Technical Report for ONR-RRR-115:

Uncertainty in Climate Change Projections

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This is a literature review based on peer-reviewed academic papers and has been written in response to an ONR request and follows ONR-RRR-055.

1. Introduction

Climate change projections are crucial for policy planning surrounding mitigation and adaptation strategies, as well as engineering design. Climate models are the prime tool for generating the information needed to create climate change projections. Multi-model ensembles of climate models are forced with scenarios of future atmospheric composition which includes greenhouse gases, and from these ensembles the emerging data are analysed to establish directions and amplitude of climate change for regions. In many cases further numerical tools are required to produce bespoke projections, for example from hydrological models in relation to flooding. These steps are necessary where the spatial scale of the climate change impact is much smaller than the scale that is resolved by the climate model itself.

Uncertainties accrue at every step in the process of producing climate change projections (Cox and Stephenson 2007). The size of the uncertainties and their relative importance depend heavily on the time scale of prediction, the variable for which prediction is being made and the region in consideration.

The kinds of uncertainties involved can be classified into:

- inherent climate model uncertainties;
- climate model uncertainties which are known to depend on issues with climate models that can be circumvented given sufficient resource;
- future emission scenarios;
- uncertainties involved in parameterisation of poorly-modelled processes

Other uncertainties include those where climate mode outputs are used to drive models of earth surface processes (Harrison et al. 2019).

Successful climate projections at small spatial scales which are useful for policymakers assume:

1. that the uncertainties in climate projections are well known and knowable
2. that the impact of climate change on Earth Surface Systems (ESS) is predictable at those scales,

3. that climate model uncertainty and system response uncertainty is fully appreciated by policymakers and end-users.

In this report, we start by assessing future emission scenarios since they are largely independent of climate model uncertainty (Section 2). The report progresses to consider issues about uncertainty inherent to climate or our understanding of climate also independent from models (Section 3). Section 4 deals with climate model uncertainty. Section 5 considers ways in which climate model uncertainty is dealt with.

General Issues:

Difference between boundary condition values and initial condition values.

There are many types of uncertainty and several of these relate conceptually to the distinction between so-called boundary value problems and initial value problems (see Pielke 1998; Rial et al. 2004; Giorgi 2005). Boundary value problems (for example atmospheric greenhouse gas concentrations) are those which set the parameters driving the evolution of the system. Uncertainties arise when the structural or architectural elements of the system are incompletely specified and the start and endpoints of system evolution are difficult to constrain. Initial value problems on the other hand, occur when the evolution of the system is driven by the precise specification of the system. Uncertainty in this evolution concerns the exact disposition of the internal states of the system. The differences between boundary value problems and initial value problems are one of scale and we must recognise that the small-scale dynamics of a system (e.g., weather) may be effectively decoupled from its large-scale average behaviour (e.g., climate). Essentially, we can see this within the context of chaotic and emergent structures in a dynamically-evolving system (e.g., Harrison 2012; Daron and Stainforth 2013).

Use of ensembles.

It has been long known that GCMs are better at simulating temperature than precipitation and that no single model is able to represent trends on a spatially-consistent basis (Crawford et al. 2019). As a result, ensembles of climate models are regularly employed as it is known that a multi-model ensemble mean (weighted or unweighted) is superior to any individual model. Climate model ensembles can be constructed in several ways, including by using a range of different models forced by emissions scenarios, or by one model run many times with perturbations in the model parameters. A common way to generate an ensemble is through sets of initial conditions containing small variations (e.g. perturbed physics ensembles) that

lead to different subsequent climate trajectories. However, it is often assumed that all models are of equal value (called model democracy) and this means that models are unweighted in the final assessments and decisions have to be made about how to construct multi-model ensembles and how to assess model 'weights' (i.e. are some models to be given more credibility in the construction of the multi-model ensemble?). If so, this can be achieved using linear regression (e.g. Kharin and Zwiers 2002), different weighting techniques (e.g. Haughton et al. 2015); historical performance (e.g. Brunner et al. 2020) and Bayesian techniques (e.g. Massoud et al. 2023.

2. Future Emission Scenarios

There is no known method for the objective generation of data sets that specify future emissions of greenhouse gases and other important gaseous constituents of the atmosphere such as aerosols. Such emissions depend on socio-economic developments in the 21st century and beyond which cannot be known given the current state of social-science theory and its poor predictive capability. However, data on likely future emissions are vital to any climate model simulation aimed at creating projections of future climate. To overcome this impasse, scenarios of future emissions have been created each of which maps onto a particular storyline of how future decades might unfold. These scenarios have changed for each of the last three rounds of Coupled Model Intercomparison Project (CMIP) modelling exercises. These are the internationally organised efforts to coordinate model experiments across the world's modelling centres. CMIP6 (Eyring et al. 2016) used Shared Socio-economic Pathways (SSPs; O'Neill et al., 2016). These scenarios show that different levels of radiative forcing can be achieved by different combinations of GHG, atmospheric aerosol loadings and land-use scenarios (e.g., Amann et al. 2013).

The key scenarios are as follows:

1. scenarios with high and very high GHG emissions (SSP3-7.0 and SSP5-8.5) and CO_2 emissions that roughly double from current levels by 2100 and 2050 respectively;
2. scenarios with intermediate GHG emissions (SSP2-4.5) and CO_2 emissions remaining around current levels until the middle of the century;
3. scenarios with very low and low GHG emissions and CO_2 emissions declining to net zero around or after 2050, followed by varying levels of net negative CO_2 emissions (SSP1-1.9 and SSP1-2.6).

In previous CMIP exercises, different scenarios were used. In CMIP5, four Representative Concentration Pathways (RCPs) namely RCP 3-PD2; RCP4.5; RCP6 and RCP 8.5 replaced the 4 SRES (Special Report on Emission Scenarios) portfolio which underpinned CMIP3 (There was no CMIP4).

CMIP output underpins the respective Intergovernmental Panel on Climate Change (IPCC) reports as follows: CMIP3-AR4; CMIP5-AR5; CMIP6-AR6.

Emission scenarios are vastly divergent covering possible futures that include the aggressive use of fossil fuels in future decades against the rapid adoption of green technologies. The emission scenarios are a prime source of uncertainty in climate change projections. For projections relating to global decadal mean annual temperature, which is the most basic metric of climate change, emission pathways dominate uncertainty especially over multidecadal to centennial timescales, and this uncertainty range increases into the future. For other variables, such as precipitation, the impact of scenario uncertainty is offset by climate model uncertainties (Figure 1).

Skill in predictions

Model skill varies considerably with location and the metrics of interest. For instance, skill for multi-year to decadal precipitation forecasts is generally much lower than for temperature. In contrast, predictions of near-surface temperature are relatively skilful over specific regions; for instance, over the North Atlantic (e.g. Boer et al., 2013; Yeager and Robson, 2017), and this is associated with the predictability of the North Atlantic subpolar gyre allowing changes in ocean conditions to be predicted several years into the future.

3. Inherent Climate System Uncertainty

The climate system is an extremely complex fluid-solid system that involves energy, mass and momentum exchanges in four dimensions continuously. Within that system there will be non-linear interactions whose behaviour will be unpredictable no matter how well developed the climate models become (and this can be reduced to an issue of chaotic and non-linear processes (see Prigogine and Nicolis 1985). Part of the unpredictability relates to the sensitivity of the climate system to the starting point from which it evolves – often called the sensitivity to initial conditions. This sensitivity is a prime reason why weather forecasts lose skill rapidly after a few days but are also relevant on climate timescales (see Figure 1) particularly in relation to sub-surface ocean conditions. On climate timescales they include changes in the modes of variability

such as El Nino Southern Oscillation (ENSO), the North Atlantic Oscillation (NAO) and Atlantic Multi-decadal Variability (AMV).

