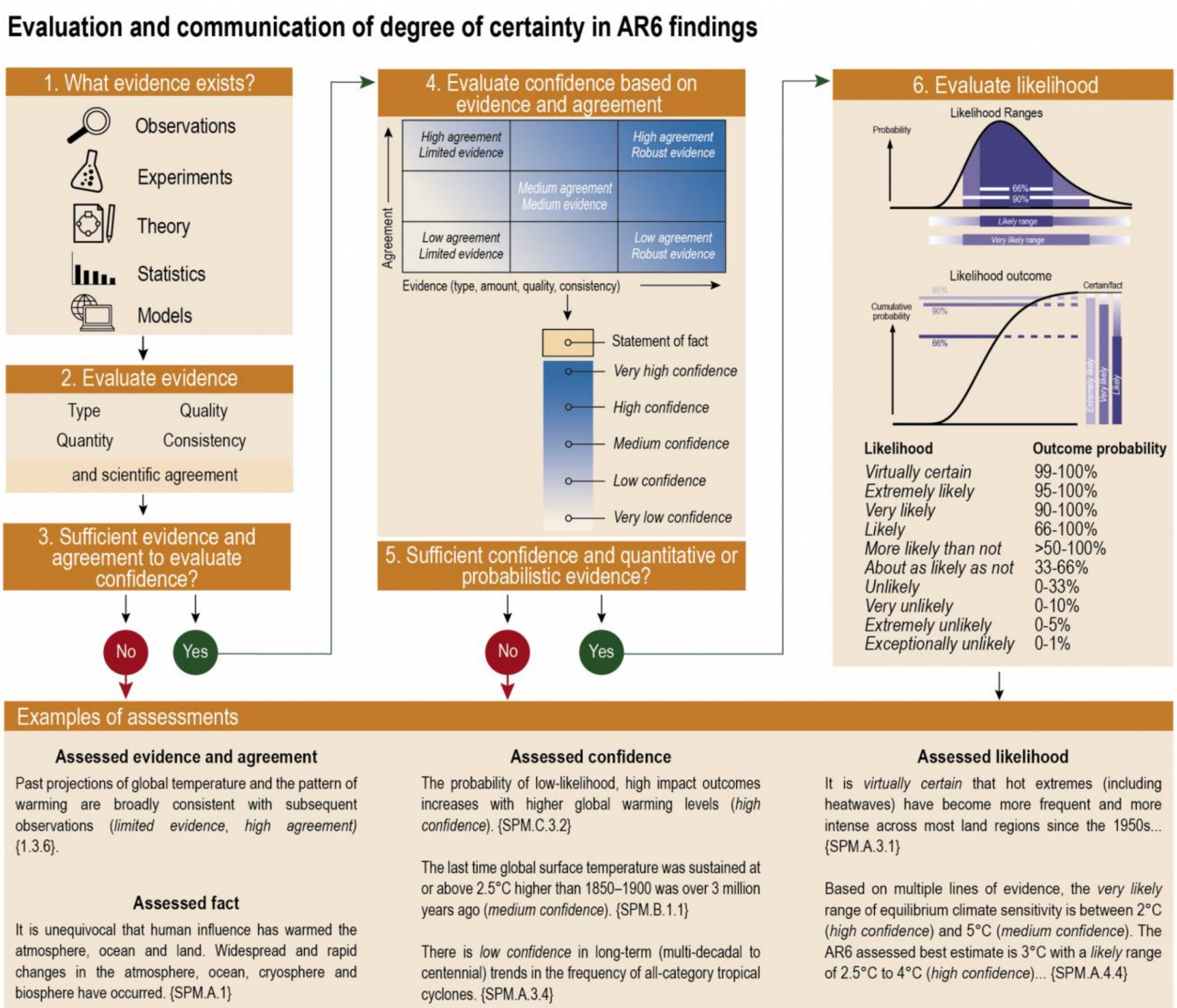

Figure 11.1: The IPCC AR6 approach for characterizing understanding and uncertainty in assessment findings. This diagram illustrates the step-by-step process authors use to evaluate and communicate the state of knowledge in their assessment (Mastrandrea et al., 2011). Box 1.1, Fig. 1, IPCC AR6.

