# Annex 3: Uncertainties in Climate Change Projections

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## A3.1 Introduction

The global emissions of carbon dioxide and other greenhouse gases change the atmospheric composition and enhance the natural greenhouse effect. The climate system responds by warming, sea-level rise, changing precipitation patterns, snow and ice melt, and so on. The overall nature, order of magnitude and many regional characteristics of this response are scientifically well-established. There are also unknowns and uncertainties, but these are not impenetrable. They can be studied in informative ways, which contributes to the utility of climate change projections. This annex provides a pragmatic overview of uncertainties in climate change projections including regional downscaling. The aim is to provide background for the discussion of climate models and climate change projections addressed by different chapters of this book.

## A3.2 Climate Models and Climate Projections

Climate models are advanced simulation tools for the climate system, and its characteristics such as temperature, precipitation, clouds, winds, snow, waves, sea ice, ocean salinity, and so on. The basis for climate models is the collected scientific understanding of the fundamental physical, chemical and biological properties and processes of the climate system. The body of climate change projections is made with global climate models (GCM). The latest generation of such projections has been coordinated under CMIP5 (The Coupled Model Intercomparison Project Phase 5; Taylor et al. 2012). Regional climate models (RCMs) are the regional counterpart of GCMs, and are used for downscaling global model projections. For additional information on climate models see Annex 2.

There are three major reasons why climate models are the key scientific tool for making climate change projections. First, the full climate system is complex and its evolution does not lend itself to analytical or statistical representations. Second, the future climate cannot be observed. Third, the present anthropogenic climate forcing combined with the present-day climate baseline, is a unique development of the Earth's climate system.

When run with the present-day atmospheric composition of greenhouse gases, solar variability and land use, climate models simulate the present-day climate. Climate models are also used to model past and alternative future climates under external forcing scenarios, such as anthropogenic greenhouse gas emissions and land use change. It is important to note that all projections are conditional to their underlying assumptions and that specific projections apply for the specific forcing scenarios used, such as the assumed future greenhouse gas emissions.

As we do not know what the 'right' future emissions are, climate simulations are not 'predictions' in the same sense that we tend to view weather forecasts. Thus, the choice of emission scenario can be considered a source of uncertainty in climate projections. Possible major changes in natural climate forcing (solar variability, volcanic eruptions etc.) are another source of uncertainty, but they are not usually considered a climate *projection* uncertainty, since the projections concern climate change due to *anthropogenic* forcing.

A second source of uncertainty in climate projections is related to the different degrees of scientific understanding of climate system processes and to what level of detail they can be modelled with available computing resources. Climate models have different resolutions and differ in terms of how

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M. Quante and F. Colijn (eds.), *North Sea Region Climate Change Assessment*,
Regional Climate Studies, DOI 10.1007/978-3-319-39745-0

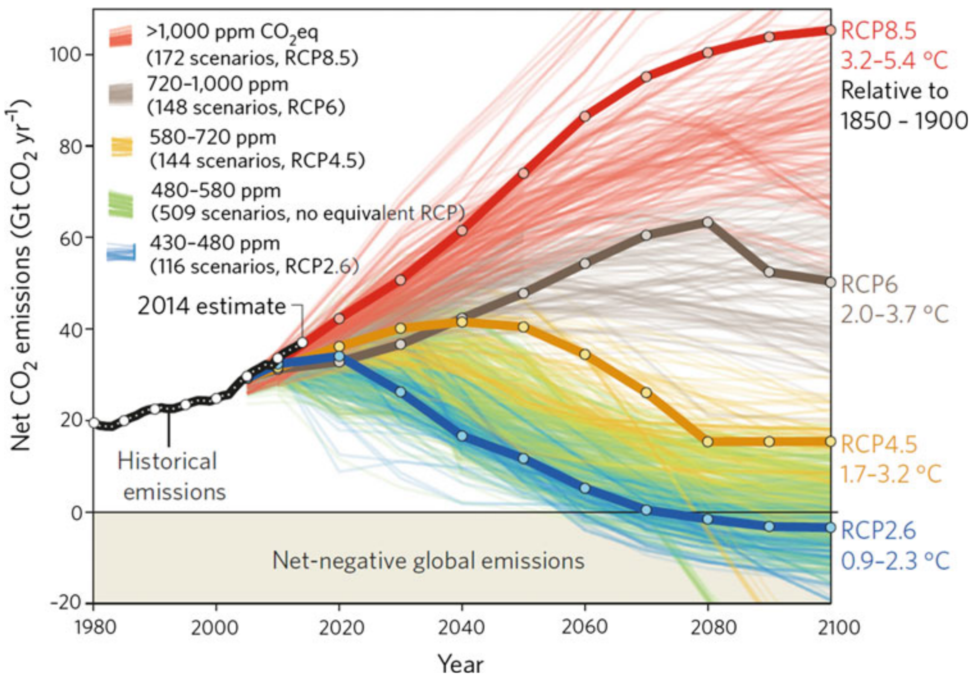


**Fig. A3.1** Carbon dioxide emission pathways until 2100: historical emissions from fossil fuel combustion and industry (*black*), and from the early 2000s, possible future pathways based on emissions scenarios also used by the Intergovernmental Panel on Climate Change in its Fifth Assessment (Collins et al. 2013; Cubasch et al. 2013; IPCC 2013a). The Representative Concentration Pathways (RCP) are used in CMIP5 (Fuss et al. 2014). Reprinted by permission from Macmillan Publishers Ltd: Nature Climate Change 4, copyright 2014

climate processes are included and parameterised. This may affect their responses to forcing and lead to different climate models depicting smaller or larger changes compared to other models.

