CLIMATE CHANGE PREDICTION

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Abstract. The concept of climate change prediction in response to anthropogenic forcings at multi-decadal time scales is reviewed. This is identified as a predictability problem with characteristics of both first kind and second kind (due to the slow components of the climate system). It is argued that, because of the non-linear and stochastic aspects of the climate system and of the anthropogenic and natural forcings, climate change contains an intrinsic level of uncertainty. As a result, climate change prediction needs to be approached in a probabilistic way. This requires a characterization and quantification of the uncertainties associated with the sequence of steps involved in a climate change prediction. A review is presented of different approaches recently proposed to produce probabilistic climate change predictions. The additional difficulties found when extending the prediction from the global to the regional scale and the implications that these have on the choice of prediction strategy are finally discussed.

1. Introduction

Climate change due to anthropogenic forcings is likely going to affect human societies and natural ecosystems in the next decades of the 21st century (IPCC, 2001). In order to assess the impacts of climate change and to develop suitable adaptation and mitigation policies, accurate climate change predictions are needed at the global and, more importantly, the regional and local scales.

The term "prediction" has been often avoided within the global change debate (the term "projection" is more often used, as described in Section 4.2) because it can be easily misinterpreted by non experts due to its use in numerical weather prediction. In fact, weather prediction aims at forecasting how specific weather patterns evolve at time scales of the order of days based on the knowledge of the state of the atmosphere at a certain time. Climate change prediction is of an entirely different nature and it is important that the end users of the climate change information understand this difference and are aware of the uncertainties and limitations underlying current predictions of climate change.

This paper presents a discussion of the concept of climate change prediction and of the approaches today available to produce climate predictions. After an analysis of the basic concept of climate predictability, the paper focuses on the issues of uncertainty and reliability associated with climate change predictions. In this regard, the problem is also addressed of the additional difficulties found when extending a climate prediction from the global scale to the regional and local

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scales. A review of different approaches recently developed to produce probabilistic climate predictions is finally presented.

The paper focuses on the physical aspects of the global change problem, i.e. it does not deal with the human dimension of global change, although the importance of this dimension is fully recognized. On the other hand, the discussion is aimed at cross-disciplinary communication at a stage in which advances in climate modeling and computing technologies allow the development of new and promising techniques for the production of a new generation of climate change predictions suitable for use in impact assessment studies.

2. Some Concepts and Definitions

It is useful to define some concepts before beginning the discussion of climate predictability. First, we are here specifically concerned with the problem of predicting climate change for the 21st century at temporal scales of multi-decadal to centennial in response to anthropogenic forcing agents. These include greenhouse gases (GHG), aerosols of anthropogenic origin (e.g. sulfate, black carbon, organic carbon, industrial dust) and changes in land surface conditions. In addition to these anthropogenic forcings, "natural forcings" external to the climate system are important and need to be considered. Natural forcings include variations in the flux of energy from the sun (or "solar forcing"), emission of gases and particulate material from major volcanic eruptions and natural aerosols (e.g. desert dust, sea salt, biogenic carbon).

The climate system includes different components strongly coupled with each other and characterized by different temporal scales of evolution: the atmosphere, the oceans, the cryosphere, the biosphere/land hydrology and the chemosphere (i.e. the chemical processes in the atmosphere, oceans and land). The atmosphere and some aspects of the chemosphere are the fastest evolving ones, with characteristic response times of up to months or years. The oceans, cryosphere and biosphere, along with some components of the chemosphere, evolve with longer characteristic times, up to multi-decadal and longer.

Human activites that lead to the generation of anthropogenic forcings have traditionally been considered as "external" to the climate system. Human societies, however, can react to climate changes through adaptation and mitigation policies, and this would in turn result in modifications of the anthropogenic forcings. Therefore, the human component of the climate system should in principle be considered as fully integrated with the others and research towards the development of fully "integrated" climate system models is indeed underway. However this is still at the initial stages and in this paper the anthropogenic forcings are considered as external to the climate system.

Finally, we define the concept of climate change simulation. The most advanced tools used for simulating climate change are coupled Atmosphere-Ocean General

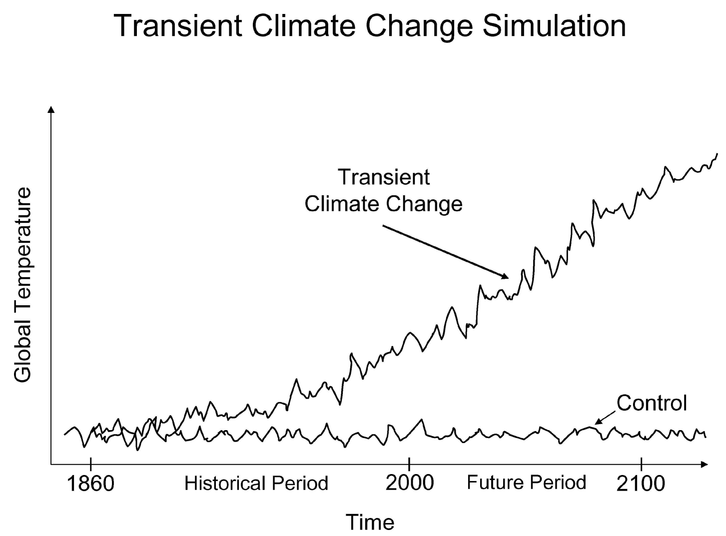

Figure 1. Illustrative example of a transient climate change simulation as measured by global temperature (see text).

Circulation Models, or AOGCMs (e.g. Washington and Parkinson, 1986). These models include descriptions of the global atmosphere, oceans, sea ice, land surface processes and simple chemistry processes. Also, AOGCMs explicitly account for the effects of anthropogenic and natural forcings.

Typically, a climate change simulation consists of a number of steps, as depicted in Figure 1. In this figure global temperature is taken as a measure of climate, but other variables such as precipitation or sea level could be used as well. First, the AOGCM is integrated for a long period of time (multi-centennial) to achieve an equilibrium across its fast and slow varying components. In these integrations the forcing agents (e.g. the concentration of GHG) are set at pre-industrial values or at values characteristic of the year 1860 (around the beginning of the modern industrial era). This simulation is generally referred to as "Control" run and provides the baseline to evaluate the performance of the model in simulating the basic state of the global climate system. At some point within the Control run, which is typically the nominal year 1860, anthropogenic and natural forcing agents are allowed to change following reconstructions of these changes during the historical period (1860 to present).

At the end of the historical period, the anthropogenic forcing agents are allowed to change as a result of given "emission scenarios." These are hypothesized future trends in emissions of GHG and aerosols (or aerosol precursors) based on hypotheses of future socio-economical and technological development (IPCC, 2000). The GHG emission scenarios are translated into GHG concentrations using biogeochemical cycle and chemistry models and these concentrations are then used as input to the AOGCM for the climate change simulation. Some models take as input also anthropogenic aerosol concentrations while other models calculate the aerosol concentration from the emission of precursors using simplified coupled chemistry models. Similarly, the evolution of land use in response to different socio-economic development scenarios can be assumed as an input to the model. To date, however, most climate change simulations have not assumed changes in land use.