Internal variability of the climate means that it is difficult to identify forced climate signals over short space and time scales (e.g., Hawkins and Sutton, 2009; Lovenduski et al., 2016; Suárez-Gutiérrez et al., 2017). The approach generally adopted to counter the sensitivity to initial conditions is to run ensembles of model experiments where the initial conditions are different from one experiment to the next.

Thus, even in an unforced world (one without anthropogenic radiative forcing) there would still be uncertainty in projecting future climate because of the operation of natural and internal climate variations, many of which are unpredictable and stochastic. These include volcanic eruptions which emit large amounts of aerosols into the troposphere and stratosphere; and changes in solar activity which changes Total Solar Irradiance (TSI). These forcings on the climate system cannot be anticipated although the impacts of these on future climate has been considered (e.g., Maycock 2016; Bethke et al. 2017). There may be ways in which climate variability interacts with and influences radiative forcing. For instance, increased volcanic activity is hypothesised to follow the melting of large ice masses as isostatic rebound perturbs ther earth's crust, and may also influence the variability of Atlantic climates.

4. Climate Model Uncertainty

This section provides details on the uncertainty which stems from the capability of climate models.

4.1 Climate model types

Climate models have been in development for at least the last 80 years and studies on the underlying physics for at least twice as long. Climate models are based on fundamental physical laws (e.g., energy, mass, and momentum conservation) and subdivide the Earth surface, oceans and atmosphere into 3D grids. The processes are discretised within grid squares and the equations governing the processes are integrated through time with the relationship between the time step in each integral and the grid square specified to rule out numerical instabilities.

The initial impetus to develop numerical models of the atmosphere came from the imperative of weather forecasting. Forecast models which specify the physics behind weather systems were

available to be adapted into climate models once the climate change issue became a line of research inquiry.

Components of the climate system, important on longer climate change timescales, including the role of oceans, were added to the model structure. By the 1980s models were relatively simple, portraying oceans with no currents and fixed atmospheric cloudiness (NRC 2012). Over the past few decades, the resolution of the models and the range of physical processes that are now included in the models has increased enormously (Figure 2). In more recent decades Global Climate Models (GCMs) have been developed by a number of modelling teams, and the outputs from these have been used extensively in IPCC reports since 1991. Much effort has also gone into developing the computer resources to run sophisticated climate models, especially as multiple simulations (ensembles) are now routinely run to evaluate model and initial condition uncertainty. The data sets bound up with climate change experiments are among the largest data sets in existence.

The size of grid squares defines the model resolution. In CMIP3 (developed for AR4; 2007), the horizontal typical resolution was about 250 km in the atmosphere and 1.5◦ in the ocean. For the 2013 AR5, the resolution of CMIP5 models increased to 150 km and 1◦ in the ocean (Stocker et al. 2013). Higher-resolution simulations down to 50 km in the atmosphere and 0.25◦ for the ocean are now performed at a few research centres (e.g., Davini et al. 2017). The oceans are typically subdivided into 30-60 layers and the atmosphere into 30-40 layers. IPCC AR5 (2013) GCMs have increased their resolution from about 50 to 25km since IPCC AR4 (2007; Haarsma et al. 2016) with Regional Climate Models (RCMs) operating at 10km or better resolution (e.g., Kendon et al 2012).

It follows that there is an array of climate model types which reflect the complicated history of their development which is superimposed on the urgent need to create better climate models for the purposes of climate change assessments (e.g., Kravtsov et al. 2018; Ridder et al. 2021).

Two prime types of numerical models used in climate change experiments are coupled (ocean-atmosphere) climate models, sometimes referred to as AOGCMs and Earth System Models (ESMs).

The key difference between AOGCMs and ESMs is that ESMs include a carbon cycle which typically includes interactive vegetation. ESMs are more realistic in terms of the processes that they include but with that comes greater degrees of freedom available to the model which often is expressed in divergent simulations of the future. In addition, in order for the models to run

sufficiently quickly, the spatial resolution of ESMs is coarse compared with AOGCMs. Regional climate models are a third key category. Global Climate Models (GCMs) are known to be of limited accuracy in predicting climate change impacts at small scales, including regional climate. Regional Climate Models (RCMS) have therefore been developed to allow climate projections down to scales of 25-50 km (see projects like PRUDENCE (Christensen et al. 2007)); down to 10km (Kendon et al. 2012); and Convection Permitting Models down to 2.2km in UKCP18 (Kendon et al. 2021) and 3km for Sub-seasonal to seasonal forecasts (e.g. Pal et al. 2019). Convection Permitting Models have been shown to have a much greater fidelity in simulating previously challenging climate systems or states which are dominated by thunderstorm systems.

4.2 Climate Model Deficiencies: missing elements in models

Climate models are without doubt one of the greatest scientific triumphs of the last one hundred years. The improvement in general numerical model capability is profound. Figure 3 illustrates this improvement between the early 1980s and present, which sees numerical model capability increasing linearly for several decades. This capability can only be demonstrated where the actual values for prior states of the atmosphere are known which is not the case for climate change over the course of the 21st century. Nevertheless, reducing the behaviour of the atmosphere to a set of equations which can be solved computationally exposes known elements of the climate system which are either not properly understood and therefore not sufficiently specified or which are reasonably understood but which cannot be properly specified in the models.

Given the long timescales over which the future climate will evolve, it is rarely possible to evaluate the accuracy of the model used to describe the system dynamics. Modellers have divided such issues into model inadequacy and model uncertainty (Stainforth et al. 2007a, b). They argue that model inadequacy reflects the degree to which models capture all the physical processes which are relevant to the system under study (Stainforth et al. 2005). There are at least three problems associated with this. First, we can have only partial understanding of all the processes that may be relevant for system development, especially those that occur over long timescales. Second, our understanding of small-scale processes must involve a form of parameterization, where the scale of model analysis is too coarse to capture all the relevant processes. Our understanding of how such small-scale processes affect the large-scale evolution of the system is, again, partial. Even if our model accurately described past system evolution, there is no guarantee that future change will similarly be defined. Third, because of

the scale of enquiry adopted, there may be elements of the system behaviour that follow from the physical processes driving the model, but which are not represented at all. As a consequence, our model only gives us a partial account of real-world processes and system behaviour, and therefore enables only a partial account of system evolution.

4.3 Deficiencies and uncertainty associated with model parameterisation.

Numerous processes important to the climate system occur at scales which are much smaller than the model grid boxes. These have to be presented via variables which are explicitly resolved – a process called parameterisation. Parameterised processes include convection, radiation, clouds, aerosol physics and dynamics in the boundary layers (e.g., Neumann et al. 2019; Hu et al. 2020). Other processes also have to be parameterised that occur at broader scales, but which are not yet resolved in climate models and these include the operation of large-scale gravity waves (e.g., Geller et al. 2011), large-scale ocean processes (Ferrari and Ferreira 2011), and land surface/boundary layer interactions.

Recently, high resolution simulations where model grid boxes are sufficiently small to represent processes such as convection, explicitly have allowed parameterisation of convection to be switched off in the models. Comparison between the version of the model with parameterised convection and versions of the model in which convection is permitted allows the error due to parameterisation to be quantified. There is clear improvement in the ability of models without parameterisation over those with parameterisation (e.g., Senior et al., 2021). However, running models with very high resolution sufficient to represent processes directly requires exponentially more computing power. Such computing power is not yet available to run global simulations for long enough to permit climate change experiments over many decades at the global scale. Were such computing power to become available, then not all parameterised processes could be dispensed with because there are currently no known equations in physics which specify a number of key processes. Many of the relationships specified in the parameterised processes are conditioned by empirical constants that are not well grounded in theory. An approach to deal with this kind of uncertainty is to run a climate model several times with differing constants specified for those values in empirical relationships that cannot be strongly defended in any theory. This approach encompasses perturbed physics ensembles (e.g., Sexton et al., 2012; Regayre et al., 2018).

