CLIMATE CHANGE – IT'S ALL ABOUT PROBABILITY

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With 11 figures and 5 tables
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Summary: The assessment of present-day and future climate change is of crucial socio-economic and ecological importance but, at the same time, subject to a variety of uncertainty factors that are partly inherent to the climate system. This implies that a statement about the Earth's future climate is definitely a probabilistic one. From a scientific point of view, probabilistic statements require the knowledge of the probability density function (PDF) of the underlying process. In this paper, we expose what we already know of the characteristics of such PDFs of climate change from coordinated climate modelling initiatives and what probabilistic statements can be derived from the quantification and evaluation of climate change in a regional and seasonal context. The first aspect addresses the changing occurrence of heat events with a relatively long return period in past climate. It turns out that particularly warm years, which only occurred once every 40 years in the past, will become typical events by the end of the 21st century. Thus, climate change can be perceived as a change in the probability of specific events. The second issue deals with the distinctness of past and future climates in the light of uncertainty. We show that this distinctness increases towards the end of our century and with the amount of greenhouse gas emissions. However, the overlapping probability of present-day and future PDFs still ranges between 10 and 30% for temperature and even beyond 90% for precipitation in some regions of the globe. The third problem is dedicated to so-called probabilistic climate predictions in the form of overshooting and undershooting probabilities given various thresholds of climate change. While for temperature, the range of probable future changes is narrow and the sign is unambiguous, the uncertainty range of precipitation changes is often larger than the mean signal. Overall, probabilistic assessments in climate change research allow for the quantification of uncertainty and, hence, provide valuable information for decision processes.

Zusammenfassung: Die Abschätzung von vergangenen und zukünftigen Klimaänderungen ist einerseits von großer sozioökonomischer und ökologischer Bedeutung, unterliegt andererseits aber vielfältigen Unsicherheitsfaktoren, die zum Teil systemimmanent sind. Dies bedingt, dass Aussagen über das zukünftige Klima der Erde unvermeidbar von probabilistischer Natur sind. Aus wissenschaftlicher Sicht erfordern probabilistische Aussagen die Kenntnis der Wahrscheinlichkeitsdichte (PDF) des zugrundeliegenden Prozesses. In diesem Artikel legen wir dar, was wir bereits über die Struktur solcher PDFs des Klimawandels aus koordinierten Klimamodellierungsinitiativen wissen und welche probabilistischen Aussagen sich daraus im Hinblick auf die Quantifizierung und Bewertung des Klimawandels im regionalen und saisonalen Kontext ableiten lassen. Die erste Fragestellung befasst sich mit der veränderten Eintrittswahrscheinlichkeit warmer Jahre, die in der Vergangenheit eine relativ lange Wiederkehrzeit hatten. Es stellt sich heraus, dass besonders warme Jahre, die früher nur alle 40 Jahre auftraten, bis zum Ende des 21. Jahrhunderts den Normalfall darstellen. Klimawandel wird also wahrnehmbar sein als eine veränderte Wahrscheinlichkeit von bestimmten Ereignissen. Der zweite Aspekt bezieht sich auf die Unterscheidbarkeit zukünftiger und vergangener Klimazustände vor dem Hintergrund von Unsicherheit. Wir zeigen auf, dass sich diese Unterscheidbarkeit mit der Zeit und mit emissionsintensiveren Szenarien erhöht. Dennoch liegt die Fehlklassifikationswahrscheinlichkeit bei der Temperatur noch zwischen 10 und 30% und beim Niederschlag sogar in einigen Regionen jenseits von 90%. Die dritte Problemstellung widmet sich den so genannten probabilistischen Klimavorhersagen in Form von Über- und Unterschreitungswahrscheinlichkeiten bestimmter Schwellwerte des Klimawandels. Während der Bereich wahrscheinlicher zukünftiger Temperaturänderungen eher schmal und die Vorzeichen eindeutig sind, ist der Unsicherheitsbereich von Niederschlagsänderungen häufig breiter als das mittlere Signal. Insgesamt ermöglichen probabilistische Abschätzungen in der Klimaänderungsforschung die Quantifizierung von Unsicherheiten und geben wertvolle Anhaltspunkte für Entscheidungsprozesse.

Keywords: Climate change, probabilistic assessment, global climate models, uncertainty, regional temperature and precipitation

1 Introduction

There is an unequivocal consensus about the fact that human activity affects the Earth's climate to a considerable extent in the climatological community and beyond (Hansen et al. 2006; IPCC 2007a). Although some media and lobbyists still cast doubt on this phenomenon most policymakers, planners and laymen are convinced that climate mitigation and adaptation will be one of the great societal

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challenges of the 21st century (Hansen et al. 2006; IPCC 2007b, c). To cope with the unavoidable part of future global warming, reliable estimates of the regional patterns and amplitudes of climate changes are urgently required. The most reliable instrument to throw light on the future perspective of climate is the use of sophisticated climate models (Murphy et al. 2004), in particular general circulation models (GCMs) preferably embedded in so-called earth system models that account for a variety of processes and interactions in the climate system (Taylor et al. 2012). However, climate models still have considerable deficiencies and differ in terms of their projected climate changes, especially at the regional scale. This is also the case for higher-resolution regional climate models (e.g., Paeth et al. 2010), although they provide some added value in shaping the regional fingerprint of temperature and precipitation changes (Paeth and Mannig 2013).

This discrepancy between the claim for precise predictions on the one hand and uncertain model results on the other hand is typical for scientific issues dealing with complex systems.

In the climate context, uncertainties arise from the approximations and omissions required when representing real-world processes in climate models. This may partly be overcome by means of model improvements and increasing computer resources. Uncertainties also relate to multi-scale internal variability and inaccurate initial conditions which are more intrinsic problems of the climate system (Palmer and Anderson 1994; Stott and Kettleborough 2002). In addition, observational data are also subject to inaccuracies and internal noise related to natural variability (Brohan et al. 2006; Hunt 2011). This implies that climate impact research and decision makers in adaptation and mitigation processes also have to cope with these uncertainties. This is not necessarily a dilemma because so-called probabilistic climate predictions that are based on the uncertainty range of the prediction tools, i.e., climate models, provide valuable information for decision making (Räisänen and Palmer 2001).

In this study, we expose why and how the climate change issue is inevitably tied to probabilistic assessments. Basically, this knowledge is not novel in the climatological community. However, after reviewing the current state of knowledge in terms of probabilistic climate change aspects, we provide a novel systematic and quantitative multilayer analysis based on a large state-of-the-art multi-model ensemble of global climate model experiments. In detail, three perspectives of defining climate change in the probability space are presented. The main goal is to demonstrate how climate impact research can profit from probabilistic climate predictions which is tantamount to a quantification – not yet reduction – of uncertainty. Finally, we discuss how uncertainties from present-day climate model projections may be decreased – or should even become larger in order to account for all possible pathways of future climate (cf. Curry 2011). The following section contours the theoretical background and the resulting hypotheses which underlie the three approaches of model data analysis described in section 4. The data sets and statistical methods considered are presented in section 3. Results are discussed in section 5 with respect to possible future treatments of uncertainty in climate change projections.

2 Theoretical background and hypotheses

The sources of uncertainty in the assessment of anthropogenic climate change are manifold and partly different for present-day and future periods (Fig. 1). From our theoretical understanding of the climate system, in particular the radiation budget and energy balance, radiative forcing by greenhouse gases (GHGs) and aerosols should noticeably affect the observed near-surface temperature over the 20th century (Fig. 1, left). In fact, temperature variability is also influenced by natural drivers of the Earth's climate, especially solar irradiation and volcanic eruptions, and internal noise arising from the interactions and feedbacks between the system components, for instance atmosphere–ocean–sea ice or atmosphere–vegetation–soil moisture (Hunt 2011; Rypdal 2012). Thus, anthropogenic forcing competes against non-anthropogenic factors, impeding the detection of man-made climate change on the basis of observational data (Stott et al. 2000; Schönwiese et al. 2010). In addition, it must be taken into account that observational data are subject to gaps, inhomogeneity and measurement errors, amounting to up to 0.2 °C even in terms of the global mean temperature (Folland et al. 2001; Hogan 2005; Brohan et al. 2006).

In future climate model projections, even more uncertainty factors exist (Fig. 1, right). First, future climate will also be affected by solar variability and volcanic activity (Stott and Kettleborough 2002; Jones et al. 2012). While volcanic eruptions cannot be predicted several years or decades ahead, there are some attempts to specify future solar irradiation changes in climate models (Lean and Rind 2009).

