Part I

Climate system science

Haroon S. Kheshgi, coordinating editor

Introduction

The Earth sciences form core disciplines contributing to the interdisciplinary assessment of human-induced climate change. Assessment exploits understanding gained from the huge, ongoing scientific endeavor to better understand the climate system as well as from interdisciplinary research to better understand how the climate system interacts with human activities. The behavior and response of the Earth system defines the links between human activities influencing the climate system, and climate system influences on society. Papers in this section provide examples of research and review of the analysis and modeling of the Earth system, and the application of such models to provide a framework to address questions associated with the following three sections of this book: impacts and adaptation, mitigation of Greenhouse gases, and policy design and decisionmaking under uncertainty.

This section examines key issues relevant to our ability to forecast future climate, construct and test models of the Earth system for use in integrated assessment, characterize uncertainty in forecasts, and analyze illustrative cases of interactions of human activities with the climate system. While the specific topics addressed in this section are hardly comprehensive, they do give examples of how interdisciplinary studies have not only drawn from fundamental understanding generated by the Earth sciences, but have also contributed to better understanding of the research needs to address societal questions and have begun to carry out this research in conjunction with specialists. Such interaction is leading to the continued and rapid advance of integrated assessment research.

From the earliest integrated assessments of climate change that sought to balance, to costs of mitigation with the benefits of avoiding climate change, climate sensitivity was seen as a key uncertainty in such analyses. Climate sensitivity is the ratio of change in global near-surface temperature to change in climate forcing, and is influenced by, for example, the uncertain response of clouds to climate forcing. Andronova and co-authors (Chapter 1) survey estimates of climate sensitivity. While the accurate determination of climate sensitivity has withstood continued efforts by climate scientists, there are a growing number of studies that document that climate sensitivity is, indeed, highly uncertain and seek to estimate its probability distribution. In particular, recent estimates include the possibility that climate sensitivity may be high, presenting challenging questions of how to plan for such an outcome should it prove true.

Observations of past climate change provide important information for testing models of the climate system, and potentially estimating model parameters such as climate sensitivity. The apparent difference in temperature trends of records of surface temperature with some records of tropospheric temperature has been a continuing controversy in climate science, given that climate models do not produce such a difference. However, existing model results considered did not include climate change driven by carbonaceous aerosols (from, for example, biomass burning); how might their inclusion affect this controversy? Penner and co-authors (Chapter 2) find that inclusion of carbonaceous aerosols actually has the opposite effect, making the discrepancy between models and *some* records even larger.

The forcing of climate by aerosols introduces a wide range of uncertainty in estimates of climate forcing. Menon and Del Genio (Chapter 3) review the range of model-based estimates of climate forcing of aerosols with a focus on carbonaceous aerosols. While the range of results of aerosol forcing is comparable to the absolute magnitude of forcing of greenhouse gases thus far, carbonaceous aerosols are simulated to have a much different, and more profound, effect on precipitation than on surface temperature. Carbonaceous aerosols present a challenge for integrated assessment models that rely on energy balance models of climate response.

Moving from records and models of past climate change, estimates of future climate change rely on simulations of climate models with their attendant uncertainties and assumptions. Kheshgi (Chapter 4) reviews methods that are being used to generate probabilistic estimates of climate change which are conditional on assumptions, with an emphasis on using past climate records for model calibration. Addressing assumptions provides a means of improving estimates of future climate change. The future acquisition of data will further constrain estimates and could, provided assumptions can be addressed, narrow the uncertainty of climate projections. Clearly, such assumptions should be considered if using generated probabilities in analyses of decisionmaking – the question remains how?

The long-term accumulation of carbon dioxide remains central to the concern for human-induced climate change. Models of the Earth system include models of global carbon cycle. Jain (Chapter 5) tests the sensitivity of a carbon cycle model for vegetation and soils to the effects of land-use change, climate change, and rising atmospheric CO_2. Offsetting effects leave large uncertainties in each effect despite constraints on the global carbon budget. Schaeffer and co-authors (Chapter 6) consider future scenarios for bioenergy and carbon sequestration in plants and soils as means to mitigate climate change. In their analysis, land-use limitations, effects on global carbon cycle, and changes in land-cover albedo each prove important in estimating the effectiveness of such options and their contribution to scenarios of the future.

The complex question of what actions are appropriate to manage climate risk has often been informed by illustrative analyses of CO_2 stabilization: what would be required to limit the concentration of CO_2 to some, as yet, undetermined level; and what would be the effects on climate? But how should other greenhouse gases be incorporated into such analyses? Wigley and co-authors (Chapter 7) consider the effects of accounting for non-CO_2 greenhouse gases (namely CH_4 and N_2O) for different effective CO_2 (i.e. radiative forcing from well-mixed GHGs) "targets" and time trajectories of

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concentrations. They consider least-cost trajectories using an energy economics model and find that in such trajectories CO_2 concentrations often overshoot their ultimate specified concentrations. Furthermore, non-CO_2 greenhouse gas mitigation plays important roles, with CH_4 mitigation providing a sensitive means of mitigating the modeled pace of temperature change.