Internal variability is a third source of uncertainty in climate projections. It is created within and inherent to the climate system itself and arises, for example, from large-scale ocean–atmosphere interaction. On regional scales, internal variability is often larger than how it manifests itself in global mean quantities. For example, interannual temperature variability is larger on the scale of, say Europe, than in the global mean.

## A3.3 Main Sources of Uncertainty

### A3.3.1 Climate Forcing

Climate projections are conditional to their underlying emission scenarios (this is referred to as 'emission uncertainty'). The higher the level of forcing, the greater the response of the climate system. As the 'correct' future emissions are yet unknown, the question of 'how much will climate change' becomes more like 'if the emissions develop this way or that way, how much will climate change?' This collapses the emission uncertainty into specific emission pathway alternatives, with the subsequent projection being specific to the particular emissions. However, as discussed below, such projections are still subject to other sources of uncertainty.

Climate projections are developed for a wide range of emission scenarios—from strong mitigation futures (low emission scenarios) to unabated emissions (high emission scenarios). Figure A3.1 illustrates the greenhouse gas emission pathways for a number of anthropogenic climate forcing scenarios (the four so-called RCP scenarios; Representative Concentration Pathways, see Moss et al. 2010. The 'representative' comes from the fact that they exemplify an even larger body of forcing scenarios from different studies; see the thick and thin lines in the graphic). The global CMIP5 climate projections are driven by these RCP-scenarios. It is not relevant here to describe in detail each of these scenarios, just to stress that each RCP implies a different amount of anthropogenic emissions and that they lead to rather different climate change outcomes for the medium term and even more so on longer time scales beyond the mid-21st century. Over the next couple of decades, anthropogenic emissions and thus atmospheric greenhouse gas levels are more or less already committed due to the existing energy-related infrastructure and investment flows, and land use change, etc. (e.g. Rummukainen 2015). In the longer term, both emission reductions and continued increases are in principle possible, depending on socio-economic developments (for example energy systems, technology, economic growth, policy, …). More information on emission scenarios is provided in Annex 4.

### A3.3.2 Model Uncertainty

Climate models employ different resolutions, different numerical techniques and different parameterisations, and these are all sources of some uncertainty. For the purposes of this Annex, this is referred to as 'model uncertainty'.

The basic equations for the atmosphere and the ocean comprise a non-linear system. In climate models, the system of these equations is solved numerically. The solution is thus an approximation. Another issue is that climate system processes occupy a very wide range of spatial and temporal scales, and scale interactions are important. While larger scales can be explicitly simulated, phenomena that occur at scales smaller than the model resolution need to be expressed in terms of resolved large-scale features, that is, 'parameterised'. Examples of such processes are turbulence, convection and the influence of detailed surface characteristics. Also, parameterisations build on physical understanding. However, the complexity of the processes and interactions opens up different ways of describing a certain process. This leads to differences between climate models which may affect their climate sensitivity and subsequently projections.

A summary measure of this is the equilibrium climate sensitivity (ECS) which is defined as the long-term global mean temperature rise due to a doubling of carbon dioxide concentration in the atmosphere. The magnitude of climate sensitivity depends on the net effect of the various changes in the climate system due to warming. For example, a warmer atmosphere can hold more water vapour, which—being a greenhouse gas—enhances the warming (this is an example of a 'positive' feedback). Other key feedback is related, not least, to clouds. How these and other aspects of the climate system respond to emissions in the climate models varies to some extent for different parameterisations. For GCMs, climate sensitivity is not a predetermined parameter but is the combined effect of all processes represented within the models, and varies from about 2 °C to around 5 °C. For emission and atmospheric concentration scenarios other than a doubling of carbon dioxide concentration in the atmosphere, the range in the projected change in temperature will differ from that which corresponds to the equilibrium climate sensitivity.

### A3.3.3 Internal Variability

Internal variability is an inherent characteristic of the climate system. Two well-known examples are the El Niño Southern Oscillation (ENSO) and the North Atlantic Oscillation (NAO). These are both intrinsic to the climate system even without external forcing. ENSO, for example, arises from the interplay between the atmosphere and the ocean. Analogous to the real system, climate models generate internal variability in the simulations, which can be compared to observed characteristics. However, climate models simulate *possible* courses of internal variability, whereas the real system follows the *actual* course. When a model is run many times with different initial conditions or other slight changes, the resulting simulations exhibit different courses of internal variability, while still possibly showing comparable climate statistics in terms of averages, trends and so on. This is embodied in the term *projection* (which is used instead of *prediction*).