An AOGCM "transient" climate change simulation for the 21st century extends from "present day" (say the year 2000) to the year 2100, so that the full AOGCM experiment extends for the 240 year period of 1860–2100 (Figure 1). This comprises the historical period [1860 – present day] and the "future" period [present day – 2100]. Some simulations (not discussed here) extend beyond 2100 to examine the multi-centennial response to anthropogenic forcings, in particular after the GHG concentration has stabilized to given levels. The Intergovernmental Panel on Climate Change (IPCC, 2000) has developed 40 scenarios of future emissions divided into four families, each characterized by a storyline of future socio-economical and technological development. Six of these scenarios, called "marker scenarios" and referred to as A1T, A1FI, A1B, A2, B1 and B2, have been identified as illustrative of the overall set and have been used in AOGCM transient simulations.

In the analysis of a climate change simulation what is most often done is to compare the climate statistics of a future period (e.g. 2071–2100) with those representative of a present day period, often chosen to be 1961–1990. Alternatively, one can analyze the trend in climate variables throughout the transient simulation. The analysis of climate change implies considerations of statistical significance of the changes and trends identified. This can be addressed with a number of statistical tools (e.g. von Storch and Zwiers, 1999) that essentially compare the magnitude of the change signal to measures of the underlying unforced variability (or "noise").

Finally, AOGCMs are used to simulate the response of the global climate system to external forcings. However, due to their relatively coarse spatial resolution (order of few hundred km), these models are often not suitable for simulating detailed regional climate patterns. Therefore a number of "regionalization techniques" have been developed in the last decade or so to enhance the regional information obtained by AOGCMs and to provide fine spatial and temporal scale climate detail (Giorgi et al., 2001a). Among these techniques are the use of high resolution and variable resolution atmospheric GCMs (Deque and Piedelievre, 1995; Cubasch et al., 1995), regional climate models, or RCMs (Giorgi and Mearns, 1991, 1999), and statistical downscaling methods (Hewitson and Crane, 1996). It is outside the purpose of this paper to describe climate models and regionalization techniques, and in this regard the reader can for example consult Washington and Parkinson (1986), Trenberth (1992), Giorgi et al. (2001a) and references therein.

3. The Concept of Climate Change Prediction

In the late 1960s and mid 1970s the chaotic nature of the climate system was first recognized. Lorenz (1969, 1975) defined two types of predictability problems:

1) Predictability of the first kind, which is essentially the prediction of the evolution of the atmosphere, or more generally the climate system, given some knowledge of its initial state. Predictability of the first kind is therefore primarily an initial value problem, and numerical weather prediction is a typical example of it.
2) Predictability of the second kind, in which the objective is to predict the evolution of the statistical properties of the climate system in response to changes in external forcings. Predictability of the second kind is thus essentially a boundary value problem.

In a predictability problem of the first kind, the predictability range is defined as the time over which we can expect a prediction to be skillfull. This depends on the temporal scale of the phenomenon under consideration. In general, the shorter the characteristic temporal scale of a phenomenon, the shorter the predictability range (Lorenz, 1969). This is because, if we compare two evolutions of a highly non-linear and chaotic system (e.g the atmosphere) starting from two slightly different initial conditions, the non-linearities in the system will make the two evolutions diverge from each other and from the initial conditions to the point that after a certain time (the predictability range) the memory of the initial conditions is essentially lost. As a consequence, the longer the characteristic time of a phenomenon, and thus its inertia, the longer the memory of the initial conditions and the predictability range. For example, cumulus convection evolves very rapidly and has a predictability range of the order of hours. Synoptic weather systems typically evolve with time scales of several days, and this is the typical scale of their predictability range. On the other hand, slower components of the climate system can be expected to be predictable at longer time scales. For instance, the El Niño Southern Oscillation (ENSO) phenomenon and other modes of the coupled atmosphere-ocean system can be predictable at time scales of seasonal to interannual, while deep ocean circulations (such as the Thermohaline Circulation or THC) can be predictable at multidecadal to centennial scales.

From these considerations it follows that, since we cannot know exactly the state of the atmosphere or any other component of the climate system, we cannot predict its evolution with accuracy past the predictability range. In this latter case, however, we can still predict the statistical behavior of the climate system in response to external forcings. This is the realm of predictability of the second kind. Climate change prediction at time scales of multi-decadal to centennial thus has a predictability component of the second kind. We cannot predict the evolution of specific weather events years or decades into the future but we can address questions such as: How will climate statistics such as mean precipitation, precipitation variability or frequency of extreme events change over the next decades in response to changes of GHG concentration?

On the other hand, because of the long time scales involved in ocean, cryosphere and biosphere processes a first kind predictability component also arises. The slower components of the climate system (e.g. the ocean and biosphere) affect the statistics of climate variables (e.g. precipitation) and since they may feel the influence of their initial state at multi decadal time scales, it is possible that climate changes also depend on the initial state of the climate system (e.g. Collins, 2002; Pielke, 1998). For example, the evolution of the THC in response to GHG forcing can depend on the THC initial state, and this evolution will in general affect the full climate system. As a result, the climate change prediction problem has components of both first and second kind which are deeply intertwined.

This concept is illustrated in Figure 2, which shows two hypotetical future climate evolutions as simulated by a climate model. In each simulation the GHG concentration increases in the same way but starting from different times of the Control run, and thus different initial ocean, sea ice and land surface conditions. As illustrated, the two climate evolutions can potentially differ both in their mean and variability characteristics. The relevance of the first kind predictability aspect of climate change is that we do not know what the initial conditions of the climate system were at the beginning of the "industrialization experiment" and this adds an element of uncertainty to the climate prediction.

Another factor that affects the prediction of climate change is the random component of both natural and anthropogenic forcings. Natural forcings such as changes in solar radiation and volcanic eruptions are essentially unpredictable, i.e we do not

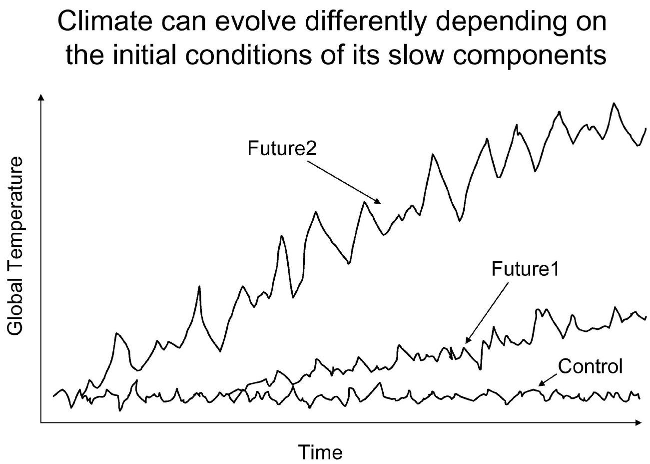

Figure 2. Illustrative example of two climate evolutions (as measured by variables such as temperature or precipitation) characterized by different mean and variability response to the same increase in GHG concentration. The differences have been exaggerated for illustrative purposes.

know if and when major volcanic eruptions and changes of solar radiation fluxes will happen in the future. Similarly, anthropogenic forcings are characterized by unpredictable factors, such as new technological discoveries, major societal changes or population decline due to large scale disease outbreaks.

To add difficulty to a prediction is the fact that the predictability of a system is strongly affected by non-linearities. A system that responds linearly to forcings is highly predictable, i.e. doubling of the forcing results in a doubling of the response. Non-linear behaviors are much less predictable and several factors increase the non-linearity of the climate system as a whole, thereby decreasing its predictability (e.g. Rial et al., 2004).

