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LIMITATIONS OF CLIMATE MODEL SIMULATIONS TO SUPPORT CLIMATE CHANGE ADAPTATION

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Academic dissertation

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Helsinki, 15.5.2014

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University of Helsinki, 2014

Abstract

Estimates of future climate conditions are commonly based on output of climate models, which have several potential purposes of use in climate change adaptation problems. In this study, data from state-of-the-art global and regional climate models were analysed, together with their relevance for applications. Impact-specific aspects of projected future climate data were analysed in two studies, the first of which focused on Finnish crop production and the second on European road network. The other three studies had a more general focus and a global domain. In these papers, projected future changes in daily temperature variability and time-dependent development of uncertainty in climate model projections were studied.

A more general viewpoint was to assess the effect of climate model development on the climate projections. More sophisticated and complex models imply more complex interactions within and between the model components. As a result, model spread in the 21st century climate change projections has increased on all time scales. Neither the extent of the reducible uncertainty, nor the means to reduce it, are known. Uncertainty in climate model projections varies with the variable, spatial scale and the statistics of interest. The effect of climate model development for annual mean climate projections is unsystematic and model-dependent, which causes multi-model mean climate projections to be mostly statistically indistinguishable between three climate model generations. Conventional analysis methods used for multi-model ensembles do not fully exploit the superior process-understanding which is present in the improved climate models.

The utility of climate models varies with the specific adaptation problem and also other information sources are often needed. For crop production in Finland, changes in water availability in the future climate are important, whereas the expected changes in climatic factors only have a secondary importance compared to process understanding when estimating future conditions of European road network. Still, the prevailing uncertainty in climate model simulations should not prevent adaptation decisions from being made, as uncertainty estimates are expected to remain comparable despite model improvement.

Keywords: climate change, climate model, adaptation, uncertainty

Contents

List of publications

This thesis consists of an introductory review, followed by 5 research articles. In the introductory part, these papers are cited according to their roman numerals. **Paper I** is reprinted under the Commons Attribution 3.0 Licence, **Papers II and V** are reproduced with permission of John Wiley and Sons, Inc. Printing permission for **Paper III** is granted by the Institution of Civil Engineers and **Paper IV** is reprinted under Taylor & Francis's author rights.

I **Ylhäisi, J.S.**, Tietäväinen, H., Peltonen-Sainio, P., Venäläinen, A., Eklund, J., Räisänen, J. and K. Jylhä (2010). Growing season precipitation in Finland under recent and projected climate, *Natural Hazards and Earth System Sciences*, 10(7):1563–1574.

II **Ylhäisi, J.S.** and J. Räisänen (2014). Twenty-first century changes in daily temperature variability in CMIP3 climate models, *International Journal of Climatology*, 34:1414–1428.

III Bizjak, K.F., Dawson, A., Hoff, I., Makkonen, L., **Ylhäisi, J.S.** and A. Carrera (2014). The impact of climate change on the European road network, *Proceedings of the Institution of Civil Engineering, Transport*, published online, DOI: 10.1680/tran.11.00072.

IV **Ylhäisi, J.S.**, Garré, L., Daron, J. and J. Räisänen (2014). Quantifying sources of climate uncertainty to inform risk analysis for climate change decision-making, *Local Environment*, published online, DOI: 10.1080/13549839.2013.874987.

V **Ylhäisi, J.S.**, Räisänen, J., Masson, D., Räty, O. and H. Järvinen (2014). How does model development affect climate projections?, *Atmospheric Science Letters*, revised.

Abbreviations

ANOVA = Analysis of variance
AR(3/4/5) = Third/fourth/fifth Assessment Report of the IPCC
CMIP(2/3/5) = Coupled Model Intercomparison Project phase (2/3/5)
CO_2 = Carbon dioxide
CORDEX = Coordinated Regional Climate Downscaling Experiment
CPDN = climateprediction.net
DJF = December, January, February
ECS = Equilibrium climate sensitivity
ESM = Earth system model
GCM = Global climate model
GFCS = Global Framework for Climate Services
ICSU = International Council for Science
IPCC = Intergovernmental Panel on Climate Change
JJA = June, July, August
MAM = March, April, May
MEM = Multi-ensemble mean
MME = Multi-model ensemble
MMM = Multi-model mean
NE = North-East
NGO = Non-governmental organization
PDF = Probability distribution function
pr = Precipitation
psl = Mean sea level pressure
RCM = Regional climate model
RCP = Representative Concentration Pathways
SNR = Signal-to-noise ratio
SON = September, October, November
SRES = Special Report on Emissions Scenarios
SW = South-West
tas = Surface air temperature
TCR = Transient climate response
WMO = World Meteorological Organization

1 Introduction

Earth's climate system is currently undergoing a rapid change, the pace of which is likely to further accelerate during the 21st century (Collins et al., 2013). Despite mitigation efforts of greenhouse gas emissions which can limit the future level of climate change (Rogelj et al., 2012), significantly different weather conditions to those observed during the 20th century will likely be observed already during the next few decades, in many parts of the world (Mahlstein et al., 2011). As this forces many natural and human systems out of their natural coping range (Yohe and Tol, 2002), corresponding adaptation measures necessarily need to be applied in order to reduce any harmful impacts induced by proceeding climate change. To be able to proactively plan and implement them, diverse information, such as that related to future climate conditions and to relevant impacts caused by it, is needed (IPCC, 2012).

The societal need for scientific information on climate change creates incentives for the scientific community to produce it (Asrar et al., 2013; Giorgi et al., 2009). This setting creates an implicit one-way supply chain, which can serve as a motivation for climate research: Through better scientific understanding, more reliable climate change projections can be achieved which again help to tackle climate change adaptation problems resulting as better decisions (Dessai et al., 2009b; Shukla et al., 2010). However, real-world applications also need socio-economic data sources (Weaver et al., 2013) and the sensitivity of the application to climatic factors can be highly variable. Adaptation can benefit from climate information, but also from the process understanding of the specific application (Füssel and Klein, 2006).

Improved scientific understanding does not automatically guarantee more accurate future climate projections globally, even though on a regional level this could be achieved (Räisänen and Ylhäisi, 2012). Uncertainty sources of climate data are not limited to differences in climate change between different models, but model simulations typically need to be post-processed because of their biases in present-day climate (Maraun et al., 2010), insufficient resolution (Fowler et al., 2007) or interpretation problems related to use of different models (Knutti, 2010). A "good" climate model is notoriously difficult to unambiguously identify (Räisänen et al., 2010). The large volume of climate model data sets can act as an obstacle for more widespread use of the models (Overpeck et al., 2011).

Climate change simulations can only be verified indirectly, either using statistical or physical performance criteria. Climate projections are typically evaluated using statistical criteria (e.g. **Papers I-V**), as the evaluation of all the processes relevant for climate variable of interest is more challenging. Identifying the subset of most important processes is case-dependent and comprehensive evaluation of them typically needs more data. In the statistical approach, the range of different future model simulations is taken to represent both the response of the climate system to forcing and the imperfect representation of it in the climate models. Assessment on the relative importance of epistemic (reducible) uncertainty compared to aleatory (non-reducible) uncertainty in future climate projections (Dessai and Hulme, 2004) is highly subjective, blurring the magnitude of potential which exists to improve future climate projections. Should this uncertainty be reduced, more tightly optimized adaptation decisions could be applied, in general.

Transformation of climate information to end users necessarily alters the content. This happens regardless whether quantitative or qualitative information is used, because of inherent cognitive processes (Kahan et al., 2012; Budescu et al., 2009). Due to societal applications, the utility of climate science can be substantially increased by the good performance of the interface between scientific and user communities (Mastrandrea et al., 2010). Several skills are needed from the people working at this science-society interface: Knowledge of the climate models and the limitations related to them, statistical methods needed to refine the data to a format that is appropriate to use, user needs and efficient methods of communication with them (von Storch et al., 2011; Swart and Avelar, 2011).

In this dissertation, previously poorly-known aspects of future climate simulations were analysed from a statistical perspective, using fairly conservative analysis methods. The general aim in **Papers I, II, IV and V** was to provide generally applicable climate information for various applications whereas application-specific climate information was provided in **Paper III**. The primary objective was to advance the interpretation of the statistical uncertainties in future climate projections. The secondary objective was to evaluate the effect of climate model development on these uncertainties, both for best-estimate (**Paper V**) and probabilistic (**Paper IV**) climate projections.

2 Review of papers and the author's contribution

This thesis consists of five peer-reviewed publications that both apply climate model projections in impact assessments (**Papers I, III and IV**) and analyze previously poorly studied characteristics related to climate model simulations themselves (**Papers II, IV and V**).

Paper I investigates the reliability of model- and observation-based precipitation products over Finland, from an agricultural perspective. For this, growing season precipitation for several interpolated observation-based products and different ENSEMBLES models are used together with process-based assessment of the results.

Paper II provides data analysis for 21st century changes in daily temperature variability as simulated by CMIP3 climate models. Metrics for quantifying the range and skewness of temperature variability are introduced and applied for the whole temperature distribution. Possible physical mechanisms underlying the changes in daily temperature variability are explored as well as the connection between mean climate conditions and the daily temperature variability.

Paper III investigates the effect of climate change for the European road network. A process-based road model is applied in order to assess the sensitivities of the road structure to weather variables.

Paper IV applies an analysis of variance method to future climate projections, using multiple scenarios from several CMIP5 and CMIP3 simulations. The total variance within each ensemble is divided into internal, model and scenario components. The relevance of each of these variance components for different user groups is discussed and a rational risk-analysis framework for engineering-type decision-making problems is shown.

Paper V applies another analysis of variance method to three generations of climate models. This is used to quantify the effects of climate model development on climate projections both from the viewpoints of an individual user and a model data provider. The paper provides an assessment of the relative importance of model development.

I am solely responsible for writing the summary part of this thesis, and I am the primary contributor in **Papers I, II, IV and V**. In **Papers II, IV, V**, I am responsible for the majority of the data analysis, writing and the original idea related to them, having a contribution of 80 % in each of them. In **Paper III**, I contributed to earlier stages of the draft through providing a detailed analysis of all the related climate variables. I also contributed to writing and the revision of the manuscript, having a 10 % overall contribution. I participated in all stages of **Paper I** and was primarily responsible for producing and revising the text and analyzing the climate model projections, having an overall contribution of 45 %.

3 Climate change adaptation

3.1 Information demands and key concepts

Climate change adaptation has been on the political agenda since IPCC AR4, as the need has gradually become evident (PielkeJr et al., 2007; Beck, 2011): any mitigation efforts take a long time to have substantial effects and climate will be changing to some extent (Rogelj et al., 2012, **Paper IV**). Oppenheimer et al. (2014) proposed a conceptual framework on the factors affecting climate-related risks (Figure 1). Here, the risk constitutes both from climatic and socio-economic factors. In general terms, exposure is defined as the presence of people and infrastructure in places (and settings) that could be adversely affected by certain climatic events and vulnerability states the predisposition to experience these adverse effects. The framework as such can be applied to climate change adaptation and Fig. 1 also demonstrates how adaptation risk assessments need socio-economic data in parallel with climate data. Focusing on climatic component is only a partial solution in several adaptation problems as development choices can also affect the risk level (e.g. Prudhomme et al., 2010; Brown et al., 2012).