Actions to mitigate GHG emissions will interact with existing policies and efforts to control air pollution. Prinn and co-authors (Chapter 8) consider how limits on emissions of air pollutants (SO_x, NO_x, CO, and volatile organic compounds, VOCs) affect modeled temperature increase via interactions in their integrated global system model. Their model contains a rich set of interactions including atmospheric chemistry that affects the concentrations of the greenhouse gases, ozone and methane, and ozone's effects on the carbon cycle of plants and soils. Their results show that, overall, air pollution controls have weak, either positive or negative, effects on modeled global temperature; but they note that additional interactions such as the effects of air pollution policy on overall demand for fossil fuels have yet to be included.

These papers give examples of varied ways that climate system science is being treated in the interdisciplinary assessment of climate change. They range from the detailed modeling and analysis of data sets and processes, to the integration of the many factors that influence climate. The depth of climate system science, and its explicit consideration of uncertainty, forms a foundation for the integrated assessment of climate change, and is driving a trend towards more complicated models – models that are more directly coupled to the current state of understanding of climate system science. The more varied, and realistic, applications of integrated assessment are requiring a more comprehensive treatment of the climate system and are broadening the focus of climate system science research. Interdisciplinary research is leading to synergies that are adding value, and are contributing to the growth of integrated assessment research.

1

The concept of climate sensitivity: history and development

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1.1 Introduction

The climate sensitivity concept (CSC) has more than a century of history. It is closely related to the concept of "climate forcing" or "radiative forcing," which was fully presented and discussed by successive IPCC Assessment Reports (e.g. see Chapter 6 Houghton *et al*., 2001). According to CSC, a change in the equilibrium global near-surface air temperature (NST) of the Earth, ΔT, due to an external disturbance of the Earth's energy balance (radiative forcing), can be linearly related to a change in the net radiation at some level in the atmosphere, ΔF. Thus,

$$\Delta T = \lambda \Delta F, \tag{1.1}$$

where λ is the climate sensitivity, which characterizes the ability of the climate system to amplify or reduce the initial temperature change initiated by the external forcing. The climate sensitivity has been estimated using Eq. (1.1) most frequently from the NST change, ΔT_{2x}, resulting from the radiative forcing due to a doubling of atmospheric carbon dioxide concentration from pre-industrial levels, ΔF_{2x}:

$$\lambda = \frac{\Delta T_{2x}}{\Delta F_{2x}}. \tag{1.2}$$

Thus ΔT_{2x} has become a surrogate for λ and has played a central role throughout the history of IPCC in interpreting the output of numerical models, in evaluating future climate changes from various scenarios, and in attributing the causes of observed temperature changes.

Between the 1960s and 1980s various types of deterministic models were used to estimate climate sensitivity, leading to a wide range of results. However, it was a mixture of modeling results and expert assessment – the Charney report of 1979 (NAS, 1979) – that established the range of 1.5 °C to 4.5 °C that was later reported in all three IPCC Assessment Reports (IPCC, 1990, 1996, 2001).

Currently the primary reason for the substantial range in model-based estimates of climate sensitivity is widely believed to be differences in their treatment of feedbacks (Schlesinger, 1985, 1988, 1989; Cess *et al*., 1996; Colman, 2003) – particularly cloud feedbacks. But systematic comparisons have not been made to confirm that this is true for the current generation of models. Within international climate modeling projects, the development of new models, together with both formal and informal model comparison exercises that are currently being conducted by various groups, suggests that a renewed focus on the reasons for different model-based estimates of climate sensitivity may be particularly useful at this time.

The probability density and cumulative distribution functions for ΔT_{2x} obtained recently using the instrumental temperatures and estimated forcing from the mid-nineteenth century to the present by four groups (Andronova and Schlesinger, 2001; Forest *et al*., 2002; Gregory *et al*., 2002; Knutti *et al*., 2002), using different methods, indicate that the IPCC range for the climate sensitivity, $1.5\,^{\circ}\mathrm{C} \leq \Delta T_{2x} \leq 4.5\,^{\circ}\mathrm{C}$, is too narrow. This is consistent with the observation that experts routinely underestimate uncertainty (Kahneman *et al*., 1982;

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Shlyakhter, 1994). The four independent estimates indicate that there is no likelihood that $\Delta T_{2x} < 0.6\,°\mathrm{C}$ (this is a particularly robust finding), but there is a 5% likelihood that $\Delta T_{2x} \geq 9\,°\mathrm{C}$.

As we show here, some recent studies suggest that new insights into the likely range of climate sensitivity may be possible through comparisons of models and observational data – contemporary, historical and paleoclimatic. Other recent studies raise issues regarding the applicability of response/forcing relationships in the climate system – such as the degree of predictability of climate and the relevance of climate predictability for estimates of climate sensitivity, and the degree to which forcings such as those due to solar variability, well-mixed greenhouse gases, and aerosols may produce different responses.

In Section 1.2 we briefly review the history of the climate sensitivity concept. Section 1.3 presents some recent developments of this concept. Section 1.4 discusses some of its possible future developments. Concluding remarks are given in Section 1.5.