11.2 Sources of uncertainties in Climate Change Projections

There are 3 distinct sources of uncertainty in global climate change projections - (1) internal variability uncertainty, (2) model uncertainty, and (3) scenario uncertainty (e.g., Hawkins and Sutton 2009).

Internal variability uncertainty: As evident from the name, this is due to the internal variability or natural fluctuations of the climate system that arise in the absence of any radiative forcing on the earth system.

Model uncertainty: This is also known as a response uncertainty. Each model has its own representation of the processes in the climate system. As such, different models respond differently to the same forcing and hence produce somewhat different climate change projections at global and regional levels.

Scenario uncertainty: This is the difference in response of a given model that can arise due to differences in the external forcing, e.g., greenhouse gas emissions under different pathways, leading to different responses and hence different climate change projections.

Dynamical downscaling uncertainty: In the case of regional climate change projections via dynamical downscaling an additional uncertainty factor arises that is associated with the different downscalers (regional climate models) used for downscaling. For example, for a given CMIP6 GCM and for a given scenario, 2 different regional climate models used for dynamical downscaling will produce somewhat different regional climate change projections. This is called the dynamical downscaling uncertainty.

The relative importance of each of the uncertainty factors changes with the time and space scale of interest. Hawkins and Sutton (2009) compared the roles of internal variability uncertainty, model uncertainty, and scenario uncertainty. Their work indicates that for time horizons of many decades or longer, the dominant sources of uncertainty at regional or larger spatial scales are model uncertainty and scenario uncertainty. However, for time horizons of a decade or two, the dominant sources of uncertainty on regional scales are model uncertainty and internal variability. In general, the importance of internal variability increases at smaller spatial scales and shorter time scales.

In Figure 11.2 we have shown the total variance and fractional variance of near-surface air temperature (tas) from CMIP6 GCMs over the V3 8 km domain, split into 3 sources of uncertainty, i.e., internal variability, model uncertainty, and scenario uncertainty, following the methodology of Hawkins and Sutton 2009. It can be seen from the left panel that the internal variability remains almost constant in time, the model uncertainty shows a steady increase in time but at a slow rate, whereas the scenario uncertainty non-linearly increases with time.

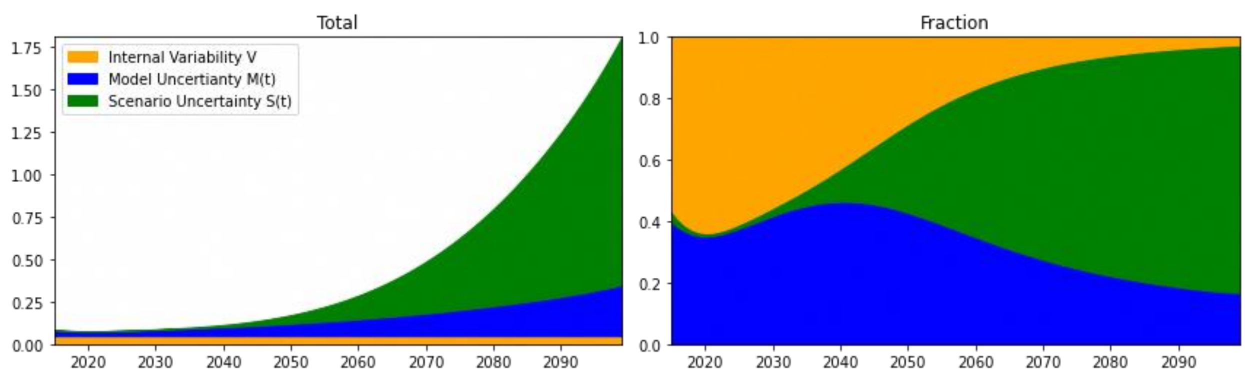

Figure 11.2: Total and fractional variance of surface air temperature over the V3 8 km domain using CMIP6 GCMs data.

From the right panel, as expected from the findings of Hawkins and Sutton (2009), on timescales of 1-2 decades the dominant sources of uncertainty are internal variability and model uncertainty, whereas on longer timescales (beyond 2 decades) scenario uncertainty is the dominant mode of uncertainty.