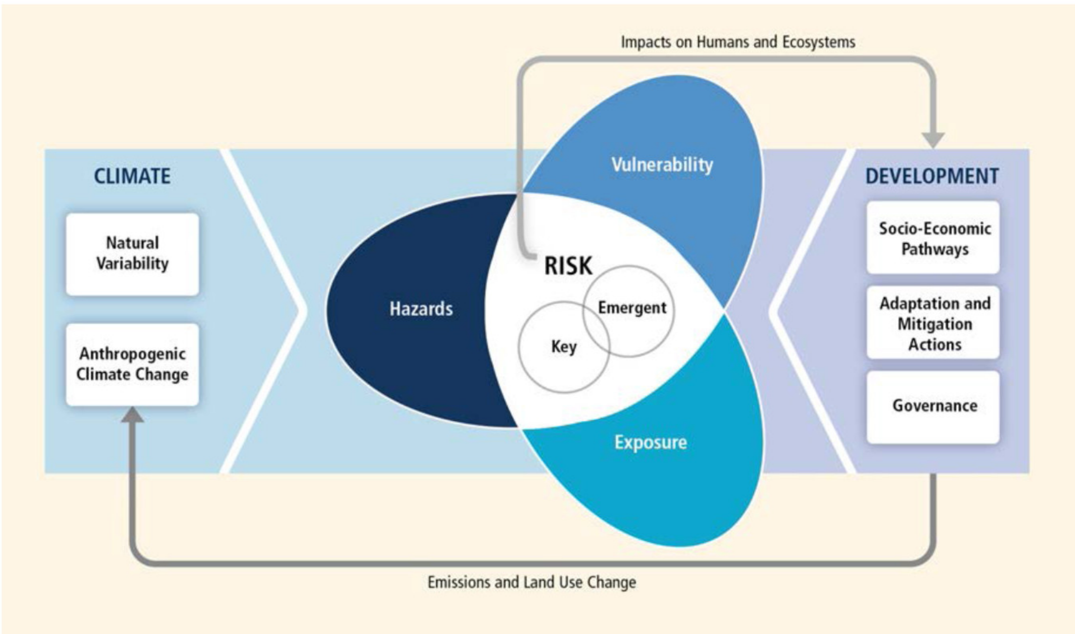

Figure 1: Factors affecting climate-related risks (Oppenheimer et al., 2014)

If adaptation is viewed from the perspective of Fig. 1, motivation for it is only partially restricted by the epistemological limits of climate prediction (Dessai et al., 2009a; Brown and Wilby, 2012) as vulnerabilities and risks of the system at hand to environmental hazards can be assessed also from a bottom-up perspective. Several adaptation assessments nowadays have combined both top-down and bottom-up approaches (e.g. Moss et al., 2010; New York City, 2013; New York City Panel on Climate Change, 2013; Smith, 1997). Interplay between different communities is important: External climate information can even appear as irrelevant to local decision-makers who have extensive internal knowledge from the local systems and their sensitivities (Mastrandrea et al., 2010; Dessai et al., 2004), whereas the climate modelling community is specifically interested from the climate component (Dessai et al., 2009b; Shukla et al., 2010).

Each societal system has its individual coping range for environmental conditions (any physical phenomena affected by climate) which they can reactively accommodate (IPCC, 2012). In the altered climatic conditions, this coping range might be exceeded and adaptating to these conditions might become increasingly more important. Assessing by how much future conditions may exceed the coping range can be done with the help of climate models (Chapter 3.3). This can be estimated in probabilistic terms as uncertainties in climate change projections affect the estimates. Small uncertainty intervals in the climate projections might be considered a desirable feature as the applied adaptation measures could be optimized to meet more narrow environmental conditions (Weitzman, 2009). Vulnerability and exposure are tightly linked with societal development (PielkeJr, 2005) and hence they can be increased or reduced independently of climatic variability (Smit and Wandel, 2006; Preston et al., 2011). Simplified, the ability to to affect these factors of risk are defined by the adaptive capacity of the system (IPCC, 2012).

One conceptual knowledge supply chain used to create estimates from altered future climate conditions is illustrated in Figure 2 (Mearns et al., 2001; Füssel and Klein, 2006). The figure illustrates the linear progress of information flow from emission scenarios to range of possible impacts. Climate models are located at the middle of this causal chain, making them affected both by emission scenarios (as they are upper in the chain) and allowing them to affect estimates of impacts (lower down the chain). Each step of the chain can be estimated using highly varying approaches, or even omitted. Each community needs some input data from the upper parts of the supply chain, in together with information on the related limitations of it. Without this information, the communities downstream the chain fail to sample the range of possible outcomes and the sensitivity of eventual adaptation decisions to them cannot be estimated. The requirement for knowledge on working practices also applies in the opposite direction: For example, climate modeling community needs to be able to respond to the needs and requirements of the impact community. Each step of the supply chain can contribute to projection uncertainty of the application-relevant climate data and consequently have the potential to affect adaptation decisions.

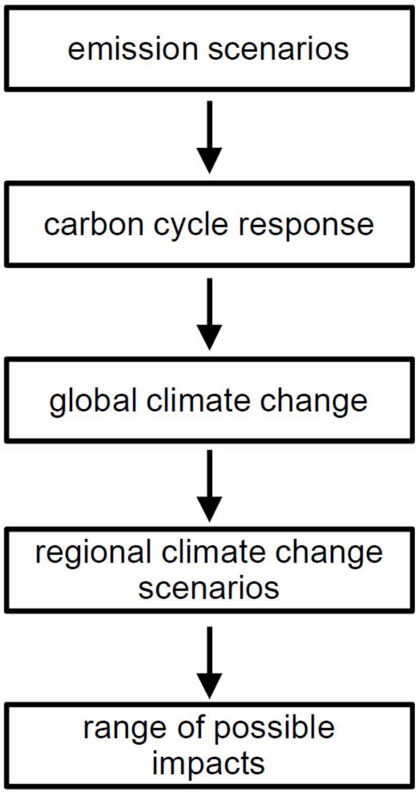

Figure 2: Knowledge supply chain of climate information (modified from Mearns et al., 2001; Füssel and Klein, 2006).

Modern view of adaptation is provided in Fig. 1, whereas the more limited framework of Fig. 2 (”impact approach” in Carter et al. (1994) or ”predict-and-adapt paradigm” in Hulme et al. (2011)) was more favoured prior to vulnerability assessments (Füssel and Klein, 2006). Prevailing uses of it can still be seen. For example, weather event attribution has been proposed to have the potential to allocate adaptation funding

(Stott et al., 2004; Otto et al., 2013; Hulme et al., 2011). Viewed strictly from this natural sciences - driven perspective, adaptation and its costs are defined as a complement to failed mitigation efforts (Beck, 2011). This linear model-of-expertise has been challenged on various levels in the adaptation literature. For example, non-linear approaches between climate and society have been implemented as a part of the RCP-scenarios (Moss et al., 2010). On a smaller scale, several authors have suggested a collaborative use of local information and large-scale information on climatic impacts (Dessai et al., 2004; Mastrandrea et al., 2010; Pidgeon and Fischhoff, 2011).

A fundamental limitation to proactive adaptation (**Paper IV**) is related to extremely long time scales related to climate change (order of decades, e.g. Mahlstein et al., 2011), compared e.g. to those of weather forecasts (order of days). This may be in discrepancy with human perception and cause decision-makers as well as the general public to be likely to forget the threats posed by climate change if severe weather events do not occur for a while (Hansen et al., 2012). Essential for the selection of climate data to be used in adaptation is to identify whether (Hallegatte, 2009) or not (e.g. **Paper III**) the climate component will experience substantial changes during the time scale related to the application.

Individual weather events have also the ability to boost adaptation assessments. For example, The city of New York has had a long history of activities related to climate change adaptation, but after the dramatic event of Hurricane Sandy a new initiative was launched to address the aims to improve the resilience of the city to harmful effects caused by climate change (New York City, 2013). The local Climate Change panel was also reconvened and the actual climate change estimates were updated (New York City Panel on Climate Change, 2013). The applied strategy here was to actively monitor earlier implemented decisions and accordingly revise them through a learning process as new information becomes available. This type of approach is highlighted also in the adaptation literature and is known as iterative risk management (e.g. IPCC-TGICA, 2007; National Research Council, 2009). This strategy can be applied under those deep uncertainties which are related to future climate change (Weaver et al., 2013) or if this uncertainty is strongly conditional on the state of the scientific understanding (**Paper IV**). If future conditions are highly uncertain, adaptation decisions of today need to be compatible with a wide range of different outcomes (Hallegatte, 2009).

3.2 Communication of climate information

3.2.1 Different user groups and their needs

How is climate information used in various applications and how is this information communicated? This is heavily dependent on the type of application and user group. Modifying the classification of Themeßl (2011), climate data user groups can be classified as

1. climate and climate impact researchers
2. environmental and conservation organisations or NGOs
3. private sector (consultants, spatial planners, architects, ...)
4. local/regional/national/multi-national public institutions and authorities
5. politicians and policy makers

In COST VALUE (2013) the users are schematically divided into first-order end users (e.g. climate researchers) who will need raw climate data for impact assessments and second-order end-users (e.g. policy-makers) who need information on the projected changes in the impacts relevant to the systems of interest. Those second-order end-users with strong systemic emphasis need holistic assessments and might only have a limited interest to apply climate projections as such. They will also need more support in interpretation of the data. The needs of first-order end-users are often more limited and less ambiguous (**Paper IV**). In the between of these schematic user groups, there are several end users that need variously aggregated climate data for further research activities (Forsius et al., 2013).

Provision of probabilistic and comprehensive climate information is vital for all user groups, as it is needed in defining the risk levels to various climate phenomena. Most applications need to take into account the whole range of climate uncertainties as equally important for them (Kunreuther et al., 2013). For local-scale adaptation, the user has no influence to development pathways of global climate and can treat climate projections as non-reflexive (**Paper IV**).

Risks can, however, be perceived very differently by different users. Their evaluation can either be based on subjective or objective criteria. Subjective risk assessments can be based to qualitative criteria and thus can be influenced by the receiver's personal opinions, world-views and cognitive processes (Kahan et al., 2012; Shanahan, 2007). This can often lead to over-confidence towards the personal beliefs of the receiver (Kahneman, 2003; Budescu et al., 2009; Mannes and Moore, 2013; Cohen, 2003; Leiserowitz, 2006). Objective risk assessments, such as cost-benefit assessments (Hallegatte et al., 2012; Weaver et al., 2013), are typically quantitative. Using this approach, a rationally behaving decision-maker will want to maximize his/her benefit on a well-defined scale (Neumann and Morgenstern, 1944). Climate model simulations in various significance levels (in addition to the most common 5 % level as e.g. in **Papers I, II and V**) translate to risk values of a Type I error (falsely rejecting the null hypothesis, i.e. models falsely simulate changes in climatic conditions) and can have relevance for applications. Over-confidence of the user, however, can increase Type II errors (failure to reject the null hypothesis, i.e. climatic conditions will change in the future despite a belief this not happening) in adaptation if the future changes in climate are not taken into account. This can result from several reasons, for example by the too large uncertainty interval in climate projections which can be judged by some users to make the projections themselves unusable (Schneider, 2009). On the other hand, a major proportion of decision-makers are risk-aversive as they give more emphasis to negative outcomes with low probabilities (Kahneman, 2003). This can favour Type I errors in adaptation if the estimated damages related to future climate events are very high.