1.2 History of the climate sensitivity concept (CSC)

The concept of climate sensitivity and the development of this concept are directly related to empirical or model estimations that established a linear relationship between radiative forcing and near-surface air temperature. CSC originated from the concept of the greenhouse effect, introduced by Arrhenius at the end of the nineteenth century (Arrhenius, 1896). Arrhenius defined the greenhouse effect in terms of ΔT_{2x}. Almost a century later, Budyko (1972) and Sellers (1969) repeated Arrhenius's calculations using more comprehensive energy balance models (North, 1981), and strongly supported the concept of the greenhouse effect. As a result, the climate sensitivity concept was promulgated.

Until the third IPCC report (IPCC, 2001), the concept of climate sensitivity was based on calculations of the equilibrium NST change. However, the third IPCC report (Cubasch *et al*., 2001) defined three measures of climate sensitivity, with the differences between the measures arising from the different types of simulations performed with the climate model.

The equilibrium climate sensitivity λ_{eq} is given by Eq. (1.1) and is estimated from climate simulations in which the radiative forcing does not vary with time after an initial change, such as for an instantaneous CO_2 doubling. Most estimations were made for λ_{eq}, which we will review below.

The effective climate sensitivity (after Murphy, 1995) is given by

$$\lambda_{\mathrm{eff}}(t) = \frac{\Delta T(t)}{F(t) - \mathrm{d}H(t)/\mathrm{d}(t)} \qquad (1.3)$$

where $\mathrm{d}H(t)/\mathrm{d}t$ is the change in heat storage of the climate system – essentially the heat taken up or lost by the ocean, obtained from climate simulations with time-dependent forcing, $F(t)$. If the radiative forcing in Eq. (1.3) were made time-independent, then $\mathrm{d}H(t)/\mathrm{d}t$ would approach zero with increasing time as the climate system approaches equilibrium and $\lambda_{\mathrm{eff}}(t)$ would approach λ_{eq}. Time series of the effective climate sensitivity demonstrate how feedbacks of the climate system evolve with time.

The transient climate sensitivity (after Murphy and Mitchell, 1995) is given by

$$\lambda_{\mathrm{trans}} = \frac{\Delta T(t_{2x})}{F_{2x}} \qquad (1.4)$$

where $\Delta T(t_{2x})$ is the change in NST when the CO_2 concentration increases to double the pre-industrial value in a transient climate simulation, particularly one in which the CO_2 concentration increases at 1% per year. Because the thermal inertia of the ocean $\Delta T(t_{2x}) < T_{2x}$, $\lambda_{\mathrm{trans}} < \lambda_{eq}$. Calculations of the transient climate sensitivity are primarily used for comparison among coupled atmosphere/ocean general circulation models because these models take thousands of years to equilibrate. However, because the actual climate system is always facing external stresses from multiple simultaneous forcings, at any particular time the climate system is facing transient sensitivity. Under slowly evolving external forcings, the transient sensitivity may be approximated by λ_{eq}.

Model-based estimation of climate sensitivity varies considerably from model to model because of different parameterizations of physical processes that are not explicitly resolved in the respective models, such as clouds. For example, energy balance models (EBMs), typically one- or two-dimensional, generally predict only the NST and frequently only in terms of its globally averaged value. The value of ΔT_{2x} obtained by EBMs ranges from $0.24\,°\mathrm{C}$ (Newell and Dopplick, 1979) to $9.6\,°\mathrm{C}$ (Möller, 1963).

Radiative-convective models (RCMs) determine the vertical distribution of atmospheric temperature and the surface temperature, virtually always in terms of their globally averaged values. As their name indicates, radiative-convective models include the physical processes of radiative transfer and convection. The value of ΔT_{2x} obtained by RCMs ranges from $0.48\,°\mathrm{C}$ (Somerville and Remer, 1984) to $4.2\,°\mathrm{C}$ (Wang and Stone, 1980).

Atmospheric general circulation models (AGCMs) simulate the vertical and geographical distributions of temperature, surface pressure, wind velocity, water vapor, vertical velocity, geopotential height, ground temperature and moisture, and the geographical distribution of snow and ice on the ground. AGCMs have been coupled with different ocean and sea-ice models. These include a swamp ocean which has zero heat capacity but infinite water, a mixed-layer ocean which has a prescribed depth, and a full dynamic ocean GCM, which is the oceanic counterpart of the AGCM. Sea-ice models range from freezing a swamp ocean (where the temperature would otherwise drop below the freezing temperature of seawater) that has only thermodynamics and no transport by wind or currents, to a fully dynamic-thermodynamic sea-ice model. In all cases the atmosphere/ocean model has a finite horizontal and vertical resolution. The value of ΔT_{2x} obtained by AGCMs ranges from 1.3 °C (Washington and Meehl, 1983) to 5.2 °C (Wilson and Mitchell, 1987).

All of the above ranges of the climate sensitivity estimates are based on a set of individual model runs and should be treated in a statistical sense as equally plausible, because each model has different sets of feedbacks, induced by different model parameterizations, built to be consistent with various observational data obtained from monitoring of the different parts of the climate system.

