

1 **CCSP Synthesis and Assessment Report 3.1**
2 **Climate Models: An Assessment of Strengths and Limitations for**
3 **User Applications**
4 **Public Review Draft**
5 **May 15, 2007**
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Executive Summary

The goal of simulating the Earth’s climate with mathematical models, using the most powerful computers available, is valid scientifically and fully consistent with the approaches being taken in many other fields of science dealing with very complex systems. These climate simulations provide the frame within which improved understanding of climate-relevant processes and improved observations are naturally merged into coherent projections of future climate change.

The science of climate models has matured to the point that many aspects of current climate models and simulations are very convincing. These form a growing set that intersects significantly with, but does not completely cover, the set of processes that are centrally important for the attribution of past climate changes and the projection of future climate.

The set of the most recent climate simulations, referred to as the CMIP3 models and utilized heavily in the Working Group 1 and 2 reports of the 4th IPCC Assessment, have received unprecedented scrutiny by hundreds of investigators with differing areas of expertise. While there are a number of systematic biases across the set of models, more generally the strengths and weaknesses of the simulations, when compared against the current climate, vary substantially from model to model. It is clear from many perspectives that an average over the set of models provides a superior climate simulation than any individual model, justifying the multi-model approach taken in many recent attribution and climate projection studies.

The pace of climate model improvement has been steady over the past several decades, but the improvement has understandably been uneven, because several important aspects of the climate system present especially severe challenges to the goal of simulation.

Climate models are compared to observations of the mean climate in a multitude of ways, and their ability to simulate observed climate changes, particularly those of the past century, have been examined extensively. However, it has proven difficult to measure the quality of climate models in such a way that the metric used is directly relevant to our confidence in the models’ projections of

1 future climate. The most appropriate ways of translating the strengths and weaknesses of the
2 simulations into confidence in climate projections remains a subject of active research.

3
4 The climate models developed in the US and around the world show many consistent features in
5 their simulations and projections for the future. However, they have not fully converged, since
6 different groups approach uncertain aspects of the models in distinctive ways. This absence of
7 convergence is one useful measure of the state of the science of climate simulation; convergence is
8 to be expected once all climate-relevant processes are simulated in a convincing physically-based
9 manner.

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14 *Climate Sensitivity*

15
16 The response of global mean temperature to a doubling of carbon dioxide remains a useful measure
17 of climate sensitivity. The equilibrium response, the response expected if one waits long enough
18 (many hundreds of years) for the system to re-equilibrate, is the most commonly quoted measure.
19 The range of equilibrium climate sensitivity obtained from models has remained robust for three
20 decades, and roughly consistent with estimates from the observations of recent climates and those
21 from the more distant past. The canonical three-fold range of uncertainty, 1.5-4.5 degrees
22 Centigrade, has evolved very slowly. The lower limit has been particularly robust over time, with
23 very few recent models below 2 degrees. The difficulty in simulating the Earth's clouds and their
24 response to climate change are the fundamental reason why it has proven difficult to reduce the
25 range of uncertainty in model-generated climate sensitivity.

26
27 Other common measures of climate sensitivity are of more relevance to the response on time scales
28 shorter than 100 years. By these measures there is considerably less spread among the models --
29 roughly a factor of two rather than three. Uncertainty still remains considerable and is not
30 decreasing rapidly, due in part to the difficulty of cloud simulation but also to uncertainty in the rate

1 of heat uptake by the oceans which rises in importance when considering the responses on these
2 shorter time scales.

3
4 Improvements in our confidence in estimates of the sensitivity of climate are most likely to arise
5 from new data streams, such as satellite platforms that are now providing a first look at the 3-
6 dimensional global distributions of clouds, and new, very computationally intensive, climate
7 modeling strategies that explicitly resolve some of the smaller scales of motion that help control
8 cloud cover and cloud radiative properties.

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11 *Regional modeling and downscaling*

12
13 Simulations by limited-area models, stretched grid models and uniformly high-resolution

14 atmospheric models forced by specified oceanic and sea ice conditions are all capable of resolving
15 phenomena too fine for standard atmosphere-ocean GCMs, such as precipitation influenced by
16 mountains and ocean-land interaction in coastal zones. These dynamical downscaling strategies are
17 beneficial when supplied with appropriate sea-surface and atmospheric boundary conditions, but
18 their value is limited by uncertainties in the information supplied by the global models. Given the
19 value of multi-model ensembles for larger-scale climate prediction, it is clear that downscaling must
20 presently be performed in a coordinated fashion with a representative set of global model
21 simulations as input, rather than focusing on the results from one or two models. Relatively few
22 such multi-model dynamical downscaling studies have been performed to date.

23
24 Statistical techniques to produce appropriate small-scale structures from climate simulations,
25 referred to as “statistical downscaling”, can be as effective as high-resolution numerical simulations
26 in providing climate change information to regions unresolved by most current global models, and
27 because of their computational efficiency they can much more easily utilize a full suite of multi-
28 model ensembles. However, the statistical methods are completely dependent on the accuracy of
29 the regional circulation patterns produced by the global models, whereas regional models, through
30 higher resolution and/or better representation of important physical processes, can often improve the

1 physical realism of the simulated regional circulation. Thus, the strengths and weaknesses of the
2 regional modeling and statistical methods are often complimentary.

3
4
5 *The quality of climate simulations*

6
7 Accurate simulation of the present-day climatology for near-surface temperature and precipitation is
8 necessary for most practical applications of climate modeling. The seasonal cycle and large-scale
9 geographical variations of near-surface temperature are indeed well simulated in recent models,
10 with typical correlations between models and observations of 95% or better.

11
12 AOGCM simulation of precipitation has improved over time but is still problematic. The correlation
13 between models and observations is 50-60% for seasonal means on scales of a few hundred
14 kilometers. Comparing simulated and observed latitude-longitude maps of precipitation reveals
15 similarity of magnitudes and patterns in most regions of the globe with the most striking
16 disagreements occurring in the tropics. In most models, the appearance of the Inter-tropical
17 Convergence Zone of cloudiness and rainfall in the equatorial Pacific is distorted, and rainfall in the
18 Amazon Basin is substantially underestimated. These errors may prove consequential for a number
19 of model predictions, such as forest uptake of atmospheric CO₂.

20
21
22 The simulation of the storms and jet streams in middle latitudes are considered one of the strengths
23 of atmospheric models because the dominant scales involved are reasonably well-resolved. As a
24 consequence, there is relatively high confidence in models' ability to simulate the changes in these
25 extratropical storms and jet streams as the climate changes. The deficiencies that still exist may be
26 partly due to insufficient resolution to resolve features such as fronts or to inadequacies in the
27 simulated interactions between the tropics and midlatitudes or between the stratosphere and the
28 troposphere. These deficiencies are still large enough to impact the ocean circulation and some
29 regional climate simulations and projections.