3.2.2 Science-policy interface

In the first half of the 20$^{\text{th}}$ century, political aspects of many scientific disciplines were rather limited and scientific ethos could ideally be considered as being guided by the four general norms (Merton, 1973):

- universalism: truth claims are independent to their protagonist
- communalism: scientific findings need to be communicated in public
- disinterestedness: science is pursued for the sake of itself and not for acquiring individual benefit

- organized scepticism: scientific findings need to be questioned and the shortcomings acknowledged

In addition to these normative principles, also political aspects have become increasingly important in many scientific disciplines (von Storch et al., 2011). Good science alone is often not enough nowadays as it is equally important to recognize who will benefit from science and why it is being done (Jasanoff, 2010). The policy-relevance is particularly true for climate science, with endless supply of applications affected by climate (Swart and Avelar, 2011) and deeply-held personal worldviews being entangled with views on the severity of climate change (Kahan et al., 2012; Nickerson, 1998). All scientists are involved in policy decision-making somehow (PielkeJr, 2007) and in climate change this is reflected for example in the involvement of scientists through the provision of information products and advice. Claims of universalism (see section 3.3), communalism (adaptation measures are applied also by the private sector, that keeps some of their assessments out of the public domain) and disinterestedness (climate change as a social phenomenon has enough plasticity to serve several interests, see also Hulme, 2009) might fail to be fulfilled. Without the organized scepticism and sufficient expertise of the scientist, the information from the climate models can be transferred in several ways to users and have very different outcomes.

PielkeJr (2007) categorizes political engagement of scientists into four distinct categories, the first two of which are not engaged with the policy process whereas the latter two are. Traditional natural scientific worldview, attempting to follow the four norms of Merton (1973), corresponds with "Pure scientist": research results are published in the literature and not transferred to policy-makers by any other means. A "Science arbiter" might be willing to provide answers to some politically-relevant and scientifically testable narrow questions if he is asked, but also avoids giving preference over policy choices. An "Issue advocate" seeks to convince the policy makers to take on a particular policy choice through using scientific knowledge as a method for this, whereas an "Honest broker" seeks to expand the range of choices the policy makers have through advising them about the science behind the issues. PielkeJr (2007) argues honest brokers as having the key responsibility in well-functioning democracies, where science alone is not able to resolve all policy questions. Whenever Mertonian norms of scientific practice (in particular universalism or disinterestedness) are violated, truth claims can pronouncedly be influenced by the scientist transferring this information.

Understanding these different alternatives to policy engagement is essential for the provision of climate change information, as the selection of appropriate engagement type depends on the application and the data user group. Pure scientists and science arbiters mostly communicate their research in as general manner as possible. They do not necessarily have a clearly-defined user group, but they might easily engage with impact modellers who mostly have well defined data needs and can interpret the model results themselves. In together with increasing number of data sources needed for the application, also the need for interpretation of climate data is increased. For policy-makers, climate consists one factor among others and a more active engagement is typically required. Essentially needed information might not be known beforehand and it might not be readily available from literature. Many political decision-makers necessarily need guidance from the scientific community and need to rely on the scientific opinion. This creates the possibility for scientific opinion to have higher importance for policy processes than "objective" scientific information as derived from climate model data (Javeline and Shufeldt, 2013). In addition to natural science -related issues (Chapter 3.3), also the selection of the used communication method can influence the content and eventual interpretation of the climate data.

The "significance" related to climate projections can be seen at two opposing feedback mechanisms which can both sustain the use of "predict-and-adapt" paradigm (Fig. 2) in applications with considerable political aspects. It might create "excess of objectivity" (Sarewitz, 2004), where the scientist is unwilling to explicitly express the political dimension of his/her scientific findings simply because of the difficulties in translating the information (e.g. Carvalho and Burgess, 2005; von Storch, 2009). On the other hand, prevailing uncertainty on climate simulations makes "stealth issue advocacy" (PielkeJr, 2007) easier as it places even more weight for subjective interpretation of the expert. Here, the aim is to make politics even though the discussion is about science. In other words, an "issue advocate" climate scientist promoting specific policy outcomes might be able to use climate data as a leverage for this purpose. Placing supremacy to "objective" scientific information implies politics and science become inseparable from each other, resulting in a decrease of quality both in scientific practice and political debate (Sarewitz, 2011). A paradox is that science thus becomes politicized and politics become depoliticized (Beck, 2011)! Politicians might consider the considerable uncertainty in climate projections as an excuse for policy inaction on adaptation decisions (Dessai et al., 2009b; Sarewitz, 2004). As summarized by Lackey (2007): "Debates of questions of science often end up serving as a surrogate polemic for the inability (or unwillingness) of decision makers to adjudicate unpleasant value and preference trade-offs.” Scientists engaging politicians with honest scientific information is important, as strongly skewed subjective provision of information politicizes science, reduces scientific credibility and might even promote inaction (Foust and Murphy, 2009).

3.2.3 Climate services

In part to help meet the United Nations Millennium Development Goals, the concept of climate services was launched in 2009 in The World Climate Conference-3 by WMO (WMO, 2011) to improve the use of climate information in various societal needs (Hewitt et al., 2012). The importance of communicating scientific information in an actionable way for several societal applications has only increased ever since (Asrar et al., 2013). Forecasting environmental changes and improving the usefulness of these forecasts for people has also been addressed as one of the five grand challenges by the International Council for Science (ICSU, Reid et al., 2010). Even though this covers a wide range of disciplines, climate services have a crucial role in this process in the interface between climate science and user communities, promoting scientific knowledge as a part of actionable products and applications. In other words, societal value of the climate model development is largely defined by the performance of climate services.

The concept of climate services is currently ambiguous, but the five goals of the Global Framework for Climate Services (GFCS) are listed by WMO (2012):

1. reduce the vulnerability of society to climate-related hazards through better provision of climate information
2. advance the key global development goals through better provision of climate information
3. mainstream the use of climate information in decision making
4. strengthen the engagement of providers and users of climate services
5. maximize the utility of existing climate service infrastructure

Fulfilling these requirements demands multi-disciplinary skills from the people working in this user interface, such as expertise related to model interpretation (science-point-of-view), use of well-documented and plausible statistical methods (technical capabilities) and insight on what information actually is useful for the users (user-point-of-view). These skills extend far beyond natural sciences as climate data is applied in many multi-disciplinary applications (**Papers I and III**). What climate data is useful and where is it needed?

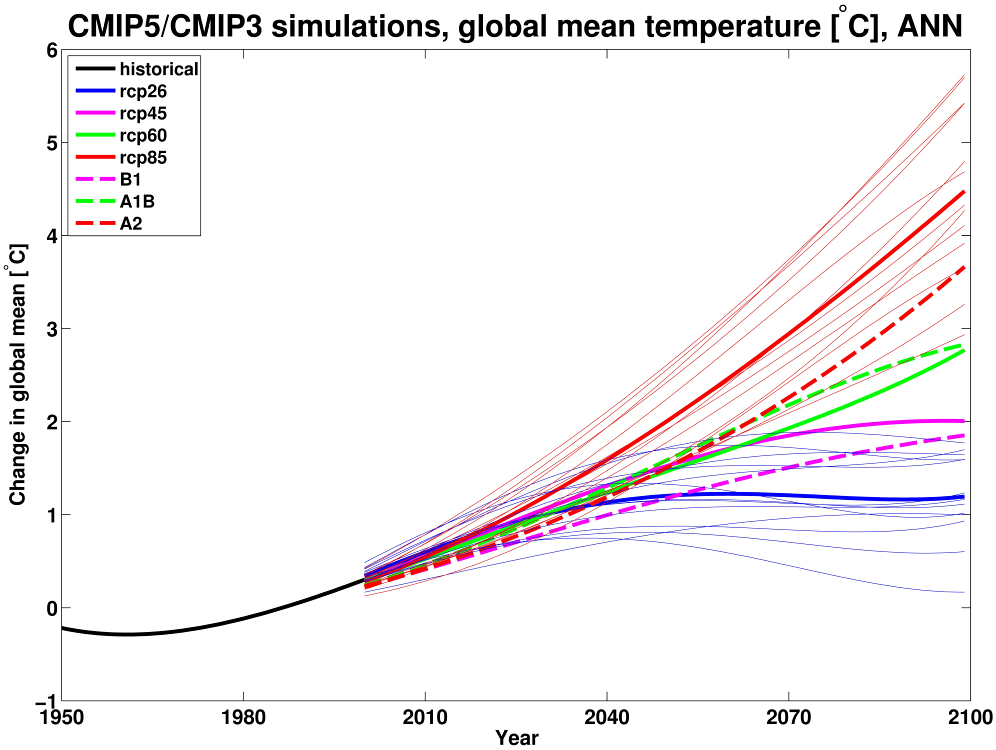

Figure 3: 11-year smoothed annual mean global mean temperature changes in CMIP3 (dashed) and CMIP5 models (solid), under several emission scenarios. The thick lines show the MMM temperature evolution, the thin lines the temperatures in individual models (shown only for rcp26 and rcp85). Figure from **Paper IV**.

Many scientifically interesting metrics have little or no use for the climate services. For example, the relevance of Figure 3 is widely acknowledged within the climate modelling community, both for comparing the behaviour of different models and assessing the sensitivity of the climate system to different emission scenarios (Moss et al., 2010). However, it only has a limited relevance for most of the local end-users (chapter 3.2.1) at a specific geographical location (Mitchell, 2003), potentially applying adaptation measures. Figure 3 also demonstrates different alternatives to policy engagement: As consensus on how to attach weights to different thin lines (individual climate models) has not been reached, uniform weighting is most commoly used. The thick lines representing different emissions scenarios, on the other hand, do not have quantitavite probabilities attached to them. Deliberate subselection within these groups can be used to influence decisions (issue advocate), whereas the reality could turn out to follow anything within this uncertainty range (or even exceed it). Individual scientists might have preference for selecting scenario or model groups, but these can be highly subjective. Through these subjective selections, climate data providers can influence the actual information content.

The needs of the climate data users are poorly known at the moment, but these questions are somewhat addressed by Swart and Avelar (2011), Kattenberg (2010), Themeßl (2011) and the ongoing COST-VALUE project (http://www.cost.eu/domains_actions/essem/Actions/ES1102). These studies, although highly limited in their extent, summarize the extremely diverse needs of the users:

- There remains a fundamental gap between the end-users and the climate model products, as available information is often not sufficient to cover all user requirements.
- Data is needed for several different seasons and not just for summer and winter months. All parts of the distribution are important. Data needs regards to temporal (highest demand for hourly and daily data, but also monthly data is needed) and spatial (from point data to 100 x 100 km resolution) resolution are very diverse.
- Information on present-day and near-future climate has the largest importance. With longer time horizon, the need for the information decreases at almost all societal sectors. Long timescales are interesting for educational and scientific purposes, but not for most real-world applications. For example, climatic timescales at which the response approaches ECS (Equilibrium Climate Sensitivity, corresponding to equilibrium response of the climate system to a forcing caused by the doubling of CO_2) are considerably longer and scientifically interesting, but have no relevance for the user community. See also **Paper IV** for discussion.