One is the presence of positive feedback mechanisms which amplify the climate response to forcings. Conversely, negative feedback mechanisms tend to render the system less responsive to forcings and thus more stable and predictable. A typical example of positive feedback mechanism is the ice-albedo feedback: GHG-induced warming produces a decrease of surface ice cover; this in turn decreases the surface albedo so that solar radiation is more effectively absorbed at the surface, which then accelerates the warming and sustains a positive feedback. A negative feedback mechanism is for example due to the carbon uptake by plants. With increased CO_2 concentration and in the absence of moisture and nutrient limitations, plants grow more effectively. This in turn increases the CO_2 uptake and reduces the growth of CO_2 concentration in the atmosphere. Other feedback mechanisms may be associated with changes in atmospheric water vapor amounts, cloud cover, ocean circulations and carbon storage (e.g. Rial et al. 2004). In some sense, mitigation policies can be considered as a negative feedback mechanism associated with the response to climate change of the human component of the climate system.

Threshold behaviors, in which a system gradually evolves until, after a certain threshold, it collapses into a different state (possibly in a quasi-irreversible way) add a strong element of non-linearity. An example of threshold behavior in the climate system is the shutdown of the oceanic THC, which may occur very abruptly either in response to external forcings or as a result of the internal variability of the climate system (Stocker et al., 2001). Instances of THC shutdown events have been for example identified as possible causes of abrupt climate changes in the past (NRC, 2002), and it has been hypothesized that intense GHG forcing might actually lead to such an event (Cubasch et al., 2001).

A third important non-linear behavior of the climate system is the presence of circulation regimes. For example, evidence has been found that the circulation of the northern hemisphere tends to preferentially reside in certain more stable configurations, or regimes (e.g. Corti et al., 1999), with relatively rapid transitions from one regime to another. As depicted in Figure 3, the anthropogenic forcing effects could manifest themselves either in changes of the frequency of occurrence of such circulation regimes (Future 1) or in changes of the structure of the regimes (Future 2) (Corti et al., 1999; Palmer, 1999). In addition, the coupled-ocean atmosphere system is characterized by a number of internal non-linear modes of

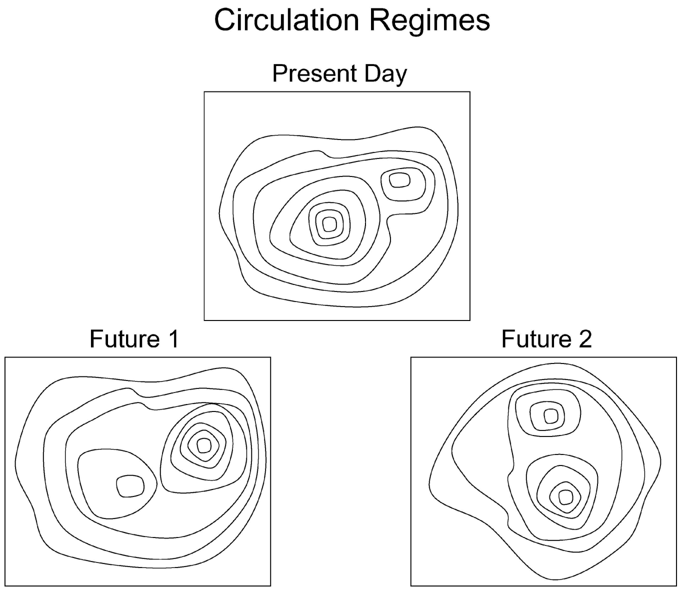

Figure 3. Illustrative example of changes in circulation regimes. The panels depict the frequency of occurrence of given circulation patterns as measured by a two dimensional phase space of the circulation characteristics (e.g. EOFs; Corti et al., 1999). Two circulation regimes (high frequency centers) are depicted for present day conditions (top panel). In Future 1 conditions, the structure of the two regimes as measured by their position in the two dimensional phase space does not change, but the frequency of occurrence of the regimes changes. In Future 2 conditions, the structure of the regimes changes, since the position of the frequency centers is modified with respect to present day conditions.

variability, such as ENSO (e.g. Philander, 1990), the North Atlantic Oscillation (NAO; e.g. Hurrell, 1995) or the Pacific Decadal Oscillation (PDO; Mantua et al., 1997). The GHG forcing can thus modify the frequency, intensity and structure of these internal modes, as well as their "teleconnection effects" on the climate of different regions (e.g. Trenberth and Hoar, 1997).

Finally, many climate processes are characterized by an intrinsically stochastic component, for example the triggering mechanism of cumulus convection (Palmer, 2001), and this makes the system less predictable. The non-linear and stochastic nature of the climate system is such that climate exhibits a pronounced level of internal unforced variability at a range of temporal scales, from sub-daily to multi-decadal. This can mask forced climate change signals, and sophisticated detection techniqes have been developed to extract the anthropogenically and naturally forced signals from the underlying internal climate variability (Mitchell et al., 2001).

Therefore, because of the stochastic component of the future anthropogenic and natural forcings, the lack of knowledge of the initial state of the climate system (particularly its slow components) and the non-linearities and stochastic elements in the behavior of climate, it is virtually impossible to exactly predict how climate, as defined by its statistics, will actually evolve in the 21st century.

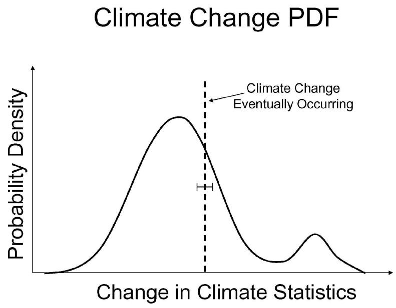

Figure 4. Illustrative example of a bi-modal PDF of possible climate changes (as defined by a statistics of interest, for example average temperature or precipitation) in response to the non-linear and stochastic nature of the climate system and of the external anthropogenic and natural forcings. It is also shown that only one of these possible changes will eventually occur, with the horizontal error bar associated with this occurrence indicating the observing uncertainties for the statistics of interest.

Rather, it is more appropriate to say that a range of future climate conditions is possible, each characterized by a certain likelyhood to occur. This can be depicted (Figure 4) as a probability density function (PDF) of future climate change as measured by the change in a certain climate statistics of interest (e.g. precipitation over a region). The PDF of Figure 4 is only hypotethical and shows the possibility of a multi-modal behavior (e.g. in response to a threshold effect), with the two modes characterized by different likelihoods to occur. As shown in Figure 4, only one of all possible futures will eventually happen but, as discussed above, this is virtually impossible to predict. A measure of the width of the distribution in Figure 4 (e.g. the standard deviation) represents the uncertainty in future climates. This is an "intrinsic" uncertainty in the sense that it is not tied to deficiences in the tools used for the climate prediction or the lack of process understanding, but it is an inherent property of the climate system. As a consequence, the objective of climate change prediction is not to attempt to predict the exact future evolution of climate but to reproduce as closely as possible the PDF of possible future climates.

This conclusion implies that ultimately a climate change prediction has to be approached in probabilistic terms. In other words the climate change information that can be provided to users is not "how climate will actually change" but is "the probability that the change in climate statistics will be within certain ranges or above certain thresholds." Another factor that substantially differentiates climate change prediction from weather as well as seasonal to interannual prediction is that, for all practical purposes, the former is not verifiable. The climate change information for the 21st century is needed now, so that suitable adaptation and mitigation measures can be evaluated. In addition, case studies similar to that foreseen for the 21st century, in which the GHG concentration might increase by factors of 2–3 within a century, are essentially unprecedented within the known history of the Earth. As a result, we have no way of verifying the model performance in the production of the climate change information of interest. Being this the case it is especially important that suitable measures and criteria be devised to assess the reliability and uncertainty of a climate change prediction.