Model uncertainty also arises because there are important drivers of future climate which cannot yet be modelled. These include some elements of landscape change such as ice sheet dynamics which are crucial to estimates of sea level rise, global albedo estimates and ocean circulation changes.

4.4 Uncertainties in specific features or components of the Earth System

This section discusses some ESS where climate model uncertainty materially reduces our understanding of the future evolution of these systems and, therefore, their impacts.

a) Sea level and ice sheet dynamics

Predicting the amount and rapidity of future sea level rise is a major issue for planners and risk managers. New infrastructure is being built near sea level (e.g., new build nuclear power sites) and risk managers are being increasingly asked to assess high magnitude and low probability sea level rise (e.g. van de Wal et al. 2022) and extreme climate and weather events with low probabilities ((i.e., 1:10,000 events). Increasingly valuable resources are at risk if rising sea levels change the magnitude and frequency of storm surges and hurricane landfalls.

Considerable modelling resources are being devoted to improving the accuracy of sea level rise models. Most of the present rise in global sea levels is currently due to the thermosteric rise, caused by expansion of the oceans as they have warmed. However, by the middle of the 21st century it is estimated that the dominant contribution will be from melting of the major ice sheets in Greenland and Antarctica (Rignot et al. 2011; Oppenheimer et al. 2019; Hanna et al. 2024).

IPCC AR4 (2007) underestimated future sea level rise because modelling of the dynamic behaviour of the ice sheets was incomplete. Since then, there have been advances in understanding ice sheet dynamics and better parameterisation of ice sheet models (e.g., Pattyn et al. 2012), although these still fail to capture crucial physical processes (Drouet et al. 2013; Pattyn and Durand 2013; Bradley and Hewitt 2024). IPCC AR5 WG1 has estimated that mass loss from the Antarctic ice sheet between 2002-2011 was 147 Gt/yr, and loss from the Greenland Ice Sheet (GIS) has increased to 25 Gt/yr over the same period. Evaluating whether these rates are part of an accelerating trend is of crucial importance and there are major challenges in modelling how ice sheet dynamics will evolve and how rapidly.

Future assessment of the dynamic evolution of the major ice sheets is hampered by a lack of understanding of the physical processes driving ice sheet melting and collapse. These physical processes include: the role of algae and aerosols in changing ice sheet albedo; the stability of grounding lines; the ways in which ice shelf and ice tongues calve and break up, the implications of this on the discharge of inland ice streams as debuttressing effects increase with ice shelf removal, and the role of meltwater in the subglacial zone of ice sheets (e.g. Davis et al. 2023).

Given our uncertainties in how ice sheets will behave in a warming world, there are clear advantages to increasing current understanding of the physical processes that need to be parameterised in climate models. For instance, recent advances have been made in understanding the migration of grounding lines (the junction in a marine-terminating ice sheet between the grounded ice and the floating ice shelf) as this is a crucial factor in explaining how ice sheets will respond to warming and sea level rise.

Ice sheet models with resolutions of 10-20km generally fail to reproduce grounding line migration (Pattyn et al. 2012) and much smaller resolutions may be required. Solving this requires either larger computational resources, or new modelling techniques but challenges in accurately using these to predict future sea level rise still remain (Drouet et al. 2013; Freer et al. 2023).

More recently, further debates have focused on the ways in which ice sheet and ice shelf processes have been parameterised. For instance, the debate about the role of Marine Ice Cliff Instability (MICI) and Marine Ice Shelf Instability (MISI) in driving ice sheet mass balance and sea level rise is currently unresolved (see Bassis and Walker 2012; DeConto and Pollard 2016; Edwards et al. 2019; Crawford et al. 2021; Schlemm and Levermann, 2021). In essence, 21st century global sea level rise projections exceed 1m under some MICI methodological choices (Edwards et al. 2019) but with wide probability intervals, and this hampers policy-relevant decisions. Similarly, the ways in which the basal regions of ice sheets interact with the surrounding ocean impacts ice sheet stability over decadal and centennial timescales (e.g. Pattyn and Morlighem 2020). Observations of the processes involved in ice sheet instability are clearly important to both developing and evaluating ice sheet models. Observations of ice sheet dynamics are difficult to obtain because the processes occur in extremely remote locations and often at depth beneath the ocean.

b) Atlantic Meridional Overturning Circulation

The Atlantic Meridional Overturning Circulation (AMOC) is the key circulation system of the Atlantic Ocean producing the conditions that warms northwest Europe. It moves around 20

million cubic meters of water per second (20 Sv). Warm surface water moves north, sinks in the North Atlantic and returns south as a cold deep current). In the past the AMOC has transitioned to a weak circulation mode (switched off) on several occasions and on these occasions, this has brought rapid and extreme cold to many parts of the globe, especially to North West (NW) Europe (e.g. during the Younger Dryas period between 12,900-11,700 years BP; Cheng et al 2020).

The AMOC is a clear example of a multi-stable component of the Earth system with two probable stable states: strong and weak circulation modes (Caesar et al. 2018; Bonnet et al. 2021). However, its sensitivity to external and internal dynamics means that modelling its future behaviour is crucial if we are to assess future climate change in the North Atlantic. Since the 1980s, concerns have been raised that the AMOC could undergo similar weakening or cessation of flow in response to global warming, although data at the time were lacking. Observations show a consistent 'cold blob' in the North Atlantic south of Greenland, and this is supported by climate model projections (Keil et al. 2020). The position of the 'cold blob' is important as it probably influences the behaviour of the summer jet stream, may enhance southerly wind flow and increase the likelihood of heat waves, and potentially increase the strength of winter storms.

From 2004 the RAPID-AMOC project has continuously monitored the AMOC, but the data set is too short to distinguish between long-term trends and short-term variability. It does show that variability is higher than thought, probably driven by wind forcing. Research has argued that a weakened AMOC produces reduced summer precipitation and increased windstorms in NW Europe (e.g. Jackson et al. 2015).

Slowdown of the AMOC (seen as a precursor to switching of the circulation and therefore rapid regional cooling) is reported by Caesar et al (2018) who used CMIP5 model projections of sea surface temperatures in the North Atlantic to compare with observations. They show that this pattern is consistent with slowdown of AMOC since the end of the 19th century. This is supported by Piecuch (2020) who reconstructed the behaviour of the Florida current (an important component of AMOC) since 1909 and shows that it is weaker now than for this time period. This reduction in northward heat transport is seen as sufficient to explain the 'cold blob'.

While weakening of the AMOC will probably cool NW Europe significantly, even during a period of rapid global warming (Weijer et al 2020), model uncertainty is significant(Lobelle et al. 2020; Jackson et al. 2023). IPCC AR6 reports that "The Atlantic Meridional Overturning Circulation will very likely decline over the 21st century for all SSP scenarios. There is medium confidence that the decline will not involve an abrupt collapse before 2100. For the 20th century, there is low

confidence in reconstructed and modelled AMOC changes because of their low agreement in quantitative trends". For CMIP6 models, "projected AMOC decline is also associated with a decline in NADW formation (Reintges et al., 2017; Weijer et al., 2020). The link between AMOC and NADW formation appears insensitive to the large range in model bias in NADW water mass characteristics".