Addressing internal variability is relevant both when evaluating climate models and when interpreting climate projections. For example, as the courses of internal variability differ in observations and models, the timing of NAO-phases (and their regional imprint on temperature and precipitation) can also differ. When comparing different climate projections, some of the difference in the projected changes may be because the models are in different internal variability states (Räisänen 2001). Internal variability can also mask—or enhance—climate change signals over some specific period. Successive changes relative to some reference period need to become sufficiently large before they become statistically distinguishable from historical climate variability (e.g. Kjellström et al. 2013).

### A3.3.4 Relative Importance of Different Sources of Uncertainty

The relative importance of the climate forcing uncertainty, model uncertainty and internal variability varies with the time horizon and the spatial scale (e.g. Hawkins and Sutton 2009).

For the next few decades, the climate forcing uncertainty is small. This is because possible future emission pathways are not likely to diverge significantly over the short term. Also, because the impact of emissions unfolds with a delay, the past and present emissions will continue to affect the climate for some time to come. Towards the end of the 21st century, emission uncertainty typically becomes the largest contributor to climate projection uncertainty if the full range of global emission scenarios is considered. If some subset of emission scenarios is studied instead, for example very ambitious mitigation scenarios, other sources of uncertainty may govern the spread of results.

The relative importance of internal variability diminishes with time, as the climate change signal increases. The relative importance of internal variability is also smaller for global mean values than for regional projections. Thus, near-term regional climate projections may show fairly different results, depending on whether the simulated internal variability enhances or dampens the climate change signals (e.g. Kjellström et al. 2013).

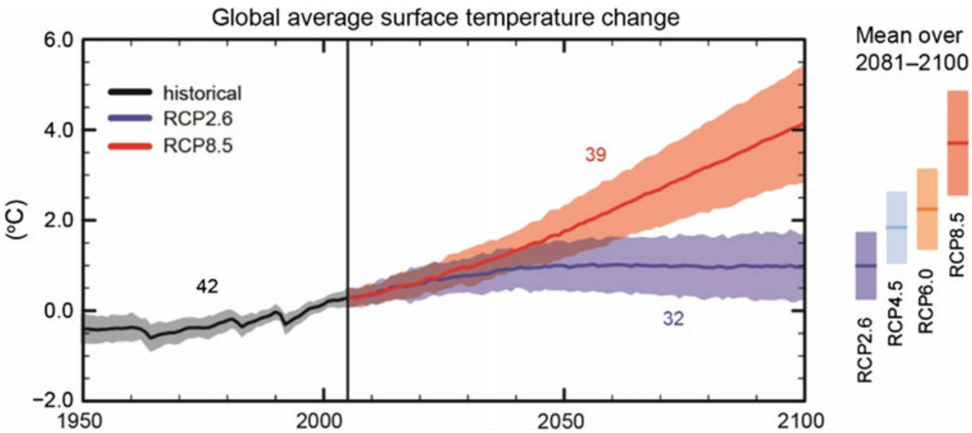


**Fig. A3.2** CMIP5 multi-model simulated change in global annual mean surface temperature through the 21st century relative to present-day conditions (1986–2005). Time series of projections (*coloured lines*) and a measure of uncertainty (*shading*) are shown for scenarios corresponding to RCP2.6 (*blue*) and RCP8.5 (*red*). *Black* (*grey shading*) indicates the modelled historical evolution using historical reconstructed forcings. The numbers of CMIP5 models used to calculate the multi-model mean are also shown (IPCC 2013b: Fig. SPM.7, panel (a). Abridged caption)

Climate projections consistently show that anthropogenic greenhouse gas emissions lead to warming, sea level rise, etc., and that smaller (larger) emissions cause less (more) warming. Model uncertainty is nevertheless a factor to consider when assessing the magnitude of the changes and in some cases also the spatial patterns. The emission uncertainty, when considering a wide range of scenarios, catches up with the model uncertainty over time. This is illustrated in Fig. A3.2, where the envelopes show a measure for model uncertainty along high (red) and low (blue) emission scenarios.

## A3.4 Quantifying and Qualifying Uncertainties

Climate models undergo continuous evaluation, not least by comparing simulations of the recent past and present-day climate to a range of observations (Räisänen 2006). Model intercomparisons provide additional information.

Overall, climate models simulate well many key aspects of the climate system, but there are also phenomena for which their performance is lower (Flato et al. 2013: e.g. Fig. 9.44). Models' performance also varies to some extent between regions, as is illustrated in Fig. A3.3. The models reproduce the large-scale features of global temperature and precipitation. The latest generation of GCMs have high pattern correlations with observations (0.99 for mean temperature and 0.82 for mean precipitation; Flato et al. 2013). In the case of temperature, relatively large model biases are nevertheless found in some coastal regions, close to sea ice edges, and in regions with major orographic features. In the case of precipitation, bias patterns are more varied. Biases can often be associated with specific physical phenomena (such as coastal temperature bias in upwelling regions) and/or resolution (such as the contrast in characteristics across the sea ice edge, or the lower resolution of orography in climate models than in reality).