1 A dominant mode of low-frequency variability in the atmosphere known as the northern and
2 southern annular modes, are very well captured in current models. These modes involve
3 north/south displacements of the extratropical storm track and dominate the observed trends in
4 atmospheric circulation in recent decades. Because of their ability to simulate the annular modes,
5 global climate models simulate fairly well the interannual variability in the polar regions of both
6 hemispheres. They are less successful at simulating daily polar-weather variability, though finer
7 scale regional simulations do simulate polar weather well, thus showing promise for improved
8 global-model simulations as their resolution increases.

9
10 In the tropics, simulations in current models are less credible. The Madden-Julian oscillation, a
11 feature of the tropics in which the precipitation is organized by large-scale eastward propagating
12 features with periods of roughly 30-60 days, is a useful test of simulation credibility in the tropics.
13 Model performance using this measure is still unsatisfactory. The “double ITCZ-cold tongue bias”,
14 in which water is excessively cold near the equator and precipitation splits artificially into two
15 zones straddling the equator, remains as a persistent bias in current coupled atmosphere-ocean
16 models. Projections of tropical climate change are adversely affected by these deficiencies in
17 simulations of the organization of tropical convection. Models typically overpredict light
18 precipitation and underpredict heavy precipitation in both the tropics and middle latitudes, creating
19 potential biases when studying extreme events.

20
21 Tropical cyclones are poorly resolved by the present generation of global models, but recent results
22 with high resolution atmosphere-only models and dynamical downscaling provide optimism that the
23 simulation of tropical cyclone climatology will advance rapidly in the coming years, as will our
24 understanding of observed variations and trends.

25
26 Land surface modeling for climate simulation has increased markedly in sophistication over the past
27 25 years, with increasing detail and range of processes included in the biological, chemical and
28 physical behavior simulated in the terrestrial portion of the climate system. Systematic programs
29 comparing land models have gradually led to greater agreement between land models and
30 observations, in part because a greater variety of observations have been used to understand and
31 constrain their behavior.

1 Land models that predict vegetation patterns are being actively developed, but the demands that
2 these models make on the quality of the simulated precipitation patterns ensures that the their
3 evolution will be gradual and tied to improvements in the regional climate simulations.

4
5 The quality of ocean climate simulations has improved steadily in recent years, owing to improved
6 numerical algorithms and more realistic assumptions concerning the mixing occurring on scales
7 smaller than the models' grid. Many of the CMIP3 class of models are able to maintain an
8 overturning circulation in the Atlantic with approximately the observed strength without the
9 artificial correction to the air-sea fluxes commonly in use in previous generations of models,
10 providing a much better foundation for analysis of the stability of this circulation.

11
12 The circulation in the Southern Oceans, thought to be of vital importance for the oceanic uptake of
13 carbon dioxide from the atmosphere, is sensitive to deficiencies in the simulated winds and
14 salinities, but a subset of the models are producing realistic circulation in the Southern Ocean as
15 well

16
17 Simulations of El Nino oscillations provide a significant success story for climate models, as these
18 have improved substantially in recent years. Most current models spontaneously generate El Nino-
19 Southern Oscillation variability, albeit with varying degrees of realism. The spatial structure and
20 period of the oscillations is impressive in a subset of the models, but with a tendency towards too
21 short a period. The bias in the intertropical convergence zone in the coupled models is a major
22 factor preventing further improvement in these models. Projections for the future of El-Nino
23 variability and the state of the Pacific Ocean are of central importance for regional climate change
24 projections throughout the tropics and in North America.

25
26 The quality of simulations of low frequency variability on decadal to multi-decadal time scales
27 varies regionally and also varies substantially from model to model. On average, the models do
28 reasonably well in the North Pacific and North Atlantic. In other oceanic regions, data paucity
29 contributes to the uncertainty in the estimation of the quality of the simulations at these low
30 frequencies.

31

1 The ocean components of current climate models do not directly simulate the very energetic
2 motions in the oceans referred to as “meso-scale eddies” . The simulation of these small scale flow
3 patterns requires horizontal grid sizes of 10km or smaller. Current oceanic components of climate
4 models are effectively laminar rather than turbulent, and the effects of these eddies must be
5 approximated by imperfect theories. As computer power increases, new models that resolve these
6 eddies will be incorporated into climate models to explore their impact on decadal variability, as
7 well as heat and carbon uptake.

8
9 Models of glacial ice are in their infancy. Glacial models directly coupled to atmosphere-ocean
10 models typically only account for direct melting and accumulation at the surface of the ice-sheets
11 and not the dynamic discharge due to glacial flow. More detailed current models that incorporate
12 this discharge typically generate discharges that change only over centuries and millennia. Recent
13 evidence for rapid variations in this glacial outflow indicates that more realistic glacial models are
14 needed to estimate the evolution of future sea level.

15
16 *Simulation of 20th century trends*

17
18 Models forced by the observed well-mixed greenhouse gas concentrations, volcanic aerosols, as
19 well as estimates of variations in the solar energy incident on the Earth and anthropogenic aerosol
20 concentrations, are able to simulate the 20th century global mean temperature record in a plausible
21 way. Solar variations are known by direct satellite measurements for the last few decades and do
22 not contribute significantly to the warming during that period. Solar variations earlier in the 20th
23 century are much less certain, but are thought to a potential contributor to the warming in the early
24 part of the century,

25
26 Uncertainties in the climatic effects of man-made aerosols (liquid and solid particles suspended in
27 the atmosphere) are a major stumbling block in quantitative attribution studies and in attempts to
28 use the observational record to constrain climate sensitivity. We do not know how much warming
29 due to greenhouse gases has been cancelled by cooling due to aerosols. Uncertainties related to
30 clouds increase the difficulty in simulating the climatic effects of aerosols, since these aerosols are
31 known to interact with clouds and potentially change cloud radiative properties and cloud cover.

1
2 The possibility that natural variability has been a significant contributor to the detailed time
3 evolution seen in the global temperature record is plausible, but still difficult to address with models
4 given the large differences between models in the characteristics of the natural decadal variability
5 that they generate. While natural variability may very well be relevant to observed variations on the
6 scale of 10-30 years, no models show any hint of generating large enough natural, unforced
7 variability on the 100 year time scale that would compete with explanations of the observed
8 century-long warming trend as being predominantly forced.