Despite the intermodal spread of overturning strength in CMIP6 is as large (10-31 Sv) as in CMIP 5, and deep convection errors are still large in CMIP6 and the shallow bias in AMOC persists (Weijer et al., 2020). IPCC reports a large discrepancy between modelled and reconstructed AMOC in the twentieth century and report *low confidence* over the realism of the 20th century modelled AMOC response.

c) Northern Hemisphere Storm Tracks

There are two main northern hemisphere midlatitude storm tracks, one across the North Pacific Ocean and one across the North Atlantic Ocean. The storm tracks comprise individual midlatitude cyclones which are key to the transport of heat and also prime determinants of the precipitation regime. The heat and pressure gradient across the midlatitude atmosphere controls the location of the storm track since the storms exist to undo the gradient and derive their energy from that gradient.

In a climate change setting there are multiple controls on the heat gradient and therefore on the location of the storm track. Some controls lead to a poleward shift in the storm track, were they to operate individually. Other controls lead to an equatorward shift. Adjustments which lead to a poleward shift include the expansion of the tropical circulation system or Hadley Cell (Grise and Davis 2020), reduction in the cross latitude surface temperature gradient (e.g. Brayshaw et al 2008), increased lower troposphere isentropic slope (Butler et al 2011), increased tropopause height (e.g. Lorenz and DeWeaver 2007) and increased Rossby phase speeds (e.g. Chen and Held 2007).

Changes in subtropical stability and increased upper tropospheric air temperatures (e.g. O'Gorman and Singh, 2013) together with a weakened Atlantic overturning circulation lead to an equatorward advance of the storm track. Any model simulation needs not only to compute each of these effects precisely and accurately but also needs to enable the same interaction between these effects as is seen in the real world (e.g. Priestley et al. 2023). This is very difficult to achieve. The upshot is that for near term projections of the northern hemisphere storm tracks there is only medium confidence (Harvey et al. 2020).

d) Carbon Cycle

Anthropogenic emissions of carbon to the atmosphere are prescribed by the emissions scenarios. Uptake of the carbon by the ocean, land surface and vegetation needs to be modelled, as does the release of further carbon such as methane from tundra areas (e.g., Koven et al. 2013). Uptake on forest stores such as the Amazon also hinge on the regional climate response to warming, particularly precipitation. In some scenarios there is considerable carbon emission from a drying Amazon (e.g., Phillips et al 2009; Carvalho et al. 2020; Ritchie et al. 2022) and a warming tundra (e.g., Knowles et al. 2019; Plaza et al. 2019; Feng et al. 2020) .

e) Arctic sea ice

Climate change in the Arctic region has considerable impacts on mid-latitude Northern Hemisphere weather and is therefore of great interest to planners and climate adaptation specialists. Enhanced warming in the Arctic region (2-3 times the GMST rise) is known as Arctic Amplification and this is seen in observations and model projections (Senftleben et al. 2020). As a result, late summer (September) sea ice extent has reduced by about 13% per decade (e.g., Taylor et al., 2017; 2022) and September sea ice volume has declined by >70% since the early 1980s (e.g., Kwok 2018; Stroeve et al., 2014; Cai et al. 2021). This means that the Arctic Ocean is likely to become sea ice–free in late summer for the first time before 2050 and this is the case for all emission scenarios under consideration.

While the satellite-based observations of decline in Arctic sea ice over the period 1979-2019 suggest this decline is linearly determined by global mean surface temperature, the model projections show considerable variability (see Taylor et al 2022). Perhaps the key uncertainty in assessments of polar climates is the snow and ice albedo feedback and its interaction with cloudiness (e.g., Screen 2017; Yu et al. 2021). The former is probably responsible for the inter-model spread in Arctic warming and sea ice extent across numerous inter-model comparisons (Holland and Bitz 2003). The dynamic features of sea ice include melt ponds, sea ice thickness and floe size and these are too small to be resolved in climate models and therefore have to be parameterised.

Other model uncertainties include the inability to distinguish between those processes driving Arctic Amplification related to warm and moist air transport from the mid-latitudes to the Arctic

(e.g. Peng et al. 2020). As a result, changes we are seeing now in mid-latitude weather and climate could be both a cause and an effect of Arctic change. There are also discrepancies between observational data which show strong Arctic to mid-latitude climate connections, while models suggest much weaker relationships. Some researchers caution that while the influence of Arctic climates on mid-latitude climate may change, this might just be an artefact of the poor ability of climate models to capture the amplitude of these processes (Screen 2017).

Overall, recent studies (e.g., Bonan et al 2021) argue that for projections of early autumn (September) sea ice area (SIA) climate model structure contributes 30-80% of the total uncertainty to 2100. For March this changes to 40-80%. Internal variability contributes up to 60% of the total uncertainty in all seasons and therefore has a major influence on model projections at long lead times. This contrasts with climate model projections on other aspects of the climate system (e.g., global and regional temperatures and precipitation) where model uncertainty and internal variability reduce over time as a proportion of total uncertainty. Scenario uncertainty in SIA varies across the seasons; its effect on summer projections is high (accounting for 70% of total uncertainty) while in winter this reduces significantly. Bonan et al (2021) suggest this is because the "smaller contribution of scenario uncertainty to total uncertainty in winter likely reflects the fact that model uncertainty is so large that it diminishes scenario uncertainty in relative terms".

5. Dealing with Model Uncertainty

a) Model Evaluation and Development

Model development is a continuous and well-resourced process in the main modelling centres. It is also reasonably competitive among the main modelling groups. For every model version that is released for an exercise such as CMIP, there will be numerous sub-versions of the model and numerous categories of code aimed at improving the model performance. Models are typically evaluated against observations of the contemporary climate. A recent breakthrough in this process is the development of the ESMvalTool (https://www.esmvaltool.org/) which is a standardised assessment process applied to models used in CMIP and IPCC. ESMValTool provides the first cross-model benchmarking on model performance. The metrics against which the models are assessed increasingly use processes as a basis for assessing the workings of the model rather than simply standardised output such as temperature. Evidence shows that models develop incrementally from one CMIP exercise to the next. However, there are key model

errors that have been in place for decades, such as the difficulty that coupled models have in simulating marine stratus cloud in the subtropics. Attempts to rectify these kinds of errors often include focused field campaigns such as ORACLES and CLARIFY which aim to retrieve observations that can be used to confront the model simulations. Without such observations it can be impossible to know what the models should be simulating.

b) Assessing model output and model selection

Hawkins and Sutton (2009) argue that uncertainties associated with internal variability and model uncertainty dominates the total uncertainty (see Figure 1). Internal variability might not be reducible by any meaningful amount, but reducing model uncertainty would pay dividends for planners and would be possible given better observational data and improvements in model structure. Reducing this uncertainty would also lead to better regional predictions and this is certainly the case for decadal timescales and regional space scales. They end by arguing that "Because the costs of adaptation are expected to be very large, the clear implication (of their work) is that *reducing uncertainty in climate predictions is potentially of enormous economic value*" (Hawkins and Sutton 2009, p. 1102 italics added).

The simplest method for dealing with multiple model simulations is to produce a mean of all the simulations – the ensemble mean (Murphy et al. 2004). This method dominated early climate change research. The underlying assumption is that the forced signal common to model responses will be retained while the noise peculiar to any one simulation will be averaged out.

Although it is still used, a number of alternative approaches have evolved over the last 20 years. These included attempts to weight variables such that not all models were treated as having the same capability in creating the ensemble mean. Model weighting seems defensible in instances where one model can be shown to have a superior ability to simulate a relevant feature compared with another. The difficulty lies in that there is no consensus on what criteria to use to weight a model. One model may seem superior to another when judged according to how realistic its large-scale simulation of the global circulation is. But that same model may reveal an unusually poor simulation of the regional climate relevant to a particular application.