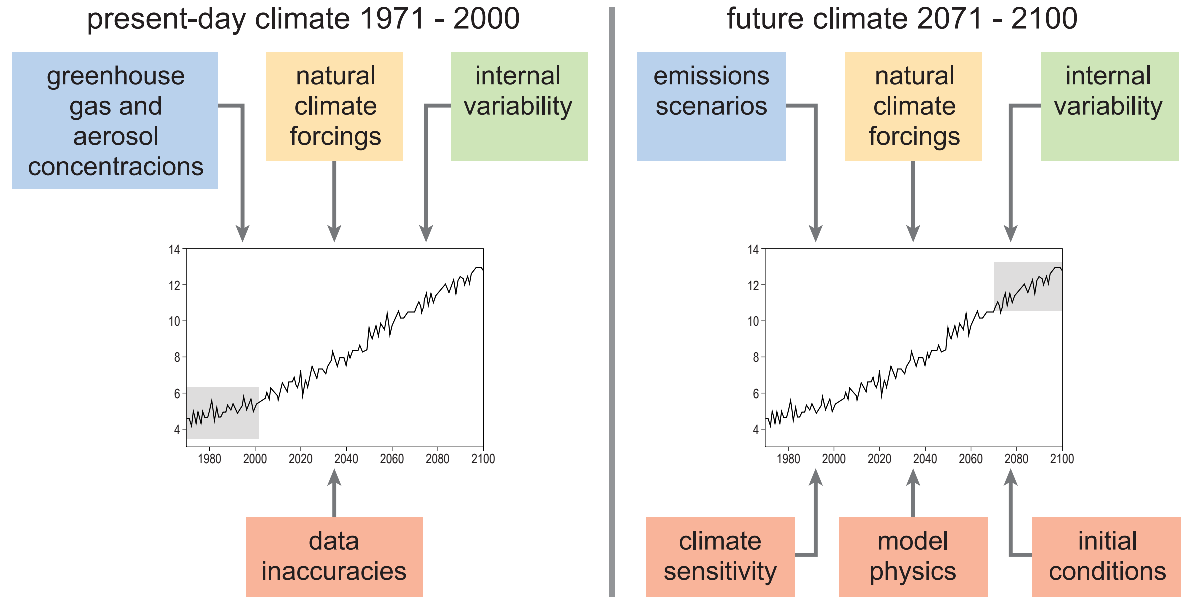

Fig. 1: Contributions to an observed present-day (left) and simulated future (right) temperature development at a given location: anthropogenic driving factors (blue boxes), natural driving factors (yellow boxes), uncertainties due to internal variability arising from climate system interactions (green boxes) and uncertainties due to lack of knowledge (red boxes)

Internal variability is included in climate models, especially in Earth system models (Taylor et al. 2012), but represents a noise component in climate projections which, like in the observations, superimposes the impact of radiative forcing and, hence, reduces the predictability of climate. Another source of uncertainty is given by the scenarios of future human activity. GHG and aerosol emissions in the 21st century are a function of the demographic, socio-economic, technological and political development on Earth and highly diverse by nature (Nakicenovic and Swart 2000; Schenk and Lensink 2007). Some aspects of human interference with climate are still not accounted for in most climate model experiments, i.e., the indirect effects of aerosols (Paeth and Feichter 2006) and the role of land-cover changes (Pielke et al. 2002; Feddema et al. 2005; Paeth et al. 2009). Climate model projections are also uncertain because state-of-the-art climate models still have important deficiencies, e.g., missing feedbacks and unresolved processes due to coarse resolution (Palmer and Anderson 1994). The latter has led to a number of parameterizations that suffer from a lack of empirical evidence and basic understanding (Palmer and Williams 2008). In addition, each model simulation requires accurate initial conditions that are not given, especially for starting times in the period of early meteorological measurements in the mid-19th century (Palmer and Williams 2008). The initial conditions affect the phasing – not the amplitude – of internal variability and, thus, contribute to this uncertainty factor. Hawkins and Sutton (2011) have shown that the spread over different climate model projections is determined by shorter-term internal variability over the first decades of the simulations, while different model parameterizations predominate towards the end of the 21st century. Note that the phasing of shorter-term internal fluctuations depends on the initial conditions, whereas the longer-term changes relate to the external forcings, e.g., increasing GHG concentrations (Palmer and Williams 2008). Finally, the prediction of future climate conditions also suffers from the uncertain climate sensitivity of the Earth (Roe and Armour 2011). Climate sensitivity is defined as the global-mean temperature change per doubling of the atmospheric CO_2 concentration (Sexton and Murphy 2012). From climate models the sensitivity has been estimated to be around 3 °C per $2xCO_2$ with a range from 2.1 °C to 4.7 °C in most recent climate model experiments (Andrews et al. 2012). It mostly depends on feedbacks considered in the simulated climate system but also relates to the parameterizations of sub-grid scale processes and, to a lower extent, to the future GHG emission paths (Roe and Baker 2007; Wang et al. 2012; Zickfeld et al. 2012). Lovejoy and Schertzer (2012) have pointed to the difficulty of deriving climate sensitivity from given meteorological measurements or proxy data. However, climate sensitivity is a crucial factor when determining the amount of GHG emissions reduction necessary to comply with a maximum warming rate of 2 °C by 2100 (Hansen et al. 2006).

It may be argued that uncertainties related to parameterizations, resolution and climate sensitivity may once be overcome when computer resources allow for a 'perfect' climate model. Setting the resolution of such a perfect model to 0.001 µm which is about the size of the smallest aerosols (Paeth and Feichter 2006), this climate system would be characterized by about 10^{49} degrees of freedom, requiring 10^{39} W to store a single time step on a common data medium. Using the entire energy of our solar system, which is in the order of 10^{49} J, we could store just 300 years of simulated climate at a one-second time step. It is obvious that such a perfect model cannot be realized and, even if it could be realized, the prediction would be imperfect because the initial conditions are still inaccurate. This implies that climate change research will always have to cope with uncertainties. In practice, climatologists assess the uncertainty range of climate model projections by realizing several model simulations with plausible but different initial conditions, different resolutions and different parameterization schemes. This has led to the coordinated multi-model ensembles of coupled GCM simulations (Meehl et al. 2007; Taylor et al. 2012). Based on this, numerous studies have identified climate change signals against the background of model uncertainty and varied initial conditions: For temperature and precipitation (e.g., Paeth and Hense 2002), for monsoons and El Niño-Southern Oscillation (e.g., Paeth et al. 2008a) as well as for extra-tropical circulation modes (e.g., Paeth and Pollinger 2010).

The scientific assessment of the probability of a specific event or groups of events is based on so-called probability density functions (PDFs). A PDF is a mathematical function defined over the feature space of a given random process (Wilks 2006). The integral over this function is always 1, corresponding to a chance of 100 % that a specific event is an element of the feature space. For instance, assuming a normal distribution as one prominent representative of such PDFs there is a chance of 100 % that the value of a specific event ranges between minus and plus infinity – at first sight a trivial statement. Accordingly, subareas under this function denote the probability of a specific range of events, e.g., the probability that an event occurs above or below a given threshold or between two given thresholds. Once the parameters of a PDF are estimated from a random sample, any overshooting, undershooting or interval probability can be computed for given thresholds or, vice versa, the thresholds – so-called quantiles – can be determined for any given probability. Both approaches are widely used in test statistics (Wilks 2006).

Assuming that climate model results represent random samples from the population of future human-induced climates, PDFs can be estimated based on the multi-model ensemble data (IPCC 2007a). In this case, the PDFs span various amplitudes of climate change as deduced from different climate model runs with different parameterizations and initial conditions. Thus, climate models tell us something about the structure of the probability space associated with uncertain climate change. The idealized view in figure 2 demonstrates how temperature at a given location shifts towards higher values depending on the SRES emissions scenarios (Nakicenovic and Swart 2000). Each scenario is represented by temperature data simulated by various climate models with different initial conditions, resolution, parameterizations, climate sensitivity and internal variability (Fig. 2, lined PDFs). While all model simulations are assigned equal probabilities, the simulated temperatures are characterized by more and less frequent values, implying that mean and extreme future temperature changes can be determined for a given sample. Assuming that each climate model is an approximation of the real climate system plus random error, the PDFs for the mean temperature in future climate are slimming (Fig. 2, shaded PDFs) because, according to classical test statistics, the standard error of the mean scales with the number of ensemble members (Sanderson and Knutti 2012). An indication of this assumption is that the multi-model ensemble mean is often closer to the observations than the best individual model experiment (e.g., Paeth et al. 2010). However, a drawback is that this assumption implies that current climate model simulations are independent of each other in a strict sense, which may not be fully given (Annan and Hargreaves 2010).

Once the probability distributions are estimated on the basis of climate model data, there are various probabilistic assessments that need to be applied to evaluate and quantify climate change in the light of model uncertainty (Fig. 3). First, the insignificance of climate changes can be expressed as the extent that the present-day and future climate PDFs overlap (top panel). In contrast, a change is evident, if the PDFs can clearly be separated from each other. Second, the shift of PDFs from present-day to future climate implies a changing frequency of a given event (middle panel), e.g., an extreme event beyond a cer-