9
10 The observed southward displacement of the Southern hemisphere storm track and jet stream in
11 recent decades is reasonably well simulated in current models, which show that it is partly due to
12 greenhouse gases but also partly due to the presence of the ozone hole in the stratosphere. Northern
13 Hemisphere circulation changes over the past decades have proven more difficult to capture in
14 current models, perhaps due to the more complex interactions between the stratosphere and the
15 troposphere in the Northern Hemisphere.

16
17 Observations of ocean heat uptake are beginning to provide a direct test of aspects of the ocean
18 circulation directly relevant to climate change simulations. Coupled models provide reasonable
19 simulations of the observed heat uptake in the oceans, but underestimate the observed sea level rise
20 over the past decades.

21
22 Model simulations of trends in extreme weather typically produce global increases in extreme
23 precipitation and severe drought, and decreases in extreme minimum temperatures and frost days, in
24 general agreement with observations.

25
26 Regional trends in extreme events are not always captured by current models , but it is difficult to
27 assess the significance of these discrepancies, and to distinguish between model deficiencies and
28 natural variability.

29
30 The use of climate model results to assess economic, social, and environmental impacts is becoming
31 more sophisticated, albeit slowly. Simple methods requiring only mean changes in temperature and

1 precipitation to estimate impacts remain popular, but an increasing number of studies are utilizing
2 more detailed information, such as the entire distribution of daily or monthly values and extreme
3 outcomes. The mismatch between the spatial resolution of models and the scale of impacts-relevant
4 climate features and of impacts models remains an impediment for certain applications.

1 **Chapter I – Introduction**

2 The use of computers to simulate complex systems has grown in the past few decades to play a
3 central role in many areas of science. Climate modeling is one of the best examples of this trend and
4 one of the great success stories of scientific simulation. It is impossible to build a laboratory analog
5 of the Earth’s climate system with all of its complexity. The successes of climate modeling allow us
6 to address many questions about the climate by experimenting instead with simulations —that is,
7 with mathematical models of the climate system.

8
9 Despite the success of the climate modeling enterprise, the complexity of our Earth imposes
10 important limitations on existing climate models. It is the purpose of this report to help the reader
11 understand the valid uses, as well as the limitations, of current climate models.

12
13 Climate modeling and forecasting grew out of the desire to predict weather. The distinction between
14 climate and weather is not sharp. Operational weather forecasting has historically focused on times
15 scales of a few days but has more recently been extended to monthly and seasonal time scales, for
16 example, in attempts to predict the evolution of El Niño episodes. The goal of climate modeling
17 can be thought of as the extension of forecasting to longer and longer time scales, with a focus not
18 on individual weather events, which are unpredictable on these long time scales, but on the statistics
19 of these events as well as on the slow evolution of the oceans and ice sheets. Whether one considers
20 the forecasting of individual El Niño episodes as weather or climate forecasting is a matter of
21 convention. For the purpose of this report, we will consider El Niño forecasting with weather, and
22 will not address it directly. On the climate side we are concerned, for example, with the ability of
23 models to simulate the statistical characteristics of El Niño variability, or extratropical storms, or
24 Atlantic hurricanes, with an eye toward assessing the ability of these models to predict how this
25 variability might change as the climate evolves in the coming decades and centuries.

26
27 An important constraint required of climate models that is not imposed on weather forecast models
28 is the requirement that the global system precisely and accurately maintain the global energy
29 balance over very long time periods. Energy balance (or “budget”) is defined as the difference
30 between absorbed solar energy and emitted infrared radiation. It is affected by a number of things
31 including human production of greenhouse gases like carbon dioxide. The decadal to century-scale

1 changes in the Earth’s energy budget that are manifested as climate change are just a few per cent of
2 the average values of the largest terms in that budget. Many of the decisions about model
3 construction described in Chapter II are based on the need to properly and accurately simulate the
4 long term energy balance.

5
6 This report will focus primarily on the most advanced physical climate models that were used for
7 the most recent international Coupled Model Intercomparison Project’s (CMIP) coordinated
8 experiments (Meehl, *et al.*, 2006), sponsored by the World Climate Research Programme (WCRP).
9 These coupled Atmosphere–Ocean General Circulation Models (AOGCMs) incorporate detailed
10 representations of the atmosphere, land surface, oceans, and sea ice. Where practical, we will
11 emphasize and highlight the results from the three US modeling projects that participated in the
12 CMIP experiments. Additionally, this report examines the use of Regional Climate Models used for
13 obtaining higher resolution details from AOGCM simulations over smaller regions. Nevertheless, it
14 must be noted that there are other types of climate models being developed and applied to climate
15 simulation. More complete Earth systems models build carbon cycle and ecosystems processes on
16 top of the AOGCMs, but are employed more for studies of future climate change and
17 paleoclimatology, neither of which is directly relevant to this report. Another class of models not
18 discussed here, but used extensively, particularly when computer resources are limited, are Earth-
19 system Models of Intermediate Complexity (EMICs). Although these models have many more
20 assumptions and simplifications than are found in the CMIP models (Claussen *et al.*, 2002), they are
21 particularly useful in exploring a wide range of mechanisms and obtaining broad estimates of future
22 climate change projections that can be further refined with AOGCM experiments.

23

24 ***Brief History of Climate Model Development***

25

26 As the possibility of numerical weather prediction developed in the 1950’s as one of the first
27 applications of computers, it became evident almost immediately that the numerical simulation
28 approach could also be used to study the climate. In 1955, Joseph Smagorinsky started a program in
29 climate modeling that ultimately became one of the most vigorous and longest-lived General
30 Circulation Model (GCM) development programs at NOAA’s Geophysical Fluid Dynamics
31 Laboratory (GFDL) at Princeton University. The feasibility of generating stable integrations of the