Decisions about which model to select are most relevant when regional model simulations are required for a particular application since regional models have to be forced by the evolving fields from a particular global model. There is seldom sufficient computing power to use all available global models to force a regional model.

Process-based model evaluation has been a feature of climate model evaluation for the last 5 years. The approach here is to establish how and why a climate model simulates a particular climate feature or change in future climate. Models which simulate climate features or future climate by means of processes which are deemed unrealistic are then regarded as outliers which can reasonably be ignored. This approach to narrowing the uncertainty range can prove to be extremely useful. Instead of building safeguards in infrastructure, for example, to accommodate an extreme outlier which stems from a particular climate model, it may be possible to demonstrate that the model simulation of that outlier is unrealistic.

For many climate impacts such as assessing hurricane impacts and ENSO, policymakers require medium timescale climate forecasts rather than projections out to the end of the century similar to those evaluated by IPCC. Such decadal forecasts are difficult to achieve because the forced climate signal (driven by GHG) is not much larger than the internal variability (Meehl et al. 2009) and this is especially true for sub-continental scales and for precipitation change (e.g. Pastén-Zapata 2022; Nourani et al. 2022). Important questions remain before such decadal forecasts are achievable. One of the most crucial is whether enough is known about ocean variability (e.g. Pacific Decadal Oscillation, Atlantic Meridional Overturning) to produce an accurate enough initial state to the climate model to predict its evolution, suggesting that IC uncertainty plays an important role at near-term climate prediction in the same ways as it does in weather forecasting.

c) How to quantify and reduce uncertainty

Some uncertainties can be reduced. For instance, internal climate variation is an intrinsic component of uncertainty and can be assessed probabilistically but cannot be reduced (see Figures 4,5,6). Model response uncertainty could be reduced, but probably only in a Bayesian context (see Sexton et al. 2012). They produce a concept called *discrepancy*, which reflects the “degree of imperfection in the climate model i.e., it measures the extent to which missing processes, choices of parameterisation schemes and approximations in the climate model affect our ability to use outputs from climate models to make inferences about the real system” (Sexton et al. 2012). This is another way of assessing model error and model uncertainty; failure to assess this increases the risk of making over-confident predictions.

Finally, there have been a number of initiatives to produce the observational and historical data with which to test climate models against known unforced variation, and to better assess the nature of natural variability. For instance, more information is required on the magnitude-frequency relationships of major floods than is obtained by relatively short instrumental records

(Longfield and Macklin 1999; Macklin and Rumsby 2007; Jones et al. 2010; CCRM 2011; Longfield et al. 2019).

In the future we will have models with much higher resolution. However, despite improvements in our understanding of small-scale physical interactions in climate systems there are still major problems in parameterising poorly-resolved processes such as gravity waves, convection and boundary layer processes. As a result, there are moves towards developing climate simulations at between 1 kilometre-scales (e.g., the Icosahedral Non-hydrostatic (ICON) model (Miyamoto et al. 2013; Neumann et al. 2019) to 4 km scales (e.g. Bretherton and Khairoutdinov 2015).

Overall, Giorgi (2010) argues that:

1. For late 21st century mean climate change projections the greatest sources of uncertainty are associated with emission/concentration scenarios and inter-model (AOGCM) configuration differences.
2. For early 21st century projections, the scenario uncertainty becomes secondary, and the contribution of internal model variability becomes of primary importance.
3. The contribution of internal variability increases when going from the global to the regional scale and it increases for higher order climate statistics.
4. Systematic model biases do not appear to strongly influence the projected changes in the majority of temperature and precipitation regional cases analysed.
5. In general, uncertainty is greater at the regional than the global scale.
6. The contribution of the different uncertainty sources vary with temporal and spatial scales.

d) The view from IPCC AR6

Given known and unknown uncertainties in climate model projections, IPCC AR6 has based assessments of future climate on numerical projections and a number of additional lines of evidence. However, they still caution that there is no clear way to weight multi-model assessments, and as a result, argue that expert judgement should be added routinely to the assessments (Masson-Delmotte et al. 2021).

It is known that CMIP6 ensembles project higher global near surface air temperature (GSAT) by the end of this century than CMIP5 because Equilibrium Climate Sensitivity (ECS) and Effective Radiative Forcing (ERF) are both higher in CMIP6 ensembles (e.g., Zelinka et al. 2020; Tebaldi et al. 2021).

In addition, in IPCC AR6 (2021, Chapter 4) the assessment of model uncertainty uses other lines of evidence. These include:

1. The CMIP6 multi-model ensemble (Eyring et al., 2016).
2. Single-model large initial-condition ensembles (e.g., Kay et al. 2015) and combinations of control runs with CMIP transient simulations (e.g., Olonscheck and Notz, 2017) to assess internal variability.
3. Assessed best estimates, *likely, and very likely* ranges of ECS and TCR, from process understanding, warming in the instrumental record, assessment of palaeotemperatures and emergent constraints (see IPCC AR6 Chapter 7). , The range of ECS and Transient Climate Response (TCR) are converted into GSAT ranges using a simple energy balance model (EBM see Held et al., 2010).
4. Model independence has also been used. This is asserted a priori and based on shared model components for atmosphere, ocean, land surface, and sea ice of CMIP5 models (Boé, 2018). Assuming model dependence means that those models with the same atmosphere or ocean component are the same model (Maher et al., 2021). Down-weighting those models sharing such components has a large impact on projections of ENSO (Jin et al 2008; Capotondi et al. 2013; Maher et al., 2021), but low impact on the ensemble mean and range of GSAT change this century. This diagnosis has not been carried out so far on CMIP6 models.
5. Using past observations of climate to assess current and future model performance. This has used simulations of GSAT in CMIP6 and has reduced model uncertainties considerably (e.g., Liang et al., 2020) and produced ice-free September conditions in the Arctic before 2050 (e.g., Olonscheck and Notz 2017).
6. Using kriging (linear inverse methods) to combine GSAT record since 1850 with the CMIP 6 historical simulations to better constrain projections has combined the entire GSAT record since 1850 with the CMIP6 historical simulations to produce constrained projections for the 21st century (Ribes et al. 2021).
7. Emergent constraints have been used with the CMIP5 and CMIP6 ensembles and have led to reduced GSAT ensemble range (e.g., Nijsse et al. 2020).
8. Using climate predictions initialized from recent observations and the Decadal Climate Prediction Project (DCPP) contribution to CMIP6 (e.g., Sospedra-Alfonso and Boer 2020).

6. Conclusions

Despite the focus on climate model uncertainty given here, it is important to state that climate models have been remarkably successful in providing credible large-scale climate projections for many years. For instance, they predicted Arctic amplification; the cooling of the stratosphere associated with GHG forcing; the differential response of land and oceans to warming and the effects of stochastic events such as the cooling associated with volcanic eruptions such as Pinatubo (e.g., Robock 2003). However, the issue of climate model uncertainty needs to be grasped by all users of climate model projections and these include adaptation planners, catastrophe modellers, infrastructure and asset managers.

With better assessment of past changes in climate, the drivers that forced these and the impacts that followed, we should be able to refine climate models so that future projections are made more robust. Understanding how climate models work, are developed, and projection uncertainty should also improve climate change resilience for society. What should be avoided are business decisions being made on the basis of incomplete understanding of climate model projections. For instance, several scientists have in the past made simplistic assertions about the likely nature of future climate in the UK, and climate sensitive sectors should be wary of such pronouncements. Clearly a better understanding of climate model uncertainty would help make better risk management decisions and these will need to be robust in the face of these uncertainties. Inevitably this will increase costs. Such costs can be controlled through earlier and deeper reductions of greenhouse gases (mitigation) – it is likely they will be considerably higher if they are delayed further.

