1 Chapter IV – Model Climate Sensitivity

2

3 The response of climate to a perturbation, like a change in carbon dioxide concentration, or in the 4 flux of energy from the sun, can be divided into two parts; the "radiative forcing" due to the 5 perturbation in question; and the "climate sensitivity", characterizing the response of the climate per 6 unit change in the radiative forcing. The climate response is then the product of the radiative 7 forcing and the climate sensitivity. While it is not always perfectly clear, this distinction is useful in 8 analyzing and discussing climate change. The utility of this decomposition is based on several 9 considerations: radiative forcing can often be usefully considered as external to the climate system; 10 climate sensitivity can often be thought of as independent of the agent responsible for the forcing; 11 and when two or more factors are simultaneously present, one can approximate their cumulative 12 effect by adding their respective radiative forcings.

13

14 Radiative forcing is typically calculated by changing the atmospheric composition or external 15 forcing very quickly and computing the net trapping of heat that occurs before the climate system 16 has had time to adjust. In the case of carbon dioxide, it has become standard to use the surface-plus-17 troposphere heating (encompassing both the surface and the altitude range of about 0-10 km in the 18 atmosphere) in the definition of radiative forcing. The direct heat-trapping properties are very well 19 characterized for the most significant greenhouse gases. As a result, uncertainty in climate 20 responses to the greenhouse gases are typically dominated by uncertainties in climate sensitivity 21 rather than in radiative forcing (Ramaswamy et al. 2001). For example, suddenly doubling the 22 atmospheric amount of carbon dioxide would add energy to the surface and the troposphere at the 23 rate of about 4 Watts per square meter for the first few months after the doubling, according to the 24 most recent estimates (Forster and Ramaswamy, 2007). Eventually temperatures would increase 25 (and climate would change in other ways) in response to this forcing, Earth would radiate more heat 26 to space, and the imbalance would be redressed as the system returned to equilibrium.

27

28 The idea of encapsulating global climate sensitivity in a single number appeared early in the

29 development of climate models (Schneider and Mass 1975). Today, two different numbers are in

30 common use. Both involve changes in global and annual mean surface or near-surface temperature.

31 (The global and annual mean is obtained by averaging over both Earth's total area and the cycle of

the seasons.) *Equilibrium warming* is defined as the long-term surface warming after atmospheric carbon dioxide has been doubled but thereafter held constant, and the climate is allowed to reach a new steady state, as described in the preceding paragraph. *Transient climate response* or TCR is defined by assuming that carbon dioxide increases by 1% per year and recording the increase in temperature at the time that carbon dioxide doubles (about 70 years after the increase begins).

7 Equilibrium warming is difficult to obtain from AOGCMs because the deep ocean takes thousands 8 of years to fully respond to changes in climate forcing. To avoid unacceptably lengthy computer 9 simulations, equilibrium warming is usually estimated from a modified climate model in which the 10 ocean component is replaced by a simplified, fast-responding "slab ocean model." This procedure 11 makes the assumption that ocean heat transports do not change as the climate changes. The 12 equilibrium response is of greatest interest when comparing climate models with paleoclimatic data, 13 while the transient climate response is of more direct relevance to the attribution of recent warming 14 and projections for the next century.

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16 US models exemplify the climate sensitivity of modern AOGCMs. Kiehl et al. (2006) examined the 17 sensitivity of three successive versions of the Community Climate System Model developed over a 18 period of a decade: CSM1.4, CCSM2 and CCSM3. Stouffer et al. (2006) and Hansen et al. (2006) 19 similarly studied the most recent GFDL and GISS models, respectively. As discussed above, these 20 (and other) models differ in their details because development teams have differing ideas 21 concerning the underlying physical mechanisms relevant for the less well-understood aspects of the 22 system. 23 Climate sensitivity is an emergent, or holistic, property of the models - it is not input into the 24 model. None of the U.S development teams engineered their models to produce a desired value of 25 climate sensitivity. 26 27 Climate sensitivity values for the US models are shown in Table IV(1). Only the higher number 28 associated with GISS Model E used a full OGCM as a part of the climate model. All other values of

equilibrium warming in the table are obtained with the OGCM replaced by a slab ocean model.