11.3 Methods to constrain uncertainties

While there are uncertainties in climate changes projections, there are methods to reduce the range of uncertainty by applying constraints. For example, one of the methods that was used to constrain the climate change projections in IPCC AR6 was the use of emulators. As highlighted in Chapter 4 (Section 4.2.1), many CMIP6 models exhibit an equilibrium climate sensitivity (ECS) of 5°C or higher (Zelinka et al., 2020), much higher than the upper value of the CMIP5 range of 4.5°C. Sherwood et al. (2020) constrained the likely and very likely ranges of ECS in CMIP6 models to 2.5°C - 4.0°C and 2.0°C - 5.0°C, respectively. Hence, the IPCC adopted the approach of employing an emulator for constraining temperature and all parameters scaling with temperature, based on the analysis of Sherwood et al. (2020).

There have been studies that have used other methods to constrain the uncertainty in climate change projections. For example, Tokarska et al. (2020) used past warming trends to constrain future warming in CMIP6 models. They reported that projected future warming is correlated with the simulated warming trend during recent decades across CMIP5 and CMIP6 models, and hence can be used to constrain future warming based on consistency with the observed warming.

Emergent constraint (Hall et al., 2019), defined as a statistical relationship, across a model ensemble, between a measurable aspect of the present-day climate (the predictor) and an aspect of future projected climate change (the predictand) is another method which is promising and being widely researched and used to constrain future climate change projections.

Another alternative method to constrain climate change projections is the storyline approach discussed in Shepherd et al. (2018). This method, although inherently subjective, provides a powerful way of interpreting climate change projections based on storylines, and either accepting or discarding the projected changes based on the confidence in the associated projected storyline.

11.4 Uncertainty in V3

The 4 types of uncertainty discussed above are also present in the V3 climate change projections presented in this report, which we explore further in this subsection.

Scenario uncertainty

The role of scenario uncertainty is shown in Figure 11.3. It shows the range (across the 3 SSPs) of changes in precipitation (%) and changes in temperature (°C) for each of the 2 km simulations over Singapore for mid- and end-century. We see from the figure that, in general, the scenario uncertainty increases in time from mid-century to end-century, as expected. However, the actual magnitude of scenario uncertainty is model-dependent. This is because the scenario uncertainty is governed by the response of a given model to different forcings, and since the differences in responses to different forcings is dependent on the model the scenario uncertainty is also dependent on the model. For example, in one of the models the scenario uncertainty in precipitation change is as high as 25% during the end-century, and similarly the scenario uncertainty in temperature projections for one of the models during the end-century is as high as 3.5°C.