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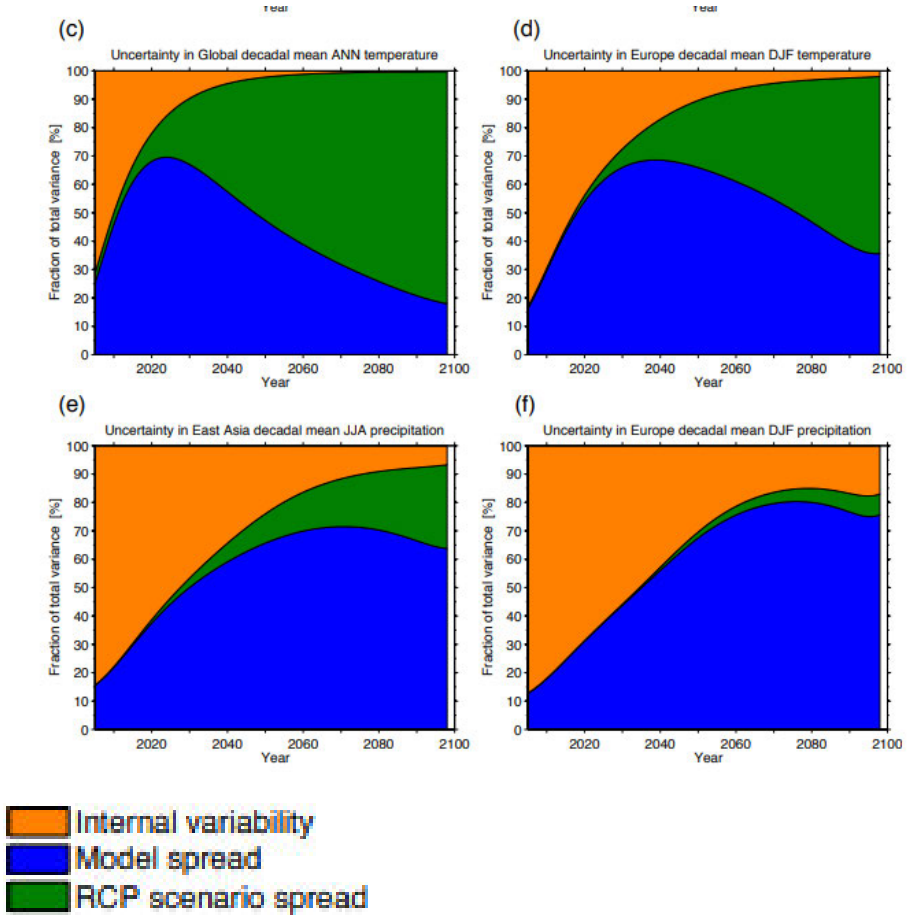

Figure 1: Sources of uncertainty in temperature and precipitation projections. Global decadal c) and European decadal DJF (d) temperature projections are compared with Asian decadal (e) JJA precipitation projections and European DJF precipitation projections (f). These are all expressed as a fraction of the total variance (from Hawkins and Sutton 2009).

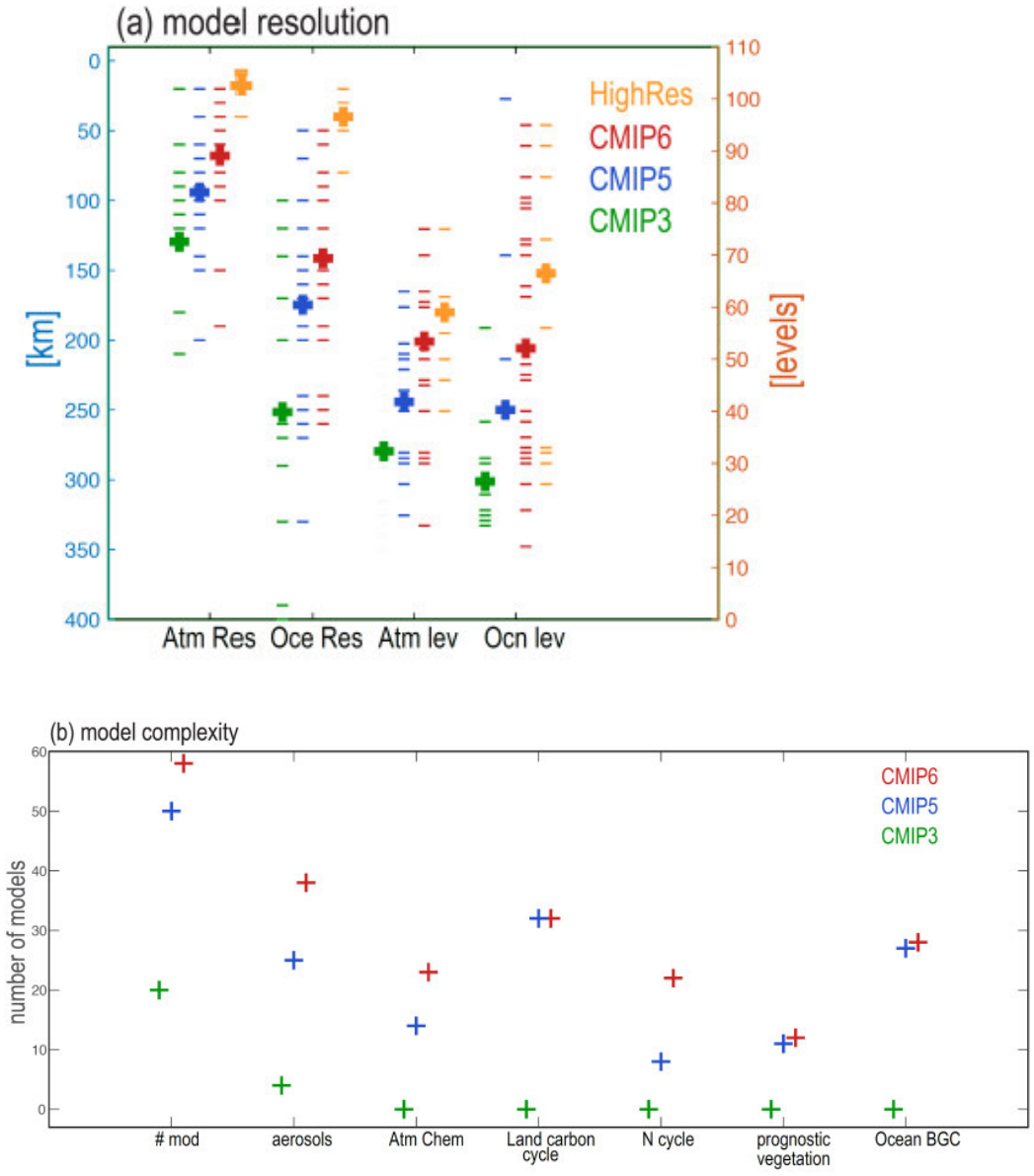

Figure 2. Improvements in climate models in resolution, complexity and representation of key variables.