- Most of the climate data users are impact researchers (constituting one step down in the linear supply chain), whereas the number of users in other user groups (climate modellers themselves, adaptation experts, research managers, policy makers) is considerably smaller.

- Almost all respondents use temperature and precipitation data. Other variables, such as those related to marine and coastal conditions (temperatures, waves, local sea level rise), to air quality, or wind patterns are required for more specific applications. The interest in snow depth and glacier data, as well as groundwater and runoff data, has been smaller but is increasing.

These diverse data needs imply that any analysis done on climate model data is potentially useful for some user groups even without establishing a direct connection to them. The provision of climate data in this manner works under the "pure scientist" paradigm: Previously poorly-known aspects of model output are analyzed using as general a focus as possible. The results are published in a journal, in the hope of maximizing the number of users exploiting the findings (**Paper II**). Most likely the worldwide "climate data market" is able to somehow exploit these findings, even though this would not be known at the time of the publishing. However, tailor-made data is needed by several adaptation applications which have highly specific climate data requirements (Kattenberg, 2010; Haanpää et al., 2009, also **Papers I and III**).

One goal of climate services is to promote the use of climate information in adaptation problems. As end-user types have different needs, not all goals of the GFCS can be achieved by just providing objective climate information (Krauss and von Storch, 2012; von Storch et al., 2011). A part of climate services can be classified as "post-normal science" (Funtowicz and Ravetz, 1993; Hulme, 2009; von Storch et al., 2011): science is primarily applied to public issues, facts are uncertain yet central to decision-making, "values in dispute, stakes high and decisions urgent" (Funtowicz and Ravetz, 1993). This problem framing involves a subjective extension: either related to interpretation of the significance of the results, personal preferences on seeing how science can be applied to the system or some other consultancy activity necessitating subjective opinions on the severity of the results. For example, estimates of global mean sea level rise in IPCC AR5 for the end of the 21st century lie between 0.26 and 0.82 m. Societal decision-making applications (e.g. building new infrastructure near the coastline today) cannot wait for the reduction of this uncertainty range. In the communication of climate science results, the community exploiting the research results is extended beyond the experts. Decision stakes and system uncertainties (covering also ethics) are accordingly often raised, as in the case of using climate model output in adaptation problems. These "extended peer communities" are manifold to those of merely applied science and personal judgments become commonly entangled with "objective" information.

3.3 Climate modelling

3.3.1 Behaviour of the climate system

Climate system as a whole can be divided into several components (Fig. 4). Each of these components can be investigated separately, but they constantly interact with each other. Because of this interaction, altered conditions in one component of the system quickly propagate to the other components. Thus, the outcome of those surface variables that are important for climate model users (see section 3.2.1) is the end result of all the interactions between the relevant processes represented in a climate model. The behaviour of surface variables cannot always be attributed to a specific set of processes, because of the mutual interaction of the components (**Paper V**).

The myriad interactions in the climate system have consequences for climate modelling. Evaluation of a GCM can be done either using physical (e.g. Schaller et al., 2011) or statistical criteria (e.g. Gleckler et al., 2008, **Papers III and V)**. Physical evaluation of model performance attributes causal relationships between different processes, whereas statistical model evaluation does not attempt to relate model improvement into any single physical process. Rather, the model performance is estimated by comparing model simulations with the observations. For some variables and areas, statistical performance can be attributed to some specific set of processes, but often this is very difficult. For obvious reasons, many users prefer using the model as a "black box", using model output only from the needed variables and leaving in-depth model validation for the model developers. This allows physical model evaluation only in those cases when the model user is aware of the most important processes affecting the surface variables at a specific geographical location. Many users simply do not have the capacity to make detailed evaluation of the model results (Swart and Avelar, 2011). Statistical model evaluation has substantial limitations, because agreement with observations can result from counteracting errors (e.g. Stainforth et al., 2007a; Knutti, 2008).

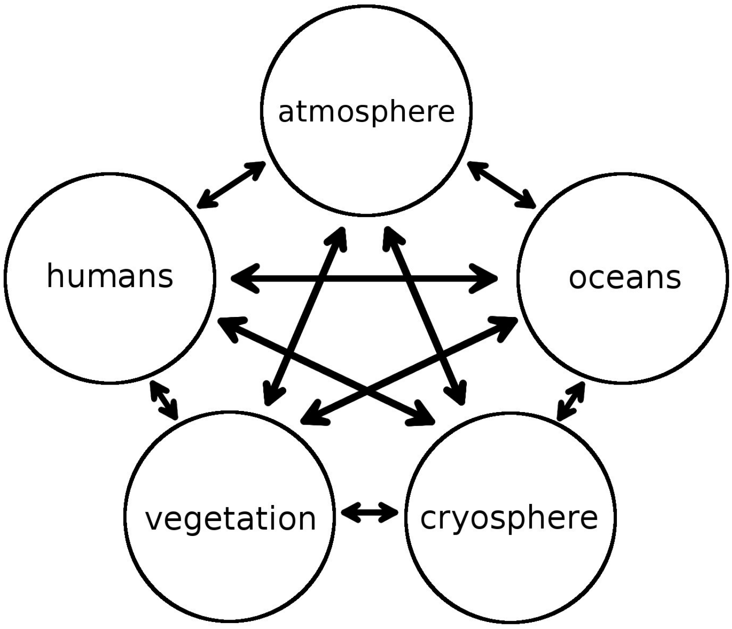

Figure 4: Components of the climate system relevant for climate change adaptation (modified from Lunkka, 2008).

The uncertainty in 21st century climate change projections can be divided to three main components (Figure 5). Due to chaotic interactions between and within different components of the climate system, a part of the climate evolution is unpredictable ("internal variability"). Even if the observational state of the climate is assimilated in the models (i.e. decadal simulations, e.g. Smith et al., 2007), this component of uncertainty only appears to be reducible for relatively short-term projections (Kirtman and Power, 2013). Over longer time scales, the failure of climate models to accurately simulate the forced response of the climate system to changes in external conditions causes increasing "modelling uncertainty". The third component, "scenario uncertainty" (Rogelj et al., 2012, **Paper IV**), is related to the evolution of the anthropogenic climate forcing and only tends to become important on relatively long time scales, because of the inertia in both the human societies and the physical climate system.

From these three uncertainty components, only modelling uncertainty can be potentially reduced (epistemic uncertainty) in long-term (>10 years) climate projections. The other uncertainty components are considered as non-reducible (aleatory uncertainty, **Paper IV**). Reduction of modelling uncertainty needs to take place through the development of climate models, but the degree of this epistemic uncertainty is not

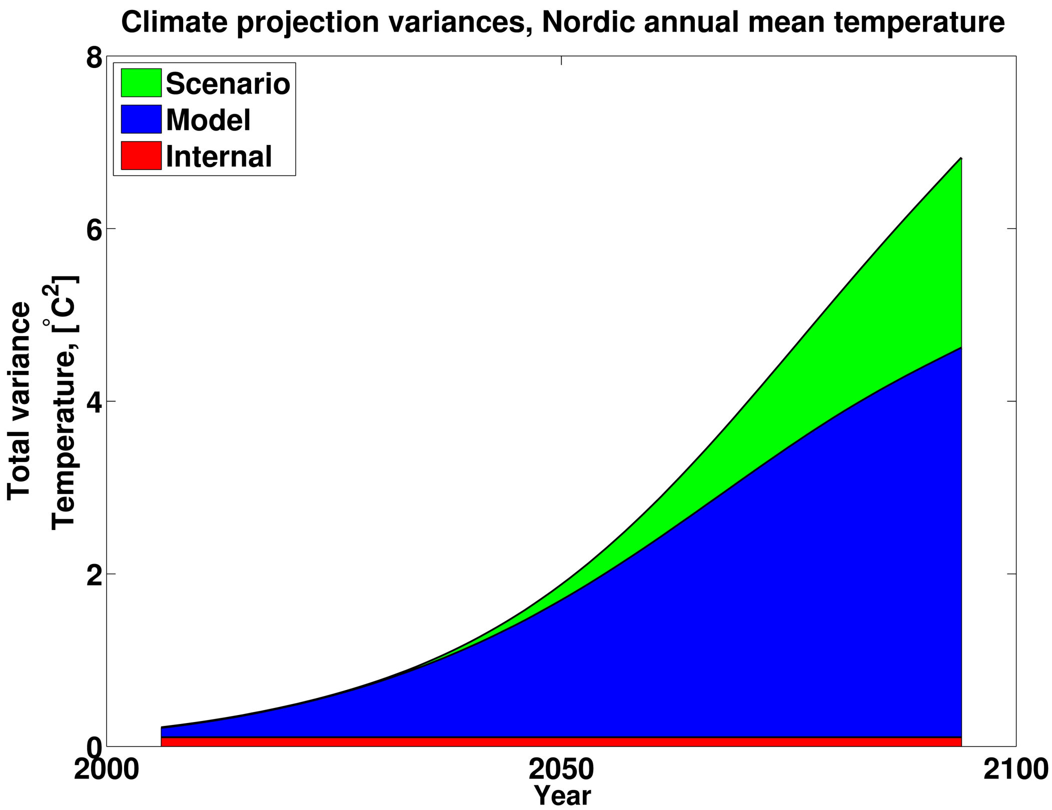

Figure 5: Variance in projections of 11-year smoothed values of annual mean temperature in the Nordic area in the CMIP5 ensemble, as divided into the contributions of scenarios, models and internal variability. The methodology and the data set used are described in **Paper IV**.

known because of the limited knowledge from the climate system and the intrinsic behaviour of it. Several independent lines of evidence indicate the ECS to have high uncertainty related to it (Knutti and Hegerl, 2008). For the more adaptation-relevant metric of TCR (Transient Climate Response, corresponding to global mean temperature increase in the time of doubling of CO_2 concentration in the idealized climate simulations where atmospheric CO_2 concentration is gradually increased 1 % / year), uncertainty estimates have remained very similar for the last 10 years despite the intensive climate model development that has taken place during this time (1 °C – 2.5 °C in Collins et al., 2013, see also **Paper V**).