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4 Table IV 1 Model sensitivity values for US CMIP3 models

Model	TCR	Equilib. warming*
CSM1.4	1.4°C	2.0°C
CCSM2	1.1°C	2.3°C
CCSM3	1.5°C	2.5°C
GFDL CM2.0	1.6°C	2.9°C
GFDL CM2.1	1.5°C	3.4°C
GISS Model E		2.7-2.9°C

1 Note that equilibrium warming is greater than TCR for any given model. This is because TCR is 2 measured before the deep ocean, with its large thermal inertia, has had time to warm fully in 3 response to doubled atmospheric carbon dioxide. Comparing different rows within any single 4 column, it is apparent that a wide range of equilibrium sensitivity values are obtained by different 5 models. Nearly three decades ago, Charney (1979) judged the range of equilibrium warming due to 6 doubled atmospheric carbon dioxide, based on the few model calculations then available, to be 1.5-7 4.5°C, a three-fold range of uncertainty. The table might suggest a reduction in this range, but 8 including other models in the CMIP3 archive expands the upper end; the full CMIP3 range is 2.1 to 9 4.4°C with a median of 3.2°C. Furthermore, a systematic exploration of plausible input parameters for a single (Hadley Centre) model gives a 5-95 percentile range of ~2-6°C, again a three-fold span 10 (Piani et al. 2005, Knutti et al. 2006). The low end of the equilibrium sensitivity range is thought to 11 12 be more certain than the high end (Bierbaum et al. 2003, Randall and Wood, 2007.) It is difficult to 13 reconcile a very low sensitivity value with the climate changes observed during the past century 14 (Andronova and Schlesinger 2001, Forest et al. 2001) and inferred for the more distant past (Hansen 15 et al. 1993, Covey et al. 1996).

16

17 The variation among models is less for TCR than for equilibrium warming because enhanced 18 equilibrium sensitivity correlates with enhanced heat transport to the deep ocean, and these two 19 effects cancel to some extent in transient simulations (Covey et al. 2003). Apart from CCSM2, 20 model TCR varies by less than 15% in the table above. Systematic exploration of model input 21 parameters in one Hadley Centre model gives a wider range, 1.5-2.6°C (Collins et al. 2006). The 22 full range in the CMIP3 archive is $1.3-2.6^{\circ}$ C, with a median of 1.6° C and with the half of the 23 models within the 25%-75% quartiles of the distribution lying within the relatively small range of 24 1.5-2.0°C (Randall and Wood, 2007).

25

Climate sensitivity can be altered in a model by modifying aspects of the models that are relatively poorly constrained by observations or theory. In an influential early paper, Senior and Mitchell (1993, 1996) demonstrated how a seemingly minor modification to the cloud prediction scheme can alter climate sensitivity. In the standard version of the model, the effective size of cloud drops is fixed. In two other versions, this cloud drop size is tied to the total amount of liquid water in the

- 1 cloud through two different empirical relationships. The equilibrium global mean warming ranged 2 from from 1.9° C to 5.5° C in response to doubling CO₂ in the atmosphere in these three models.
- 3

Studies of the CCSM family of models provide another example of this problem. Kiehl et al.
(2006) found that a variety of factors are responsible for differences in climate sensitivity among the
models of this family. Most notably, the generally lower sensitivity of CCSM2 (evident in Table
IV(1)) is mainly due to a single change (relative to CSM1.4 and CCSM3) in the model's algorithm
for simulating convective clouds. CCSM3's formulation reflects intensive efforts to represent
climate processes more accurately than its predecessors CSM1.4 and CCSM2, but it is not clear
whether the resulting global climate sensitivity is closer to reality.

Fig. IV A below shows how equilibrium warming due to doubled atmospheric carbon dioxide varied during the development of the most recent GFDL models. The dramatic drop in sensitivity between model versions p10 and p12.5.1 was unexpected. It followed a reformulation of the model's treatment of processes in the lower atmospheric boundary layer which, in turn, affected how low level clouds in the model respond to climate change.