(a) Evolution of model horizontal resolution and vertical levels.
(b) Evolution of inclusion of processes and resolution from CMIP Phase 3 (CMIP3) to CMIP6

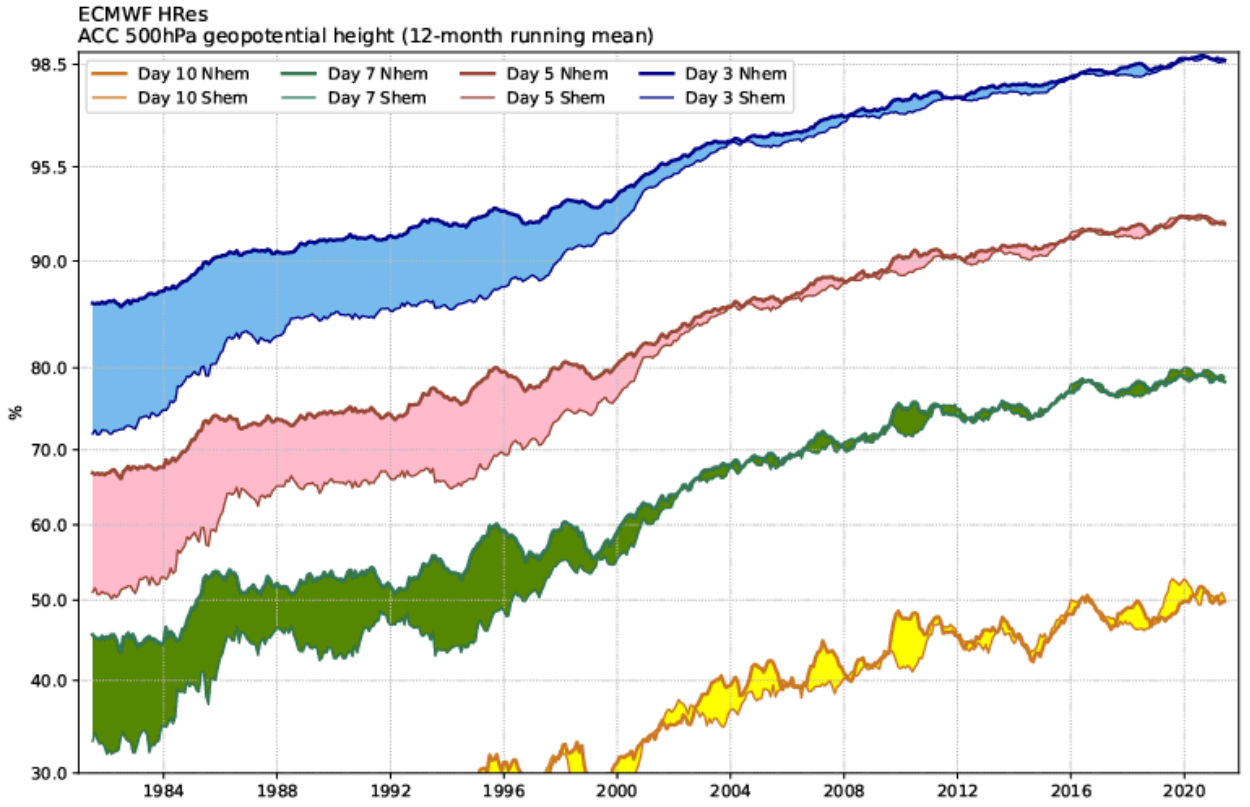

Figure 3. Anomaly correlation of ECMWF 500hPa height forecasts

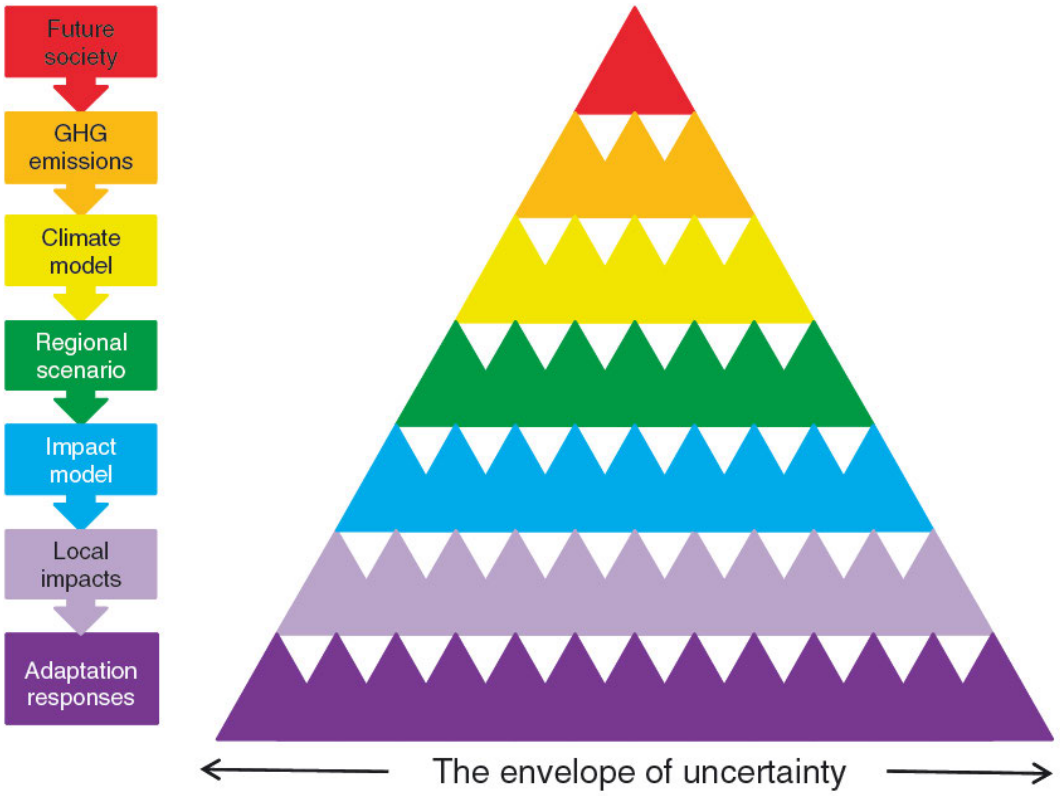

Figure 4. The cascade of uncertainty (from Wilby and Dessai 2010). This proceeds from a variety of socio-economic and demographic pathways to GHG concentrations, outcomes from global and regional climate models, local impacts on human and natural systems and adaptation responses. The increasing number of triangles represent the increasing number of permutations and therefore increasing envelope of uncertainty.