3.3.2 Interpretation of climate model data

To characterize the uncertainty in climate change, *de facto* methods of deriving possible future outcomes are multi-model ensembles (hereafter MMEs, see IPCC, 2010) and perturbed-physics ensembles (Stainforth et al., 2005). MMEs, especially those collected for different phases of the Coupled Model Intercomparison Project (CMIP), are in considerably more widespread use, with hundreds of publications using the output data from these models (Sanderson and Knutti, 2012). Regardless of the widespread use of MMEs, their interpretation is complicated for a number of reasons, and they are therefore often quoted as "ensemble of opportunity" (e.g. Tebaldi and Knutti, 2007):

- Models are not independent from each other (Knutti, 2010; Masson and Knutti, 2011a)
- MME is not designed to optimally sample the modelling uncertainty (uncertainty range is likely to be an underestimate, see van Oldenborgh et al., 2013)
- model performance on present-day climate only has a weak connection to the climate change estimates (Räisänen et al., 2010)
- non-uniform weighting of the models in the ensemble cannot be deemed as being superior over the equal weighting in many cases (DelSole et al., 2013; Räisänen et al., 2010; Weigel et al., 2010; Giorgi and Coppola, 2010)
- the number of simulations from a single modelling centre typically is not in any way limited (Knutti, 2010)
- different participating models have mutually differing levels of sophistication between them
- datasets used in model evaluation may not be independent to those that have been used to tune the models (Flato et al., 2013; Knutti, 2008)

Regardless, one common purpose of MMEs is to sample modelling uncertainty by using the inter-model spread as an approximate estimate for this. Inter-model spread can be used as such (**Papers I, II, IV, V**) or assumed to be an underestimate of "true" uncertainty (Schneider and Kuntz-Duriseti, 2002). The number of models contributing to MMEs has been argued to be too small (Räisänen et al., 2010; Knutti, 2010), so that they merely provide a minimum range of irreducible uncertainty (Stainforth et al., 2007b). CMIP ensembles simulate substantially smaller range of climate sensitivities compared for example to the climateprediction.net (CPDN) ensemble (Stainforth et al., 2005), which has a substantially larger sample size (Rowlands et al., 2012). However, observational data indicates the largest climate sensitivity values (>5.6 K) in CPDN as being implausible (Tett et al., 2013).

Another important and related feature is the difference between "truth-plus-error" (model mean is assumed to represent "true" value) and "indistinguishable" (true value belongs to the same statistical distribution with the models) paradigms (Sanderson and Knutti, 2012). The "truth-plus-error" paradigm undoubtely is to a large extent applied in model development (see Fig. 6), as new model versions tend to agree better with observations than the previous ones. However, climate projections might be improved under both paradigms in parallel. The larger number of models in MME results in a reduction of the multi-model mean (MMM) error, which makes MMM projections more accurate under the "truth-plus-error" paradigm. In a similar manner to weather forecasts, the "indistinguishable" paradigm might, however, be more appropriate to apply for long-term future climate projections (Sanderson and Knutti, 2012; Annan and Hargreaves, 2010).

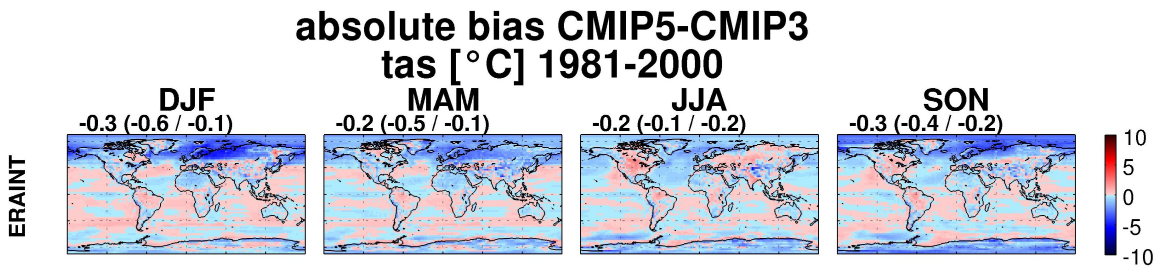

Figure 6: Absolute mean temperature bias in CMIP5 MMM minus absolute mean temperature bias in CMIP3 MMM, compared to ERA-Interim. The numbers above the figure panels show globally averaged mean values (land areas / sea areas). The same models are used as in **Paper V**, except for HadGEM-models being omitted.

The averaging of the results from several models is in line with the "truth-plus-error" paradigm and is found, in part due to statistical reasons (Sanderson and Knutti, 2012), to provide better agreement with observations than most individual models (e.g. Lambert and Boer, 2001; Gleckler et al., 2008; Meehl et al., 2007). When combining the model output by using MMM, physical consistency of individual model simulations might be lost. Averaging can only be done to certain metrics and not to the time series as such (Knutti et al., 2010). Expert judgment plays an important role when combining model results.

Problems in interpreting climate model output are also associated with the climate model biases, as model simulations never correspond perfectly to the observations. In order to be able to use climate model output to estimate the range of possible impacts, this bias often needs to be eliminated from the model projections. The bias in present-day climate is typically assumed to remain constant also in the climate change projections (Maraun, 2013; Maurer et al., 2013).

The body of literature cited in this section demonstrates that climate model projections are also constrained by issues beyond physical process understanding. Post-processing of climate model data also consists an important component in deriving estimates of future climate. This might be further emphasized if statistical (e.g. Wilks, 1992) or empirical-statistical (e.g. Rahmstorf et al., 2012; Benestad et al., 2012) methods are used for deriving local future climate conditions. These methods typically apply large-scale climate change projections from global climate models.

Regardless of the controversial issues related to climate model data interpretation, the resulting estimates of future climate change and its' impacts are quantitative and often treated as "semi-objective" in many impact studies. Reliable climate data serves as a necessary starting point in impact studies, but does not alone guarantee reliable estimates of impacts (which themselves might constitute more relevant information for adaptation). Typically, the relative importance of climate model data becomes smaller further down the modelling chain. For example, Bosshard et al. (2013) show that climate models only can explain less than half of the variance in future estimates of runoff, as the used climate model post-processing method and hydrological model have equally important contributions. Furthermore, post-processing variance is likely to be even larger if multiple methods are taken into account (Räty et al., 2014). Comprehensive assessment of these different uncertainty components would require all of the used methods and models to be assessed simultaneously. As this is not often possible, expert elicitation on the sensitivities of the impact model output to various factors becomes important. Assessment of climate impacts requires expanded focus compared to climate modelling. Uncertainty does not always "explode" in the causal chain, but needs to be assessed case by case.

4 Key findings and their relevance

4.1 Summary of the papers

The different studies included in this thesis are not obviously connected (except for **Papers IV and V**), but they have a unifying theme of interpreting climate model projections and using them in applications. Different sets of climate models are used in each study, based on data availability and suitability for the corresponding research question. This data, comprising future climate simulations run both with GCMs and RCMs, is summarized in Table 1.

Table 1: Climate model data used in different papers. See the papers for references and detailed lists of used models.

Paper	data set (no. of simulations)	resolution	emission scenarios
I	ENSEMBLES (13)	monthly	SRES A1B
II	CMIP3 (15)	daily	SRES A1B
III	GCM-forced RCAO (2)	6-hourly	SRES A2 and B2
IV	CMIP3 (14), CMIP5 (13)	monthly	three SRESs, four RCPs
V	CMIP2, CMIP3, CMIP5 (13)	monthly	pre-industrial, 1% CO_2 / year

Papers can be classified into two groups, which differ between their end users, policy engagement and on whether the information provided is focused enough to support adaptation. In this dissertation, the majority of the results (**Papers II, IV and V**) are analysed using as broad a perspective as possible (Chapter 4.2). These papers all focus to analysis of climate model results without extending the focus to impacts (Fig. 2), to which they rather constitute some of the boundary conditions. Chapter 4.3 studies **Papers I and III** that both focus to a specific impact application. This focus on a specific impact needs information also from other sources (Fig. 1, discussion on this is provided also in **Paper IV**).

The four scientific norms (Chapter 3.2.2) in each of these papers are preserved as well as possible. Following traditional scientific practice, the used methods and the sensitivity of the results to them are documented in detail, except (for the need of conciseness) in **Paper III**. Despite the aim to maintain this general perspective, a subjective component is also evident in each paper which needs to be interpreted together with the findings. The choice of using very conservative methods in all papers (models are uniformly weighted and 95 % confidence intervals are used to assess statistical significance) does not umambiguously provide superiority compared to alternative methods, but rather corresponds with the majority of the existing literature (e.g. Collins et al., 2013) where they are being used. The results of the **Papers I, II and III** are conditional on the emissions scenarios used, the selection of which is based mostly on the data availability. The sensitivity of the results to this is not speculated in the papers. This conditionality also affects the results of **Paper V**, which is more severely affected by data availability.

All papers apply a statistical viewpoint to the analysis of climate model results. In **Papers II and V**, implications for extending this interpretation to cover physical cause-effect relationships are presented as well.

4.2 Climate papers

The conceptual approach in **Papers II, IV and V** largely corresponds with the idea of a pure scientist and science arbiter, as no specific end user group (chapter 3.2.1) was attached in these papers. The analysis done in **Papers II and IV** can be exploited by any end user group whereas the relevance of **Paper V** is smaller for most end users and higher for climate modelling community. At best, the potential of these studies to affect adaptation is limited to the climate component in Fig. 1. A special theme in **Papers IV and V** was to estimate the effect of climate model development to this climate component. This was assessed both for multi-model mean (**Paper V**) and probabilistic climate projections (**Paper IV**). For those end users or climate modellers still fostering the "predict-and-adapt" -paradigm (e.g. Füssel and Klein, 2006), these papers have actual implications for adaptation.

The key results of **Paper II** are shown in Figures 7 and 8. Figure 7 shows the projected changes in the width of the daily mean temperature distribution. This width is defined as the difference between the 5th and 95th percentiles of the distribution after the removal of annual cycle. The first row suggests that the temperature distribution will become narrower in the future climate over the Northern Hemisphere high latitudes in all seasons except local summer, when it is projected to become wider over the land regions. However, as the model responses vary considerably (inter-model std in the second row), the signal-to-noise ratio (defined as the MMM divided by std, third row)

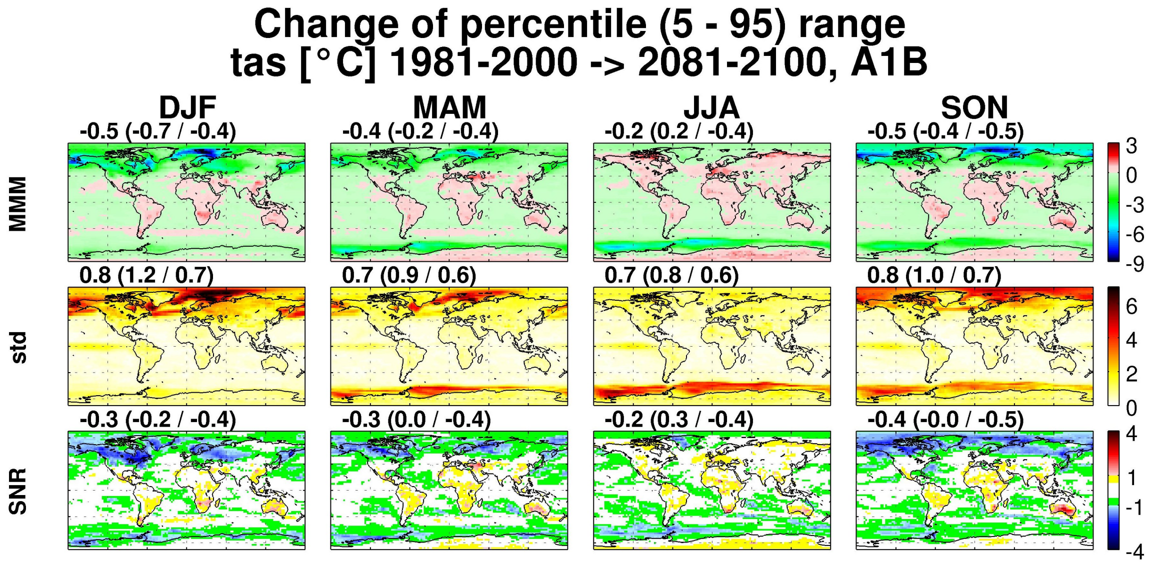

Figure 7: Projected changes (for the years 2081-2100 as compared to 1981-2000) in the width of the daily mean temperature distribution, as simulated by 15 CMIP3 GCMs under the SRES A1B emissions scenario. The first row shows the MMM, the second row the inter-model std and the third row the signal-to-noise ratio (SNR, MMM divided by std). The values above each panel show the global mean (land area mean / sea area mean). Figure from **Paper II**.