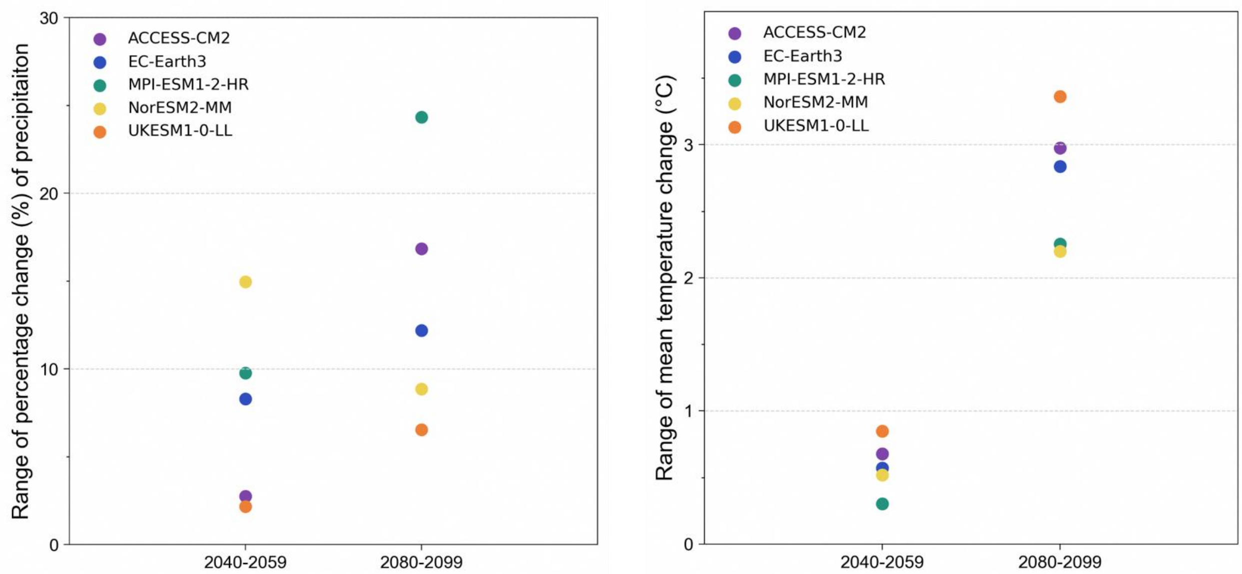

Figure 11.3: Projected range of precipitation change (%; left panel) and temperature change (ºC; right panel) across SSP scenarios during mid-century (2040-2059) and end-century (2080-2099) for the five 2 km downscaled simulations over Singapore. Each dot represents the difference between the minimum and maximum values (across the 3 SSPs) for the individual models.

Model uncertainty

The next source of uncertainty we look at is the model uncertainty. Figure 11.4 shows the future range of precipitation change and temperature change across models during mid-century (2040-2059) and end-century (2080-2099) under the 3 SSPs for the five 2 km downscaled simulations over Singapore.

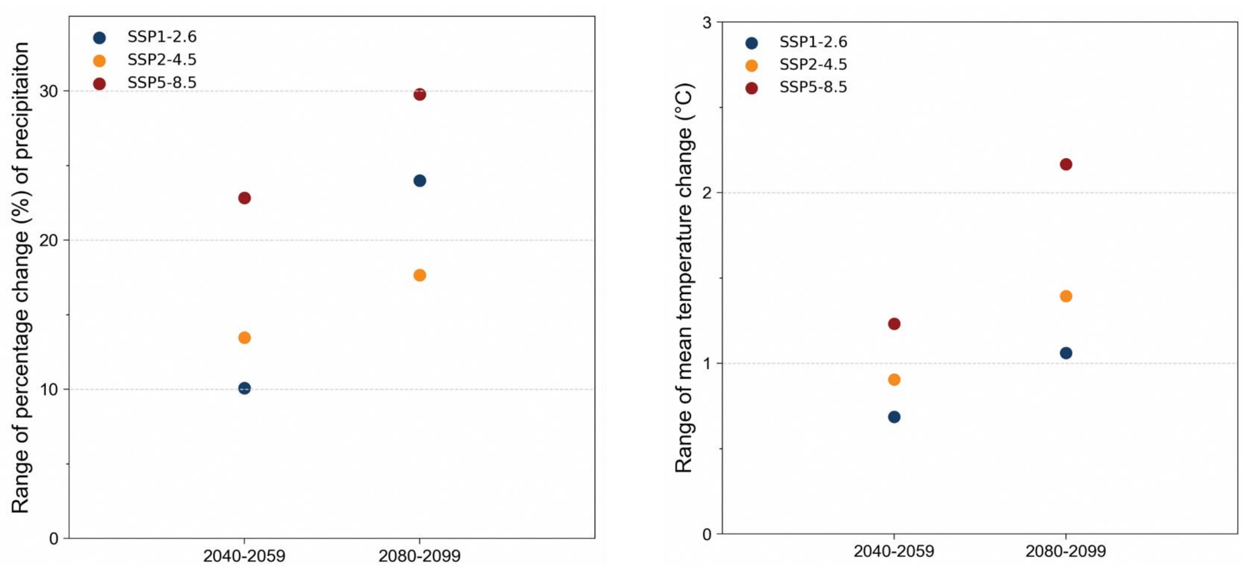

Figure 11.4: Projected range of precipitation change (%; left panel) and temperature change (ºC; right panel) across models during mid-century (2040-2059) and end-century (2080-2099) under the 3 SSPs for the five 2 km downscaled simulations over Singapore. Each dot represents the difference between the minimum and maximum values (across the 5 models) for the individual SSPs.