The growing amount of empirical temperature data has resulted in numerous attempts to use these data to estimate the climate sensitivity inversely. Budyko (1972) made the earliest such estimate of the climate sensitivity using paleodata of northern hemisphere temperature and atmospheric carbon dioxide concentration for six paleoclimate epochs (a review of these earlier estimates can be found in Schlesinger [1985]).

The pre-instrumental proxy record consists of quantities that are sensitive to temperature, such as the thickness and isotopic composition of the annual growth rings of trees and corals, and the annual layers of glacial ice; the relative abundance and isotopic composition of planktonic (living near the sea surface) and benthic (living near the sea floor) foraminifera (shell-covered species) that, after dying, fall to the sea floor where they are covered up by the sedimentary material raining down from above; and the relative abundance of pollen in the annual growth layers of sediment at the bottom of lakes (Ruddiman, 2000). These proxy data are converted into temperatures using statistical relations that have been developed based on the present climate. The reconstructed temperature for any paleoclimate gives the temperature difference from the present, ΔT_s. This is used to estimate the climate sensitivity from

$$\Delta T_{2x} = \left(\frac{\Delta F_{2x}}{\Delta_F}\right)\Delta T_s \qquad (1.5)$$

where ΔF is an estimate of the radiative forcing. The range using paleo-based methods is 1.4 °C (Hoffert and Covey, 1992), for the lowest estimation, to 6.0 °C (Barron, 1994), for the highest estimation. There are at least three factors that lead to uncertainty in the estimates of ΔT_{2x} by the paleo-calibration method. First, the proxy data for temperature are not global in extent, hence their global average is uncertain, and their conversion to temperature is also uncertain (Mann and Jones, 2003). Second, estimation of the radiative forcing for paleoclimates relative to the present climate is difficult and thus uncertain. Third, the sensitivity of paleoclimate temperature changes from the present climate may be different from the sensitivity of future human-induced temperature changes from the present because the active feedbacks in each period are different.

Tol and de Vos (1998) (TdV) made one of the first inverse estimations of the probability density function (pdf) of climate sensitivity. They used a simple statistical model and Bayesian updating in combination with expert opinion and observational constraints on the initial (prior) pdf of ΔT_{2x}. They found that large values of ΔT_{2x} cannot be excluded and that the posterior pdf is strongly dependent on the prior pdf.

Starting with the analysis by Andronova and Schlesinger (2001), referred to below as AS01, there have been a handful of estimates of the pdf and cumulative density function (cdf) for ΔT_{2x} using simplified climate models (SCM) to replicate the temperature changes observed since the middle of the nineteenth century. Andronova and Schlesinger (2001) used an SCM consisting of an EBM coupled to an upwelling – diffusion model of the ocean to simulate the change in hemispheric-mean temperatures from 1765 to the present for prescribed radiative forcing. Sixteen radiative forcing models (RFMs) were examined with all possible combinations of: (1) anthropogenic radiative forcing consisting of greenhouse-gas (GHG) forcing due to the increasing concentrations of CO_2, methane, N_2O, chlorofluorocarbons and tropospheric ozone, and the direct (clear air) plus indirect (cloudy air) radiative forcing by tropospheric sulfate aerosols (SO_4); (2) volcanic radiative forcing; and (3) solar radiative forcing. The values of ΔT_{2x} and the unknown sulfate forcing in reference year 1990, $\Delta F_{ASA}(1990)$, where ASA is anthropogenic sulfate aerosol, were estimated for each RFM by optimizing the fit of the simulated and observed global-mean temperatures (GMT) and the interhemispheric temperature differences (ITD), respectively. The difference between the observed and simulated GMT and ITD was bootstrapped to generate 5000 samples of the unforced noise to which was added the simulated temperature signal to create 5000 surrogate observational hemispheric temperature records. For each ensemble member thereof, the values of ΔT_{2x} and ΔF_{ASA} (1990) were estimated using the same procedure as used for the single real observational record. This method of estimating the climate sensitivity does not depend on priors for the estimated quantities, but rather on the combination of the three types of radiative forcing, anthropogenic, solar and volcanic, and the natural variability of the observed temperatures. The resulting (AS01) cdf for ΔT_{2x} has a mean value of 3.40 °C, a 90% confidence interval of 1.0 °C to 9.3 °C, and a 54% likelihood that ΔT_{2x} lies outside the IPCC range of 1.5 to 4.5 °C.

Gregory *et al.* (2002) (GEA02) estimated climate sensitivity from

$$\Delta T_{2x} = \frac{\Delta \overline{T}'}{\overline{Q}' - \overline{F}'}, \qquad (1.6)$$

where $\Delta \overline{T}'$ is the change in the observed global-mean near-surface temperature between 1861–1900 and 1957–1994, $\overline{Q}'$ is the change in the estimated radiative forcing between the two periods, and $\overline{F}'$ is the change in heat uptake between the two periods – calculated by an SCM for the earlier period and estimated from observations for the latter. Normal probability distributions are assumed for $\Delta\overline{T}'$, with 2σ between 0.302 °C and 0.368 °C; $\overline{Q}'$, with 2σ between -0.3 and $+1.0$ W/m^2; and $\overline{F}'$, with 2σ between 0.00 and 0.32 W/m^2. A singularity exists where $\overline{F}'$ approaches $\overline{Q}'$. When $\overline{F}'$ is larger than $\overline{Q}'$, this implies a negative sensitivity, which was rejected because it would make the climate system unstable to natural variations.