5 dioxide from intermediate ("p") model versions leading to GFDL's CM2.0 and CM2.1.

6 Equilibrium warming was assessed by joining a simplified slab ocean model to the atmosphere, land

7 and sea ice AOGCM components. The later versions include sea ice motion (dynamics) as well as

8 sea ice thermodynamics.

Better understanding of Earth's climate sensitivity, with potential reduction in its uncertainty, will
require better understanding of a multitude of climate feedback processes (Bony et al. 2006). We
discuss two of the most important of these feedback effects below. The strengths of these feedbacks
are most frequently described by the resulting change in the heating of the troposphere-plus-surface
per degree warming of global mean temperature, in units of W/m2/K.

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8 Cloud Feedbacks

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10 Clouds reflect solar radiation to space, cooling the Earth-atmosphere system. Clouds also trap 11 infrared radiation, keeping the Earth warm. The net effect depends on the height, location, 12 microphysical and radiative properties of clouds, and their appearance in time with respect to the 13 seasonal and diurnal cycles of the incoming solar radiation. Cloud feedback refers to the changes in 14 cloud amounts and properties that can either amplify or moderate a climate change. Uncertainties 15 of cloud feedbacks in climate models have repeatedly been identified as the leading source of 16 uncertainty in model-derived estimates of climate sensitivity (e.g., Cess et al 1990; Randall et al. 17 2000; Zhang 2004; Stephens 2005; Bony et al. 2006; Soden and Held 2006). The fidelity of cloud 18 feedbacks in climate models is therefore important to the reliability of their prediction of future 19 climate change.

20

21 Several diagnostic methods have been used to evaluate and understand cloud feedbacks in AGCMs.

22 One method is referred to as partial radiative perturbation (PRP) (e.g., Hansen et al. 1984;

23 Wetherald and Manabe 1988; Zhang et al. 1994; Soden et al. 2004; Soden and Held 2006). A

second method uses the changes in cloud radiative forcing (CRF) (Cess and Potter 1988). The CRF

approach is more commonly used because of convenience of calculation and, most importantly, the

26 availability of satellite data for comparison. There are significant differences between the

diagnosed feedbacks from the two methodologies (Zhang et al. 1994; Coleman 2003; Soden et al.

28 2004), with the PRP estimates, considered to be more appropriate for feedback analyses, producing

29 cloud feedbacks that are more positive by roughly $0.6 \text{ W/m}^2/\text{K}$, causing some confusion in the

30 literature on cloud feedbacks. The differences between models are similar using either technique,

31 and both correlate well with the climate sensitivity across models.

Early GCM cloud feedback studies diagnosed positive cloud feedbacks (Hansen et al. (1984);
Wetherald and Manabe (1988)) using the PRP approach. In an influential work, Cess et al. (1990)
used the response of models to a simple warming or cooling of the oceans by 2°K as a surrogate
climate change and diagnosed the cloud feedbacks in 19 GCMs using the CRF approach, showing a
wide range of values from negative to strongly positive. Many subsequent studies with other GCMs
also showed large sensitivity of cloud feedbacks to the formulation of model physics (e.g., Le Treut
et al. 1994; Yao and Del Genio, 2002; Soden et al. 2004; Yokohata et al., 2005).

9

10 Many recent studies have focused on categorizing and decomposing the model cloud feedbacks 11 according to the simulated meteorological conditions, rather than lumping them into a single global 12 number. Williams et al. (2003), Bony et al. (2004), and Wyant et al. (2006) showed that in the 13 tropical region, the CRF response differs most between models in subsidence regimes in which deep 14 convection is suppressed, and not primarily in the regions of deep convection, suggesting a 15 dominant role for low-level clouds in the diversity of modelled tropical cloud feedbacks. Others 16 have also diagnosed errors in the simulation of particular cloud regimes or in specific dynamical 17 conditions (Klein and Jakob, 1999; Tselioudis et al., 2000;; Webb et al., 2001, Norris and Weaver, 18 2001; Jakob and Tselioudis, 2003; Williams et al., 2003; Bony et al., 2004; Lin and Zhang, 2004; 19 Ringer and Allan, 2004; Bony and Dufresne, 2005; Del Genio et al., 2005; Williams et al., 2006; 20 Wyant et al., 2006). Zhang et al. (2005) evaluated clouds in ten AGCMs and showed that even 21 though they simulate reasonable radiation balance at the top of the atmosphere, models have 22 systematic compensatory cloud biases. Common among them are overestimation of optical thick 23 clouds and underestimation of middle and low clouds. The biases are large enough to affect the 24 ability to simulate cloud feedback in a climate change.