Multi-model ensembles are a useful way to provide some quantification of uncertainties. While multi-model mean can be a useful indicator of trends, the spread of model results informs on uncertainty ranges due to internal variability and model uncertainties. A model can also be run a number of times with small variations to parameters in the parameterisations, within reasonable ranges, to gauge the significance of related model uncertainties (Murphy et al. 2004).

## A3.5 Downscaling

The resolution of global models is typically lower than is desirable for climate impact studies and regional climate assessments. In regions with homogeneous physiographical features, or for large-scale time-averaged quantities, GCM-data may be sufficient as such or after interpolation. In many regions, however, while being conditioned by the large-scale conditions, local-to-regional climates are also significantly influenced by effects of variable land and ocean basin forms and heterogeneous surface characteristics. High resolution also facilitates simulation of small-scale temporal behaviour, such as extreme precipitation. RCMs are used for downscaling GCM output. This is also coined 'dynamical downscaling'. (Statistical downscaling is another method, but does not concern climate models.)

Dynamical downscaling extends information from global models with additional local-to-regional scale detail

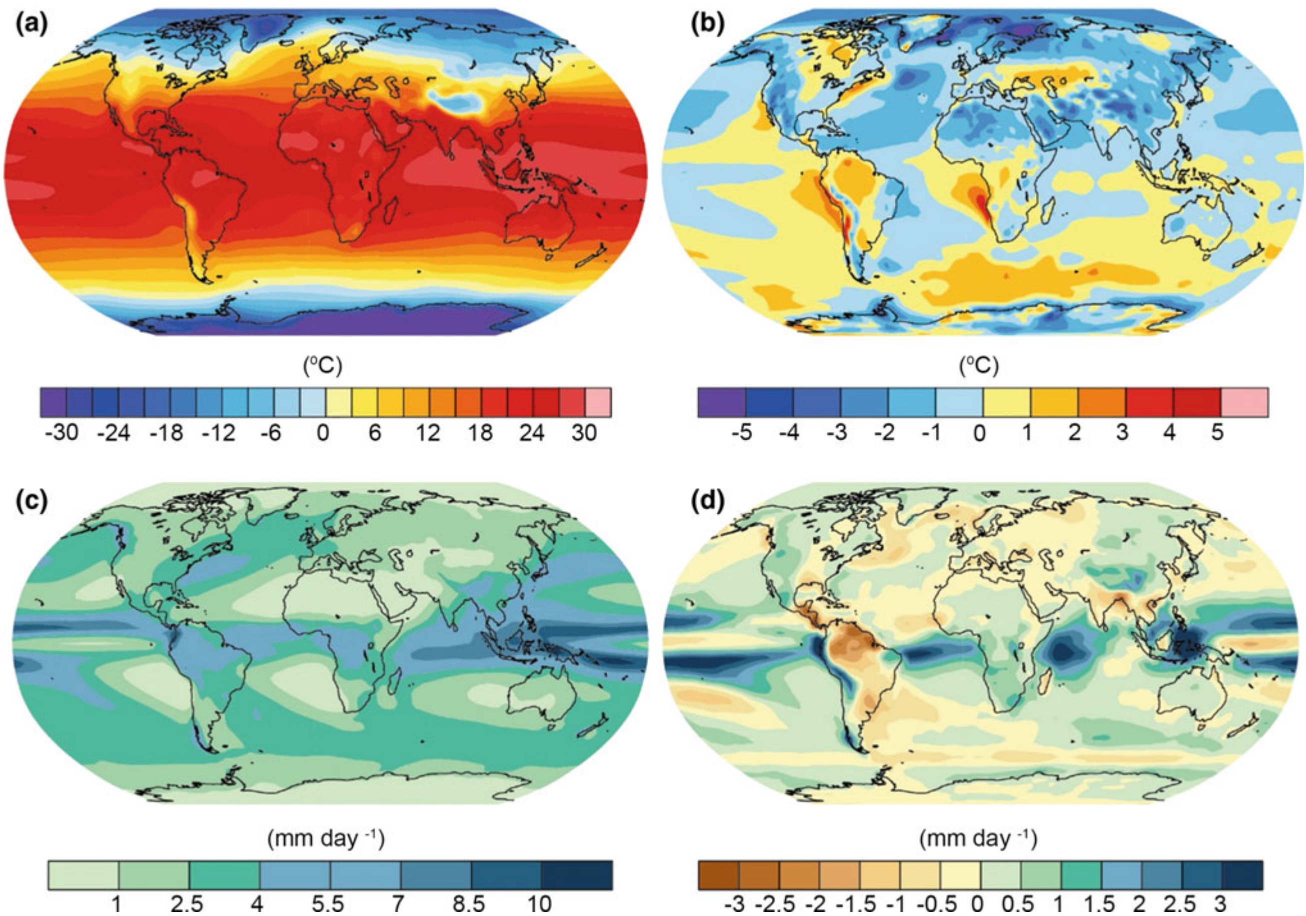


**Fig. A3.3** Annual-mean surface (2-m) air temperature (°C) for the period 1980–2005: **a** multi-model mean for the CMIP5 experiment, **b** multi-model-mean bias as the difference between the CMIP5 multi-model mean and the climatology from ECMWF reanalysis of the global atmosphere and surface conditions (ERA)-Interim (Dee et al. 2011). Annual-mean precipitation rate (mm day$^{-1}$) for the period 1980–2005: **c** multi-model-mean in the CMIP5 experiment, **d** difference between multi-model mean and precipitation analyses from the Global Precipitation Climatology Project (Adler et al. 2003). Note the different scales for the respective mean and bias maps (Flato et al 2013: Figs. 9.2 and 9.4, panels (**a**) and (**b**). Abridged