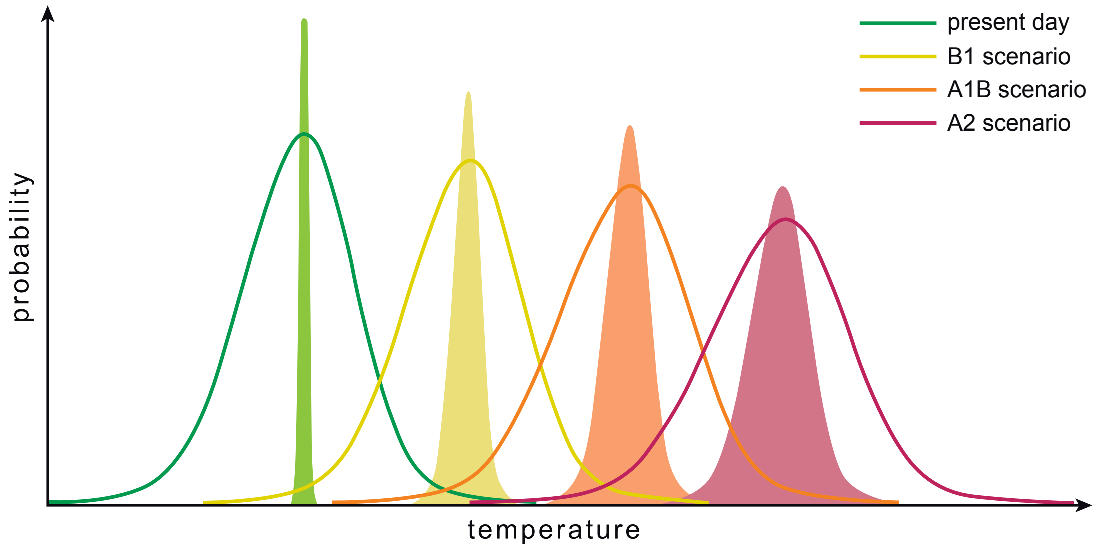

Fig. 2: Idealized structure of the PDFs of observed present-day and simulated future temperature at a given location, referring to the whole sample of given data (lines) and to the respective mean values of the samples (shaded) for three different SRES emissions scenarios

tain threshold (Hennessy et al. 1997; IPCC 2007a). Only for Europe, a number of studies have focused on changing return times of extreme precipitation (Palmer and Räisänen 2002; Christensen and Christensen 2003; Fowler and Kilsby 2003; Paeth and Hense 2005) and heat waves (Kyselý 2010; Nikulin et al. 2011). They agree that the frequency of heat and heavy rain events will increase in the course of global warming. Third, given a PDF of possible future climate states, over- and undershooting probabilities can be determined for various thresholds of climate change (bottom panel). In this schematic example, the probability is 5 % that the warming rate at a given location exceeds 4.5 °C. This means that there is a 5 % chance to draw a climate model simulation with warming larger than 4.5 °C out of the population of possible future climates. This leads to the approach of probabilistic prediction (Rougier 2007; Sexton et al. 2012). While probabilistic predictions allow for a quantification but no reduction of uncertainty (Collins et al. 2006), they provide important information for decision processes in climate change adaptation. Some decisions, for instance in insurance industries, are traditionally taken in a probabilistic context (Murnane 2004; Dlugolecki 2008).

Based on the conceptual model from figure 3, we investigate a set of hypotheses that are often stated in the context of anthropogenic climate change. We proceed in a systematic way by accounting for different regions across the globe in the framework of a state-of-the-art multi-model ensemble of climate change experiments:

1. Warm events with long return times under present-day climate conditions will become typical events by the end of the 21st century.
2. PDFs of current and future regional climate are less overlapping for enhanced than for mitigated emission scenario and less overlapping for temperature than for precipitation.
3. Probabilistic predictions of regional temperature and precipitation reveal a higher level of uncertainty for precipitation than for temperature, possibly not only in terms of the amplitude but also of the sign.

While these hypotheses appear to be well-established because they sound plausible in the light of global warming, they still require a systematic and quantitative assessment on the basis of state-of-the-art climate model simulations (cf. IPCC 2007a; Watterson 2008). The following section describes how these hypotheses will be tested in terms of model data and statistical methods.

3 Data and methods

In this study, the probabilistic assessment of regional climate changes is based on the Coupled Model Intercomparison version 3 (CMIP3) data set (Meehl et al. 2007). This multi-model ensemble is composed of 23 ocean-atmosphere coupled climate models at horizontal resolutions between 120 and 500 km (Tab. 1). A total of 207 centennial runs is available for the 20th century and the SRES emis-

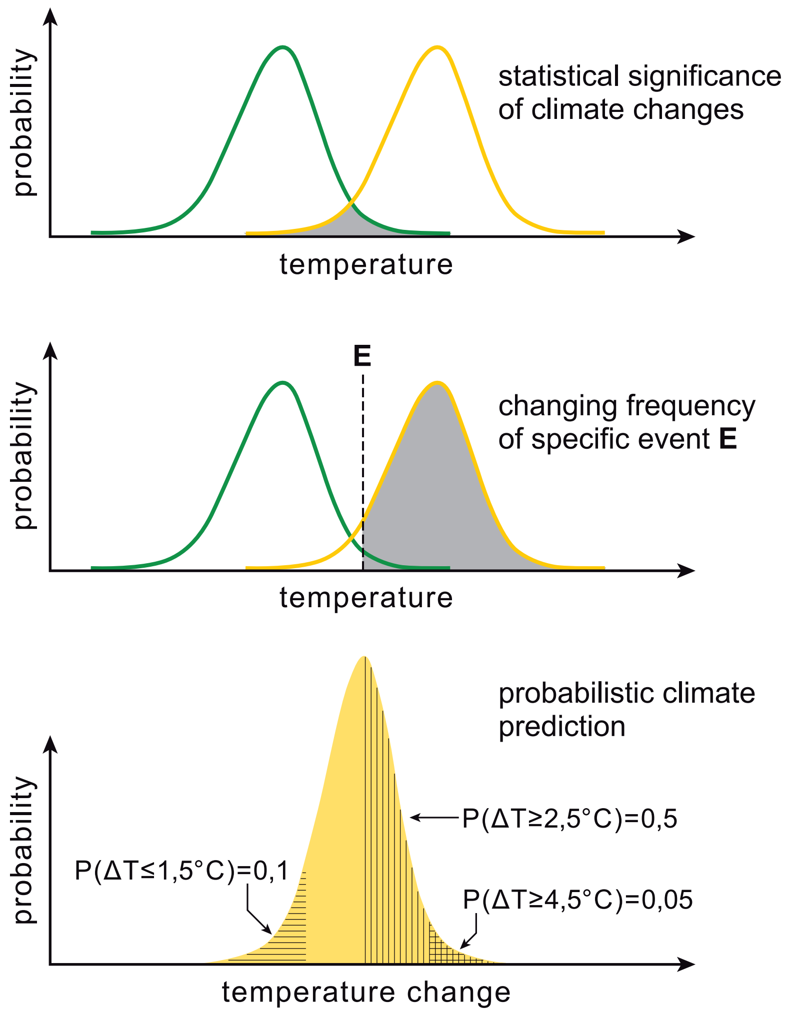

Fig. 3: Probabilistic assessments arising from the comparison between PDFs of present-day (green) and future (yellow) temperature under a given scenario. Shaded areas represent a measure of probability for a statistically insignificant change in the variable or process which is described by these PDFs (top panel), for a changing occurrence of a given event (middle panel) and for the under- or overshooting of a given threshold of climate change (bottom panel).

sions scenarios B1, A1B and A2 (Nakicenovic and Swart 2000). The CMIP3 data set has been widely used for climatological applications and represents state-of-the-art of climate modelling until the CMIP5 project is accomplished during 2013 (Taylor et al. 2012). Numerous studies have dealt with the validation of the individual ensemble members and the ensemble mean and have concluded that CMIP3 is a useful tool to study climate change down to the scale of continents and larger regions (IPCC 2007a). Note that the PDFs of past climate shown in this study are based on climate model simulations, which may have some bias with respect to observations. This is admissible because we stress the future changes within each model simulation.

We considered monthly temperature averaged to seasonal and annual means as well as monthly precipitation added up to seasonal and annual sums for the analysis. For comparison and combination, all data sets are interpolated to a common 3° x 3° resolution. The probabilistic predictions and the overlapping of PDFs are investigated at the level of regional means. According to the definition of hot spot regions of climate change (Giorgi 2006; Diffenbaugh and Giorgi 2012), twelve regions were selected of which six are shown in this study as representatives of different climate zones. The Mediterranean Basin and Central America are assumed to have the highest signal-to-noise ratio with respect to 21st century temperature and precipitation changes (Giorgi 2006; Diffenbaugh and Giorgi 2012). Greenland is im-

Tab. 1: Considered global climate model simulations from the CMIP3 initiative (cf. Meehl et al. 2007) with horizontal resolution and available ensemble members for the 20th century (20C) and 21st century under emissions scenario B1, A1B and A2

Model	Horizontal resolution	20C	B1	A1B	A2
BCCR	~300 km	1	1	1	1
CCSM3	~150 km	7	9	7	4
CGCM3	~400 km	1	5	5	5
CGCM3.1	~300 km	1	1	1	–
CNRM	~300 km	1	1	1	1
CSIRO3	~200 km	3	1	1	1
CSIRO3.5	~200 km	1	1	1	1
ECHAM5	~200 km	4	3	4	3
ECHO-G	~400 km	5	3	3	3
FGOALS	~300 km	3	3	3	–
GFDL2	~250 km	3	1	1	1
GFDL2.1	~250 km	3	1	1	1
GISS-AOM	~400 km	2	2	2	–
GISS-EH	~500 km	5	–	3	–
GISS-ER	~500 km	9	1	5	–
INGV	~120 km	1	–	1	1
IPSL	~300 km	1	1	1	1
MIROC3.2H	~120 km	1	1	1	–
MIROC3.2M	~300 km	3	3	3	3
MRI	~300 km	5	5	5	5
PCM	~300 km	4	2	4	4
UKMO-C	~300 km	2	1	1	1
UKMO-G	~200 km	2	–	1	1
Total		68	46	56	37

portant in terms of its potential contribution to future sea-level rise (Hansen et al. 2006). The Tibetan Plateau plays a major role in the Asian monsoon system (Paeth et al. 2008a). Southern Africa is particularly embedded in tropical teleconnections and interactions with the surrounding oceans (IPCC 2007a). Germany was chosen because it is characterized by a high density of population and infrastructure.