3.1. REGIONAL VS. GLOBAL CLIMATE CHANGE PREDICTION

Changes in globally averaged climate are primarily determined by the radiative budget of the coupled atmosphere-ocean-land system, modulated by internal non-linear feedbacks and modes of variability (e.g. Stocker et al., 2001). Hence, a positive global radiative forcing (e.g. due to GHG) generally results in global warming and in an increase of global precipitation in response to increased evaporation from the warmer land and ocean surfaces (Allen and Ingram, 2003). This is shown by all global model simulations (Cubasch et al., 2001).

As the scale of interest is refined, several factors make climate change prediction more difficult. First, changes in circulation features, even relatively minor, can have profound regional impacts. For example, horizontal displacements of storm tracks due to differential horizontal heating do not affect much the global precipitation change, while they may cause large increases in precipitation over some regions and corresponding decreases over other regions. Therefore in order to predict regional climate changes it is necessary to predict the details of changes in atmospheric circulations.

Secondly, regional climates are affected by fine scale forcings and processes, such as due to complex topography, coastline and land use features, atmospheric aerosols and other pollutants (Giorgi and Mearns, 1991). In many cases these forcings and processes are not adequately represented in climate models (Giorgi et al., 2001a). On the other hand, in some regions stationary forcings, such as due to topography, may actually increase predictability by "locking" the local response to large scale changes in circulations (e.g. Boer, 1994).

Thirdly, the effects of circulation regimes and internal modes of variability are most important at the regional scale. In particular, often the climate of a region is affected by processes occurring in remote regions through teleconnection patterns involving the interaction of local energy sources with large scale circulations. For example, it is well known that the NAO strongly influences the climate of Europe and areas of North America (Hurrell, 1995). Similarly, ENSO is a major source of variability over many tropical regions (e.g. Philander, 1990). The aerosol forcing over certain regions can also have substantial climatic impacts over remote regions (e.g. Menon et al., 2002).

Finally, climate variability tends to increase at fine scales. As an illustration of this, Figure 5 shows the scale dependency of interannual variability of precipitation (Giorgi, 2002b), and it can be seen that this dependency is increasingly pronounced as the spatial scale is refined. The main implication of this scale dependency is that the extraction of a detectable climate change signal from the underlying natural variabiliy is much more difficult at fine regional scales than large scales.

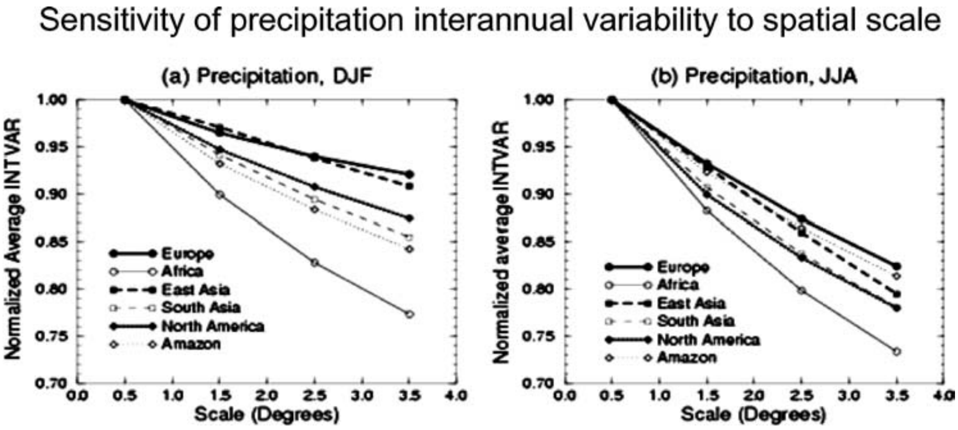

Figure 5. Scale dependency of seasonal (DJF, JJA) precipitation interannual variability over different regions of the World (from Giorgi, 2002b). The interannual variability (INTVAR) is measured by the coefficient of variation of seasonal precipitation calculated over the 30-year period of 1961–1990.

All the factors mentioned here clearly point to the difficulty of predicting regional climates. This difficulty is magnified by the fact that limitations in computing resources do not allow the explicit representation of fine scale processes in AOGCMs, so that the combined use of different modeling tools is currently required to obtain fine scale regional climate information.

4. Uncertainties and Methods in Climate Change Prediction

4.1. SOURCES OF UNCERTAINTY

In Section 3 we defined the objective of a climate change prediction as the production of a PDF of possible future climates as defined by the statistics of a given variable of interest. Figure 6 depicts an example of such prediction overlaid to the PDF of possible actual futures of Figure 4. The width of the PDF is a measure of uncertainty and this is generally different between the prediction and the "actual" future climate PDF. This difference measures the added uncertainty to the "intrinsic" one (see Section 3) introduced by the imperfect knowledge of relevant processes and the deficiences in the models, data and methods used to produce the prediction (Jones, 2000; Visser et al., 2000). If we had a perfect climate system model, a perfect observing system and a perfect knowledge of the statistical behavior of the external forcings, this added uncertainty would be eliminated and the uncertainty in the prediction would essentially reflect the stochastic and non-linear nature of the climate change problem. It is thus important to understand and assess the contributions of different sources of uncertainty in a climate change prediction, so that "bottleneck steps" in the prediction process can be identified and improved.

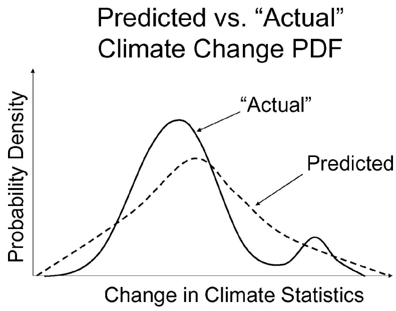

Figure 6. Illustrative example of a predicted vs. the "actual" climate change PDF of Figure 4. The differences between the predicted and actual PDFs are a result of: (1) Imperfect knowledge of relevant processes; and (2) added uncertainties due to deficiences in the models and assumptions used to produce the prediction.

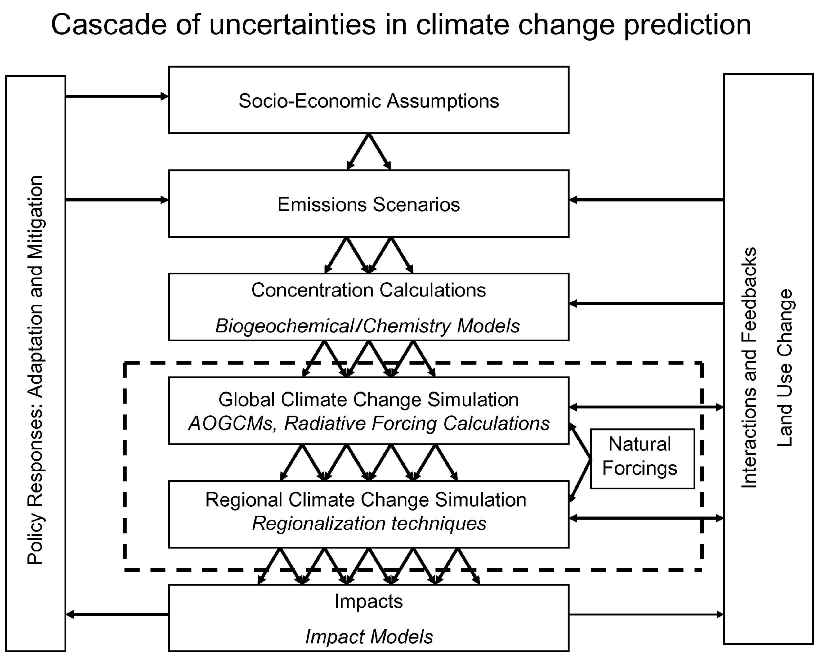

Figure 7. Cascade of uncertainties in a climate change prediction. The dashed line encompasses the climate simulation segment of the cascade (adapted from Mearns et al., 2001).