We see from the figure that, in general, the model uncertainty increases with time and is higher in the end-century as compared to the mid-century. We also find that the model uncertainty is highest for the SSP5-8.5 scenario. For example, the model uncertainty in projected precipitation change over Singapore could be as high as 30% under SSP5-8.5 during the end-century, and that for projected temperature change could be as high as 2.2°C under SSP5-8.5 during the end-century.

Dynamical downscaling uncertainty

Next, we turn to the dynamical downscaling uncertainty. Another dynamical downscaling model, the Weather and Research Forecasting (WRF) model, was used to perform a parallel version of a subset of the simulation conducted with SINGV-RCM, making use of two global models (EC-Earth3 and MPI-ESM1-2-HR) and three time periods (historical, SSP2-4.5, and SSP5-8.5).

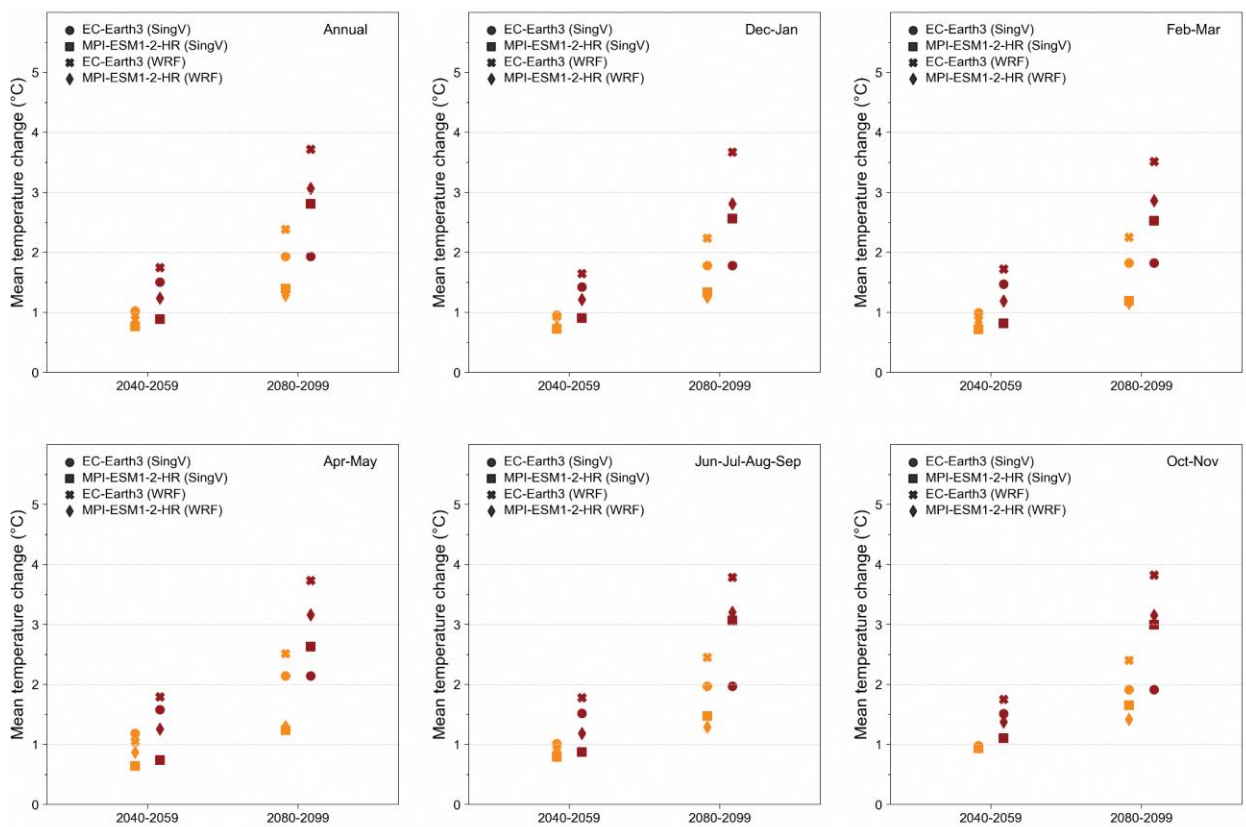

Figure 11.5: Comparison of projected change in mean near-surface air temperature over Singapore in the SSP2-4.5 (orange) and SSP5-8.5 (deep red) scenarios using SINGV-RCM and WRF downscaled from EC-Earth3 and MPI-ESM1-2-HR for mid and end century at 8km resolution.