Forest *et al.* (2002) used the Massachusetts Institute of Technology two-dimensional (latitude–altitude) statistical-dynamical model to simulate climate change from 1860 to 1995, varying ΔT_{2x}, oceanic vertical heat diffusivity, K, and anthropogenic aerosol forcing for the 1980s decade relative to pre-1860. They used optimal fingerprint detection in latitude, altitude and time of the simulated climate change in the observed climate change for surface air temperature, ocean temperature (0 to 3000 m) and tropospheric temperature. Their optimal fingerprint detection algorithm was based on pattern matching for the patterns for surface, upper-air, and deep-ocean temperature changes. The comparison was made for four zonal bands (90° S–30° S, 30° S–0°, 0°–30° N, 30° N–90° N) for decadal-mean temperature for the 1946–95 period relative to the 1906–95 climatology using an observational data mask. A goodness-of-fit statistic was computed for each of the three quantities. In the optimal detection, noise estimates for each diagnostic were obtained from two atmosphere/ocean GCMs. The surface and upper-air diagnostics reject similar regions, namely low K and high ΔT_{2x}, while the ocean diagnostic rejects high K and high ΔT_{2x}. Rejection regions shift to higher ΔT_{2x} for increasing negative aerosol forcing. Bayes' theorem was used to update the pdfs of parameters from an assumed starting (prior) pdf. The resulting ΔT_{2x} cdfs for a uniform starting pdf is wider than for the expert prior pdf – the 90% confidence interval for the uniform prior is 1.4 °C to 7.7 °C, and for the expert prior is 1.4 °C to 4.1 °C. For further references, we will call the resulting cdfs (FUN02) and (FEX02), respectively.

Knutti *et al.* (2002) (KEA02) used a climate model of reduced complexity – a zonally averaged dynamical ocean model coupled to a zonally and vertically averaged energy- and moisture-balance model of the atmosphere – to make 25 000 Monte Carlo simulations of the changes in the surface temperature from 1900 to 2000 and the ocean heat uptake from 1955 to 2000. They used multiple values of ΔT_{2x}, distributed uniformly over 1 °C to 10 °C, and indirect aerosol forcing in 2000, uniformly distributed over –2 to 0 W/m^2. They found that the climate sensitivity is only weakly constrained by the ocean heat uptake, which gave $\Delta T_{2x} = 5.7 \pm 3$ °C (one standard deviation). When they used the surface temperature as a constraint, it gave $\Delta T_{2x} = 4.6$ °C, with a range of 1.8 °C to 8.7 °C. As shown by KEA02, the 95% confidence interval for ΔT_{2x} is 2.2 °C to 9.1 °C.

Knutti *et al.* (2003) used a neural-network-based climate-model substitute to produce a large number of ensemble simulations similar to Knutti *et al.* (2002). They assumed a uniform prior distribution of the climate sensitivity and found that the surface warming in 2100 exceeded the range projected by IPCC for almost half the ensemble members. They noted that reduction of the uncertainty in climate sensitivity requires a significant reduction in the uncertainties of the observational temperatures, as well as better constraints on the reconstructed radiative forcing.

Figure 1.1a summarizes all estimates of the climate sensitivity described in this section. In this figure, we sorted the estimates into two groups: the deterministic estimates, based on estimation of the single number, and the probabilistic estimates, based on constructing a probability density function (pdf) or cumulative density function (cdf). The left part of Figure 1.1a presents ranges of the climate sensitivity based on the deterministic estimates. The right side of this figure presents ranges of the probabilistic estimates based on the 90% confidence interval of the probabilistic estimates. Among the deterministic estimates we have included the IPCC range. Among the probabilistic estimates we have included an estimate given by the Charney report of 1979 (NAS, 1979), namely. "3 °C with a probable error of ±1.5 °C," which we have interpreted as the 50% confidence interval, labeled as NRC79. The range cited by IPCC originated from NAS (1979). Also, in this figure we have included an expert elicitation of 16 climate "experts" performed by Morgan and Keith (Morgan and Keith, 1995) of Carnegie-Mellon University (CMU95) five years after the IPCC First Assessment Report was published. For this we combined the 16 experts' opinions in terms of their mean estimation and variance cited in Morgan and Keith (1995) into a single cdf, under the assumption that each of the 16 estimations is normally distributed. It is seen that the CMU95 cdf has a non-zero probability that $\Delta T_{2x} < 0$. This non-zero probability occurs because three of the "experts" had a non-zero probability that $\Delta T_{2x} < 0$.