By nature, probabilistic issues are sensitive to the assumed statistical model of the underlying process. According to IPCC (2007a), we use the normal distribution as statistical approach for the model-based PDFs of climate change, implying the assumptions that the spread over climate models is symmetric around the ensemble mean and each simulation approximates the real system plus a random error (cf. Sanderson and Knutti 2012). The normal distribution is given by

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} \cdot e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} \quad , \quad -\infty < x < \infty \qquad (1)$$

where μ is the expectation and σ the dispersion of the distribution (Wilks 2006). For μ and σ the mean and empirical standard deviation, respectively, over the CMIP3 ensemble members are taken as unbiased estimators. To evaluate whether this statistical fit is appropriate, a Kolmogorov-Smirnov (KS) test was applied (Wilks 2006). The error level is set to 10% in order to facilitate the rejection of the null hypothesis. As the latter says that the fit is appropriate, this makes the test more conservative.

Changing frequencies of specific events (hypothesis 1) and over- and undershooting probabilities for given thresholds (hypothesis 3) are determined by integration of the normally distributed PDFs. The intersection of PDFs (hypothesis 2) is measured by the overlapping probability (OLP). Given two PDFs with μ_1 and μ_2, where $\mu_1 \leq \mu_2$, and intersection S, the OLP is calculated by integrating the left PDF from S to ∞ and the right PDF from -∞ to S and adding both integrals (see grey shading in the top panel of figure 3; Wilks 2006; Paeth et al. 2008b).

4 Probabilistic assessments

4.1 Changing probabilities of warm events (hypothesis 1)

With respect to the changing frequency of specific events in a GHG-induced climate, we focus on annual and seasonal temperature anomalies because distinct changes are to be expected (e.g., IPCC 2007a; Kyselý 2010; Nikulin et al. 2011). Note that the change in the frequency of warm events is also a function of the considered time scale: For monthly and, in particular, daily values, the variability is higher and, hence, the increase in probability is presumably smaller. As a threshold for a warm event, we define the warm annual or seasonal temperature extreme at every model grid box that had a statistical return time of 40 years during the period 1875-1990. This is equivalent to the upper threshold of the 95 % confidence interval around the mean value over the same time interval. The return value itself is not displayed for the period 1875–1990. It is a function of latitude, altitude, continentality, etc., and basically corresponds to the global distribution of mean temperature (cf. Paeth and Hense 2005). The temperature threshold in every grid box is retained and applied to future periods under various emissions scenarios.

Figure 4 depicts the relative frequency of annual temperature values above the threshold during 25-year time slices into the 21st century under the A1B emissions scenario. Until 2025, the return time of warm events will hardly change over mid-latitude oceans, but its occurrence may increase to more than 70 % in some tropical regions. In the global mean, the relative frequency rises to around 40 %. This means that a particularly warm year that occurred once in

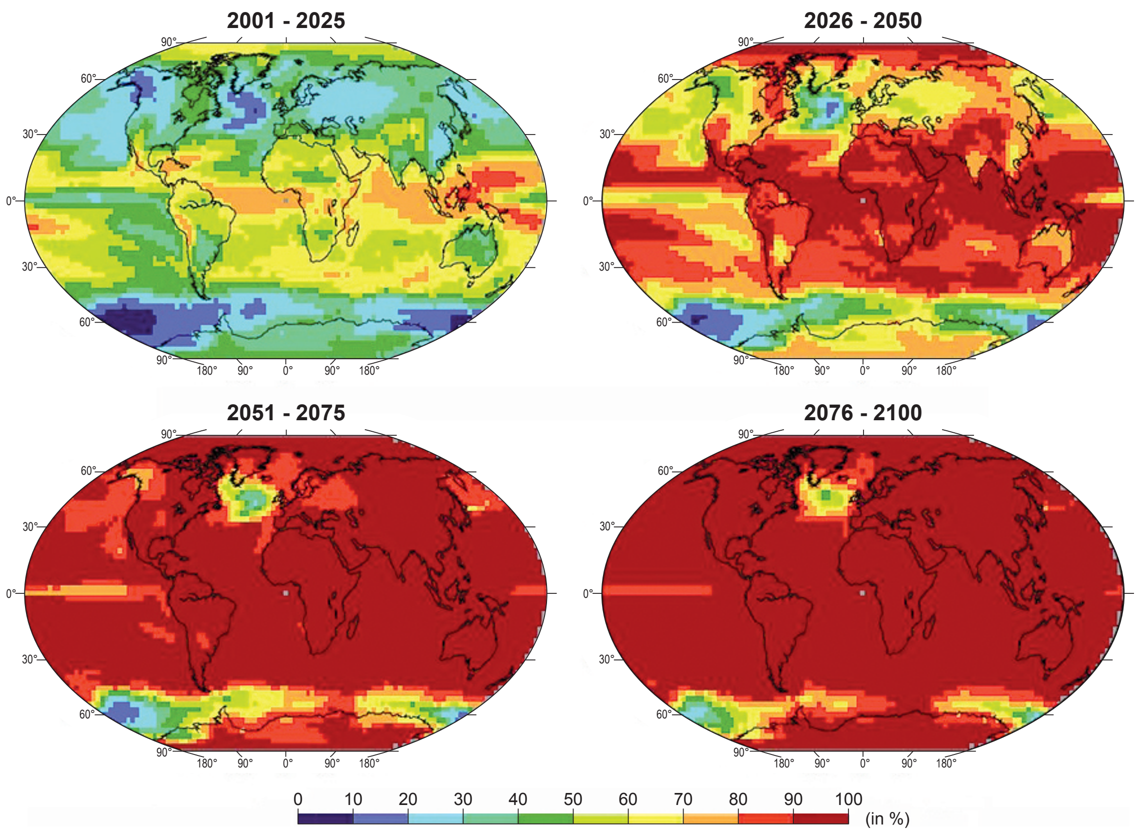

Fig. 4: Relative frequency in % of warm annual temperature extremes with a 40-year return time in past climate during four time slices in the 21st century under A1B emissions scenario

40 years during the reference period 1875–1990, may be observed in 16 out of 40 years in the near future. Towards the end of the 21st century, this change will be even more dramatic: Extremely warm years are predicted in more than 90 % of the years to come and, hence, these become typical events (cf. Kyselý 2010). This is how climate change will be perceived: As an increasing frequency of weather situations that favour warm temperature anomalies. Some exceptions with low sensitivity are found over the mid-latitude oceans. This is in agreement with other studies and probably related to a regional cooling effect by an attenuated North Atlantic thermohaline circulation (cf. IPCC 2007a). In addition, enhanced cloudiness due to more intense extra-tropical cyclogenesis may play a role as dampening mechanism (Paeth and Pollinger 2010).

The tendency towards more frequent extremely warm years is also a function of the future GHG emissions (Fig. 5). The general pattern is virtually the same under the B1, A1B and A2 scenarios. The most striking fact is that under the mitigation scenario (B1), the relative frequency of warm events will also be beyond 90 % by the end of the 21st century in most regions of the globe. This implies that regardless of the future emissions path, warm years are saturating towards 2100, becoming normal instead of extreme events. Some more differences among the scenarios are found over the North Pacific and parts of Eurasia.

A more differentiated picture is drawn for seasonal temperature extremes (Fig. 6). The probability of extremely warm seasons increases more in the low and high latitudes whereas the mid-latitudes may respond to a lesser extent. Over the Northern Hemisphere oceans, the increase is lower during the cold season (JFM), supporting the hypothesis that reduced thermohaline circulation and/or enhanced cyclogenesis plays a role. Around the Antarctic this explanation is less apparent but still the dampening effect is most pronounced during Southern Hemisphere winter (JAS).

4.2 PDFs of past and future climate (hypotheses 1-3)

Based on six regional means, figure 7 shows the Gaussian PDFs of annual temperature during past and future time slices under the A1B emissions scenario. The PDFs relate to means over 30 years from every model simulation and, hence, correspond to the case of the shaded PDFs in figure 2 (cf. Sanderson and Knutti 2012). At this level, the criterion of the KS test is not taken into account and all PDFs are drawn for illustration. The basic structure is alike in all regions: The PDFs shift towards a higher temperature mean from the early 20th to the late 21st century. Simultaneously, the PDFs also broaden, except for the Tibetan Plateau, implying that the spread among climate model simulations increases with time. This is in agreement with IPCC (2007a) and can be explained by the fact that climate models with different resolved processes and climate sensitivity progressively diverge with simulation time.

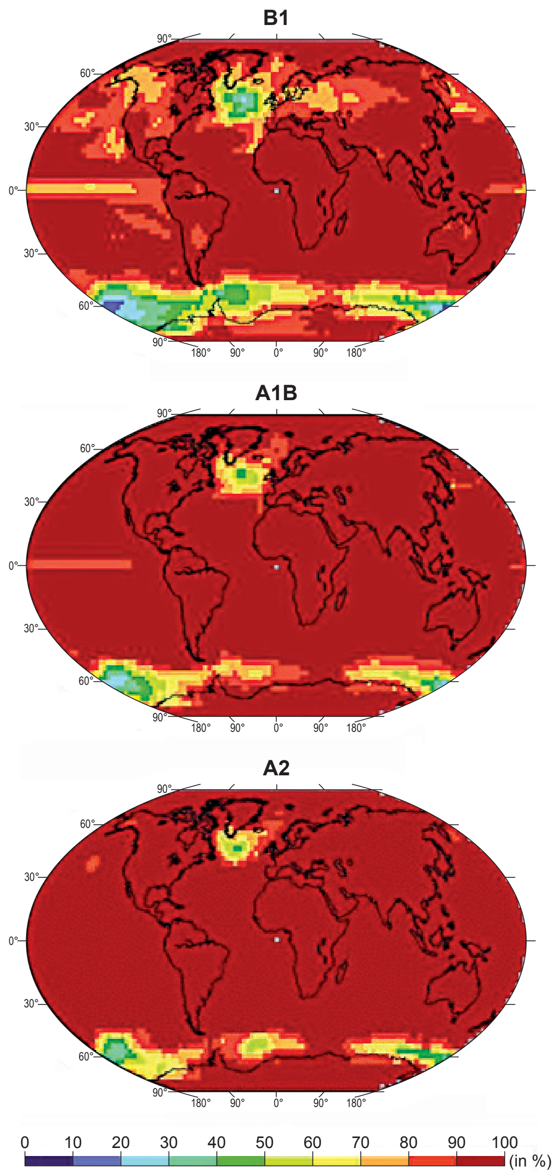

Fig. 5: Relative frequency in % of warm annual temperature extremes with a 40-year return time in past climate during the period 2076-2100 under different emissions scenario