is small over most world regions. Assuming a Gaussian distribution, absolute SNR of 1 (2) corresponds to ca. 84 % (98 %) confidence level of daily temperature distribution increasing / decreasing in width over these areas. Risk levels for any values of change (the value of interest is application-dependent) could be derived using MMM and std. The 5-95 percentile interval covers only 90 % of all days, but the result of decreasing variability can be extended to cover the whole distribution, including the most extreme simulated values during these time periods.

Figure 8 in part explains the physical connection behind the relatively high SNR values over the high latitudes in Fig. 7. This is related to the migration of the 0 °C borderline and is visible in particular over the oceans where sea ice is projected to melt due to climate change (first row). The high temperature variability near and slightly poleward of the mean sea ice edge is attributable to both the interannual variability of the sea ice conditions and the strong sensitivity of the local temperature to advection (mild air from the open ocean / cold air from the ice-covered area) when ice isolates the

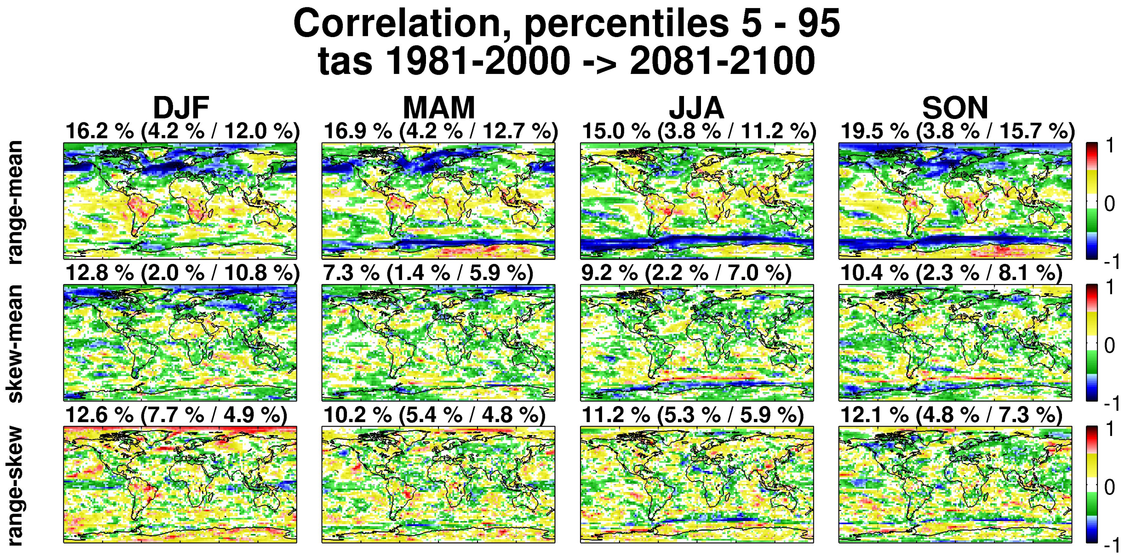

Figure 8: Grid-point-wise inter-model correlation between the changes in different statistical moments of the distribution of daily mean temperatures from 1981-2000 to 2081-2100, as simulated by 15 CMIP3 GCMs under the SRES A1B emissions scenario. Correlations are shown between the changes in mean temperature and distribution width (first row), mean temperature and distribution skewness (second row), and distribution width and distribution skewness (third row). Statistically significant correlations (95 % level) are shown in blue (negative) and red (positive). Values above each panel show the global fractions of the areas with significant correlations (positive/negative). Figure from **Paper II**.

air from the open water. Those models projecting a higher daily mean temperature change in the local winter also also tend to project a larger decrease in temperature variability, most likely due to a larger reduction in sea ice cover. The results look considerably more scattered for the relationship between the changes in mean temperature and distribution skewness, the areas of significant correlations being located at higher latitudes and appearing as less systematic. Nevertheless, physical attribution is also possible for the changes in skewness: over ice- and snow-covered areas, 0 °C can act as an upper limit for the daily mean temperatures, making distribution skewness more negative if the mean temperature is slightly below this threshold. Over many regions, future changes in the range of daily mean temperature variability can be more plausibly estimated than changes in its distribution skewness. A similar connection has been found between mean and extremes of daily precipitation (Benestad et al., 2012). Weighting the model results based on this physical connection and the corresponding temperature bias might, in principle result in higher SNR values in Fig. 7 for some regions at mid-to-high latitudes (Räisänen et al., 2010).

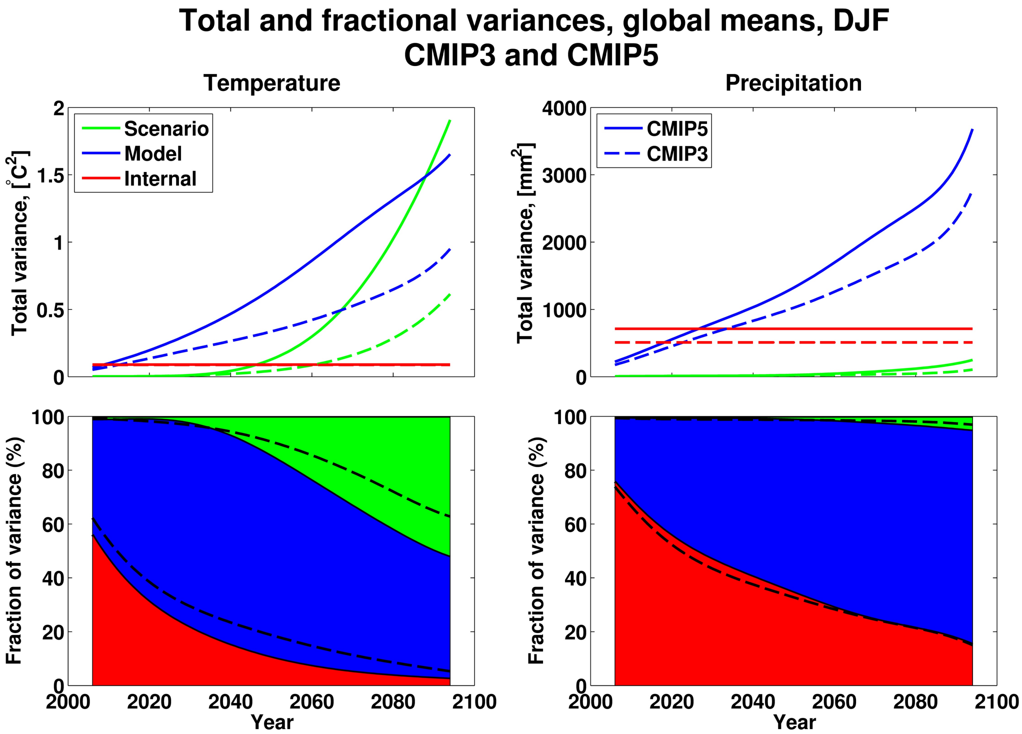

Figure 9: Globally averaged variance components (as in Fig. 5) in the 21st century DJF climate projections as derived from 14 CMIP3 (dashed lines) and 13 CMIP5 models (solid lines), for mean temperature (left) and total precipitation (right). Absolute variances are shown on the top row, relative variances on the bottom row. Figure from **Paper IV**.

The most important generally applicable results of this thesis are based on **Papers IV and V** and are shown in Figs. 9 - 11. Figure 9 shows the three variance components (see also Fig. 5) in the 21st century climate simulations as derived from CMIP3 and CMIP5 ensembles. An increase is seen in each of these variance components, both for mean temperature and precipitation. The relative importance of the different uncertainty components is affected by both the time scale and the climate variable considered. On all time scales, internal component is relatively more important for precipitation than for temperature. With the longer time scales, the differences between different socio-economic scenarios become important as the scenario variance non-linearly increases after mid-century (green lines). Modelling uncertainty as defined here, to a first-order approximation, is quadratically dependent on the global mean temperature change (Mitchell, 2003) and increases throughout the 21st century. The relatively linear behaviour of the modelling uncertainty component in Fig. 9 is due to averaging across all of the forcing scenarios. In the long-term, modelling uncertainty for precipitation is relatively larger compared to that of temperature for two reasons: Precipitation simulations are affected by several microphysical processes for which the level of scientific understanding is worse, in addition to which they are more sensitive to changes in atmospheric circulation patterns. Caused by this modelling uncertainty and internal variability of the climate, different models disagree even on the signs of the projected changes over several regions of the world (Knutti and Sedlacek, 2013). Also the assumption of linearly scalability of local precipitation with the global mean temperature or precipitation is considerably worse as compared to temperature (Frieler et al., 2012). These effects are more important than the choice of the emission scenario. Besides future lead time, both the temporal and spatial scales affect the total uncertainty in the climate projections (Masson and Knutti, 2011b; Räisänen and Ylhäisi, 2011). This should be remembered in any adaptation problem. Even though the results in **Paper IV** are generally applicable, they depend on the used climate variable (and its statistical parameter) of interest which is application-specific.

The results are somewhat unsurprising for scenario uncertainty, as one of the four RCP scenarios (Moss et al., 2010) used in CMIP5 assumes much smaller greenhouse gas emissions than any of the three SRES scenarios (Nakicenovic et al., 2000) used to force the CMIP3 models. For model variance, the result is somewhat less intuitive, but was also anticipated well before CMIP5 data became available (Hannart et al., 2013; Trenberth, 2010; Dessai et al., 2009b; Hallegatte, 2009): More complex climate models are able to simulate more complex interactions taking place in the Earth system (Fig 4), which corresponds to *increased* variance in climate projections. This finding suggests that a large fraction of the modelling uncertainty component can be assumed to be irreducible through the model development process. Further investments in climate model development will not necessarily help to reduce the model spread, as the epistemic component of it is not known. It will help even less to increase the policy relevance of the models.