caption)

(Rummukainen 2010; Rockel 2015; Rummukainen 2016). Many RCMs feature an atmospheric and a land surface component, in which case sea-surface temperature and sea ice information is provided from the driving global model, which also provides the other boundary conditions for the regional model (see below). Regional interaction between the atmosphere and the ocean is not dynamic in such RCMs. There are, however, also regional ocean and coupled atmosphere–ocean RCMs (e.g. Döscher et al. 2002; Schrum et al. 2003), for example for the Baltic Sea, the North Sea, the Arctic Ocean and the Mediterranean Sea.

The same overarching sources of uncertainty apply for both global and regional climate models. An RCM covers a specific limited area domain (cf. Fig. A3.4). RCMs feature the same basic equations as GCMs, and are thus subject to emission uncertainty and model uncertainty, and generate internal variability. In terms of projections, RCMs are also affected by their boundary conditions, that is, the GCMs that are being downscaled. In a way, GCM uncertainty could be likened to emission uncertainty in the sense that a particular RCM projection is conditional to the choice of the emission scenario and the boundary conditions. The latter comprise large-scale inflow and outflow (winds, temperature, humidity) into and from the regional domain, from the driving GCM. RCMs can also be provided with boundary conditions from global reanalyses (e.g. Dee et al. 2011), which is often the case in model evaluation studies as comparison with actual observations is more straightforward than in the case of runs with boundary conditions from GCMs.

A key motivation of RCMs is that they facilitate simulations at higher resolution. Today, RCMs are starting to provide climate simulations at resolutions of 1–10 km, compared to around 25 km some 5–10 years ago, and 50 km or more some 10–15 years ago.

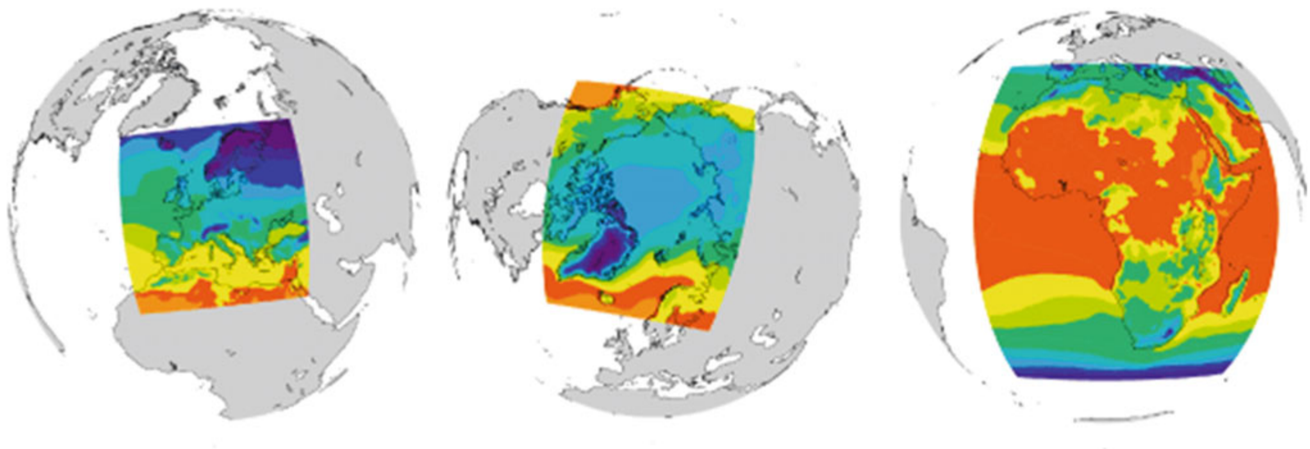

**Fig. A3.4** Three examples of a regional climate model domain; for Europe, the Arctic region and Africa. The colours indicate simulated temperature climate. Figure courtesy of the Swedish Meteorological and Hydrological Institute (SMHI)