25

Soden and Held (2006) evaluated cloud feedbacks in 12 CMIP3 coupled models using simplified PRP calculations. They showed positive cloud feedback in all models, ranging from $0.14 \text{ W/m}^2/\text{K}$ to $1.18 \text{ W/m}^2/\text{K}$. The highest values raise the equilibrium climate sensitivity from typical values of 2K for CO₂ doubling, a typical value in the absence of cloud feedback, to roughly 4K. Comparing with the earlier studies of Cess (1990) and Coleman (2003), the spread among GCMs has become somewhat smaller over the years, but it is still very substantial.

2 Results are beginning to emerge from a new class of much higher resolution atmospheric 3 simulations. Using the surrogate climate change framework of Cess (1990) in which ocean 4 temperatures are warmed uniformly, Miura et al. (2005) carried out experiments with a global 5 model with 7 km resolution, obtaining a climate sensitivity that is significantly reduced by strong 6 negative (CRF) feedback outside of the tropics. A multi-grid technique in which high resolution 7 cloud models are embedded in each grid box of a traditional GCM was utilized by Wyant et al. (2006) and generated a negative CRF response of $-0.9 \text{ W/m}^2/\text{K}$ in the same Cess framework 8 9 (corresponding to roughly neutral PRP cloud feedbacks). Much work will be required with these 10 new types of models before they can be given substantial weight in discussions of the most probable 11 value for cloud feedbacks, but they are hinting that the feedback may be less positive than is typical 12 in the CMIP3 AGCMs. Results from this new generation of models will be of considerable interest 13 in the coming years. 14 15 Several questions remain to be answered about cloud feedbacks in GCMs. The physical 16 mechanisms underlying cloud feedbacks in different models must be better characterized, so that we

17 can better appreciate which features and mechanisms in these models are robust across the models 18 and which are not. It is not clear how best to judge the importance of model biases in simulations of 19 the current climate, and in the simulations of cloud changes in different modes of observed 20 variability. In particular, it is unclear how to translate these biases into levels of confidence in the 21 simulations of cloud feedback processes in climate change scenarios. New satellite products such 22 as those from active radar and lidar systems will undoubtedly play vital role in cloud research in the 23 coming years, and are providing more confidence that progress on these difficult questions can be 24 achieved.

25

26 Water Vapor Feedback

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Analysis of the radiative feedbacks in the CMIP3 models (Soden and Held, 2006) reaffirms that water vapor feedback, the increase in heat trapping due to the increase in water vapor as the climate warms, is fundamental to their climate sensitivity. The strength of the water vapor feedback in these models is typically close in magnitude but slightly weaker than that obtained by assuming that
relative humidity remains unchanged as the climate warms.

3

4 A trend towards increasing column water vapor in the atmosphere consistent with model 5 predictions has been documented from microwave satellite measurements (Trenberth, et al 2005) 6 and excellent agreement has been found between satellite observations and climate models 7 constrained by the observed ocean surface temperatures (Soden, 2000). These studies increase 8 confidence in the model's vapor distributions more generally, but they are dominated by changes in 9 the lower troposphere and do not directly address the bulk of the water vapor feedback issue. This 10 feedback is primarily a consequence of increases in water vapor in the tropical upper troposphere. 11 Studies of vapor trends in this region are therefore of central importance. Soden (2006) presents 12 analysis of radiance measurements (from the infrared sounder on NOAA satellites) that relative 13 humidity has remained unchanged in the upper tropical troposphere over the past few years, which 14 combined with temperature measurements provides evidence that water vapor in this region is 15 increasing.