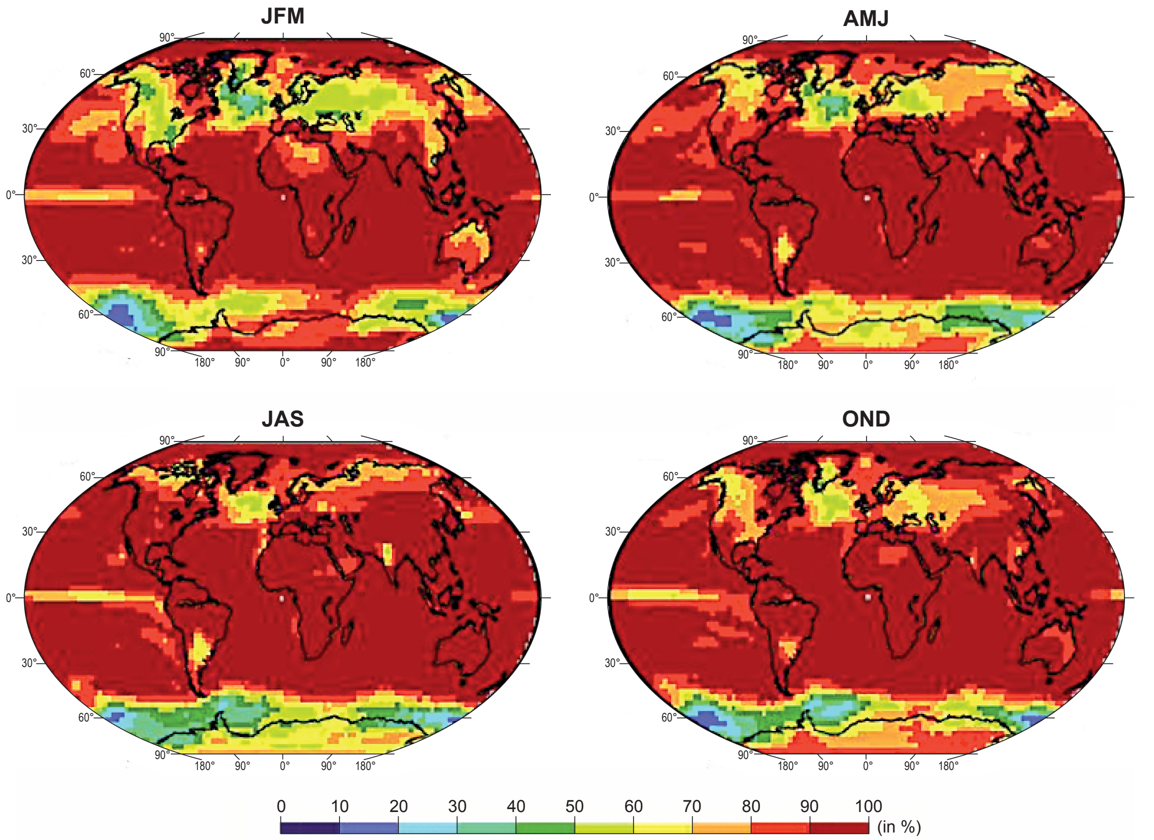

Fig. 6: Relative frequency in % of warm seasonal temperature extremes with a 40-year return time in past climate during the period 2076–2100 under A1B emissions scenario

In detail, there are some remarkable differences between the regions: The PDFs are generally broader in higher-latitude and higher-altitude regions than in tropical and subtropical areas, simply because internal variability is more pronounced (cf. Paeth and Hense 2002). At the same time, the shift is stronger – around 5 °C in Greenland and Tibet versus 3 °C in Central America and Southern Africa. In both respects, the Mediterranean region and Germany as representatives of the mid-latitudes lie in between.

In terms of annual precipitation, the picture is more diverse (Fig. 8). More abundant precipitation is simulated in Greenland and over the Tibetan Plateau, drier conditions may prevail across the Mediterranean Basin and Central America, hardly any changes are found over Germany and Southern Africa. Interestingly, the PDF is rather narrow for the last time slice over the Mediterranean region, indicating a certain convergence of all considered model runs for a drier climate (cf. Christensen and Christensen 2003; Paeth and Hense 2005; Giorgi 2006). However, all regions have one feature in common: The shift of the mean clearly stands back from the dispersion of the PDFs, impeding the detection of annual precipitation changes against the background of internal variability and model uncertainty (cf. Paeth and Hense 2002).

The shift of the PDFs is also a function of the emissions scenario (Fig. 9). It is obvious that A1B and A2 scenarios are closer to each other than to the B1 scenario (cf. IPCC 2007a). Precipitation in Southern Africa responds to none of the GHG scenarios. In some cases, the width of the PDFs is smallest for the A2 scenario. While this is somehow counterintuitive in the light of different climate sensitivities in the models, it could simply be due to the smaller ensemble size of the A2 scenario (see Tab. 1).

Figure 10 illustrates that temperature and, especially, precipitation changes can also be differentiated seasonally. In winter, the PDFs tend to be broader because internal variability is more expressed. An exception is Southern African rainfall where winter (JAS) is characterized by a dry season. In this region, the seasonal changes are contrary with winter drying and more rainfall in summer, leading to no changes in the annual totals (cf. Fig. 8).

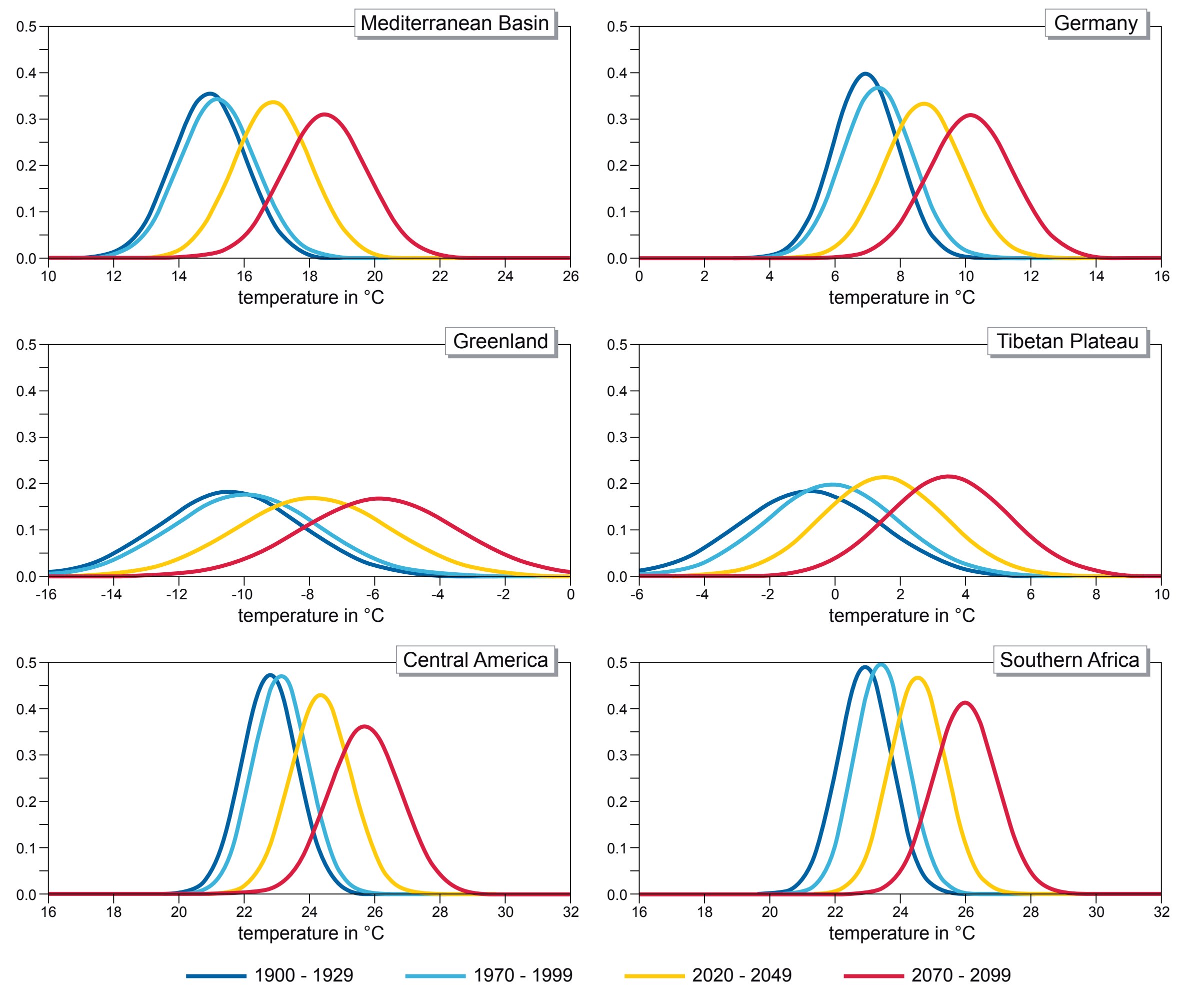

Fig. 7: PDFs of simulated annual temperature in six target regions during four time slices in the 20th and 21st century under A1B emissions scenario