Figure 7 illustrates the uncertainty cascade associated with the sequence of steps involved in a climate change prediction (as described in Section 2). Each step is characterized by an uncertainty which is transmitted to the next step in a cascade process that determines the overall uncertainty of the prediction (Mearns et al., 2001). Here we focus on the uncertainty associated with the steps enclosed by the dashed line of Figure 7, i.e. the uncertainty related to the climate simulation process. The elements that contribute to this uncertainty are depicted in Figure 8.

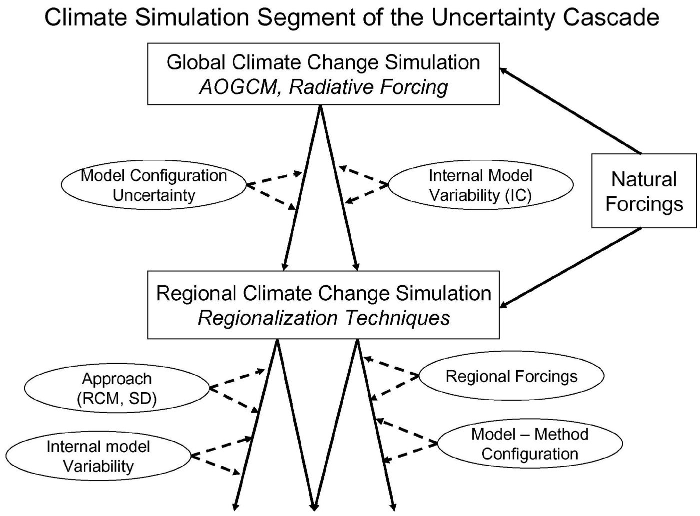

Figure 8. Climate simulation segment of the uncertainty cascade of Figure 7.

In AOGCM simulations, uncertainty is due to three major contributing factors. The first can be called "model configuration" uncertainty. It relates to the choice of a model configuration, for example horizontal and vertical resolution, physics parameterization schemes, parameter values and numerical algorithms. The choice of a given model configuration is generally based on both scientific and computational considerations. As a result of this choice, which generally differs across models, different AOGCMs can simulate quite different climate responses to the same GHG forcing. For example global temperature changes from 1990 to 2100 in the nine AOGCMs analysed by Cubasch et al. (2001) varied by up to 3–4°C across models for the same emission scenario. Similar conclusions are found when using different physics parameterizations or model parameters within a single model (Murphy et al., 2004).

The concept of model-configuration uncertainty is closely related to that of climate sensitivity, which is defined as the global near surface temperature response to a doubling of carbon dioxide concentration (e.g. Cubasch et al., 2001). In the last few generations of coupled climate models the range of climate sensitivity across different modeling systems has remained fairly high, from 1.5 to 4.5°C (Cubasch et al., 2001). This is primarily due to the model representation of different feedbacks in the climate system, such as the sea ice albedo feedback, the water vapor feedback and the cloud-climate feedback.

The model configuration uncertainty increases as we move to the regional scale. Giorgi and Mearns (2002) analyzed the temperature and precipitation changes between the periods 2071–2100 and 1961–1990 in the same set of 9 AOGCMs of Cubasch et al. (2001) over 22 regions of sub-continental size. They found that the range of regional temperature change varied across models by 3–10°C over different regions, with the largest range found in northern high latitude regions. For regional precipitation change the range was even larger, and in many regions a general disagreement across models was found not only in the magnitude but also in the sign of the change. The model configuration uncertainty thus provides a dominant contribution to the uncertainty cascade, and in fact about half of the overall range in the IPCC global temperature change estimates has been attributed to this factor (IPCC, 2001).

The uncertainty due to internal model variability (Figure 8) is attributed to the dependency of the climate change simulation on the unforced variability of the system and the initial state of the ocean and land conditions. A few studies have assessed the role of this uncertainty source, both at the global (e.g. Boer et al., 2000; Johns et al., 2001) and the regional scale (Giorgi and Francisco, 2000; Giorgi, 2002a), by analyzing ensembles of climate change simulations starting at different times within long control simulations. When looking at average changes, the uncertainty associated with the internal model variability appears to be much lower than the model configuration uncertainty (Giorgi and Francisco, 2000). In other words, average changes do not seem to depend strongly on the initial conditions of the slow components of the climate system. However, Giorgi (2002a) found that the internal model variability was comparable to the model configuration uncertainty when looking at regional scale interannual variability. This points to the fact that the role of different uncertainty sources depends on the climate variable of interest.

Finally, a third source of uncertainty is associated with the stochastic nature of future natural forcings (see Section 3). Estimates of this uncertainty source show that it can be significant, although less important than the uncertainty associated with anthropogenic forcings in the 21st century (Stott and Kettleborough, 2002).

When regional climate information is produced by "post-processing" AOGCM fields via different regionalization techniques, further uncertainties are added to the climate prediction (see Figure 8). These are of different nature. First, sub-AOGCM grid scale forcings, such as complex topography and coastline features, can profoundly affect the local climate change signal both in sign and magnitude (e.g. Giorgi et al., 1994; Jones et al., 1997). The choice of different regionalization approaches ("approach uncertainty") can affect the climate change simulation (Murphy, 1999, 2000). In addition, regionalization tools are characterized by the model configuration uncertainty (Giorgi et al., 2001a; Hewitson and Crane, 1996) and the uncertainty related to internal model variability (Giorgi and Bi, 2000; Christensen et al., 2001).

4.2. METHODS TO PRODUCE PROBABILISTIC PREDICTIONS OF CLIMATE CHANGE

As mentioned, the term projection has been most often used in the climate change debate. Essentially, a projection of climate change differs from a prediction in that a scenario of future emissions is assumed without giving it any specific likelihood of occurrence. A projection thus tells us what the climate response would be when assuming a future forcing scenario. In this sense, most climate change studies to date can be effectively considered as sensitivity studies rather than attempts at climate change predictions (e.g. Jones, 2000).

If we however assign a probability to a certain emission scenario (or to the underlying assumptions) we are effectively attempting a probabilistic prediction of the socio-economic and technological development that define the scenario. As a result, we set the grounds for an actual probabilistic prediction of climate change. A number of approaches have been recently proposed to produce probabilistic predictions of climate changes, which ultimately result in the generation of simulated PDFs of future climate conditions, or climate changes, as measured by statistics of interest. A fundamental problem with producing PDFs of climate change is that in principle a sufficient number of realizations is needed to explore the phase space of possible change conditions taking into account the full range of uncertainties implied by the steps in Figure 7.