The right vertical axis of Figure 1.1a shows the climate sensitivity estimates in terms of the climate system's total feedback, calculated as defined by Schlesinger (1985, 1988, 1989):

$$f = 1 - \frac{(\Delta T_{2x})_o}{\Delta T_{2x}}. \tag{1.7}$$

Here $(\Delta T_{2x})_o = G_o \Delta F_{2x}$ is the change in global-mean near-surface air temperature without feedback due to a doubling of the pre-industrial CO_2 concentration with radiative forcing $\Delta F_{2x} = 3.71$ W/m^2 (Myhre *et al.*, 1998).

$$G_o = \frac{T_s}{(1-\alpha_p)S} = 0.30\ \mathrm{K/(W/m^2)} \tag{1.8}$$

is the gain of the climate system without feedback, with $T_s = 288$ K the present global-mean NST, $S = 1367$ W/m^2 the present solar irradiance and $\alpha_p = 0.3$ the present planetary albedo. If $\Delta T_{2x} \geq (\Delta T_{2x})_o$, $f \geq 0$, and if $\Delta T_{2x} < (\Delta T_{2x})_o$, $f < 0$.

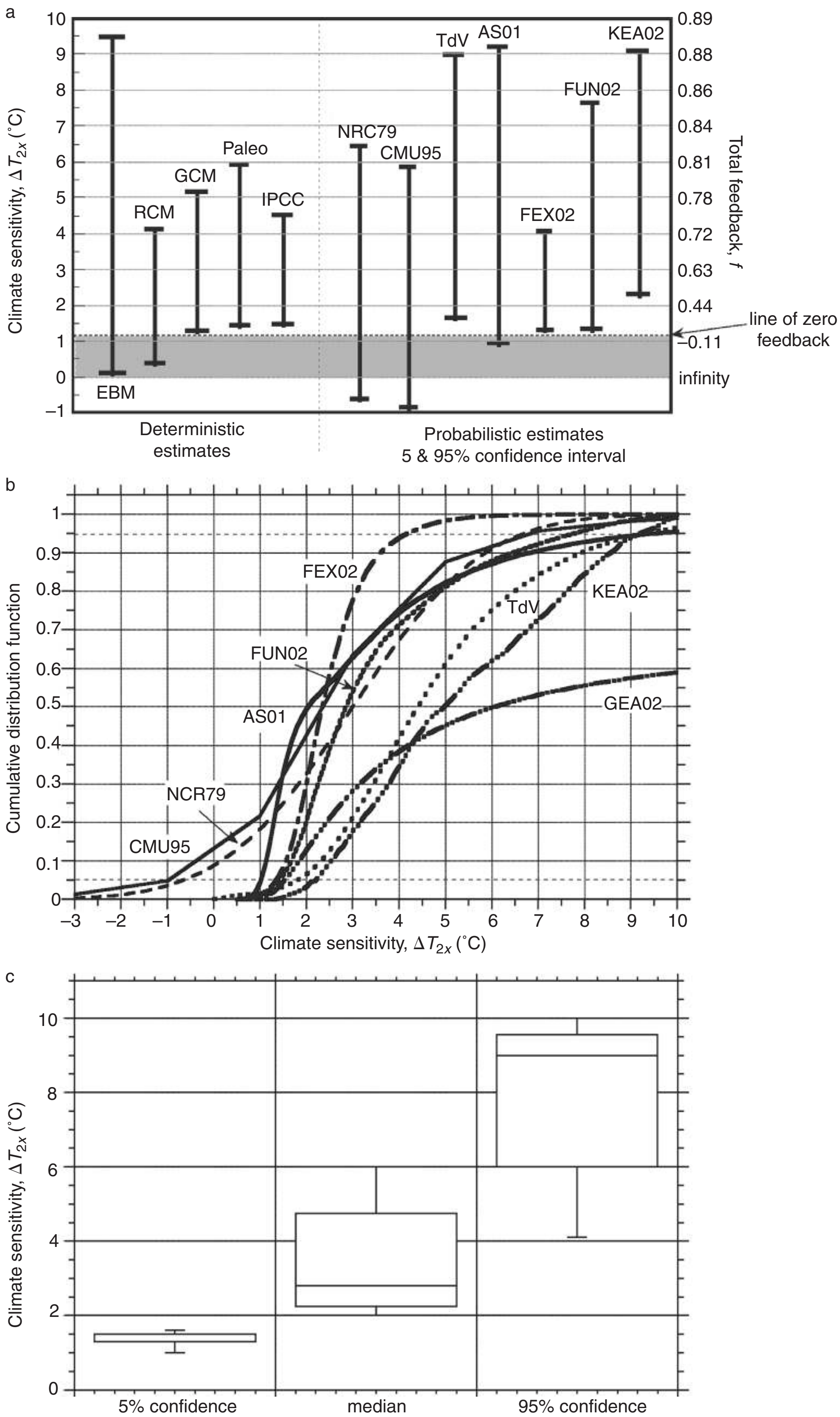

Figure 1.1 Estimations of the climate sensitivity (see explanations in the text).

As can be seen from Figure 1.1a, there are only a few estimates for which the net feedback of the climate system is negative.