4.3 Overlapping probabilities (hypothesis 2)

The shift of the mean is a measure of the climate change signal, while the width of the PDFs is an indication of noise. The OLP arises from a combination of both and indicates to what extent PDFs of past and future climate can be distinguished from each other. The smaller it is, the higher the signal-to-noise ratio of a given climate change. The OLPs in table 2 refer to the regional-mean PDFs of annual temperature displayed in Figs. 7 and 9. Note that the KS test has identified all of the PDFs that were considered to be normally distributed. OLP is quite high for a low amount of GHG concentrations, i.e., the period 2020–2049 under B1 scenario, and in high-latitude and high-elevation areas. In Tibet it amounts to 81 %. Thus, there is a high chance to assign a given year to the wrong PDF, present-day or early 21st century under B1 scenario. Indeed, figure 7 demonstrates the substantial overlapping of the PDFs. Towards the late 21st century the OLP decreases noticeably. This particularly holds for the A2 scenario where OLP ranges between 12 % and 35 % depending on the region. Again, the Mediterranean Basin is characterized by the clearest signal in most scenarios and time slices (cf. Giorgi 2006).

Concerning annual precipitation, some PDFs were found to be not normal, especially for the Tibetan Plateau, hence, they were excluded from the analysis. The OLPs in table 3 relate to the PDFs in figures 8 and 9. According to the remarkable overlapping of the PDFs, OLP is substantial in all regions, time slices and emissions scenarios. It tends to be lower towards the end of the 21st century and under the A2 scenario. The lowest value is achieved for the Mediterranean region where it still amounts to 56 %. In Germany, OLP is around 90 %, reflecting the insensitivity of annual (but not seasonal) precipitation

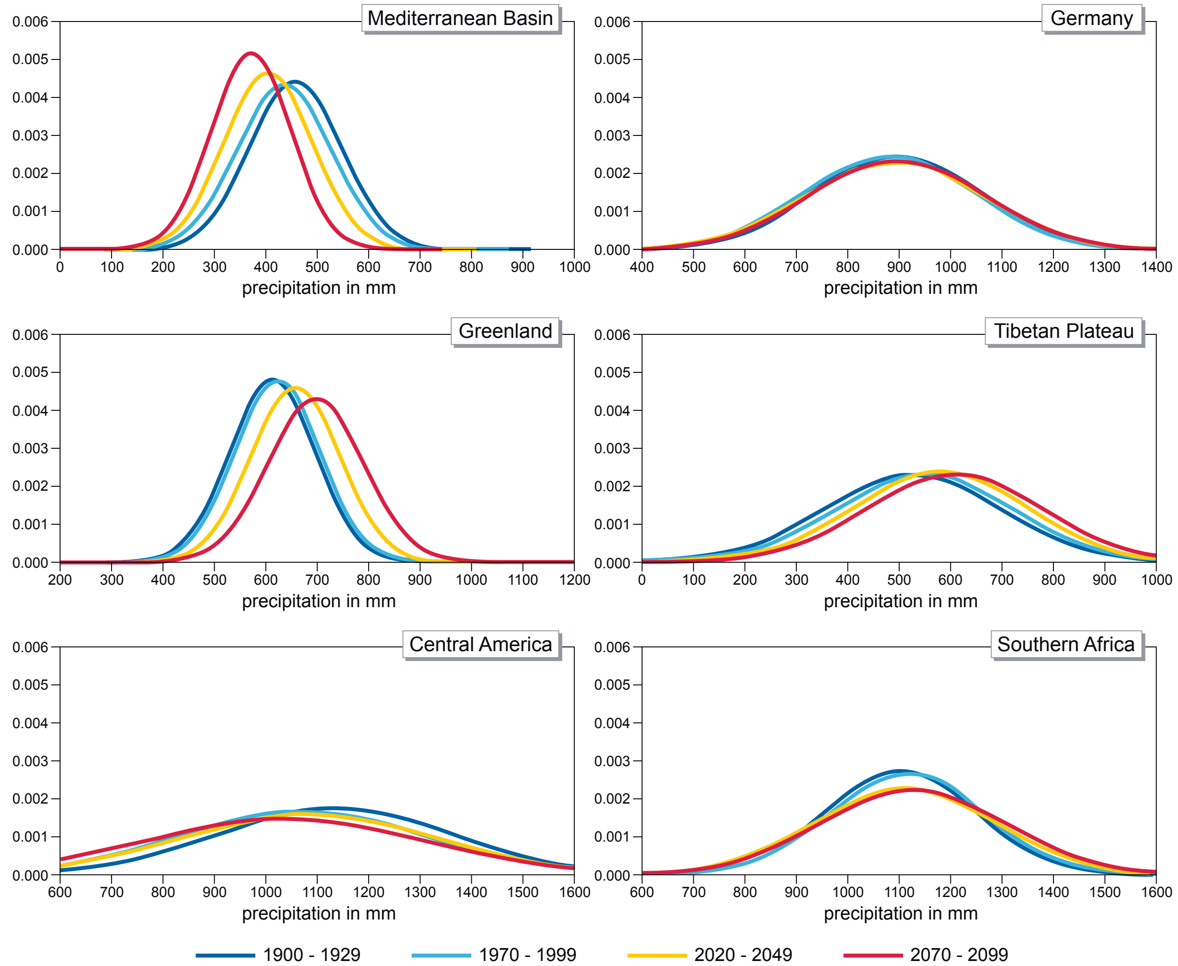

Fig. 8: PDFs of simulated annual precipitation in six target regions during four time slices in the 20th and 21st century under A1B emissions scenario

to radiative forcing. In the case of Germany, it has to be noted that the region is smaller than the other ones and model uncertainty as well as internal variability increases from the global to the regional scale (Paeth and Mannig 2013).

4.4 Over- and undershooting probabilities (hypothesis 3)

For a given change in annual temperature table 4 lists the over- and undershooting probabilities derived from the temperature PDFs in figures 7 and 9. The information reads as follows: For example, the mean temperature change (ΔT) over the CMIP3 multi-model ensemble amounts to 2.5 °C in the Mediterranean region under B1 emissions scenario. Thus, there is a 50 % chance that the real warming rate is higher or lower, since the PDFs are symmetric. The probability that the temperature change will be more than 1.5 °C (ΔT-1) is 81 %; complementarily, it is 19 % that the warming is below 1.5 °C. A much higher temperature rise of 4.5 °C (ΔT+2) still has a probability of 4 % but it is more likely (96 %) that this threshold will not be exceeded. Comparing these probabilistic predictions among different regions and scenarios reveals that a high probability – typically around 67 % – is assigned to a temperature change ranging in the interval ΔT±1 °C which implies that warming prevails everywhere, and a very high probability around 93 % is given to the interval ΔT±2 °C. In that case, slight cooling lies in the confidence interval of temperature change in Central America and Southern Africa. An exception occurs in Tibet and Greenland, where temperature changes beyond the ΔT±2 °C thresholds are more likely because the PDFs are broader (see Fig. 7). This is also the reason for the somewhat higher probabilities of