16

17 One can use observations of interannual variability in water vapor to help judge the quality of 18 model simulations. Recently, Minchswaner, et al (2006) have compared the interannual variability 19 in humidities in the highest altitudes of the tropical troposphere, as measured by infrared limb sounding satellites, with CMIP3 20th century simulations. Both models and observations show a 20 21 small negative correlation between relative humidity and tropical temperatures, due to in large part 22 to a tendency for lower relative humidity in warm El-Nino years and higher values in cold La Nina 23 years. However, there is a suggestion that the magnitude of this co-variation is underestimated in 24 most of the models. Looking across the models, there is also a tendency for models with larger 25 interannual variations in relative humidity to produce larger reductions in this region in response to 26 global warming, suggesting that this deficiency in interannual variability might be relevant for 27 climate sensitivity. Thus, this study provides indirect evidence suggesting that the feedback for the 28 very highest levels of the tropical troposphere may be overestimated somewhat in models. 29

30 The potential for the uncertainties in cloud feedbacks to impact water vapor feedbacks in the 31 tropics, through evaporation of condensate, remains a possibility. But analyses examining the

extent to which tropical humidities can be understood without considering sources from condensate,
 such as Dessler and Sherwood (2000) continue to suggest that effects of this kind are small.

3

The CMIP3 simulations of the water vapor climatology has also been critically analyzed (e.g.,
Pierce et al, 2006). Despite uncertainties in the observations, some systematic deficiencies are
clear, but just as for clouds, it is not straightforward to judge which kinds of deficiencies in the
models are of most concern for estimating feedback strength.

8

9 The strength of water vapor feedback varies somewhat across models, but its strength is inversely 10 correlated with the lapse rate feedback (Zhang et al, 1994; Soden and Held, 2006). The latter is a 11 way of accounting for the fact that temperatures do not warm uniformly in response to greenhouse 12 gas increases. In particular, models generally predict that that the tropical upper troposphere warms 13 more rapidly than the surface. Due to the increased infrared emission to space from the warm upper 14 troposphere, the surface need warm less for the system to come to energy balance with the radiative 15 forcing, providing a negative feedback on surface temperatures. Since much of the water vapor 16 feedback comes from the tropical upper troposphere as well, there is some cancellation between these two effects, resulting in a net feedback ranging from $0.8-1.2 \text{ W/m}^2/\text{C}$ in the CMIP3 study of 17 18 Soden and Held (2006). There is considerably less scatter among the models when one sums the 19 water vapor and lapse rate feedbacks than in either of these individual contributions in isolation. 20

22

21 Disparities In Imposed Radiative Forcing

23 While increases in the concentration of greenhouse gases provide the largest change in radiative 24 forcing during the twentieth century (IPCC AR4), other forcings must be considered to account for 25 the observed change in surface air temperature. The burning of fossil fuels that releases greenhouse 26 gases into the atmosphere can also create aerosols (small liquid droplets or solid particles that are 27 temporarily suspended in the atmosphere) that cool the planet by reflecting sunlight back to space. 28 In addition, there are changes in land use that change the reflectivity of the earth's surface, as well 29 as variations in sunlight impinging on the earth, among other forcings. In this section, we briefly 30 discuss the extent to which twentieth century radiative forcing is known. Further information is 31 provided in Forster and Ramaswamy (2007).