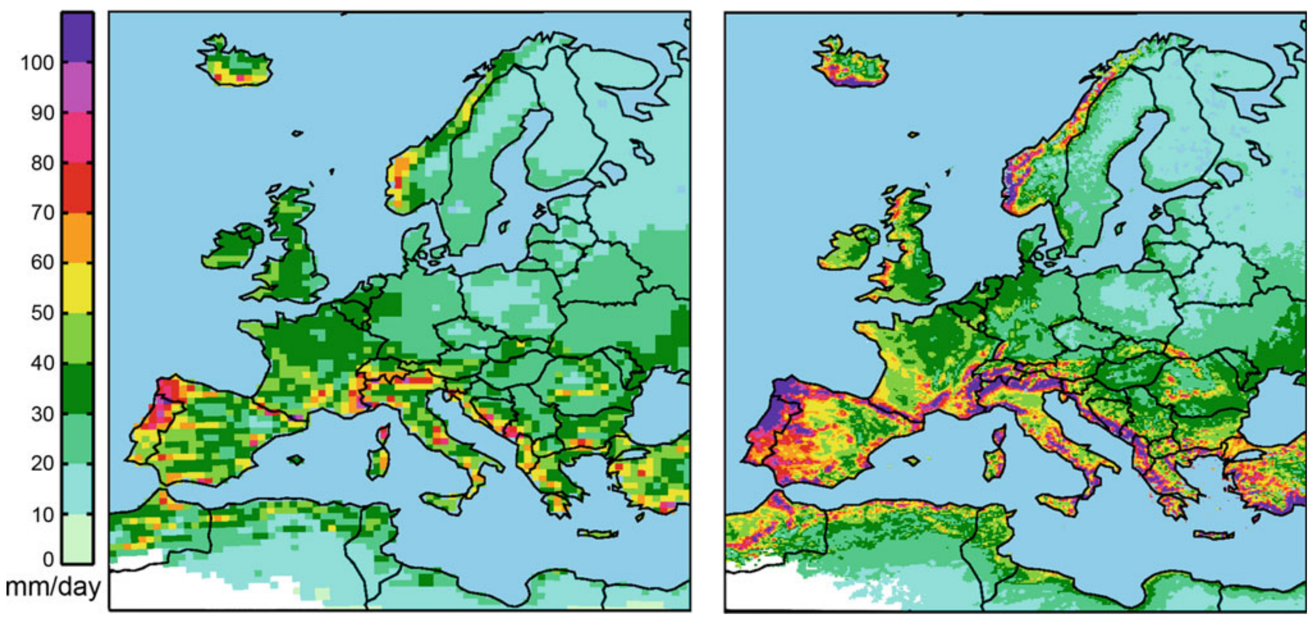


**Fig. A3.5** Simulated precipitation intensity with a 20-year return period in winter and for 1971–2000 from a 50-km RCM run (*left*) and a 12-km RCM run (*right*). Differences are evident along many coastlines and in regions of variable orography. Figure courtesy of SMHI

Compared to GCMs, in RCMs extremes can be studied more explicitly, geographical detail resolved better (consider an extreme case of a coarse resolution model for the Nordic region; would it be better to wholly open up the connection between the Baltic Sea and the North Sea by removing Denmark, or totally close off the Baltic Sea?) and suchlike. Figure A3.5 provides an illustrative example of how geographical patterns of extreme precipitation may be simulated in an RCM at two different resolutions. Precipitation patterns and amounts are positively affected, for example, in mountainous regions and along western coastlines.

Figure A3.6 shows an example of RCM projections, for wintertime warming in Europe. Here, a specific RCM has been used to downscale three projections from one GCM which has been run with three different emission scenarios. In all cases, the warming increases with time (compare the panels in each row from left to right), and is greatest towards the north-east. Larger emissions cause greater warming (compare the rows in each column). An indication of internal variability is evident not least in the first two columns. Even though the recent past and near-future emissions are comparable, the regional temperature changes differ. Here, internal variability either enhances or reduces the long-term