Figure 1.1b presents cdfs of the probabilistic estimates of the climate sensitivity briefly described in this section. As can be seen, the lower end of the climate sensitivity estimates has a much smaller range of uncertainty than the upper end. For illustrative purposes Figure 1.1c summarizes the uncertainty range in terms of box plots for the 5th, 50th and 95th percentile values of the cdfs for ΔT_{2x}. This figure is based on six pdfs shown on Figure 1.1b: TdV, AS01, FEX02, FUN02, KEA02 and GEA02. There is disagreement about the median ΔT_{2x}, from 2.2 °C to 5.0 °C, and the 95th percentile, from 7.5 °C to 10.0 °C. These empirical studies, based on observations of the present climate, indicate that there is more than a 50% likelihood that ΔT_{2x} lies outside the canonical range of 1.5 °C to 4.5 °C, with disquietingly large values not being precluded.

1.3 Recent developments

The concept of equilibrium climate sensitivity served well for comparison of sophisticated climate models. In addition it helped to understand some of the models' feedbacks, which might work as well in the real climate system (Cess *et al.*, 1996; Colman, 2003). However, researchers were always dissatisfied with the wide range of uncertainty in the estimates of climate sensitivity. This is mostly because: (1) uncertainties in the observational data do not allow reduction of the uncertainties in the magnitude of the models' parameters; (2) the model parameterizations, which reflect the models' inability to explicitly resolve all the physical processes in the climate system, may not represent actual feedbacks; and (3) it is not a trivial task to apply advanced mathematical methods to estimate climate sensitivity and, moreover, make an insightful interpretation of the results. This is why recently questions have been asked about the usefulness of the climate sensitivity concept, among which are these. (1) Is the climate sensitivity a robust characteristic of the climate system that is useful in climate economics and policy making? (2) If not, should we look for another important climate variable, or should we live with the uncertainties until they are resolved to some degree? (3) Should we look for another concept to characterize the climate system behavior? Some of those questions are nicely highlighted in the previous IPCC reports. The second IPCC report (IPCC, 1996, Chapter 2) introduced the concept of radiative forcing, stated how fast and slow feedbacks in the climate system relate to the climate sensitivity, and discussed the robustness of the linear relationship between forcing and response for different forcings. The third IPCC report (IPCC, 2001, Chapter 6) paid much more attention to the assessment of the concept of the radiative forcing as an important part of the concept of the climate sensitivity. Below we present some new developments.

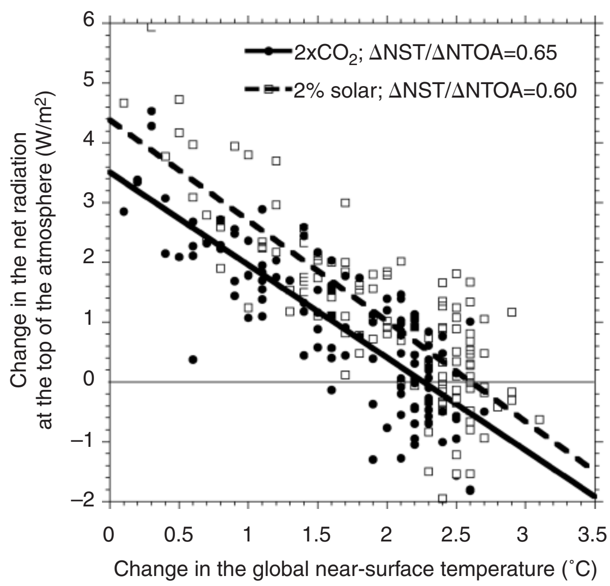

Figure 1.2 Linear regression between near-surface temperature, NST, and change in the net radiation at the top of the atmosphere, NTOA.

The procedure of calculating climate sensitivity from general circulation models, whether coupled to a non-dynamic model of the upper ocean (mixed-layer ocean model) or to a dynamic model of the full ocean, is complicated (Wetherald and Manabe, 1988). There are many uncertainties in how to perform the calculation, mostly related to where in the atmosphere and when the forcing and temperature changes should be sampled. Recently, Gregory *et al.* (2004) used a simple method of monitoring the ratio of the change in the global net radiation at the top of the atmosphere to the change in the global near-surface temperature, which approaches the equilibrium climate sensitivity as the model approaches its equilibrium climate change.

To illustrate this method, we applied it to compare the sensitivities of our 24-layer troposphere-stratosphere general circulation model (Yang *et al.*, 2000; Yang and Schlesinger, 2002; Rozanov *et al.*, 2002a, 2002b, 2004) coupled to a mixed-layer ocean model (24-L AGCM-ML) for two disturbances: a CO_2 doubling and a 2% increase in the amount of incoming solar radiation. Figure 1.2 presents a scatter diagram of the change in the monthly mean global net radiation at the top of the atmosphere (NTOA, at 1 hPa) against the change in monthly mean global NST for both experiments, together with respective linear regressions. In this figure, the change in NTOA initially is due to the perturbation and subsequently decreases as the change in NST increases and the climate system approaches its new equilibrium. The intercept of the regression line with the *x*-axis approximates the equilibrium change in NST due to the disturbance. The slope of the regression line, ΔNST/ΔNTOA, approximates the sensitivity of the model to the disturbances. Thus, if the regression lines for different disturbances are parallel to each other, then for these disturbances the model's sensitivities are the same. In the case presented in Figure 1.2, the 24-L AGCM-ML has approximately the same sensitivity to the CO_2 doubling and 2% increase in solar irradiance. Obviously, there are some shortcomings in this approach, which are discussed in Gregory *et al*. (2004). The simplicity of the presentation and interpretation, however, makes this method well suited for estimating the equilibrium climate sensitivity, without any additional calculations of the forcing.