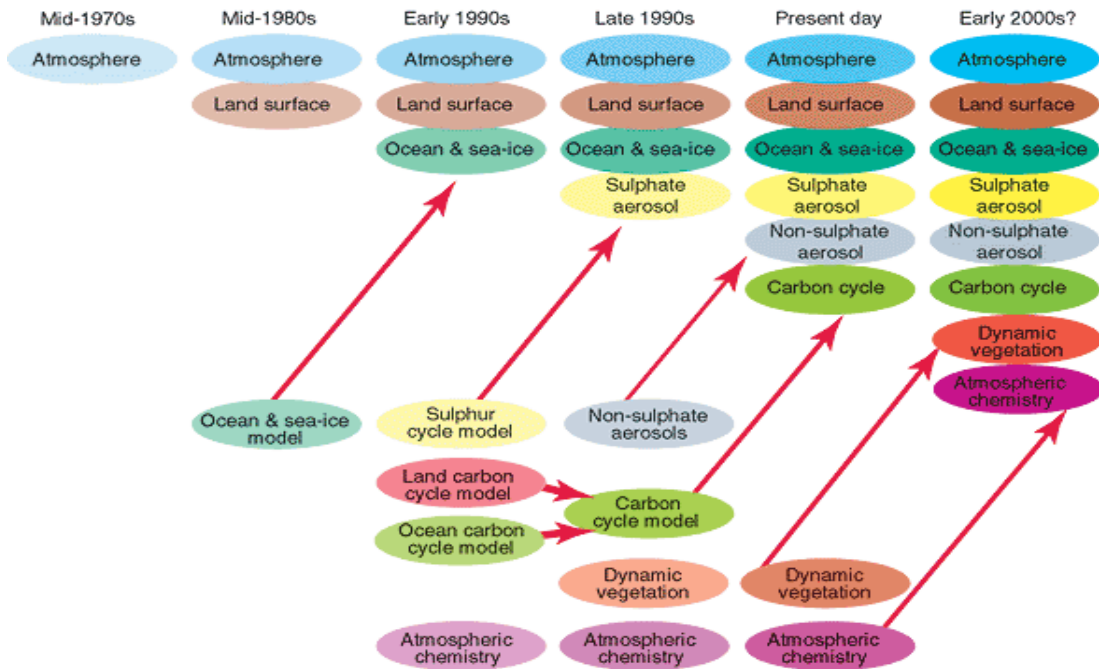
1 atmospheric equations for arbitrarily long time periods was demonstrated by Norman Phillips in
2 1956. The University of California at Los Angeles began producing Atmospheric General
3 Circulation Models (AGCMs) beginning in 1961 under the leadership of Yale Mintz and Akio
4 Arakawa. This program influenced others in the 1960's and 1970's, leading to modeling programs
5 found today at NASA laboratories and several universities. At Lawrence Livermore National
6 Laboratory, Cecil E. Leith developed an AGCM in the early and mid-1960's. The U.S. National
7 Center for Atmospheric Research (NCAR) initiated AGCM development in 1964 under Akira
8 Kasahara and Warren Washington, an effort that ultimately evolved into the construction of the
9 Community Climate Model, a predecessor to the present Community Climate System Model. Also
10 in the 1960's and 70's, efforts in climate simulations developed throughout the world, with major
11 centers emerging in Europe and Asia.

12
13 Additions to the original atmospheric general circulation models used for weather analysis and
14 prediction were needed to improve weather simulations and forecasts as well as to make climate
15 simulations possible. The early weather models focused on fluid dynamics rather than on radiative
16 transfer and the atmosphere's energy budget, which are of central importance for climate
17 simulations. Furthermore, as one focuses on time scales longer than a season, the oceans and sea ice
18 must be coupled to the more rapidly evolving atmosphere. Thus, ocean and ice models have been
19 coupled with atmospheric models. The first ocean general circulation models were developed at
20 GFDL by Bryan and Cox in the 1960's, and then coupled with the atmosphere by Manabe and
21 Bryan in the 1970's.

22
23 Climate models began to be used in research on carbon dioxide and climate in the mid-1970's. Two
24 important studies, the *Study of Critical Environmental Problems* and the *Study of Man's Impact on*
25 *Climate*, both endorsed the use of GCM-based climate models to study the possibility of
26 anthropogenic climate change. Beginning in the late 1980's, several national and international
27 organizations were formed with the purpose of assessing and expanding scientific research related
28 to global climate change. These developments spurred interest in developing and improving climate
29 models. The work of the Intergovernmental Panel on Climate Change (IPCC), beginning in 1987,
30 had as a primary focus of Working Group 1 scientific inquiry into atmospheric processes governing
31 climate change. The **IPCC**, 1990: *Scientific Assessment* (Houghton *et al.*, 1990) stated, "Improved

1 prediction of climate change depends on the development of climate models, which is the objective
2 of the climate modeling programme of the World Climate Research Programme (WCRP).” The
3 United States Global Change Research Program (USGCRP), established in 1989, designated
4 Climate Modeling and Prediction as one of the four high-priority integrating themes of the program
5 (CEES, 1991). The combination of steadily increasing computer power and research spurred by the
6 WCRP and USGCRP has led to a steady improvement in the completeness, accuracy and resolution
7 of AOGCMS used for climate simulation and prediction. A classic figure from the Third IPCC
8 Working Group I Scientific Assessment of Climate Change in 2001 depicts this evolution in **Figure**
9 **I.A.** The comprehensive climate models that contributed results to the Third Climate Model
10 Intercomparison Project (CMIP3) that was utilized by the Fourth IPCC Assessment were generated
11 by 3 groups in the US (GFDL, NCAR, and the NASA Goddard Institute for Space Studies (GISS)),
12 and groups in the U.K., Germany, France, Japan, Australia, Canada, Russia, China, Korea, and
13 Norway.
14
15

The Development of Climate models, Past, Present and Future



Source: IPCC 2001

CCRP SP Brief 1-4-07

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1
2 **Figure.I.A** Historical development of climate models (From IPCC, 2001).
3
4 *Climate model construction*
5
6 Comprehensive climate models are constructed using expert judgments to satisfy many constraints
7 and requirements. The overarching considerations are the determination of the most important
8 climate features that should be accurately simulated and the scientific understanding of these
9 features that guide one towards the most powerful simulation strategies and algorithms. Typically,
10 the basic requirement is that models should simulate features that are important to humans,
11 particularly surface variables, such as temperature, precipitation, windiness, and storminess. This is
12 a less straightforward requirement than it seems, since a physically-based climate model must also
13 simulate all of the complex interactions in the coupled atmosphere–ocean–land surface–ice system
14 that are manifested as the climate variables of interest. For example, jet streams at altitudes of 10
15 kilometers above the surface must be accurately simulated if the models are to generate midlatitude
16 weather with realistic characteristics, since the midlatitude highs and lows that we see on surface

1 weather maps are intimately associated with these high-altitude wind patterns. As another example,
2 one cannot simulate the basic temperature decrease from the equator to the poles without taking into
3 account the poleward transport of heat in the oceans, some of this heat being carried by currents 2 or
4 3 kms deep in the oceanic interior. Our models should correctly produce not just the means of
5 variables of interest, but also extremes and other measures of natural variability. Finally, they
6 should be capable of simulating the changes in those statistics that result from the relatively small
7 changes in the Earth's energy budget that result from natural and human actions.