To give an example, for all the 40 IPCC emission scenarios a range of biogeochemical and chemistry models and relative model configurations should be used to produce concentration scenarios. For each of these, a range of AOGCMs should be used to simulate the resulting climate change, each model performing ensembles of realizations with different ocean/sea ice initial conditions and model structural configurations. Then, a range of regionalization methods and models, with different structural configurations could be used to provide fine scale information to be eventually utilized in an analogous range of impact models. It is evident that such a process may require millions of simulations with complex models. This is clearly not feasible.

As a result, approaches have been proposed to explore the climate change phase space in a simplified way. Here we can divide these approaches into three categories: (1) Use of simplified models and of prescribed PDFs to describe the uncertainty of various model parameters; (2) Enlargement of the simulation sample size of an AOGCM via suitable approximations and statistical techniques; (3) Use of information from ensembles of simulations with different AOGCMs. It is not the purpose of this paper to provide a comprehensive review of all studies related to these three approaches. Rather, we provide examples to illustrate the underlying conceptual methodologies.

As an example of the use of simple climate models to produce probabilistic climate change predictions we can take the study of Wigley and Raper (2001). They used a simplified climate modeling system consisting of a carbon cycle model (Wigley, 1993) and a coupled Upwelling Diffusion / Energy Balance Model (Wigley and Raper, 1992; Raper et al., 2001) to calculate PDFs of global temperature change in response to the full range of IPCC emission scenarios. The various sources of uncertainty described above were compounded into those of five key factors in the modeling system: GHG emissions; parameters in the carbon cycle model that generates the GHG concentrations; aerosol forcing; global climate sensitivity;

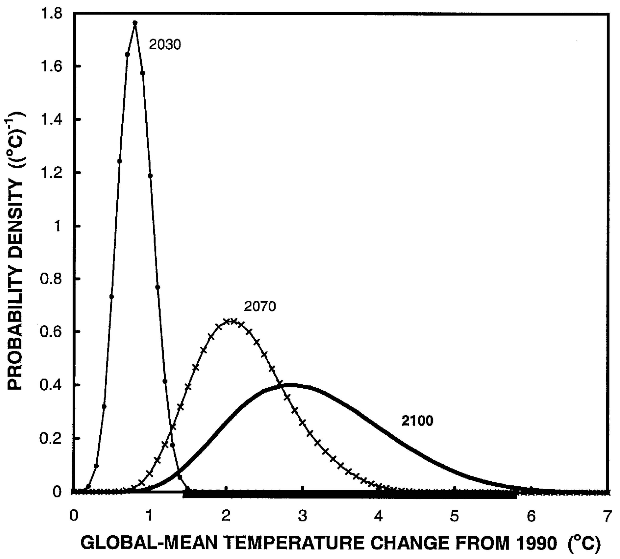

Figure 9. PDF of global temperature change at different times into the 21st century as simulated by the simple model approach of Wigley and Raper (2001).

vertical ocean mixing (which determines the lag between forcing and response). The uncertainty in these factors was accounted for by assuming that they followed prescribed PDFs. For example the emission scenarios were assumed to be all equally likely (uniform PDF), while the climate sensitivity was assumed to follow a uniform or a log-normal distribution. This can be considered as a Bayesian-type analysis (Moss and Schneider, 2000) because it implies a subjective prior judgement of the shape of the PDF of the critical parameters. By running many realizations with the simple model in order to cover the different combinations of parameter PDF, Wigley and Raper (2001) produced as end result the PDFs of global mean temperature change shown in Figure 9.

As pointed out by one of the reviewers, one of the shortcomings of the Wigley and Raper (2001) work is that IPCC (2000) did not assign any likelihood to the SRES scenarios (they were considered equally plausible, not equally likely), so that assigning PDFs to the scenarios might go against their fundamental design. This problem has been circumvented by more recent work in which the uncertainty associated to the emissions of GHG and aerosols was investigated using simplified Earth System Models (Forest et al., 2002; Webster et al., 2002, 2003) or Integrated Assessment Models (IAMs, Mastrandrea and Schneider, 2004). In these models an economics/technology component is coupled to the physical models in order to calculate emissions based on the economy and technology response to climatic forcings. By assuming PDFs of different quantities of the economics and emission models, the phase space of emissions can be explored with an approach conceptually similar to that of Wigley and Raper (2001). Another example of application of a simple model to generating PDFs of climate sensitivities is that of Andronova and Schlesinger (2001), who studied the effects of the uncertainty in radiative forcing and natural climate variability.

The advantage of the use of simple models is that they are computationally inexpensive, and thus they allow to explicitly cover the phase space of the uncertainty in key parameters. However, the information that can be obtained from these models is necessarily limited. They can reproduce reasonably well the global temperature behavior of full AOGCMs, and hence they can provide information on global temperature change. However, they cannot reliably provide regional information or information on changes in other climate variables of interest (e.g. precipitation, circulations) and different climate statistics (e.g. variability and extreme events). In addition, simple one-dimensional or two-dimensional models cannot simulate many non-linear dynamical behaviors of the climate system, which we have seen are very important at the regional scale. Scaling techniques have been developed in order to relate regional changes to global temperature changes (e.g. Mitchell et al., 1999). They have been proven useful to downscale temperature, however their applicability to a wide range of variables and climate statistics has yet to be proven. The recent development of Intermediate Complexity Models (e.g. Claussen et al., 2002), which account for most of the non-linear behaviors of the atmosphere, may allow the application of three-dimensional simplified models to climate prediction.

As an example of climate change PDF produced with a single AOGCM, we use the work of Stott and Kettleborough (2002). They used the Hadley Centre AOGCM to produce probabilistic predictions of global temperature changes at different decades within the 21st century (see Figure 10) for different emission scenarios. First, a PDF of scaling factors is calculated, by which the model

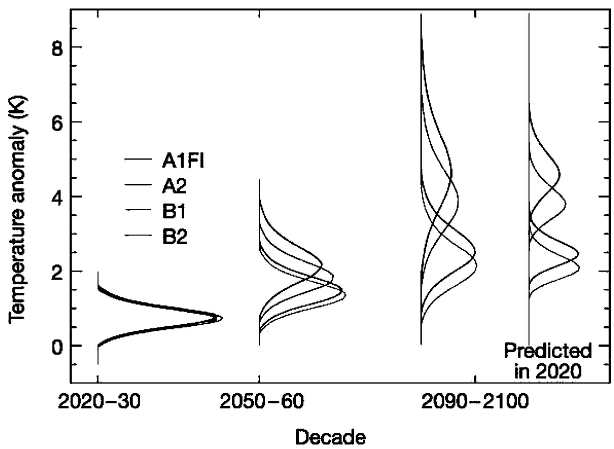

Figure 10. PDF of global temperature change for four IPCC emission scenarios at different times into the 21st century as simulated by the AOGCM-based approach of Stott and Kettleborough (2002).

response to different forcings (GHG, aerosols, natural) can be multiplied and still match the observed record for the 20th century. The spread of this PDF is determined by the interdecadal internal variability of the model, which provides different estimated contributions of the external forcings to the 20th century warming. The scaling factors are a measure of the forcing-response relationship in the model and are calculated using an optimal fingerprinting technique (Stott et al., 2001).