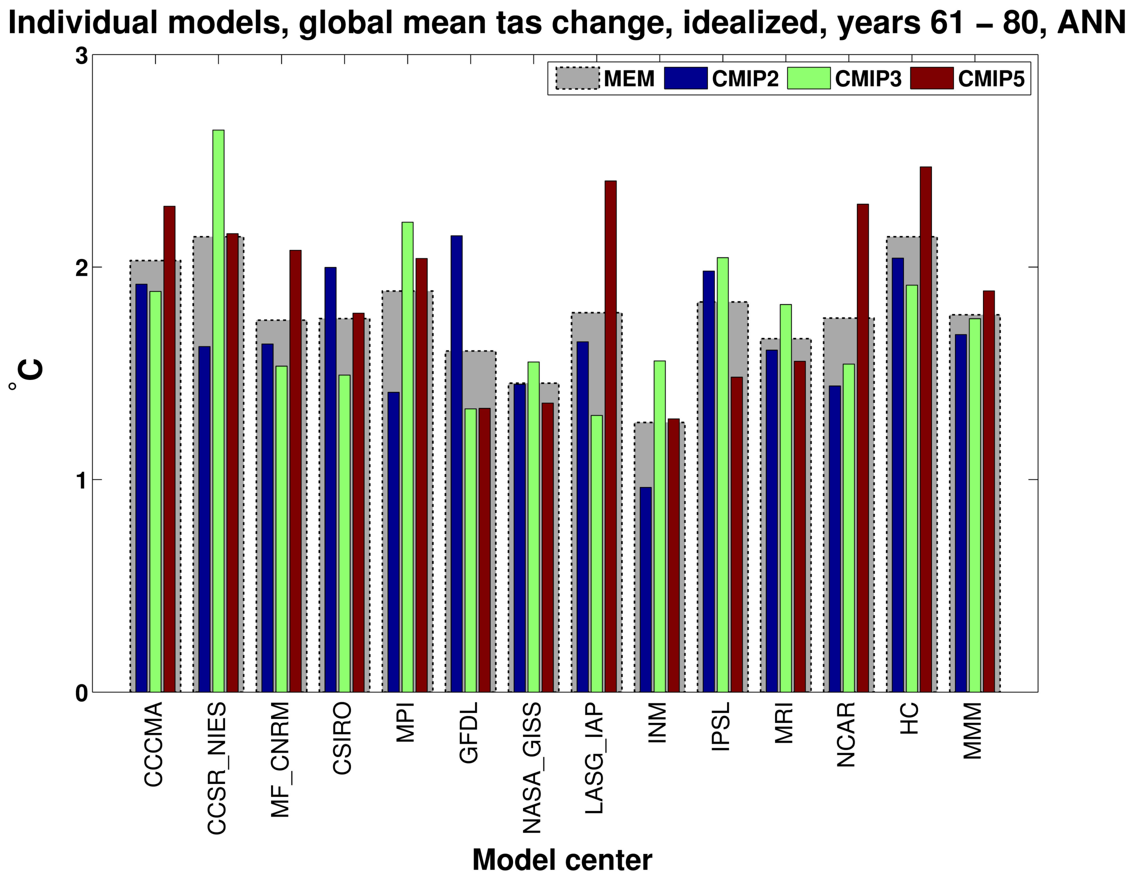

Figure 10: TCR estimates from three CMIP ensembles and their corresponding multi-ensemble mean (MEM) as provided by the models of 13 climate modelling centre and their MMM (last column). Figure from **Paper V**.

The challenges in climate modelling are illustrated in Figure 10, which shows TCR estimates from three model generations and their corresponding MMM. The estimates from the three model generations are statistically indistinguishable. Strictly statistical interpretation of climate model output indicates no apparent benefit from using the latest generation of climate models over the older ones as the differences between the samples might be due to random effects. In-depth assessment of the three CMIP ensembles is given in Fig. 11, which shows the fraction of total variance in those idealized simulations with gradually increasing CO_2 as divided into three components: typical inter-model differences (the systematic differences which exist between climate models from different modelling centres regardless of their model version, i.e. the variance

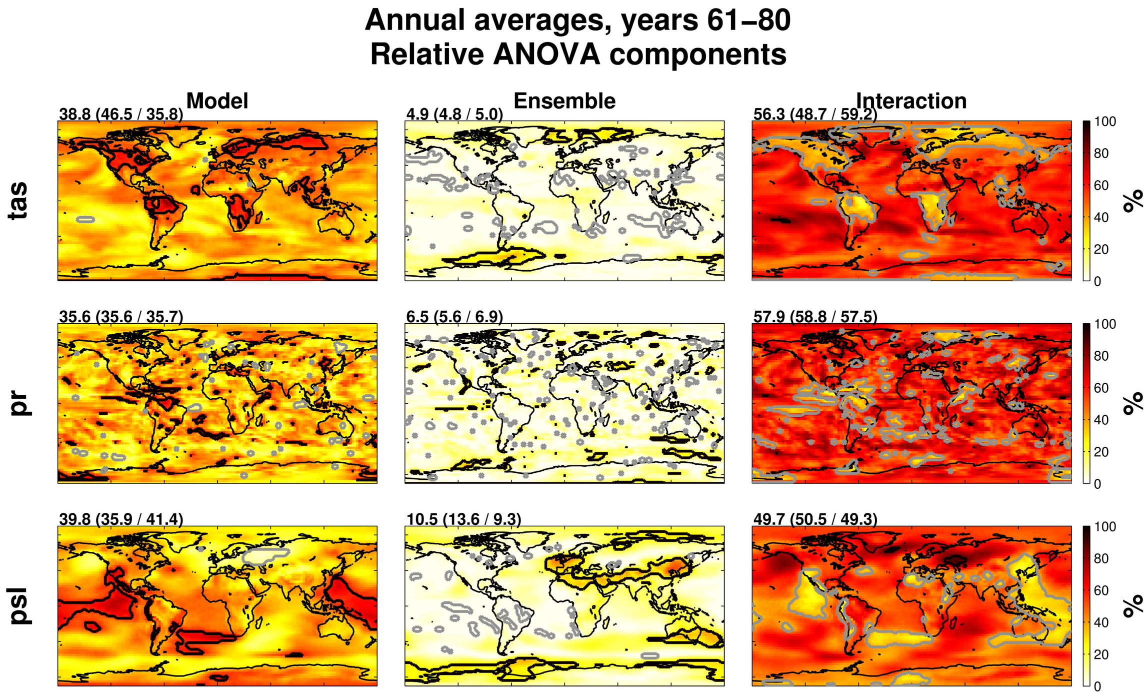

Figure 11: Maps for three variance components (one for each column, see text and **Paper V** for details) as calculated from three CMIP ensembles (as in Fig. 10) for years 61-80 in idealized climate change simulations with gradually increasing CO_2. Annual mean surface temperature in the first row, total precipitation in the second row and sea level pressure in the third row. Areas where the variances are significantly larger (smaller) than expected for random data (95 % confidence level with a two-sided test) are contoured in black (grey). Figure from **Paper V**.

between the 13 MEMs in Fig. 10, in column 1), differences between the three MMM estimates (the systematic part of the variance which is induced by the model development and is shared by each of the models, in column 2) and the model-dependent part of model development (the unsystematic part of the variance which the climate model development and the implementation of new model versions cause for climate change projections – residual term, in column 3). Most importantly, the systematic part of model development shared by each model (middle column) is very small compared to the unsystematic part (right column). This indicates that using an ensemble comprising of single simulations from each individual climate model is subject to considerable amount of randomness in a statistical sense. As the ensemble variance component is very small, each of the three MMM estimates differ very little from each other. The mutual ordering of these three uncertainty components depends on the sample size, but appears to the users of CMIP data as in Fig. 11. By comparing the relative variance components to those that could have been achieved by using purely random, normally distributed data, the obtained inter-ensemble differences in temperature change (middle panel) are statistically significant only in limited regions near the sea ice edge, where the change in model behaviour may be attributable to sea ice processes which have been improved in the new model versions. For precipitation, the effects of model development have been very unsystematic and model-dependent, and the differences between the three MMM estimates allow no physically based attribution. For sea level pressure, significant effects of systematic model development are seen over relatively wide areas, but physical attribution of them is unclear. The model (institute) variance component is statistically significant over many land areas for temperature and over ocean areas for sea level pressure. As these systematic differences between the models from different institutions cannot be explained by internal variability alone, physical constraints could be used to rank and possibly weight model outputs in ensembles. Doing this prior to combining the information from multiple models could have prospects in providing more reliable climate change projections (Knutti, 2010).

The results of **Papers IV and V** are somewhat disappointing, as further climate research does not seem to either reduce the uncertainty in the model projections or alter the projected MMM estimates. This may result both from the experiment design and the applied methodology. The interpretation of the MMM estimates is difficult as it being physically inconsistent. If all climate models contributing to renewed CMIP would have been similarly improved from their previous version regards to some locally important process description, the simulations would likely share a larger common component and allow the new MMM estimate to be statistically different from to previous one. However, these improvements are unlikely to be similar across various models and the resulting "benefit" in climate projections might be smoothed out under a purely statistical interpretation of the projections.

From a probabilistic standpoint, a larger uncertainty interval is unlikely to be desired by anybody. In general, larger modelling uncertainty component in CMIP5 simulations makes optimization of adaptation assessments harder, as applied measures need to be compatible with a wider range of future outcomes. The results do not encourage use of "predict-and-adapt" paradigm: From the perspective of any end user involved in adaptation this would further politicize climate science and shift focus away from the effective application of climate projections. As reminded by Dessai et al. (2009b), our abilities to predict several socio-economic variables are considerably worse compared to our ability to predict future climate change. The lack of accurate predictability of the climate is not a valid reason to postpone adaptation decisions and would be very short-sighted as a considerable part of the uncertainty is a fundamental characteristic of the climate system itself and might largely be irreducible. This conclusion is supported by the large interaction component in Fig. 11.

These results in together with the existing adaptation literature suggest that also other steps in the knowledge cycle in addition to climate modelling require close attention, if the overarching goal is to contribute in improved adaptation. Currently prevailing statistical methodologies used to compose climate projections could be accompanied with physical constraints and parallel runs whenever possible. Implications for climate modelling community are twofold as affected by the scenario uncertainty (see Fig. 5): In the long-term (short-term) climate projections, modelling uncertainty is relatively higher for precipitation (temperature) and model development efforts should be invested to processes affecting this variable as the potential to constrain uncertainty through better process understanding remains higher.

The effects of climate model development to model projections can also be seen in the key findings of AR5 (IPCC, 2013, Table SPM.1). In the Table, confidence statements are assessed both for occurred changes and the likelihood of further changes for specific extreme events. Even though extreme events are more impact-relevant quantities compared to those in **Papers I, IV and V**, the findings are partly in line with this dissertation: Confidence levels for the projected future to incorporate further changes in the water cycle have been revised, whereas confidence on changes of temperature-related climate events have remained similar. Due to the relatively larger role of internal variability in the early 21st, the confidence levels for the related changes are lower compared to the late 21st century changes. Even though the revised confidence levels in general are higher, the statement alone does not allow an assessment of the uncertainty which is related to the projections. Improved climate models undoubtely have had an important role in the attribution of the human contribution to observed changes, as all the condifence levels of all the quantities have been revised. The implications of improved attribution, however, remain controversial for adaptation (Hulme et al., 2011).