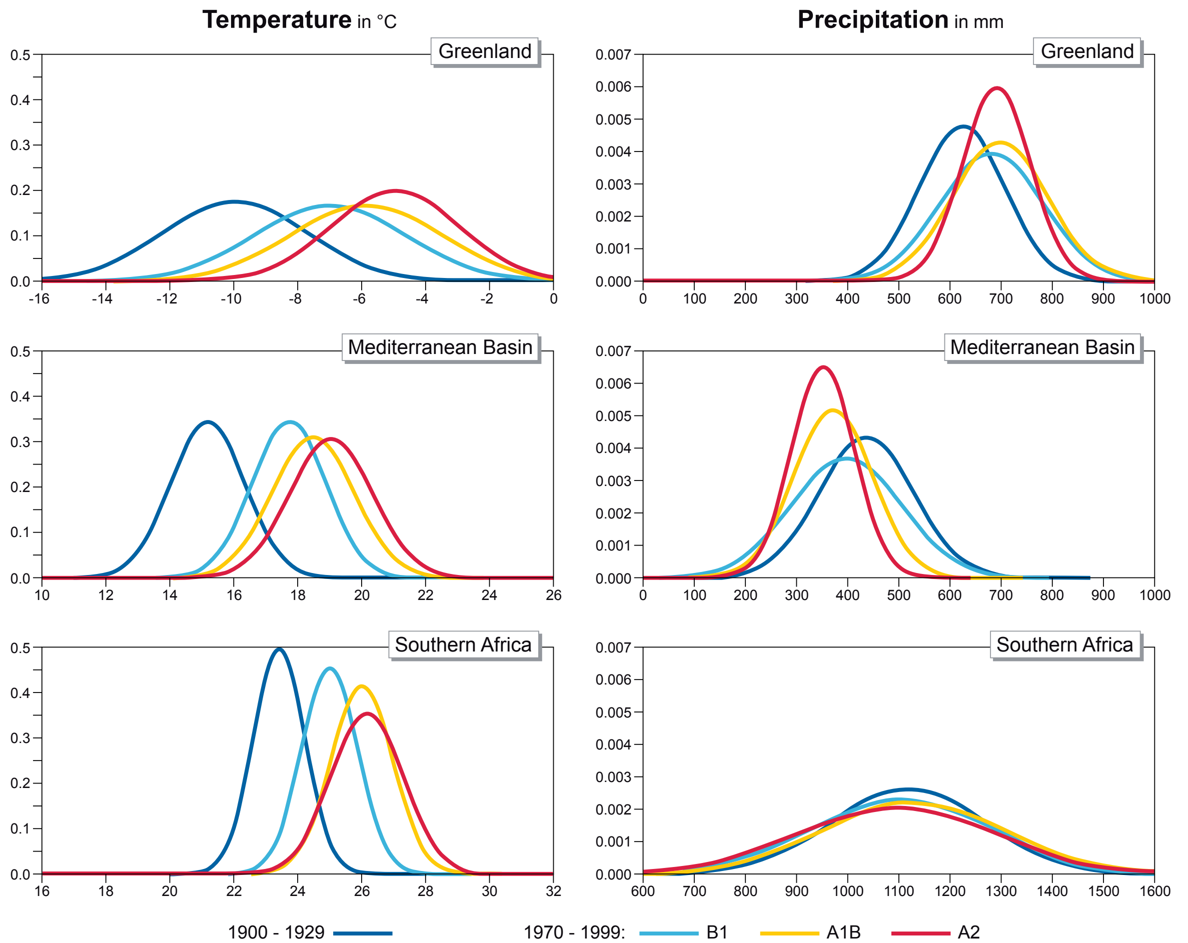

Fig. 9: PDFs of simulated annual temperature (left) and precipitation (right) in three target regions during two time slices in the 20th and 21st century under different emissions scenario

large deviations from the ensemble-mean change under the A2 scenario.

In terms of annual precipitation, some over- and undershooting probabilities cannot be determined because the associated PDFs are not normally distributed (Tab. 5). The lower and upper thresholds of precipitation changes around the mean are set to -40 mm and +50 mm. These thresholds mostly comprise a change of sign, implying that the confidence intervals include positive and negative precipitation changes. And yet there is a high probability (~40–70 %) that these thresholds are still exceeded or undercut. Thus, in most regions and scenarios, not even the sign of the precipitation signal can be assessed with some certainty. In the low latitudes the situation is the worst. The most confident prediction can be made for Mediterranean precipitation with a probability of 53 % that the decrease of annual rainfall ranges between 34 mm and 124 mm.

5 Discussion

It has been shown that an adequate assessment of anthropogenic climate change must be a probabilistic one. Three examples of evaluating the probability space of future climate were selected and applied to the CMIP3 multi-model ensemble. The first approach is dedicated to the changing occurrence of warm events that were characterized by a long return time before 1990. It is found that extremely warm years and seasons, which occurred once in 40 years during the reference period, will become normal years in the future. Thus, hypothesis 1 can be substantiated. This tendency is independent of the emissions scenario and slightly dampened over the mid-latitude ocean basins, possibly due to regional cooling by an attenuated North Atlantic thermohaline circulation or enhanced cloudiness related to intensified cyclogenesis (cf. IPCC 2007a; Paeth and Pollinger 2010). This

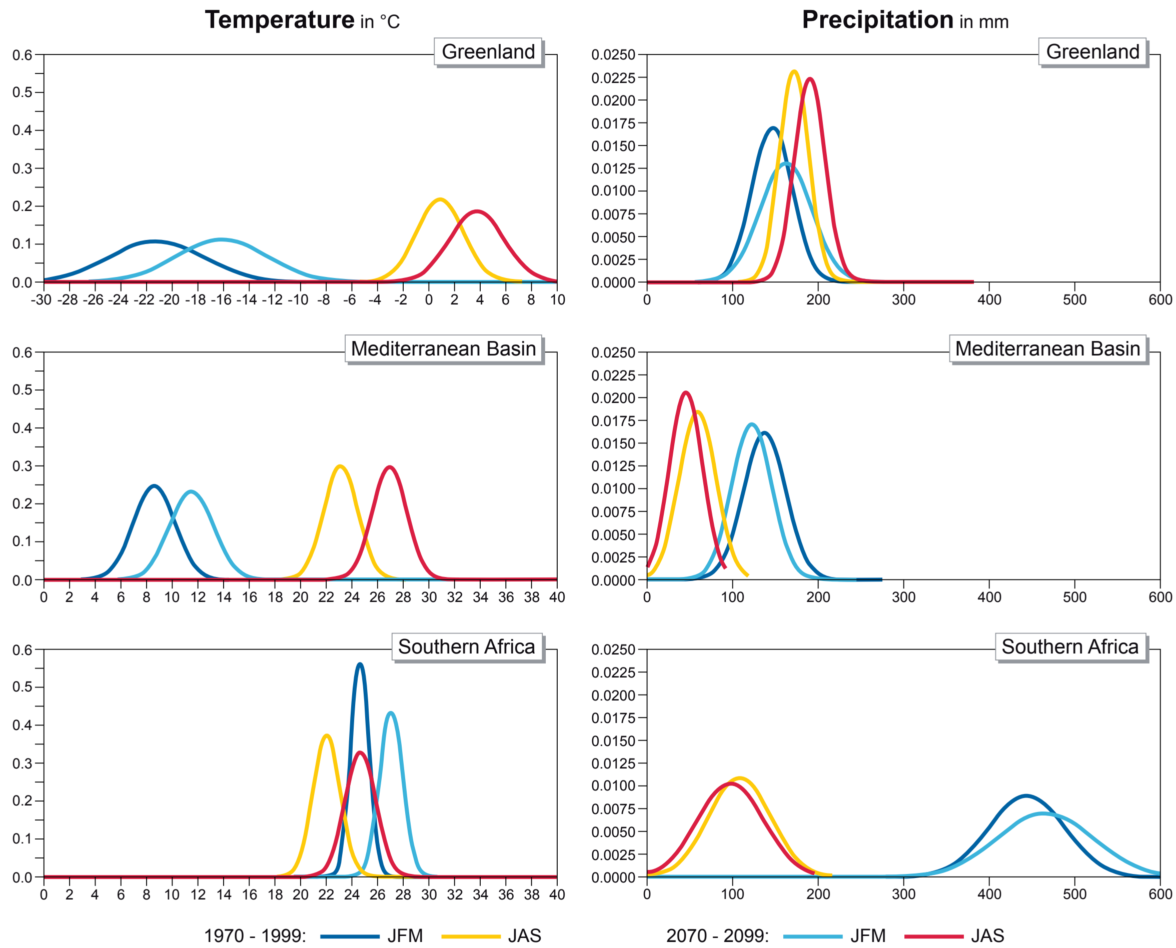

Fig. 10: PDFs of simulated summer and winter temperature (left) and precipitation (right) in three target regions during two time slices in the 20th and 21st century under A1B emissions scenario

demonstrates how we will experience climate change: Rare events in the past will become usual events in the future. This particularly holds for warm anomalies (Kyselý 2010). The frequency of extremely warm years partly increases by a factor of up to 40.

The second approach deals with the OLP as a measure of distinction between PDFs of past and future climate. It increases with the dispersion of the PDFs and decreases with the shift of the mean. Thus, it can be interpreted as an inverse signal-to-noise indicator. The OLP is much higher for precipitation than for temperature changes because the PDFs of precipitation are characterized by substantial model uncertainty and internal variability. This implies that our second hypothesis can also be confirmed based on the CMIP3 model data set. By the end of the 21st century, the lowest OLP values will occur under the A2 emissions scenario for annual temperature in the Mediterranean region, in Central America and Southern Africa, amounting to less than 20%. This allows for a proper attribution of temperatures in individual years to either of the PDFs, present-day or future. The OLP approach gives support to the picture of temperature as a reliable and precipitation as a noisy detection variable (Paeth and Hense 2002; IPCC 2007a; Hawkins and Sutton 2011).

The third approach computes over- and undershooting probabilities for different thresholds of future temperature and precipitation changes. It turns out that the range of possible future precipitation changes is quite large in all considered regions. Even the sign of the changes is often not clear as supposed by hypothesis 3. In terms of temperature, it is likely that the warming rate varies by no more than ±1 °C around the mean change over all ensemble members.

In summary, all three hypotheses raised in section 2 could be confirmed. The most precise predictions with the highest signal-to-noise ratio in CMIP3

Tab. 2: Overlapping probability in % for annual temperature referring to different regions, future time slices and emissions scenarios, compared to reference period 1970-1999. Note that all considered PDFs are normally distributed according to the KS criterion

	B1		A1B		A2	
Region	**2020-2049**	**2070-2099**	**2020-2049**	**2070-2099**	**2020-2049**	**2070-2099**
Mediterranean	46	27	47	18	49	12
Germany	61	39	54	23	58	20
Greenland	69	52	66	38	59	24
Tibet	81	60	68	36	81	35
Central America	57	36	49	18	58	17
Southern Africa	62	34	50	14	65	15

Tab. 3: Overlapping probability in % for annual precipitation referring to different regions, future time slices and emissions scenarios, compared to reference period 1970-1999. Gaps denote PDFs that are not normally distributed according to the KS criterion

	B1		A1B		A2	
Region	**2020-2049**	**2070-2099**	**2020-2049**	**2070-2099**	**2020-2049**	**2070-2099**
Mediterranean	89	83	86	70	79	56
Germany	90	87	96	95	92	91
Greenland	84	–	84	68	84	65
Tibet	–	–	–	–	–	–
Central America	97	96	98	93	96	89
Southern Africa	94	93	93	91	–	–

can be made for temperature in the Mediterranean region, Central America and Southern Africa and for Mediterranean precipitation. These regions have been identified as hot spots of climate change (Giorgi 2006; Diffenbaugh and Giorgi 2012). It is obvious that such probabilistic predictions based on the uncertainty of climate model projections are relevant and impact research and adaptation (cf. Räisänen and Palmer 2001). For instance, decision makers may choose a low scenario of future climate change in order to save money for a specific adaptation measure. However, the probability is high that real climate change will be larger than the assumed threshold and the adaptation measure will prove to be insufficient. In contrast, they may opt for a high scenario which reduces the risk but enhances the costs. Economic decisions, e.g., in insurance industry, are typically based on uncertainty and arise from probabilistic assessments (Murnane 2004; Dlugolecki 2008). Another example for a probabilistic issue comes from regional planning: Nuclear power plants in Germany have to be built at locations that are supposed to withstand a flood event with a return time of 10,000 years (Ehrhardt and Weis 2000). Applying the same safety standard to future climate change would lead to an upper threshold of temperature change that is exceeded with a probability of no more than 0.01 %. Note that under the A2 scenario, there is still a probability of 18 % that the warming rate in Germany will be larger than 5.2 °C (see Tab. 4)!