The radiative forcing can be quantified in different ways, as outlined by Hansen, et al 2005. The 2 3 radiative response to CO_2 doubling at the top of the atmosphere can be computed for example, by 4 holding all atmospheric and surface temperatures fixed, by allowing the stratospheric temperatures 5 to adjust to the new CO₂ levels, by fixing surface temperatures over both land and ocean and 6 allowing the atmosphere to equilibrate, and fixing ocean temperatures only and allowing the 7 atmosphere and land to equilibrate. Comparing model forcings in the literature is made more 8 complex because of differing definitions in different papers. Compared to the pre-industrial, present-day forcing in GISS modelE is 1.77 W/m^2 when computed with fixed ocean temperatures 9 (Hansen et al. 2007), but it is 2.1 W/m² in the GFDL CM2.1 model (I. Held, personal 10 11 communication) using the same definition, while it is 2.6 W/m^2 if only the stratosphere is allowed 12 to adjust (D. Schwarzkopf, personal communication). Variations in radiative forcing among models 13 introduce uncertainty in the simulation and attribution of twentieth century climate change. 14 15 Greenhouse gases like carbon dioxide and methane have atmospheric lifetimes that are long 16 compared to the time required for these gases to be thoroughly mixed throughout the atmosphere. 17 Trends in concentration are consistent throughout the world, and have been measured routinely 18 since the International Geophysical Year in 1958. Measurements of the gas bubbles trapped in ice 19 cores give the concentration prior to that date with less time resolution. While changes in 20 greenhouse gas concentration are accurately known, the associated radiative forcing varies among 21 climate models. This is partly because GCM radiative calculations need to be computationally 22 efficient, necessitating various approximations to calculations based upon the most accurate 23 laboratory spectroscopic data and radiation algorithms. Using changes in well-mixed greenhouse 24 gases, including carbon dioxide, methane, nitrous oxide and chlorofluorocarbons, measured 25 between 1860 and 2000, Collins et al (2006) compared the radiative forcing computed by climate 26 models (including CCSM, GFDL, and GISS) for clear sky conditions in midlatitude summer. The 27 GCM values were further compared to line-by-line (LBL) calculations, where fewer approximations 28 are made, and small differences result mainly from the omission of particular absorption bands 29 (Collins et al 2006). The median LBL forcing at the top of the model by greenhouse gases is 2.1 30 W/m^2 , and the corresponding median among the climate models is higher by only 0.1 W/m^2 . 31 However, the standard deviation among model estimates is 0.30 W/m2 (compared to 0.13 for the

1 LBL models). In general, forcing calculated by the CCSM and GISS models is on the high side of 2 estimates, while the GFDL model is on the low side. For a doubling of greenhouse gas 3 concentration, CCSM and GISS calculate forcing at the top of the atmosphere of 3.95 and 4.06 4 W/m2, respectively, while the GFDL model calculates 3.50 W/m2 compared to the all-model 5 average of 3.67 +/- 0.28 W/m2 (W. Collins, personal communication), for this particular 6 atmospheric profile. LBL calculations are not available for the entire globe, and uncertainties in the 7 observed 3-dimensional cloud distribution create additional uncertainties in the forcing 8 computations. But based on these most recent comparisons with LBL computations, it is reasonable 9 to assume that radiative forcing due to carbon dioxide doubling in individual climate models, 10 including the US models, may be in error by roughly 10 percent.

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12 Aerosols have short lifetimes, on the order of a week or so, that prevents them from dispersing 13 uniformly throughout the atmosphere, in contrast to well-mixed greenhouse gases. Consequently, 14 aerosol concentrations have large spatial variations, which are currently not measured with 15 sufficient detail. Global radiative forcing by aerosols has historically been estimated using physical 16 models of aerosol creation and dispersal constrained by the available observations. Recent estimates 17 center around -1.5 W/m2 (Anderson et al., 2003). Satellite retrievals are increasingly used to 18 provide direct observational estimates, which range from 0.35-0.25 W/m2 (Chung et al 2005) to -19 0.5-0.33 W/m2 (Yu et al 2006) to -0.8-0.1 W/m2 (Bellouin et al 2005) (??). That these estimates do 20 not overlap suggests that there are assumptions that are not represented in the formal uncertainty 21 analysis of each study. In particular, each calculation must decide how to extract the anthropogenic 22 fraction of aerosol within each column. Because aerosol species are not retrieved directly, and the 23 instruments cannot identify the original source region, this extraction is uncertain. In the absence of 24 species identification, the optical properties used in the calculation of radiative forcing are also 25 imprecisely known. Future satellite instruments will identify aerosol type with greater accuracy, 26 improving the forcing estimates.