The effects of the future natural forcings (solar and volcanic activity) and the internal unforced variability of the climate system were also approached in a probabilistic way. To describe the former, Stott and Kettleborough (2002) estimated the variance of the global mean temperature response to the solar and volcanic forcings in their 20th century simulations and assumed that the future global temperature response can be described as a normal distribution with the same variance. Similarly, the effect of the internal variability was described as a normal distribution with variance estimated from an external forcing-free control simulation.

By random selection from the relevant PDFs, the distributions of scaling factor, externally-forced natural variability and internal variability were finally combined to provide a PDF of the global temperature response to anthropogenic forcings (Figure 10). The assumption of scaling and of normal distributions for the forced and internal natural variability thus effectively allows one to enlarge the sample size used to construct the predicted PDF. This concept of forcing-response scaling is also used by Allen et al. (2000) to estimate the uncertainty in climate predictions for the early decades of the 21st century.

The concept of factor scaling is adequate for global temperature predictions (Allen et al., 2000). However, its applicability to the regional scale and to variables different from temperature is more questionable since, as mentioned, regional processes are more non-linear in nature. As a result, approaches to the prediction of regional climate changes have mostly relied on the direct use of output from ensembles of AOGCM simulations. In this regard, the studies of Räisänen and Palmer (2001), Palmer and Räisänen (2002), Giorgi and Mearns (2002, 2003) and Murphy et al. (2004) are here highlighted.

Räisänen and Palmer (2001) and Palmer and Räisänen (2002) used the ensemble of 19 CMIP simulations (Coupled Model Intercomparison Project; Meehl et al., 2000) to estimate probabilities of climate change at time of CO_2 doubling in transient climate change simulations with a 1%/year CO_2 concentration increase. Their approach is borrowed from seasonal climate prediction, whereby the probability of regional climate change (e.g. for temperature or precipitation) exceeding a given threshold is given by the fraction of the total number of model simulations that predict such a change. Palmer and Räisänen (2002) then extended this method to the prediction of changes in the probability of occurrence of extreme seasons. In their approach, the probability of a season being outside the 2 or 3 standard deviation range is calculated as the fractional number of seasons in the full ensemble of model simulations that exceed this range. This probability was shown to significantly increase over some regions in doubled CO_2 conditions.

In these studies each model simulation was treated as equally believable. Therefore the best estimate climate change derived from the ensemble of models was given by the ensemble average change, with a corresponding measure of uncertainty being the standard deviation of the changes. Giorgi and Mearns (2002, 2003) attempted to take into account the quality, or reliability, of the model simulations in their "Reliability Ensemble Averaging (REA)" method. In the REA method each model simulation is assigned a "reliability" parameter which accounts for different criteria of model reliability.

One of these criteria is the ability of the model to simulate historical climate conditions. The better a model performance in this respect, the more reliable we can expect this model to simulate climate changes. Another criterion often used to assess reliability is the agreement across models: a prediction is deemed more reliable if different models tend to agree on the magnitude and sign of the prediction (Giorgi et al., 2001b). For example, two models were not included in the IPCC final estimate of global temperature change uncertainty (1.4–5.8 °C by 2100) because they were considered to be outliers compared to the others (Cubasch et al., 2001). A third criterion of model reliability, which however has been little used to date, is the model ability to simulate climate conditions different from present, such as paleoclimates. This criterion can be especially useful to verify a climate prediction system as the climate change signal becomes stronger into the 21st century.

Regardless of the specific criteria used to establish a model reliability, the REA method provides a conceptual and quantitative framework for using such criteria in the analysis of ensembles of climate change simulations (Giorgi and Mearns, 2002). In the REA method the best estimate change is given by a weighted average of the changes simulated by individual models, with the weighting factor given by the reliability parameter. Similarly, the uncertainty range is measured by the weighted root mean square distance of the individual simulated changes from the REA average change (analogous to the standard deviation if all the models are equally weighted). A further advantage of the REA method is that it allows a quantitative measure of the overall reliability in the prediction, which is given by the REA weighted average of the models' reliability parameter. This is important information to assess the quality of the prediction.

More recently, Giorgi and Mearns (2003) extended the REA method to the calculation of probabilities of regional climate changes being above given thresholds. Figure 11 shows probabilities of surface air temperature and precipitation changes for the last three decades of the 21st century calculated for different regions of the world and based on an ensemble of 9 AOGCM transient climate change simulations. In the calculation of these probabilities, the likelihood associated to a given model simulation is assumed to be proportional to the reliability parameter. This adds a Bayesian element to the method, in that a subjective assumption is made

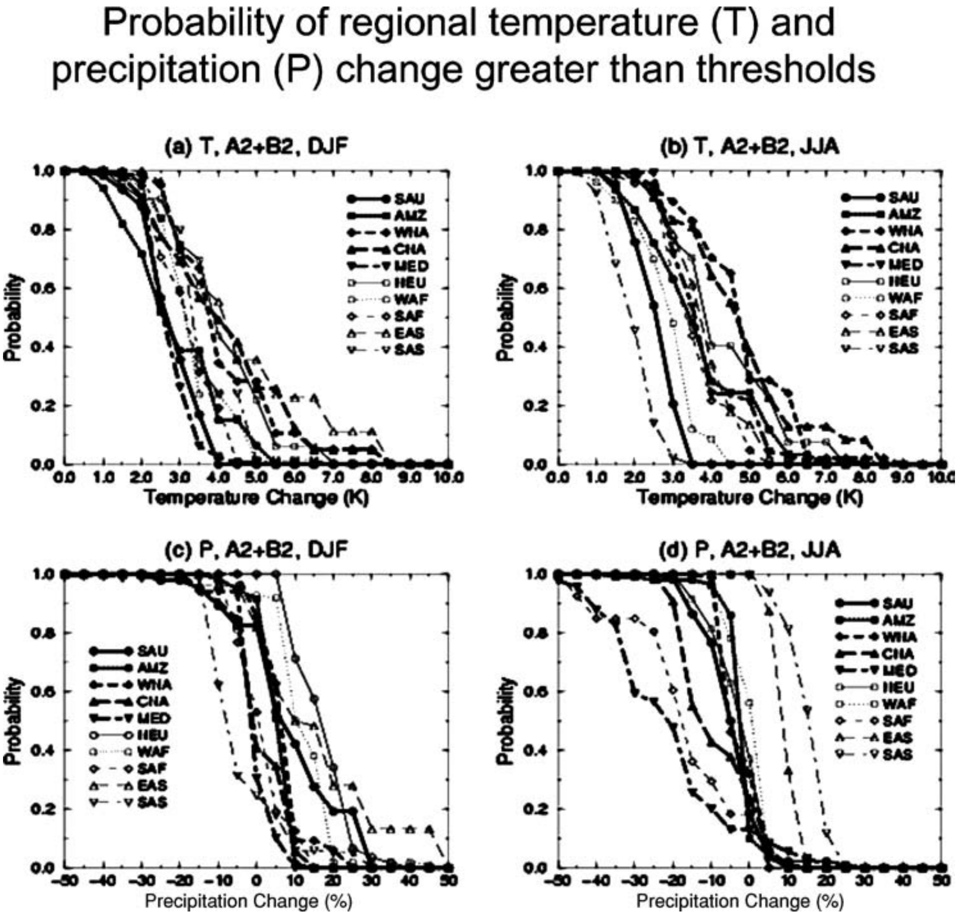

Figure 11. Probability of seasonal (DJF, JJA) temperature and precipitation changes being above given thresholds as calculated via the REA method of Giorgi and Mearns (2002, 2003). The changes are calculated for the 2071–2100 period compared with the 1961–1990 period. Data from 9 different AOGCM simulations for 10 regions of sub-continental scale are used (from Giorgi and Mearns, 2003).

of the likelihood of a model prediction. The REA method has been extended to a rigorous Bayesian treatment by Tebaldi et al. (2005).