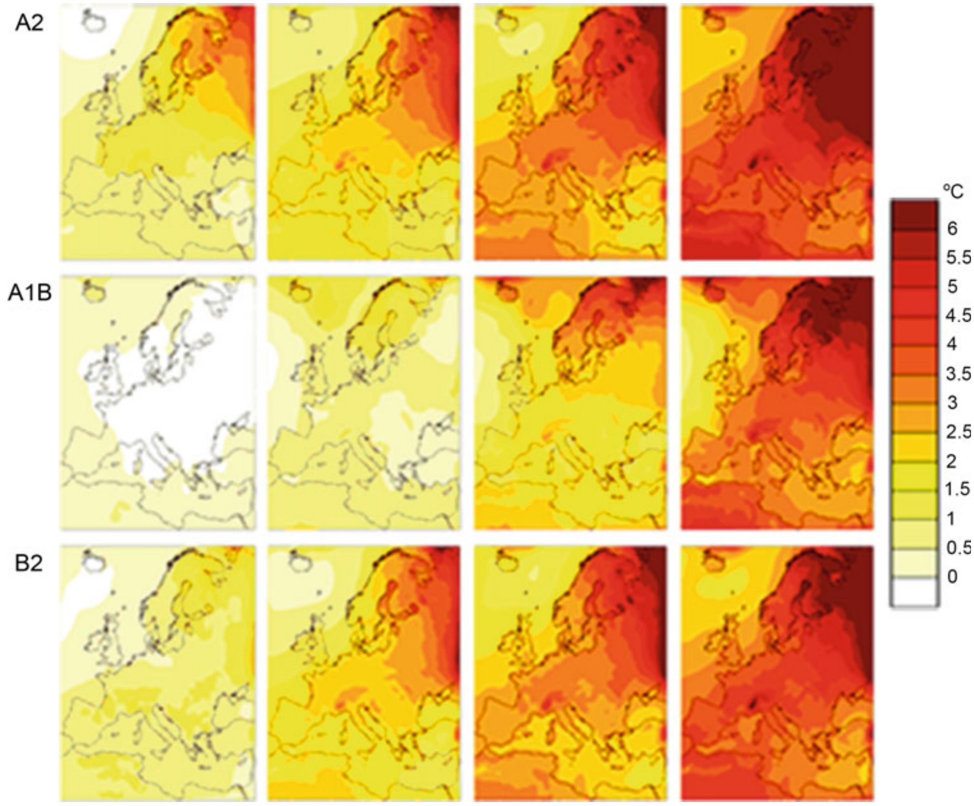


**Fig. A3.6** Projected winter season (DJF) temperature increase (°C) for Europe under three emission scenarios (among these, the greenhouse gas emissions are largest for the SRES A2 scenario and lowest for the SRES B2 scenario; these are from an earlier scenario compilation compared to the RCPs). The same global climate model (GCM) and regional climate model (RCM) are used in all cases. The columns depict, from left to right, projections for the thirty-year periods 1981–2010, 2011–2040, 2041–2070 and 2071–2100, compared to 1961–1990. Based on Kjellström et al. (2005)

trend, depending on the particular projection. With time, the warming increases and its magnitude surpasses the internal variability amplitude, after which the differences between the projections are primarily governed by emission scenarios.

The choice of GCM also matters. If the RCM and the emission scenario are the same, differences between regional projections should be due to the choice of GCM (including its climate sensitivity, internal variability and possible model biases), and internal variability generated in the RCM. For large forcing, the latter can be expected to be small especially for temperature change. For other aspects, such as precipitation and wind, it may still be considerable, if the forced change is small and/or the phenomenon is characterised by large variability, such as extreme winds.

Figure A3.7 shows regional temperature and precipitation projections for the Baltic Sea region for the early, mid- and late 21st century, based on data both directly from GCMs and after their downscaling with an RCM. Temperature changes on this scale are comparable between GCMs and RCMs. The same applies for precipitation in winter for this region, but less so in summer. For the latter, the precipitation change in the GCMs varies from decreases to increases, whereas the range after downscaling is from no change to increases. There is also a tendency for larger (smaller) changes after downscaling than the direct GCM results in winter (summer).

## A3.6 Discussion and Conclusion

All models and all observations are subject to some uncertainty, whether this is due to limitations in understanding, the instrument, model or experimental design, or some other reason. However, these uncertainties can be understood and communicated in ways that both highlight the robust knowledge and inform usefully on its limitations.

Climate models are the primary means for acquiring scientifically sound information on alternative future climates. Climate projections have utility, but also uncertainties. Uncertainties are, however, bounded and can be studied and characterised in informative ways. Continued climate system observations (such as on the deep ocean heat content) and increasing computing capacity (to allow for increased model resolution, larger model ensembles, incorporation of new model components) can contribute to reducing these uncertainties. Nevertheless, climate projection uncertainty will never be reduced to zero. Even if climate models were perfect depictions of the climate system, uncertainty related to climate forcing, i.e. the future emissions, would still persist. Also, there is no reason to expect that the time evolution of simulated internal variability should match the observed one other than statistically.

In terms of long-term global climate projections, uncertainty on future emissions is of primary importance. Larger