27

Global forcing by aerosols is estimated by the IPCC AR4 as -0.2 + -0.2 W/m2, according to

29 models, and -0.5 +/- 0.4 W/m2, based upon satellite estimates. This represents decreased

30 uncertainty compared to the 2001 IPCC estimate of -0.9 +/- 0.5 W/m2. However, this represents

31 only the direct radiative forcing by aerosols: that is, the change in the radiative fluxes through

1 scattering and absorption of photons by aerosol droplets or particles. Aerosols also act as cloud 2 condensation nuclei, and alter radiative forcing by clouds. For example, an increase in aerosol 3 number increases the condensation nuclei available for cloud droplet formation, which has the 4 potential to increase cloud droplet number. If the total cloud water is unchanged by the aerosols, the 5 cloud will nonetheless be brighter because a larger number of smaller cloud droplets have a larger 6 cross-sectional area for reflection of sunlight. This is the first aerosol indirect effect (Twomey 7 1977). Smaller cloud droplets are also thought to slow the coalescence and growth of rain droplets, 8 reducing precipitation efficiency and extending the cloud lifetime: the second aerosol indirect effect 9 (Albrecht 1989). Aerosol changes to cloud droplet density can also alter dynamical mixing within 10 the cloud, affecting cloud cover and lifetime (Ackerman et al, 2004). Because of the complex 11 interactions between aerosols and dynamics along with cloud microphysics, the aerosol indirect 12 effect is very difficult to measure directly, and model estimates vary widely. This effect was 13 generally omitted from the IPCC AR4 models, although it was included in GISS modelE where 14 increased cloud cover due to aerosols results in a twentieth century forcing of -0.87 W/m2 (Hansen 15 et al 2007).

16

17 Other model forcings include variability of solar irradiance and volcanic aerosols. Satellites 18 provide the only measurements of these quantities at the top of the atmosphere. Prior to the satellite 19 era in the 1970's, solar variations are inferred using records of sunspot area and number and cosmic 20 ray-generated isotopes in ice cores (Foukal et al 2006), which are converted into irradiance 21 variations using empirical relations. The US CMIP3 models all use the solar reconstruction by 22 Lean et al (1995) with subsequent updates. Prior to the satellite era, volcanic aerosols are inferred 23 from surface estimates of aerosol optical depth. The radiative calculation requires aerosol amount 24 and particle size, which is inferred using empirical relations with optical depth derived from recent 25 eruptions. The GFDL and GISS models use updated versions of the Sato et al (1993) eruption 26 history, while CCSM uses Ammann et al (2003).

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Land use changes are also uncertain, and can be of considerable significance locally, but global
models typically show very modest global responses, as discussed in Hegerl and Zwiers, 2007.

1 Studies attributing 20th century global warming to various natural and human-induced forcing 2 changes are clearly hindered by these uncertainties in radiative forcing, especially in the solar and 3 aerosol components. Recent satellite measurements of solar irradiance are of vital importance 4 because they show that the Sun's contribution to the rapid warming of the past several decades is 5 small. The relevance of solar energy output changes for the warming earlier in the 20th century is more uncertain. Given the solar reconstructions in use in the CMIP3 models, much of the early 20th 6 7 century warming is driven by solar variations in these models, but uncertainties in these 8 reconstructions do not allow confident attribution statements concerning this early century 9 warming. The large uncertainties in aerosol forcing are the most important reason that one cannot use the observed late 20th century warming to provide a sharp constraint on climate sensitivity. We 10 11 do not have good estimates of the fraction of the greenhouse gas forcing that has been cancelled by 12 aerosols.