Murphy *et al*. (2004) presented the Perturbed Physics Ensemble Method (PPEM) to estimate the pdf of climate sensitivity for an atmospheric general circulation model coupled to a mixed-layer ocean model. PPEM consists of running multiple realizations of the model with subjectively selected model parameters chosen randomly, one by one, from their subjectively prescribed range. In terms of computing costs, this method has become possible owing to the appearance of faster computers and massive parallelization of a model's code. One of the limitations of PPEM is that the set of the perturbed parameters is chosen by expert opinion and this may omit key model parameters. Another important limitation is that parameters are tested one by one and their synergetic effect on the climate sensitivity is not considered. And computer power still remains a major limiting factor for this kind of "massive" experiment. However, if it is possible to eliminate most of the shortcomings and use it for many GCMs, PPEM should give some very useful insights on GCMs and their climate sensitivities.

Figure 1.3 presents a comparison of the climate sensitivity values from Murphy *et al*. (2004) with other estimations. Figure 1.3a and 1.3b compares two cases from Murphy *et al*. (2004) with some of the estimates presented in Figure 1.1, namely the deterministic climate sensitivity range for existing GCMs, the expert elicitation CMU95, and FEX02 and AS01 which have the smallest and largest 90% confidence interval for climate sensitivity, respectively. The estimates of Murphy *et al*. (2004) have a 90% confidence interval for climate sensitivity of 1.8 °C to 5.2 °C for M1, where all model versions are assumed equally likely, and 2.4 °C to 5.2 °C for M2, which accounts for a reliability-based weighting of model versions according to the climate Prediction Index described in Murphy *et al*. (2004). It can be seen that both M1 and M2 are closest to FEX02, which uses an expert prior, and they are similar to the deterministic range for GCMs with a slightly higher minimum estimation. Recently, Stainforth *et al*. (2005), using the PPEM method, obtained the range of the climate sensitivity 1.5 °C to 11.5 °C by varying combinations of perturbations in six model parameters. This large range of uncertainties for a GCM brings up an old question of the validity of some GCM parameterizations, especially of cloud microphysics.

We note that the idea of computing the sensitivities of a model to its parameters is not new. Hall *et al*. (1982) applied the adjoint method (AM), formulated by Cacuci (1981) for use in numerical models, to calculate the sensitivities of a simple radiative-convective model and later the two-layer AGCM of Oregon State University (Hall, 1986) to a CO_2 doubling. The AM allowed the calculation of all linear sensitivities of each model parameter to the perturbation and to the initial conditions, all in one model simulation. However, at that time the application of the AM to larger models did not look feasible, because of the technical burden of re-writing the model code to include the model's adjoint equations and the mathematical problem of inverting large matrices. Thus, AM was not widely accepted by the "climate sensitivity community." But AM has been extensively applied by the "data assimilation community," who developed the Tangent and Adjoint Model Compiler (TAMC) to automatically generate adjoint model code. TAMC has been used to monitor and predict the linear tendencies of model variables. Further information is available at www.autodiff.com/tamc/.

Large numerical models calculate the climate sensitivity directly, but a similar value of the climate sensitivity may be obtained by different models even if they have different representations of the models' physical processes. Learning about new parameterizations for the subgrid-scale processes, inventing and applying new techniques for tuning model parameters, and systematic comparison of the models and their modules will definitely improve the models, if and only if the observational data have satisfactory temporal and spatial resolution and low observational errors. Thus most likely we will not be able to learn the "true" climate sensitivity from the large models soon, at least not from the IPCC Fourth Assessment Report (AR4) planned for 2007.

Inverse estimations of climate sensitivity depend heavily on the uncertainties in the observations. As an example, Figure 1.4 compares the observed historical hemispheric temperature departures of Jones and Moberg (2003), J2003, and Folland *et al*. (2001), F2001, and Figure 1.5 shows the influence of their differences on the estimate of climate sensitivity. Figures 1.4a and 1.4b present a comparison of these data for northern and southern hemispheres, respectively. It can be seen that the northern hemisphere data are very close to each other, while for the southern hemisphere the F2001 record is warmer in general than the J2003 SH record. Figures 1.4c and 1.4d shows the temporal behavior of the first two principal components of the temperature departure time evolution extracted using Singular Spectrum Analysis for the northern and southern hemispheres, respectively. Again, it can be recognized that in the southern hemisphere there are considerable differences in the temporal behavior of the two data sets. These differences make a major input into representation of the natural and forced variability of the observed temperature departure. Figure 1.5 shows the estimation of climate sensitivity using the inverse technique presented in Andronova and Schlesinger (2001), briefly described in the previous section. This technique is based on bootstrapping the residuals – the difference between the observed and simulated temperatures. Figure 1.5 shows the climate sensitivity estimated for four radiative forcing models used by Andronova and Schlesinger (2001): G – greenhouse gases only, GA – greenhouse gases and anthropogenic sulfate