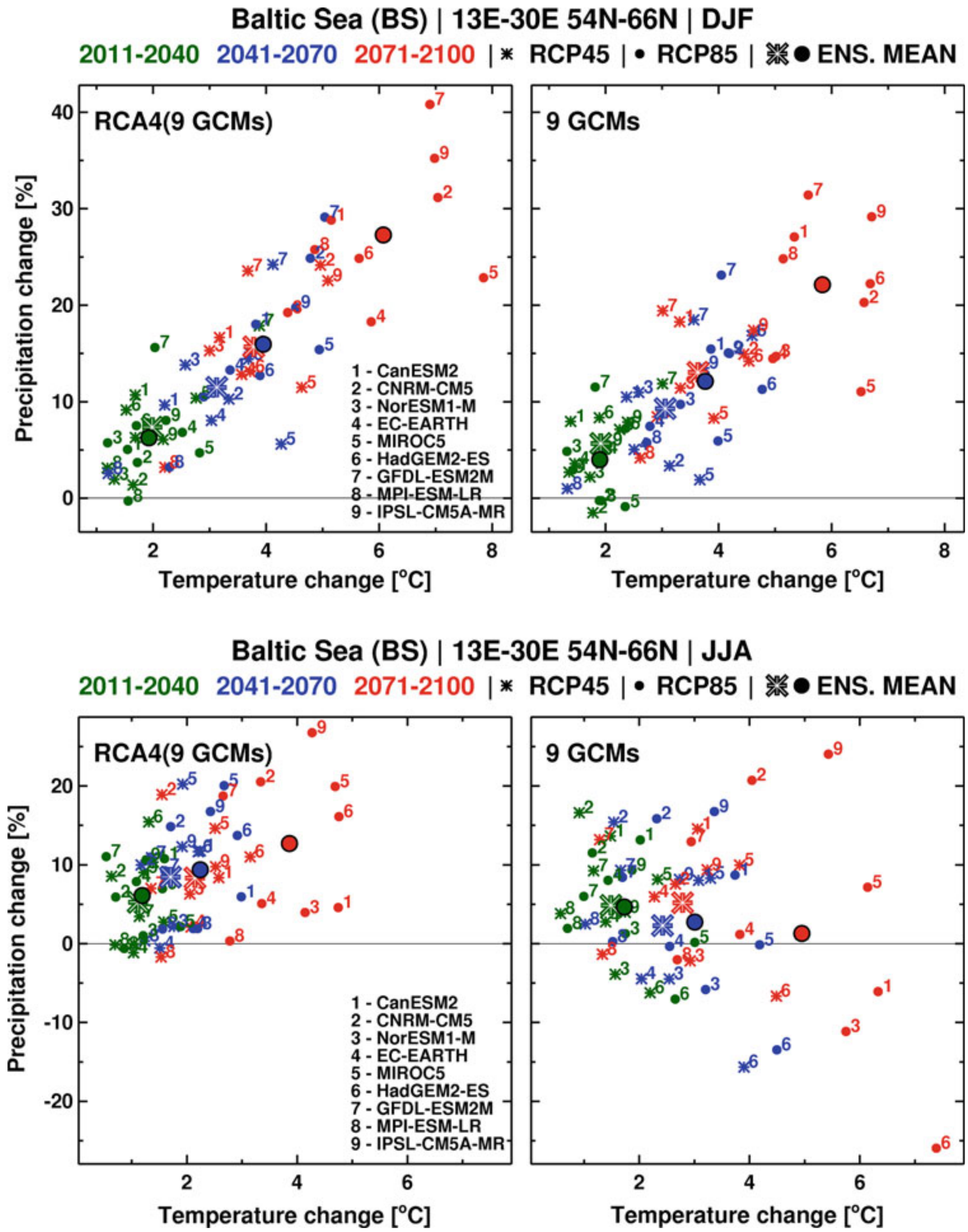


**Fig. A3.7** Results from nine GCMs (*right-hand panels*; the numbers identify the GCMs) and after downscaling with the Swedish RCA4 regional climate model (*left-hand panels*). The plots show projected winter (DJF, *upper*) and summer (JJA, *lower*) precipitation and temperature changes for the Baltic Sea region as a whole. Two different climate forcing scenarios (RCP4.5 and RCP8.5) underlie these projections. They are identified by different symbols as depicted at the top of the panel. The colours indicate results for successive 30-year periods during the 21st century. The large symbols correspond to the GCM and RCM ensemble means, in the respective plots. Figure courtesy of SMHI

emissions lead to larger changes and smaller emissions to smaller changes. But how large and, respectively, how small, is subject to model uncertainty, i.e. how well relevant climate processes are represented. For the near-term, uncertainty related to internal variability can be comparable to model uncertainty, whereas emission uncertainty is small. Internal variability becomes less of a concern with increasing projection time horizon (i.e. mounting cumulative emissions), especially at a global scale.

Downscaling inherits uncertainties already present in the driving global model and the underlying emission scenario. Downscaling can, however, improve the projections by taking into account the effect of topography on near-surface climate phenomena, which in many cases is relevant for temporal and spatial information, for example in regions and at scales on which orography and land-sea distribution is important. Downscaling is also useful for studying phenomena with high spatial and/or temporal resolution, such as precipitation extremes.

Uncertainties in climate change projections need to be studied, characterised and managed. Although use of single projections can provide an example of alternative possible future conditions in an application, it is generally advisable to use results from many climate models in climate scenario analysis or impact assessment. This makes it possible to highlight robust outcomes as well as to identify results that should be considered more uncertain. A further alternative to the use of many single scenarios can be the generation of probabilistic projections, such as ensemble means and spreads, for applications which have the possibility to use such information.

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