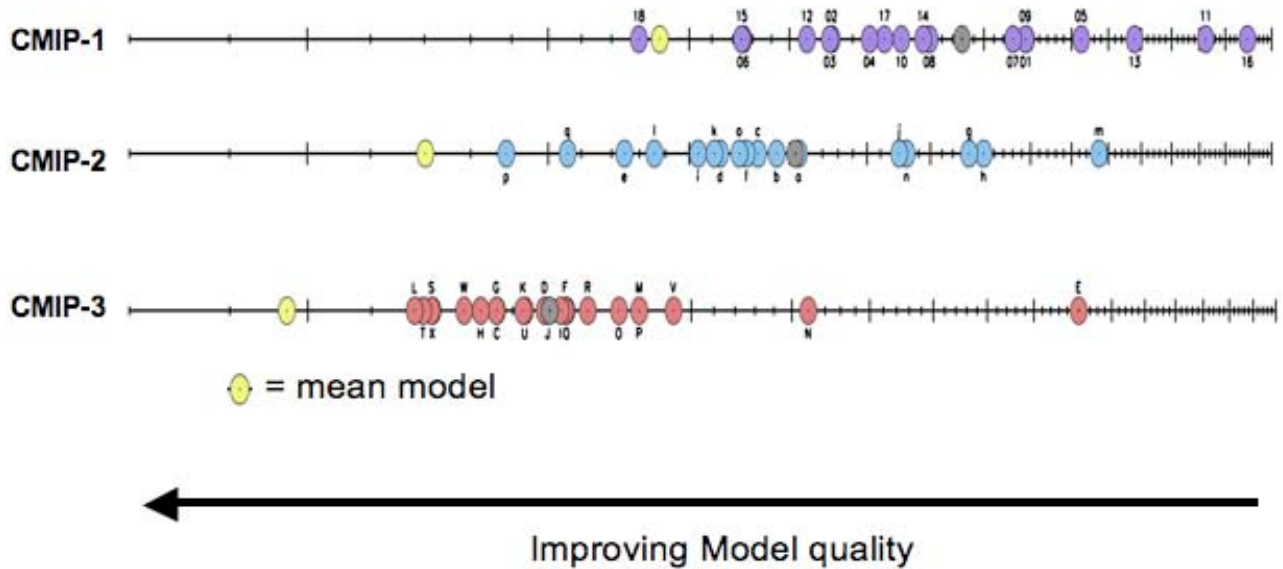
8
9 Climate processes operate on time scales ranging from several hours to millennia, and spatial scales
10 ranging from a few centimeters to thousands of kilometers. Principles of scale analysis, fluid
11 dynamical filtering, and numerical analysis are used to make intelligent compromises and
12 approximations to simplify the system sufficiently to make it tractable to formulate mathematical
13 representations of the processes and their interactions. These mathematical models are then
14 translated into computer codes, which are executed on some of the most powerful computers in the
15 world. Available computer power helps determine the types of approximations required; as a
16 general rule, increasing computational resources allows modelers to formulate algorithms that are
17 less dependent on relatively uncertain methods (referred to as "closure" or "parameterization"
18 schemes) for taking into account unresolved motions and processes, thereby producing simulations
19 that are more solidly founded on established physical principles. Climate simulations must always
20 be designed so that they can be completed and analyzed by scientists in a timely manner.

21
22 Climate models have shown steady improvement over time as computer power has increased, as our
23 understanding of physical processes of climatic relevance has increased, as data sets useful for
24 model evaluation have been developed, and as our computational algorithms have improved.

25 **Figure I.B** shows one attempt at quantifying this improvement. It compares a particular metric of
26 climate model performance among the CMIP1 (1995), CMIP2 (1997) and CMIP3 (2004) ensembles
27 of AOGCMs. This particular metric assesses the performance of the models in simulating the mean
28 climate of the late 20th century as measured by a basket of indicators, focusing on aspects of the
29 atmospheric climate for which observational counterparts are deemed adequate for this purpose.
30 The ranking of models according to individual members of this basket of indicators varies greatly,
31 so this aggregate ranking is dependent on how one weights the relative importance of different

1 indicators. But the general conclusion of an improvement in climate simulation quality is robust to
2 these changes in weighting factors. The construction of metrics for evaluating climate models is
3 itself a subject of intensive research and will be covered in more detail in Chapter II.

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4 **Figure.I.B** One possible composite metric for the evaluation of climate models, focusing primarily on the
 5 atmospheric circulation (Kim and Riechler, 2007., based on PCMDI CMIP-1, CMIP-2, and CMIP-3 archives
 6 Each oval corresponds to a single model, with model quality improving towards the left. Yellow ovals mark
 7 the quality of the climate obtained by averaging all of the available models. The CMIP-1 model archive was
 8 generated from models available around 1995, the CMIP-2 models around 2000, and the CMIP-3 models
 9 around 2005.

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Also, shown in **Figure I.B** is the same metric evaluated from the climate obtained by averaging over all of the AOGCMs in the CMIP1, CMIP2, and CMIP3 archives. The CMIP3 “ensemble-mean” model performs better than any individual model by this metric, and by many others. This kind of result has convinced the community of the value, at this point in time, of a multi-model approach to climate change projection, in which a number of modeling centers work on their own distinctive approaches to the fundamental fluid dynamical simulation problem as well as the many issues related to the parameterization of unresolved processes. Our understanding of climate is still insufficient to justify the construction or identification of a single model that we can confidently judge to be the best possible model. It is generally felt to be more appropriate, in any assessments focusing on adaptation or mitigation strategies, to take into account, in an appropriately informed manner, the attempts at climate simulation underway around the world.

The remaining sections of this report describe climate model development, evaluation and applications in more detail. Chapter II describe the development and construction of models and how they are employed for climate research. Chapter III discusses Regional Climate Models and their use in “downscaling” global model results to specific geographic regions, particularly North America. The concept of climate sensitivity, which is the response of a surface temperature to a specified change in the energy budget at the top of the model’s atmosphere, is described in Chapter IV. A survey of how well important climate features are simulated by modern models is found in Chapter V, while Chapter VI depicts the near-term development priorities for future model development. Finally, Chapter VII illustrates a few examples of how climate model simulations are used for practical applications. A detailed References section follows Chapter VII.

1 **Chapter II - Description of Global Climate System Models**

2
3 Modern climate models are comprised of a system of model components, each of which simulates a
4 different part of the climate system, and usually can be run independently for certain applications.
5 Nearly all of the CMIP3 class of models are composed of four primary components, the
6 atmosphere, land surface, the ocean and sea ice. The atmospheric and ocean components are known
7 as “general circulation models” or GCMs, because they explicitly simulate the large scale global
8 circulation of the atmosphere and ocean. Sometimes, climate models are referred to as coupled
9 atmosphere-ocean GCMs, which may be misleading, because a coupled GCM model can be
10 employed to simulate aspects of weather and ocean dynamics, without being a climate model. What
11 follows in this chapter is a description of the major components of a modern climate model, and
12 how they are coupled together and tested for climate simulation.