While probabilistic prediction is based on a quantification of uncertainty (Collins et al. 2006), it does not achieve a reduction of uncertainty. In principle, such a reduction would be the silver bullet because climate predictions would become more precise and adaptation and protection measures more targeted. It was discussed before that part of the uncertainty is inherent to the climate system, especially internal variability arising from the unknown initial conditions. Nonetheless, improved climate model approaches may contribute to a lower dispersion of PDFs over climate model projections. Referring to figure 1, climate model predictions for the 21st century would certainly profit from the inclusion of future changes in solar irradiation (cf. Lean and Rind 2009), from a more detailed assessment of feedbacks in the climate system as a key to climate sensitivity and internal climate variability (cf. Roe and Armour 2011), and from an enhanced spatial resolution so

Tab. 4: Changes of annual temperature between 1970-1999 and 2070-2099 for different regions and emissions scenarios with the mean change in °C over all CMIP3 simulations (ΔT), the overshooting probability for threshold ΔT-1 °C and the overshooting probability for threshold ΔT+2 °C in %

Region	B1			A1B			A2		
	ΔT	>ΔT-1	>ΔT+2	ΔT	>ΔT-1	>ΔT+2	ΔT	>ΔT-1	>ΔT+2
Mediterranean	2.5 °C	81%	4%	3.3 °C	78%	6%	3.8 °C	78%	7%
Germany	2.0 °C	80%	5%	2.9 °C	78%	6%	3.2 °C	77%	18%
Greenland	3.0 °C	67%	20%	4.1 °C	66%	20%	5.0 °C	69%	16%
Tibet	2.0 °C	71%	15%	3.6 °C	71%	14%	3.6 °C	71%	14%
Central America	1.7 °C	84%	3%	2.6 °C	82%	4%	2.9 °C	79%	6%
Southern Africa	1.6 °C	88%	1%	2.6 °C	85%	2%	2.8 °C	81%	4%

Tab. 5: Changes of annual precipitation between 1970-1999 and 2070-2099 for different regions and emissions scenarios with the mean change in mm over all CMIP3 simulations (ΔP), the undershooting probability for threshold ΔP-40 mm and the overshooting probability for threshold ΔP+50 mm in %. Gaps denote PDFs that are not normally distributed according to the KS criterion

Region	B1			A1B			A2		
	ΔP	<ΔP -40	>ΔP +50	ΔP	<ΔP -40	>ΔP +50	ΔP	<ΔP -40	>ΔP +50
Mediterranean	-39 mm	36%	33%	-65 mm	31%	26%	-84 mm	26%	21%
Germany	43 mm	39%	36%	15 mm	41%	39%	34 mm	40%	38%
Greenland	58 mm	–	–	73 mm	34%	30%	66 mm	28%	23%
Tibet	56 mm	–	–	58 mm	–	–	37 mm	38%	35%
Central America	-22 mm	44%	42%	-31 mm	44%	43%	-45 mm	45%	44%
Southern Africa	-12 mm	41%	39%	12 mm	41%	39%	-20 mm	–	–

that uncertainty due to model physics is reduced (cf. Palmer and Williams 2008). Indeed, some studies reveal that the spread of temperature projections in some regions may be reduced by model improvement whereas precipitation changes are still controlled by internal variability (Hawkins and Sutton; Rowell 2012). Another option is to allow model simulations to learn from observational data (Piani et al. 2005). Observations can be used to filter those simulations which are closest to the real climate system according to specific criteria. This has been successfully carried out for various climate indicators (Min and Hense 2006; Paeth et al. 2011; Paeth 2012). However, the performance of a climate model may be best in a certain region or process but worst in another one, leading to the problem of assigning universal weights to the model runs (Räisänen and Ylhäisi 2012). In fact, weighting of the CMIP3 ensemble members did not have a noticeable effect on the PDFs because all state-of-the-art climate models appear to be equally plausible in the light of current knowledge, data and computer resources (Räisänen and Ylhäisi 2012; Sanderson and Knutti 2012). In addition, it cannot be concluded from model-based PDFs of past climate whether the PDFs of future climate are under- or over-dispersive. The PDFs are too broad when available data are not sufficiently used to calibrate the models, whereas they are too narrow when the models' structure is quite similar, not covering the data uncertainty in the model parameterizations (Sanderson and Knutti 2012).

Therefore, some authors have suggested that the uncertainty of future climate projection may be underestimated by the CMIP3 multi-model ensemble (Curry 2011; Hawkins and Sutton 2011). One way to overcome the constraints of current climate models is to realize perturbed physics ensembles where several model parameters are randomly disturbed (Palmer and Williams 2008). This requires a much larger ensemble size than in CMIP3 or CMIP5, amounting to more than 10,000 simulations (Jackson et al. 2004). Figure 11 compares the PDF of global-mean temperature for the period 2071-2100 between the CMIP3 multi-model ensemble and an ensemble of 10,000 simulations with perturbed physics using an energy balance model (Paeth 2012). It is obvious that the disturbance of model parameters leads to a noticeably higher dispersion of the PDF of future temperature under A1B emissions scenario. This implies that very high warming rates become more likely, but the same is true for a global cooling. This has also been shown by Stainforth et al. (2005) on the basis of a global GCM, whereas Collins et al. (2011) pointed to similar PDFs for the CMIP3 multi-model ensemble and a perturbed physics ensemble.

Our study has demonstrated that future climate change can be quantified in a probabilistic sense, i.e., in the light of the various sources of uncertainty as illustrated in figure 1. Our statements on climate change are more informative than classical trend analyses and test statistics because they comprise a quantification of uncertainty and, hence, provide an appropriate framework for decisions that are typically based on the behavior of a high-dimensional chaotic system. Nonetheless, the question remains whether our probabilistic predictions based on CMIP3 have to be revised in either direction: Towards broader PDFs (Fig. 11, red line) because CMIP3 is under-dispersive or towards optimized PDFs (Fig. 11, green line) because climate models can still learn from the data. The upcoming CMIP5 multi-model data will provide new insights into this problem using new emissions scenarios and Earth system models of higher complexity (Meinshausen et al. 2011; Taylor et al. 2012). Nevertheless, the preliminary study by Knutti and Sedláček (2012) has not yet revealed distinct differences between PDFs from CMIP3 and CMIP5.

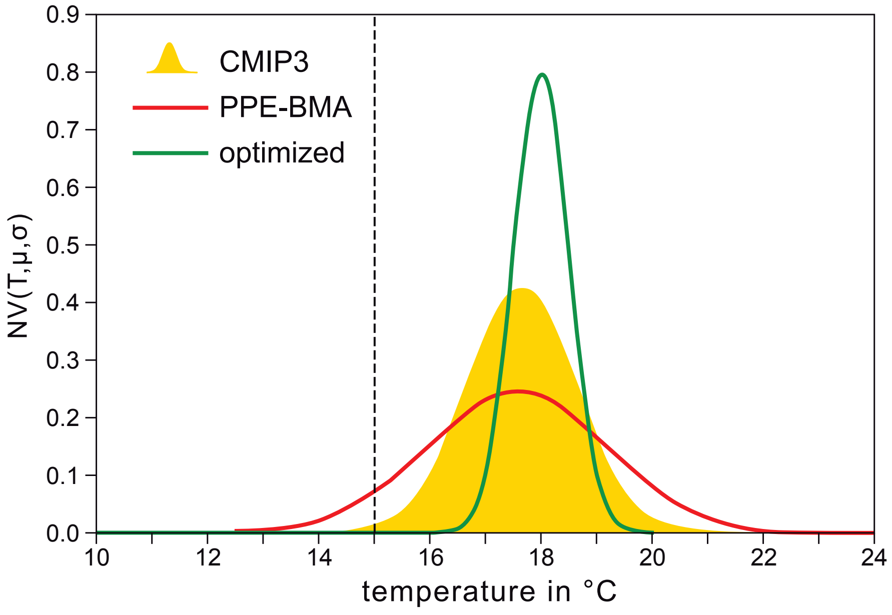

Fig. 11: PDFs of simulated global-mean temperature for the period 2071-2100 under emissions scenario A1B from the CMIP3 multi-model ensemble of global climate models, from a perturbed physics ensemble (PPE) with an extended energy balance model (EBM) (cf. Paeth 2012) and from a virtual optimized multi-model ensemble. The dashed line indicates the present-day temperature level

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