13

14 Ocean heat uptake/content related to climate sensitivity

15

16 The uncertainties associated with modeling of the uptake of heat by the ocean are significant in our 17 understanding of the robustness of the estimates of the Earth's future global temperature. The 18 degree to which the ocean takes up heat inversely affects the earth's surface temperature (e.g. Sun 19 and Hansen 2003). Studies show (e.g. Volker et al. 2002) that CO_2 uptake by the ocean is also 20 linked in complicated ways to the ocean's temperature. In an AOGCM, the ocean component's 21 ability to take up heat is dependent upon how a model defines the physics to handle the mixing of 22 heat and salt and how it transports heat between the low latitudes (where heat is taken up by the 23 ocean) and high latitudes (where heat is given up by the ocean). The processes involved make use 24 of several parameterizations (see section describing the ocean component of an AOGCM) and these 25 parameterizations have their own uncertainties. Hansen et al. (1985) and Wigley and Schlesinger 26 (1985) explored, early on, the important role of the ocean in moderating global temperatures and 27 associated uncertainties in mixing parameters. Thus, as part of understanding any given model's 28 climate sensitivity value, it is necessary to also understand its ability to accurately represent the 29 ocean's mixing processes and the transport of the ocean's heat as well as feedbacks between the 30 ocean, ice, and atmosphere.

1 Unfortunately, the relative importance of the uptake rate as compared to other processes, including 2 feedbacks between the ocean and atmosphere, is still an open research topic. The uncertainties in 3 the estimates of ocean uptake are not well understood. Comparisons of ocean heat uptake with 4 respect to climate sensitivity mostly compare a few runs of the same model and runs between 5 different AOGCMs. Raper et al. (2002) examined climate sensitivity and ocean heat uptake in a 6 suite of recent AOGCMs. They calculated the ratio of the change in heat flux to the change in 7 temperature (defined as the "ocean heat uptake efficiency": k by Gregory and Mitchell 1997) and 8 found a general trend in the models that lower ocean uptake efficiency values were associated with 9 lower climate sensitivity values. In an example that compares a current generation of AOGCM to 10 previous generation AOGCMs, Kiehl et al. (2006) demonstrate that the atmospheric component of 11 the models is the primary reason for different climate sensitivities and the ocean component's ability 12 to uptake heat is of secondary importance. How the atmosphere affects the ocean's surface density is 13 the important factor, rather than the particular aspects of the ocean component that is being used. 14 The ocean heat uptake efficiency values calculated, in this second study, are not consistent with 15 Raper et al. (2002), in that the model with the highest ocean heat update efficiency has the lowest 16 climate sensitivity and the reasons for the differences are not understood. In a related study, 17 Stouffer et al. (2006), using a different current AOGCM, conclude that a more realistic Southern 18 Hemisphere atmospheric jet may produce a more realistic representation of the ocean's heat uptake 19 in this region.

20

21 Impact of climate sensitivity on using model projections of future climates

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23 This chapter -- and most investigations -- emphasize the global and annual mean of surface 24 temperature change, even though practical applications of climate change science involve particular 25 seasons and locations. The underlying assumption is that local climate impacts scale with changes 26 in global surface temperature. Results of idealized simulations (the transient climate response 27 experiments discussed above) indicate that this assumption may indeed be a reasonable first 28 approximation to model behavior. Figure IV-B-1 shows, for North America, the ratio of the 29 warming near the time of atmospheric carbon dioxide doubling (TCR as defined above) to its global 30 mean value for the "average" CMIP3 model and each of the three US models. In all cases, the 31 warming generally increases with latitude, and interior regions warm more than coastal areas. The

similarity of the four maps indicates a rough agreement of "scaled" regional warming among the
models. The agreement occurs despite ~50% differences in globally averaged surface temperature
change among the US models (Table IV.1).

4

5 Figure IV-B-2 shows the analogous results for precipitation change. Here the changes are generally

6 positive in the Eastern US and negative in the Western US, consistent with the general finding that

7 wet areas become wetter and dry areas become drier in global warming scenarios. The ratios of

8 local to global mean precipitation change (which in turn scales with global mean temperature

9 change) are again quite similar among the three US models as well as the "average" CMIP3 model.

- 1 Figure IV B 1 Ratio of annual local surface temperature change to annual global surface
- 2 temperature change in mean CMIP3 model and three US CMIP3 models for idealized CO₂
- 3 doubling.

Change in tas over North America relative to global change



- Figure IV B 2 Ratio of annual local precipitation change to global annual precipitation change in
 mean CMIP3 model and three US CMIP3 models for idealized CO₂ doubling.



Change in prover North America relative to global change