13

14 *Atmospheric General Circulation Models*

15
16 Atmospheric general circulation models (AGCMs) are numerical programs that calculate the state
17 variables of the atmosphere, such as temperature, pressure, humidity, kinetic energy, etc, as a
18 function of space and time. . The set of model equations is formulated by using geophysical fluid
19 dynamics theory and physical laws governing the exchanges of the mass and energy. because of the
20 various assumptions and approximations that are made to more complete equations of classical fluid
21 dynamics. The atmosphere can be thought of as a thin spherical shell of air that envelopes the earth.
22 For climate simulation, typically only the lowest 20-30 km or so of the atmosphere, the troposphere
23 and part of the stratosphere, are explicitly simulated. Within this volume all weather occurs because
24 it contains over 95 % of the mass and virtually all of the water vapor. Because of disparity between
25 the scales of the horizontal and vertical motions resolved in typical global models, the horizontal
26 motions are treated differently than vertical motions by the model algorithms. The resulting basic
27 set of equations is often referred to collectively as the primitive equations (Haltiner and Williams,
28 1980),

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1 Although nearly all AGCMs use the same primitive dynamical equations, they use different
2 numerical algorithms to solve them. In all cases, the atmosphere is divided into discrete vertical
3 layers, which are then overlaid with a two dimensional horizontal grid, producing a three
4 dimensional mesh of grid elements. The set of primitive equations is then solved as a function of
5 space and time on this mesh. The portion of the model code governing the fluid dynamics explicitly
6 simulated on this mesh is often referred to as the model's "dynamics." Computational solutions of
7 the model dynamics can be grouped into four categories: spectral methods, finite difference
8 methods, semi-Lagrangian methods, (Washington and Parkinson, 2005) and finite volume methods
9 (Lin and Rood, 1996). The majority of the climate models use the first two approaches, Even with
10 the same numerical approach, AGCMs differ in spatial resolutions and configuration of model
11 grids. Some models have few layers above the troposphere (the moving boundary between the
12 troposphere and stratosphere), while others could have as many layers above the troposphere as in
13 it. AGCMs all use transformed equations to treat the Earth's surface as a constant coordinate
14 surface so that the specification of heat, moisture, trace substances and momentum exchanges
15 between the earth's surface and the atmosphere can be simplified. Numerical algorithms of AGCMs
16 should preserve the basic conservation of mass and energy of the atmosphere. Typical AGCMs have
17 spatial resolution of 200 kilometers in the horizontal and 20 levels below the altitude of 15 km.
18 Because numerical errors often depend on flow patterns, there are no simple ways to assess the
19 accuracy of numerical discretization of AGCMs. Therefore, AGCMs are tested using a series of
20 both idealized and realistic test cases (e.g. Held and Suarez, 1994) before being included in a
21 climate model. Table 1 lists the specifications of numerical approaches and resolutions of some
22 AGCMs.

23
24 All GCMs use parameterizations, or approximate sub-models, to simulate many processes that are
25 too small, or operate on time scales too fast, to be resolved on the grid of the model dynamics.
26 Some of the most important parameterizations are those that calculate radiant energy (or
27 "radiative") transfer, cloud formation and dissipation, the vertical motions on small scales caused by
28 thunderstorm clouds (cumulus convection), and turbulence and subgrid scale mixing. The radiative
29 transfer code computes the absorption and emission of electromagnetic waves by air molecules and
30 atmospheric particles. Most atmospheric gases absorb and emit radiation at discrete wavelengths,
31 but the computational costs are too high to perform this calculation at individual wavelengths.

1 AGCMs use approximations, which differ among models, to group bands of wavelengths together
2 in a single calculation. Most models have separate radiation codes to treat solar or visible, radiation
3 differently from the much longer wavelength terrestrial, or infrared, radiation. The radiation
4 calculation includes the effects of water vapor, carbon dioxide, ozone, and clouds. Many models
5 also include aerosols and trace gases such as methane. Validation of the AGCM radiation codes is
6 often done offline against resolved wavelength model calculations which, in turn, are compared
7 against laboratory and field observations

8
9 For cloud calculations, AGCMs treat ice and liquid water as part of the atmospheric state variables.
10 Some models also separate cloud particles into ice crystals, snow, graupel, cloud water, and
11 rainwater. Empirical relationships are used to calculate conversions between different particle types.
12 The representation of these processes on the scale of model grids is particularly difficult. It relies
13 heavily on empirical formulations because of the lack of sub-grid scale information. This includes
14 the calculation of cloud amount, which greatly affects radiative transfer and model sensitivity.
15 Current models use one of the following two methods to calculate cloud amount: statistical
16 distribution of thermodynamic and hydrological variables within a grid box, or prognostic cloud
17 amount calculation. The statistical method may use simple model diagnostics, such as relative
18 humidity, or more sophisticated calculations with higher order of moments of moisture contents. A
19 sample of cloud schemes used in AGCMs is listed in Table II 1. None of the current AGCMs
20 calculates size-resolved cloud particles nor do they treat the effects of and non-spherical ice
21 particles.

22
23 Cumulus convective transports, which are important in the atmosphere but cannot be explicitly
24 resolved at GCM scale, are calculated using convective parameterization algorithms. Most current
25 models utilize a cumulus mass flux scheme patterned after that proposed by Arakawa and Schubert
26 (1974), in which the upward motion is the convection is envisioned as occurring in very narrow
27 plumes that takes up a negligible fraction of the area of a grid box. Schemes differ in the techniques
28 used to determine the amount of mass flowing through these plumes, and the manner in which air
29 is entrained and detrained by the plume as it rises. Most models do not separately calculate the
30 area and vertical velocity of convection, but try to predict only the product of the mass and the area,
31 or the convective mass flux. Most current schemes do not account for the differences of convection

1 between organized mesoscale systems and simple plumes. The turbulent mixing rate of updrafts and
2 downdrafts with the environments, and the phase changes of water vapor within the convective
3 systems with a mix of empiricism and constraints due to the moist thermodynamics of rising air
4 parcels.. Some models also include a separate calculation of shallow, non-precipitating convection
5 (or “fair-weather cumulus cloud) with different assumptions from those for deep convections. .
6 Cloud generated by cumulus convection should therefore be thought as based in large-part on
7 empirical relationships. Convection schemes used in AGCMs are listed in Table II 1.