Finally, Murphy et al. (2004) extended previous approaches in order to generate PDFs of climate sensitivity based on a relatively large ensemble (55 members) of global model simulations with the Hadley Centre AOGCM. The different simulations varied in the value of relevant model parameters with the constraint of yielding results consistent with observations. In the generation of the PDF Murphy et al. (2004) used weighting factors conceptually similar to the reliability factors of the REA method but based on a greater number of model variables. They then explored the phase space of climate sensitivity by linearly compounding the contributions of different model parameters.

5. Summary and Discussion

The main argument of this paper is that, because of the very nature of the problem, climate change prediction needs to be approached in a probabilistic way. This implies that a climate change prediction essentially consists of the construction of a PDF of possible changes which accounts for the uncertainties underlying the different steps involved in the prediction. As we discussed, a portion of this uncertainty is intrinsic to the climate system (including the human component) and thus cannot be reduced. In fact, it would be desirable to capture the full range of possibilities described by the intrinsic uncertainty, including in particular low probability/high impact events. On the other hand, another portion of the uncertainty range is attributable to deficiences and approximations in the modeling tools utilized to make the prediction. It is therefore important that the causes of this segment of the uncertainty range are fully understood and that this understanding leads to a reduction of this uncertainty.

To fully cover the phase space of climate change accounting for all sources of uncertainty is a formidable task. Some of the methods reviewed here attempt to cover this space by utilizing simple models or enlarging the simulation sample size via suitable assumptions and techniques. These approaches have proven to be very useful to understand the uncertainties related to climate change prediction. However, they are mostly viable for globally averaged changes, a limited number of variables (e.g. temperature) and low order statistics (e.g. average changes). Regional climates are highly non-linear and often the climate change information is needed for higher order statistics (variability and extremes) and multiple variables (e.g. precipitation, wind intensity, solar radiation etc.). In this case the main source of climate change information is provided by three-dimensional climate models. In this regard, methods have been reviewed in which the climate change information is drawn from ensembles of different AOGCM experiments.

With these premises and within the framework of limited, although rapidly increasing, computational resources available for climate change research, the question is posed of how to best approach the problem of climate prediction. The basic issues underlying this question are, in the opinion of the author, the following:

1) The climate change information should be provided at scales suitable for impact assessment studies. This implies that fine scale regional and possibly local information is needed.
2) All important climate system processes and feedbacks should be accounted for in the models. This implies that comprehensive models should be used to fully understand the climate change processes and produce credible predictions. In this regard, a prominent missing component in most climate change simulations to date is land use change and biosphere–atmosphere feedbacks. Studies have indicated that these processes can be important in modulating the climate change signal especially at the regional scale (Cox et al., 2000;

Chase et al., 2001; Zhao et al., 2001, 2002; Friedlingstein et al., 2003). Another important missing forcing in most current climate change experiments is that due to carbonaceous aerosols (e.g. Menon et al., 2002).

3) The climate change phase space should be covered sufficiently well to yield robust PDFs. This implies the need of large ensembles of climate change simulations with different forcings, model configurations, initial conditions and regionalization techniques.

Given limited computing resources, the three points above require a suitable compromise between model resolution, complexity and simulation sample size. Figure 12 depicts a possible strategy to climate change prediction that aims to achieve such a compromise. The strategy is based on the use of a set of different comprehensive climate system models with intermediate atmospheric resolution, say 1–2 degrees, run for large ensembles of simulations accounting for the uncertainties in anthropogenic forcings (GHG concentration, aerosols, land-use change), internal variability and feedbacks in the climate system, external natural forcings and model-related uncertainties. Global climate models with these intermediate resolutions appear capable of reproducing the main features of the general circulation of the atmosphere (McAvaney et al., 2001; Giorgi et al., 2001a).

Once this set of simulations is completed, some cluster-type analysis could be performed to group the large ensemble of simulations in primary "modes" of change. The emphasis in this excercise could be on major changes in circulation structure and regimes, coupled variability modes and components of the hydrologic cycle. As a third step, different regionalization techniques could be applied to provide fine scale regional information for cases representative of the major change modes identified.

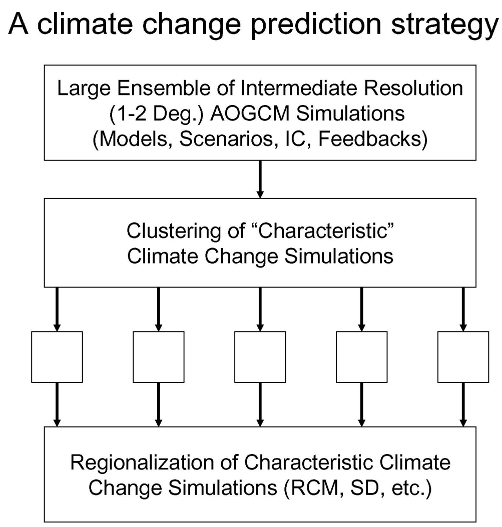

Figure 12. Depiction of a possible strategy for climate change prediction (see text).

Regardless of the specific strategy adopted, it is essential that the phase space of climate change is extensively explored and that predicted probabilities of change are provided to the end users in order to carry out risk analysis. An important step towards this goal is to assign likelihoods to the emission scenarios or to the underlying assumptions and parameters. The IPCC Third Assessment Report expressely avoided this (IPCC, 2000). However, as we have seen, individual research efforts are already applying PDFs to the scenarios so that inevitably this is a task that the scientific community will have to soon take on (Schneider, 2001, 2002). In principle, of course, a rigorous climate change prediction should be carried out with fully integrated climate system models including the impact and human components. In this case, the GHG emissions would be directly calculated by the model instead of being specified through scenarios. Research in this direction is in its early stages and, as we have seen, some simplified integrated assessment models are today available (e.g. Webster et al., 2003; Mastrandrea and Schneider, 2004).

Increasing attention is going towards assigning likelihoods and reliability to model simulations. Although this can be done within a formal framework, such as in the REA method, it still requires a subjective component in the evaluation of a climate change simulation, especially in view of the fact that such simulation cannot be easily verified against observations. The problem of climate change prediction has thus an inherent Bayesian component whose implications need to be fully explored. Criteria for evaluating the reliability of a prediction need also to be better elucidated within rigorous quantitave frameworks (Zwiers and Zhang, 2003).

In conclusion, the availability of a hierarchy of climate system models of increasing complexity allows us to move from a stage of sensitivity and process studies to a stage in which we can start to produce actual probabilistic predictions of climate change for use in impact assessment work. This is made possible also by the recent tremendous development in computer technology, which has led not only to the construction of supercomputers of unprecedented power (e.g. the Earth Simulator) but also to desktop technology powerful enough to run global and regional climate models. The latter has enlarged substantially the scientific community actively engaged in climate modeling, as for example in the *climateprediction.net* project. It can thus be envisioned that the climate change phase space can be explored through large international collaborative projects.

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