Figure 11.5 shows the projected percentage change of near-surface air temperature over Singapore in the SSP2-4.5 (orange) and SSP5-8.5 (deep red) scenarios using SINGV-RCM and WRF downscaled from EC-Earth3 and MPI-ESM1-2-HR for mid and end century at 8 km resolution. Across the scenarios and time periods, near-surface air temperature downscaled from WRF are generally warmer, with differences within ~2°C. Note that the uncertainty is a nonlinear combination of both the parent GCM and downscaler; for example, relative to SINGV-RCM, WRF amplifies the warming in Dec-Jan at the end-of the century for EC-Earth3 much more than it does for MPI-ESM1-2-HR. The spread also increases in SSP5-8.5 as compared to SSP2-4.5, and in many cases in the end-century as compared to the mid-century. The results increase our confidence in the projection of warming over Singapore in the future under the SSP scenarios.

Figure 11.6 shows the projected percentage change of precipitation over Singapore in the SSP2-4.5 (orange) and SSP5-8.5 (deep red) scenarios using SINGV-RCM and WRF downscaled from EC-Earth3 and MPI-ESM1-2-HR for mid and end century at 8 km resolution. Even when downscaled with forcings from the same GCM, RCMs can predict different signs of change (e.g., downscaling of EC-Earth3 over annual timescales in the end of the century, shown by the crosses versus circles). The percentage change can be larger for Feb-Mar, which is a climatologically dry month. Similarly, using two different GCM forcings on the same downscaler can give projections of opposing signs (e.g., downscaling using WRF over annual timescales for SSP5-8.5, as seen by the cross and diamonds). It is not obvious whether the spread in RCM or spread in GCM contributes more to the overall uncertainty. For example, in the end-century in Feb-Mar under SSP5-8.5, the uncertainty from considering the additional regional model WRF (circle and cross) is smaller than that of considering an additional GCM (circle and square), but the opposite is true for its mid-century counterpart. Considering the analysis of Figure 11.5 and Figure 11.6 reveals that we have a high certainty in future warming over Singapore as compared to changes in rainfall.