4.3 Impact papers

The focus in **Papers I and III** is narrower, both in relation to their spatial domain and the types of applications motivating the analysis. However, this does not necessarily limit the number of potential end user groups (as defined in Chapter 3.2.1) of **Paper I**, as the climate information in these papers is still somewhat general and can be used in any application which is sensitive to them. The implications of climate projections for the specific applications in the papers are also presented. Although publishing these results in the literature alone does not correspond to being an ”honest broker”, this information could be promoted in such a way in other contexts as they have some implications for adaptation over these sectors. This is possible because vulnerability and exposure components (Fig. 1) are also, to some extent, taken into account in these papers by including a process-based point-of-view for the impacts. These impacts, rather than climate change alone, serve as the primary reason for adaptation in these studies. Climate models in these studies are applied using both top-down (**Paper I**) and bottom-up oriented (**Paper III**) approaches.

Table 2 (from **Paper I**) shows the growing season precipitation climatology in two regions of Finland for three observational products and ENSEMBLES climate models in present-day climate. The maximum of the growing season precipitation occurs in August for both study regions, whereas the crop productivity of most Finnish cultivars can suffer from water shortages during the early part of the growing season (May-June). Sufficient water availability during these months is crucial for crop yields. Climate models typically simulate too much precipitation, as MMM values are larger than observations in almost all cases. Removing this bias from the simulations prior to calculating future precipitation was done here using the delta change method (Räty et al., 2014). Also the choice of the precipitation product which is used to correct the bias has a marked influence. The FMI_grid product has the highest information content out of the three products, both regards to the number of precipitation stations over both areas and the used resolution. For CRU, the information content is the lowest. Here, this translates to higher estimates of precipitation over the study area for FMI_grid, and lower for CRU. Figure 12 presents the projected changes in growing season precipitation climatology as simulated by the climate models. Except for August, projected mean precipitation increase is statistically significant on a 2,5 % risk level. Precipitation shortage during the critical months of May and June is expected to become less severe on average.

Table 2: Growing season mean precipitation values (units in mm) for the years 1961-2000 over two study regions over Finland. FMI_grid, E-OBS and CRU are gridded precipitation products, MMM the multi-model mean and std the inter-model standard deviation. Table from **Paper I**.

Month	FMI_grid	E-OBS	CRU	MMM	std
NE region					
May	43.7	39.4	35.7	64.6	15.9
June	64.7	58.7	56.5	77.3	16.5
July	72.7	67.7	63.5	89.7	22.2
August	87.3	79.3	72.6	94.6	23.2
September	66.2	59.8	54.6	87.8	18.6
MJJAS	334.5	304.8	282.8	414.0	86.0
SW region					
May	34.9	33.3	33.5	59.8	11.3
June	52.5	50.2	46.8	66.8	15.5
July	74.5	74.5	71.4	74.2	17.6
August	78.1	77.5	75.8	78.4	18.7
September	61.3	61.0	61.3	75.7	13.9
MJJAS	301.4	296.6	288.6	354.9	67.1

The conclusions of **Paper I** alone, however, are inadequate in providing all the needed information even for the climate component of adaptation. The increase in average precipitation conditions does not take into account the inter-annual variability (see Fig. 3 in the Paper) and also evaporative losses affecting total water budget are expected to increase in warmer climate conditions. These processes affecting the vulnerability of agricultural applications were not analysed in depth, as the primary purpose of the paper was to analyse different observational precipitation data sets and projected precipitation changes of the different RCMs. As projected precipitation estimates provided in the paper are generally applicable and well documented, they could also be used for other purposes as, for example, to estimate flood conditions. For flood applications and many others as well, several other information sources are likely to be needed in parallel to the results presented in the paper. The findings of the paper do, however, have the potential to influence further crop breeding, which is a long-term excercise (Forsius et al., 2013).

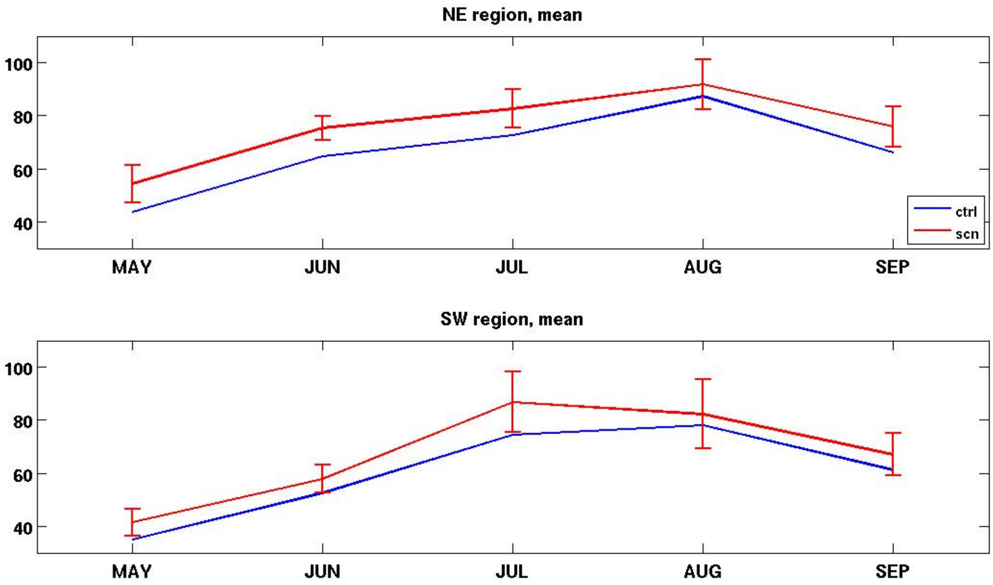

Figure 12: Growing season MMM precipitation changes from 1961-2000 (FMI_grid observations, blue) to 2061-2100 (climate projections, red) over two regions in Finland, as simulated by 13 ENSEMBLES RCMs. The error bars around the MMM line show the standard deviation of inter-model spread for each individual month. Figure from **Paper I**.

The results of **Paper III** are considerably less general, as the key climate variables affecting road conditions are application-specific and might have little relevance for users in other societal sectors. The main focus of the paper was to apply a bottom-up approach by using a process-based road model and to assess the sensitivity of it to climatic variations of temperature and precipitation. This was complemented by using a top-down approach and providing estimated impacts of road network to the projected conditions of other key climate variables. As was found out in the numerical analyses, condition of the road surface layer seems to be a considerably more important factor in defining proper water runoff treatment as compared to the actual distribution of precipitation events. Typical high-traffic roads are very effective in draining the surface runoff water even from the most severe precipitation events, whereas those roads with heavy cracks in them are unable to drain runoff water fast enough. As a result, water is able to penetrate into the road sub-base layer and may thus deteriorate the road structure. As the maintenance life time of most roads (in the order of 20 years) is considerably smaller compared to climatic time scales, bottom-up process understanding of the road structure and properties constitutes a much more important factor for efficient adaptation as compared to being able to accurately estimate the projected climatic changes within this time period. This conclusion outweighs the sensitivity of the projected climate model results to various factors and emphasizes concentrating on the vulnerability component of adaptation in this specific application. Climate change was estimated as also being able to indirectly affect the exposure component, as the movement of people will alter the road traffic volumes and maintenance strategies in different geographical areas. In the conclusions of the paper, iterative risk management and application of existing practices from areas with current climate conditions similar to those projected, were also highlighted as suitable adaptation strategies. In all, the prospect for facilitating adaptation problems in **Papers I and III** by focusing solely on the reduction of epistemic uncertainty in climate change projections seems unlikely.

5 Discussion and conclusions

In this thesis, widely used climate model data were both applied in impact studies and analysed focusing on previously unstudied aspects. Both best-estimate and probabilistic future climate projections were analysed. The findings of this dissertation give rise to two main conclusions:

1. If multi-model ensembles are assessed from a purely statistical viewpoint using traditional analysis methods ("one model - one vote"), the derived climate projections are unlikely to be substantially changed through the development of the climate models themselves. This is caused both by structural differences between climate models and by chaotic behaviour of the climate system.

   (a) For most parts of the world, multi-model mean projections are statistically indistinguishable across several model generations. The user is able to see hardly any significant differences between them as the mutual ordering of individual model projections inside the uncertainty cloud varies between consecutive model generations. Model-dependent component of model development is considerably larger than the collective component shared by each of the models.

   (b) By using in-sample variance as a measure of uncertainty, probabilistic RCP-projections acquired from CMIP5 have a larger uncertainty compared to the SRES-projections of CMIP3, both for modelling and scenario components. If these simulations are used for adaptation, optimization of different applications to climate correspondingly becomes harder. In case the application is highly sensitive to climate, postponing adaptation decisions in the hope of having more narrow uncertainty intervals at disposal in the future is judged as a highly unwise strategy. This, however, might depend on the scale of the application and the climate variable of interest.

   Due to persistent model-specific differences, physical model evaluation should be incorporated whenever physically understandable and statistically robust cause-effect relationships are identified. At local scale there might remain more potential to improve projections through process understanding. Finding universally applicable constraints, however, is harder if the model simulations are analysed in a general manner without a spefic application in mind. Physical model interpretation can possibly allow more confidence to be attached to multi-model results, as purely statistical approaches suffer from several limitations.

2. Subjective interpretation of the climate projections is often necessary, as the used data set and applied methods might be ambiguous. This, together with the specific information demands of several applications, encourages climate services to act as "honest brokers" whenever tailor-made estimates from future climate are needed. Adaptation requires interplay between the user and climate communities as the prior knowledge on the importance of the vulnerability (climate) component might be unknown for climate modellers (application users). Comprehensive adaptation assessments for specific application typically require information from both components, the relative importance of which can vary substantially. Top-down and bottom-up approaches can be used in parallel in many assessments.

Adaptation to climate change seems unavoidable, because of the long time scales related to any mitigation efforts. The utility of future climate simulations depends on the time scale of the application and whether it is sufficiently long to be affected by climate change. The information provided by the climate models can be accommodated to adaptation assessments using several approaches, either using generally applicable and conservative methods (**Papers I and II**) or by using application-specific quantities and incorporating these with detailed process understanding of the application (**Paper III**). A generally applicable approach allows the data to be easily used in several societal applications, but is unlikely able alone to provide sufficient information for any of them. On the other hand, directly engaging with applications allows the provision of sufficient and contextually relevant climate information.

Emphasis on the scientific uncertainties alone is unlikely to encourage people to make adaptation assessments, but their proper acknowledgement is necessary to guide the available resources in an efficient manner. In adaptation problems, natural scientific part typically needs to be incorporated with the sensitivity assessment of the system for climatic constraints (**Paper III**). The gap between end-user needs and the ability of climate models to provide the required information will remain fundamental for several years to come, which allows subjective interpretation of the results. Climate modelling community should not advocate specific policy, but on the contrary: it needs to actively engage with the user interface and promote good application-specific communication approaches.

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