8
9 All AGCMs compute turbulent transport of momentum, moisture, and energy in the atmospheric
10 boundary layer (ABL) near the surface. A long-standing theoretical framework, “Monin-Obukhov
11 Similarity theory” is used to calculate the vertical distribution of turbulent fluxes and state variables
12 in a thin air layer of tens of meters adjacent to the surface. Above that, turbulent fluxes are
13 calculated based on covariances and closure assumptions for the ABL which differ among AGCMs.
14 Some models use high order closures in which the fluxes or second order moments are
15 prognostically calculated. Other models calculate the fluxes diagnostically. Turbulent ABL fluxes
16 heavily depend on surface conditions such as roughness, soil moisture, and vegetation. Besides
17 explicit calculation of boundary layer turbulence, all models use additional diffusion schemes to
18 either calculate the impact of “clear air turbulence”, or to damp artificial numerical modes
19 introduced in the discretization of the model. Table II.A lists turbulent schemes in AGCMs.

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Table II. 1. Physical parameterization schemes in a sample of AGCMs.

	Resolution	Convection	ABL	Stratiform Clouds	Convective Clouds	Cloud Microphysics
CAM3	T85L26 (1.4°x1.4°) Spectral	Mass Flux [Hack 1994; Zhang and McFarlane, 1995]	1 st order non- local [Holtslag and Boville, 1993]	Diagnostic (RH based) [Kiehl <i>et al.</i> , 1996]	Diagnostic [Rasch and Kristjansson, 1998]	Rasch and Kristjánsson [1998]
GFDL	2.5°x2.0°L24 Finite Difference	Mass flux (RAS) [Moorthi and Suarez, 1992]	Cloud entrainments [Lock <i>et al.</i> , 2000; GFDL GAMDT, 2004]	Prognostic [Tiedtke, 1993; GFDL GAMDT, 2004]	Prognostic [Tiedtke, 1993; GFDL GAMDT, 2004]	Rotstayn [1997], GFDL GAMDT [2004]
GISS	4°x5° L12 Finite Difference	Mass flux [Del Genio and Yao, 1993]	2 nd order [Cheng <i>et al.</i> , 2002]	Diagnostic (RH based) [Del Genio <i>et</i> <i>al.</i> , 2004]	Diagnostic [Del Genio <i>et</i> <i>al.</i> , 2004]	Del Genio <i>et al.</i> [2004]
GSFC	2.5°x2° L40 Finite Volume	Mass flux (RAS) [Moorthi and Suarez, 1992]	2.5 order [Helfand and Labraga, 1988]	Diagnostic (RH based) [Del Genio <i>et</i> <i>al.</i> , 2004]	Diagnostic [Del Genio <i>et</i> <i>al.</i> , 1996]	Del Genio <i>et al.</i> [1996], Sud and Walker [1999]
HadAM4	3.75°x2.5°L30 Finite Difference	Mass flux [Gregory and Rowntree, 1990; Gregory and Allen, 1991]	1 st order with cloud entrainment [Lock <i>et al.</i> , 2000; Martin <i>et al.</i> , 2000]	Diagnostic statistical [Smith, 1990; Pope <i>et al.</i>].	Diagnostic [Gregory and Rowntree, 1990]	Wilson and Ballard [1999]
ECHAM5	T63L31 (1.9°x1.9°) Spectral	Mass flux [Tiedtke, 1989; Nordeng, 1994]	1 st order, [Brinkop and Roeckner, 1995]	Prognostic statistical [Tompkins, 2002],	Diagnostic [Roeckner <i>et</i> <i>al.</i> , 1996]	Lohmann and Roeckner [1996]
LMD	3.75°x2.5°L19	Emanuel	1 st order [Li,	Statistical	Statistical	Le Treut and Li

	Finite Difference	[1991]	1999]	[Le Treut and Li, 1991]	[Bony and Emanuel, 2001]	[1991]
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Ocean General Circulation Models

General overview: The ocean (Ocean General Circulation Models: OGCM) component of the current generation of climate models can be placed into one of two general categories. All the models are fully four dimensional primitive equation models and are coupled to the atmosphere and ice models through the exchange of fluxes of heat, temperature, and momentum at the boundary between components.. TableII 2 gives a brief summary of the major differences between the models described in the next paragraphs. Like the atmosphere, the horizontal dimensions of the ocean are much larger than the vertical dimension, again resulting in separating the processes that occur in the vertical from those that occur in the horizontal. Unlike the atmosphere, which only has to deal with terrain differences at the lower boundary, the ocean has a much more complex, three-dimensional boundary, with continents and submarine basins and ridges. Further, the fluid behavior of sea water is very different than that of air, resulting in a slightly different set of equations controlling ocean fluid dynamics.

The models utilized by the three US climate modeling groups that contributed models to the CMIP3 archive are used here to illustrate some of the choices made by ocean modelers.

An important category of OGCMs are referred to as Z-level models in which the model’s vertical levels are calculated at fixed distances below the surface. (Many of these models are based on the early efforts of Bryan and Cox (1967) and Bryan (1969a, b). The GFDL and CCSM ocean components fall into this category (Griffies *et al.*, 2005, Smith and Gent, 2002The models are similar in that the fundamental physical quantities advancing in time are the same. These quantities are velocity, potential temperature, salinity, sea surface height, and any number of specific passive tracers that maybe included for a given simulation. The two modeling efforts use similar horizontal resolution at about the same order: 1 degree or 110 km for most of the Earth and about 1/3 of a degree at the equator. Usually the models have increasing resolution between 5°N and 5°S to increase their ability to simulate important equatorial processes.

1 The vertical and horizontal structure of the models can also differ and are listed in Table II 2. The
2 CCSM OGCM's horizontal grid has its north pole displaced onto a land coordinate (a so-called
3 stretched grid) and the GFDL models use a grid that has three poles (Murray, 1996). There is an
4 explicit treatment of the bottom boundary and overflow regions in the GFDL models (Beckman and
5 Doscher, 1997) to improve the down-slope flow of water. Such treatment of the overflows should
6 improve the representation of deep ocean waters (Roberts and Wood, 1997), but problems remain
7 (Griffies *et al.*, 2005).

8
9 The second category of OGCMs includes those developed by GISS. There are two different ocean
10 models that are used in the GISS simulations: the "Russell Ocean" (GISS-ModelE-R and GISS-
11 AOM: Russell *et al.*, 1995, Russell *et al.*, 2000) and the "HYCOM Ocean" (GISS-ModelE-H: Sun
12 and Bleck, 2001; Bleck 2002; Sun and Hansen, 2003; **Hybrid Coordinate Ocean Model**). The
13 fundamental (prognostic) variables for the E-R and AOM simulations are potential enthalpy (rather
14 than potential temperature), salt, mass, vertical gradients of potential enthalpy and salt, in addition
15 to velocity. At this time, these models are run at a resolution much lower than the models of the first
16 category (see Table 2 The vertical coordinate is defined in units of mass/unit area (while in category
17 1, the unit is meters).