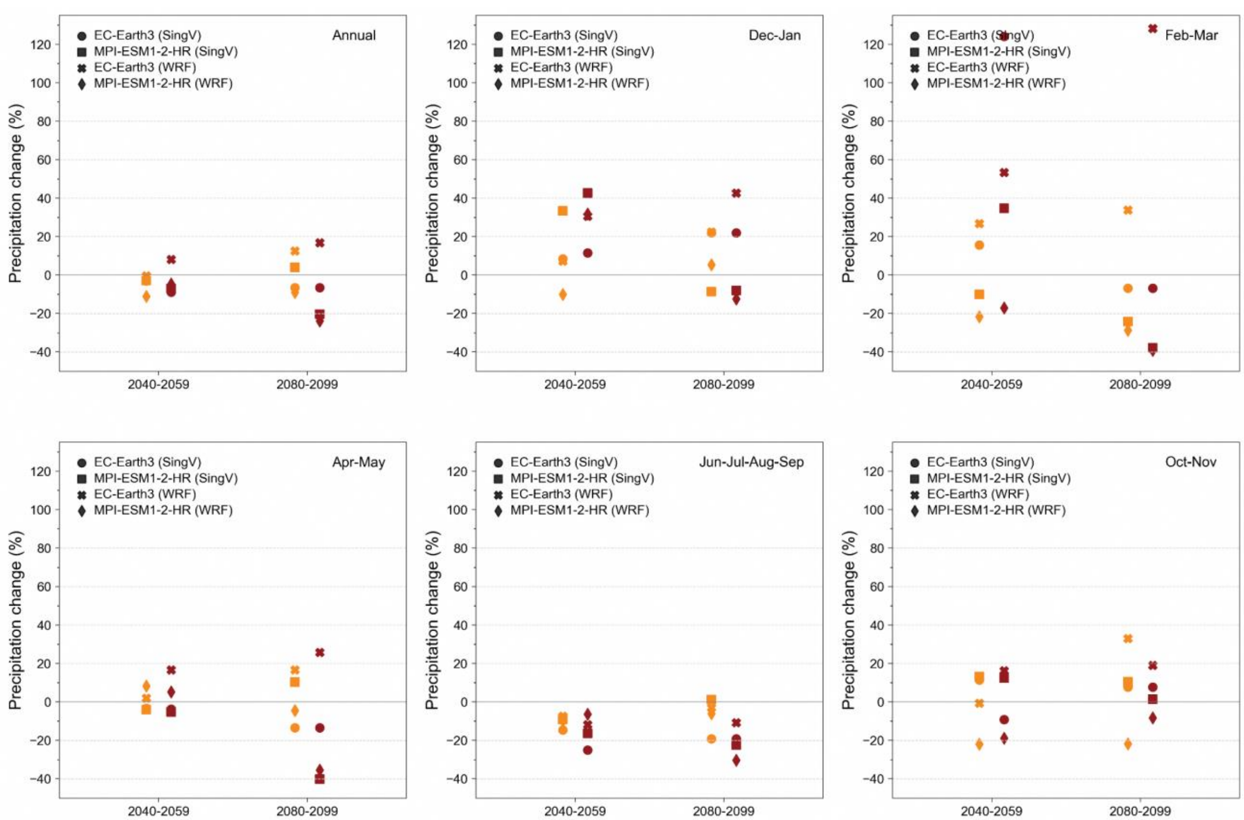

Figure 11.6: Comparison of projected percentage change of precipitation over Singapore in the SSP2-4.5 (orange) and SSP5-8.5 (deep red) scenarios using SINGV-RCM and WRF downscaled from EC-Earth3 and MPI-ESM1-2-HR for mid and end century at 8km resolution.

Internal variability uncertainty

As explained in Section 11.2, internal variability is inherent within the climate system. As such, in addition to being present in GCMs, this variability is present within all the downscaling results and observed trends shown in this report. By presenting climatological averages over twenty years, we aim to reduce the impact on variability in assessing the potential of changes in the middle or end of the century. Nevertheless, decadal variability from the models could still influence the results. The role of such variability becomes particularly important over small spatial scales, such as local changes over Singapore (Chapter 10).

11.5 Summary

Future climate projection for Singapore is challenging. In particular, Singapore is located in between two much larger areas where increases in rainfall are projected on one side and decreases on the other for most of the seasons. This is related to the complex and seasonally-varying regional climate drivers in the SEA region, and surely makes projections of rainfall change particularly challenging for Singapore, especially given its small size.

The contents of this chapter aim to provide guidance to the users of the bias-adjusted projections over Singapore (Chapter 10) about the reliability and robustness of the projections, given the uncertainties inherent in climate projections.

Our analysis shows that the scenario uncertainty increases in time from mid-century to end-century, while also being model-dependent. For example, in one of the models the scenario uncertainty in precipitation change is as high as 25% during the end-century, and similarly the scenario uncertainty in temperature projections for one of the models during the end-century is as high as 3.5°C.

Model uncertainty also increases with time and is larger in the end-century as compared to the mid-century. Model uncertainty is also largest for the SSP5-8.5 scenario. For example, the model uncertainty under SSP5-8.5 during the end-century can be as high as 30% for projected precipitation change and 2.2°C for projected temperature change.

Dynamical downscaling uncertainty can affect the change in sign of precipitation change for individual models, and lead to temperature changes within ~2°C.

Given the presence of the sources of uncertainty described in Section 11.2, we are more confident in the projections that remain qualitatively similar despite the time period/scenario/model used in the analysis. We are also more confident in changes that are consistent with the changes in the regional and global climate system, especially if they are supported by theoretical understanding.

For the purpose of using the model results, the mean or median of the multi-model ensemble could be used to provide an indication of the change. However, for robust decision making, it may be useful to consider the full multi-model range of the variables of interest.

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