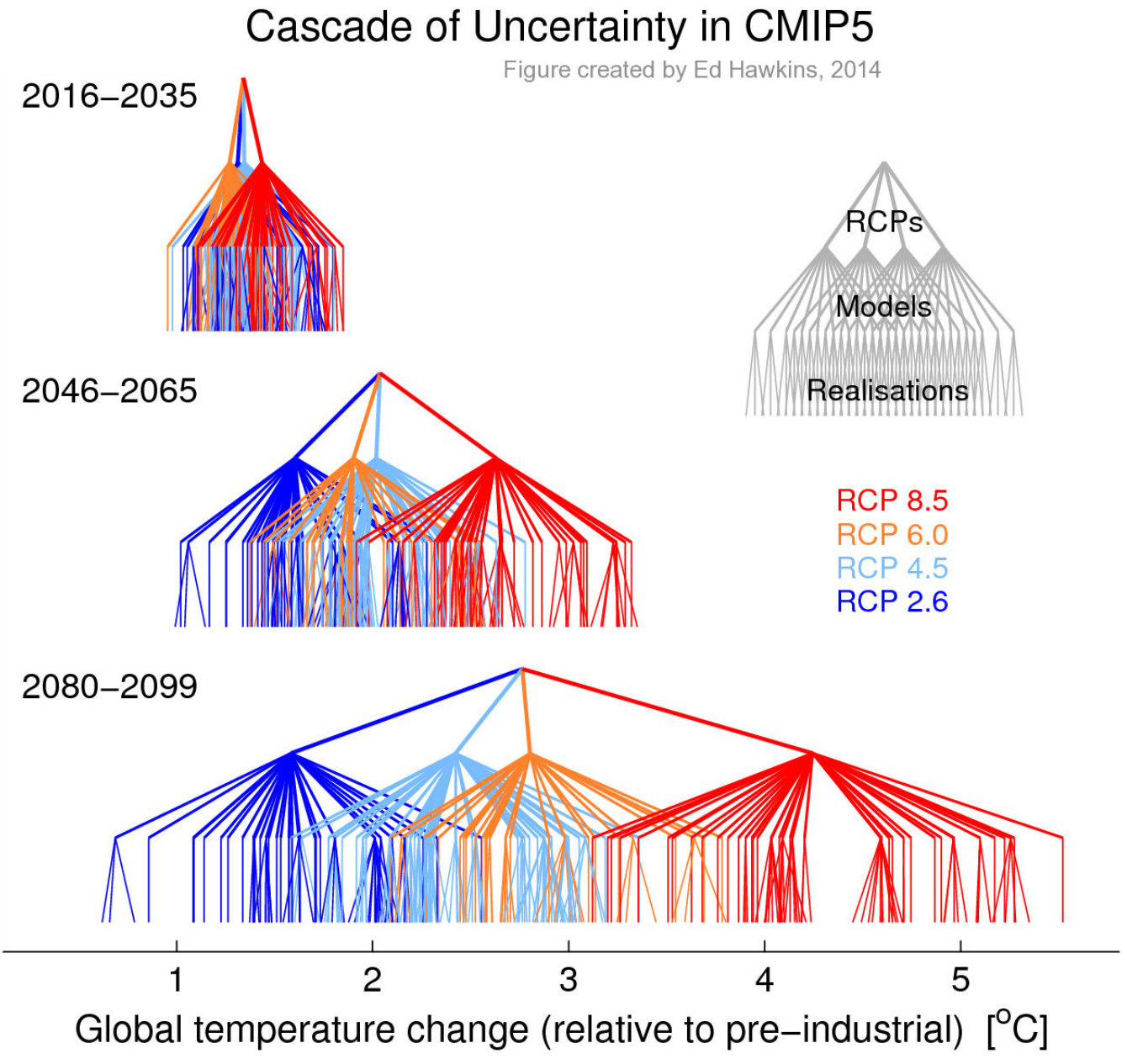

Figure 5. The 'cascade of uncertainty' in global mean surface temperature from the CMIP5 simulations for different time periods as labelled. The three levels of the pyramid highlight the uncertainty due to the choice of RCP, GCMs and realisation of climate variability. Unfortunately, not all the simulations have multiple realisations, resulting in a vertical line in the lowest layer. The intersection on the top row for each time period is the multi-scenario, multi-model, multi-realisation mean.

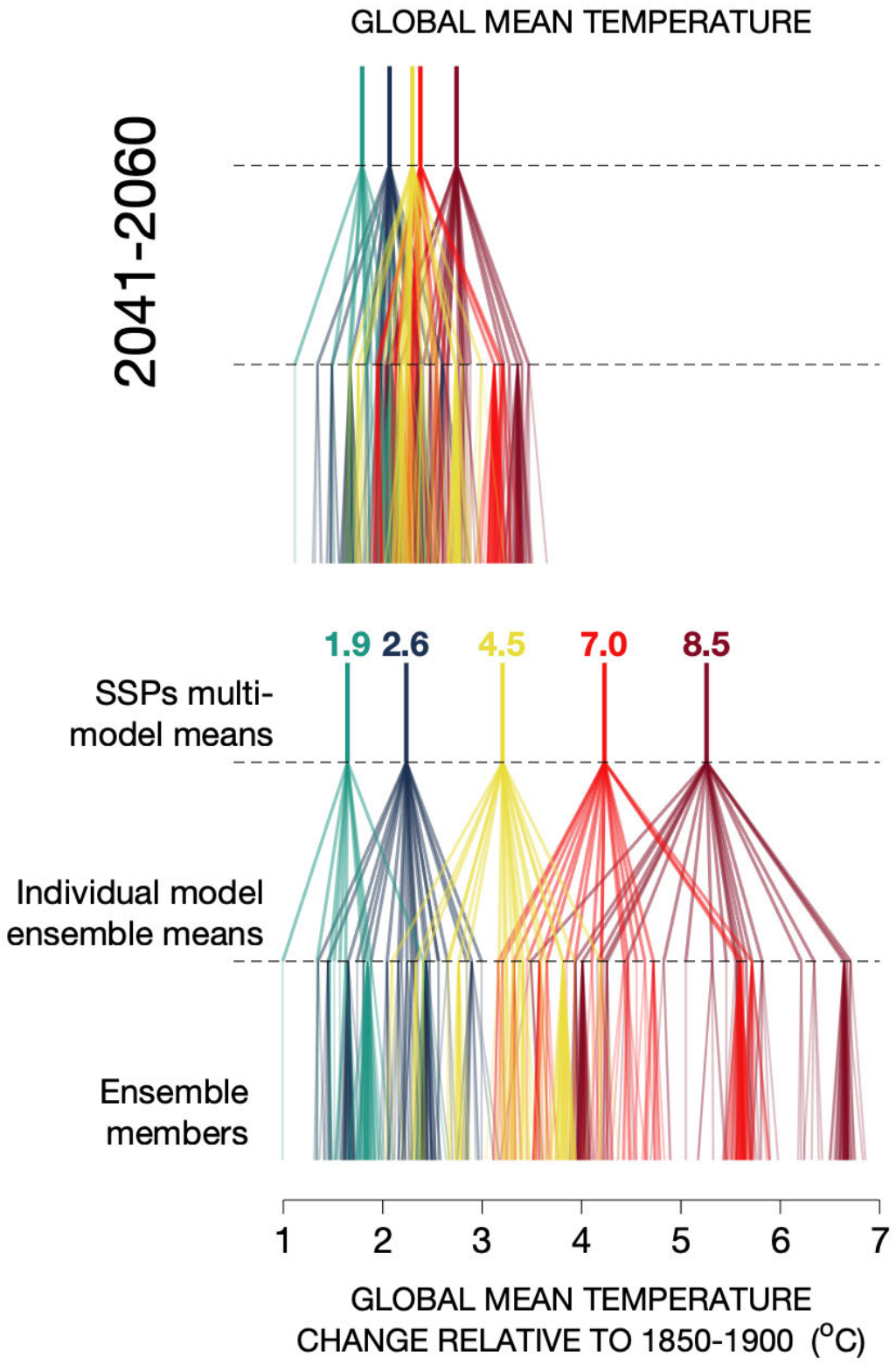

Figure 6. Changes in GSAT (left), northern South America (region NSA) temperature change (middle), and East Asia (region EAS) summer (JJA) precipitation change (right) are shown for two time periods (2041–2060, top, and 2081–2100, bottom). The SSP-radiative forcing combination is indicated at the top of each cascade at the value of the multi-model mean for each scenario. This branches downwards to show the ensemble mean for each model, and further branches into the individual ensemble members, although often only a single member is

available. These diagrams highlight the relative importance of different sources of uncertainty in climate projections, which varies for different time periods, regions and climate variables.

For global mean temperature, the role of internal variability is small, and the total uncertainty is dominated by emissions scenario and model response uncertainties. Note that there is considerable overlap between individual simulations for different emissions scenarios even for the mid-term (2041–2060). For example, the slowest-warming simulation for SSP5-8.5 produces less mid-term warming than the fastest-warming simulation for SSP1-1.9. For the long-term, emissions scenario uncertainty becomes dominant (from IPCC AR6 WG1).