18
19 The HYCOM OGCM (GISS-EH) fundamental variables include temperature, salinity, layer
20 thickness, and velocity,. The horizontal grid is different from the others described. It is two grids,
21 with one a Mercator grid to 60°N with a resolution of 2° and it is patched (i.e. boundary values
22 exchanged at each time step) to a North Pole grid defined as 1° at 60°N to 0.5° at the North Pole.
23 The vertical grid is a complex or "hybrid" with a z-level grid (units meters) to represent the mixed
24 upper ocean and layers below represented as density layers (Bleck, 2002).

25
26 The analyses of the simulations, in most cases, are performed on the model fields that are
27 interpolated to a common grid. This interpolation may introduce small inaccuracies (AchutaRao *et*
28 *al.*, 2006) in the results of analyses of a model, but is not considered significant. For example, no
29 more than 3% of heat content change can be associated with regridding errors at the end of a
30 simulation.

31

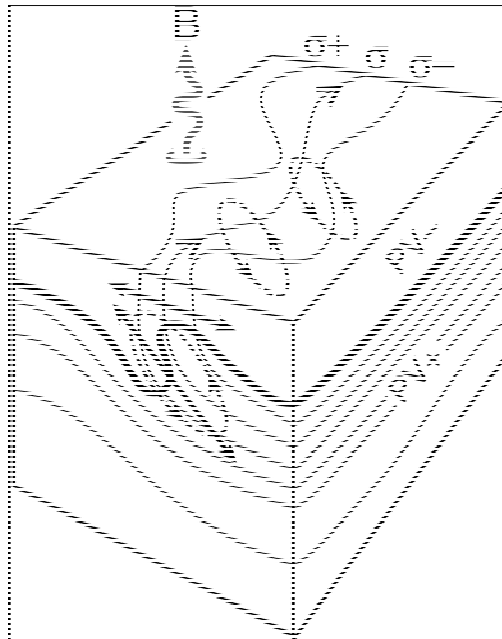
1 Table II 2 Ocean CGM Characteristics

Model	Resolution Long x Lat L = Levels	Diabatic Mixing	Adiabatic Mixing	Primary Variables	Other Comments
CCSM3 POP	320x395 L40	KPP	GM	Velocity, T, S, SSH, ideal age	z-level vertical coordinate
GFDL: CM2: OM3	360x200 L50	KPP	GM	Velocity, T, S, SSH, ideal age	z-level vertical coordinate
GISS: AOM	90x60 L16	KPP	none	Potential Enthalpy, velocity, salt, mass	z*vertical coordinate
GISS: ER	72x46 L16	KPP	GM	See AOM	See AOM
GISS EH:	180x90	Kraus- Turner	No special treatment	T, S, SSH, mass flux, velocity	Isopycnal Vertical coordinate

2

1
2 **Parameterization**
3 *Ocean Mixing:* At the interface of the atmosphere and the ocean, the sea surface temperature plays a
4 critical role in the climate problem. Processes that control mixing in the ocean are complicated and
5 take place on small scales (order of centimeters) in the turbulent regime near the surface (the mixed
6 layer). Within the stratified, adiabatic interior of the ocean, mixing is influenced by the exchange of
7 water on scales on the order of meters to kilometers (**Figure II.A**). The current ocean components
8 of climate models are at resolutions that are greater than either of these scales. The mixing of the
9 ocean contributes to the ocean's stratification and heat uptake. This stratification, in turn, affects the
10 circulation patterns on temporal scales of decades and longer. It is also generally felt (Schopf *et al.*,
11 2003) that the mixing schemes in the ocean modeling components contribute significantly to the
12 uncertainty in the estimates of the ocean's contribution to the predictions of climate change.

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4 **Figure II.A.** Schematic showing the interaction of a mixed layer (low Potential Vorticity: PV) with the
5 stratified interior (high PV) in a strong frontal region with outcropping isopycnal surfaces, , undergoing
6 cooling, “B” indicates where eddies forming along the front play a central role in controlling horizontal fluxes
7 through the mixed layer and quasi-adiabatic exchange between the mixed layer and the interior. This
8 process is poorly observed, understood and modeled and must be parameterized in large-scale models.

9 (from *Coupling Process and Model Studies of Ocean Mixing to Improve Climate Models - A Pilot Climate*

10 *Process Modeling and Science Team*, a US CLIVAR white paper by Schopf, Gregg, Ferrari, *et al.*, (2003).

1
2
3 For turbulent mixing of the upper ocean at the boundary with the atmosphere, the current generation
4 of climate models (resolutions on the order of degrees) parameterizes the processes primarily
5 through the use of several different approaches. Large *et al.*, (1994) also provides a more complete
6 comparison of these mixing schemes. While not all international AOGCMs use the K-profile
7 Parameterization (KPP; Large *et al.*, 1994) scheme, most of the major US climate models
8 incorporate a version of the scheme. Li *et al.*, (2001) showed that in the tropical Pacific, the use of
9 the KPP scheme for handling the mixed layer of the upper ocean reduced the error in the simulation
10 as compared to observations over a simulation that used a more simplified method (Pacanowski and
11 Philander, 1981).

12
13 The adiabatic mixing, related to the interactions of eddy motions, generally is handled through the
14 incorporation of the methods of Gent and McWilliams (GM) (1990) and Griffies (1998). Eddies
15 will generally mix the ocean on constant density surface. The GM method incorporates various
16 separate parameters that include the scale of the process to be considered and a parameter related to
17 the ability of a parcel to move up and down. For any model the parameters are set so that coefficient
18 related to diffusivity is high in the boundary currents and low in the interior of the ocean (Griffies *et*
19 *al.*, 2006). The ocean's flow is effected by the eddies, leading to adjustments in how much heat is
20 moved through the oceans, and thus impacts the climate characteristics of the ocean.

21
22 To accurately represent ocean mixing at scales important to climate, other processes may need to be
23 represented explicitly or parameterized in the model. These include incorporation of tidal mixing
24 and more accurate representation of interactions with the ocean's bottom. Some of the models also
25 include a scheme for handling tidal mixing (Lee *et al.*, 2005). The limited study of Lee *et al.* (2005)
26 shows that the tidal mixing enhanced the ventilation of the surface waters and increased the
27 formation of deep water in the Labrador Sea by homogenizing the salinity distribution but did not
28 have a major effect on the overturning circulation. It is still an open discussion on the importance of
29 tidal mixing in ocean in relationship other larger scale changes occurring in the ocean related to
30 climate. A few OGCMs also explicitly treat the bottom boundary and sill overflows (Beckman and
31 Doshier, 1997).

1
2 **Other parameterizations:** Another aspect of the model that is available to climate modelers when
3 running the simulations is the explicit treatment for handling the penetration of sunlight (and thus,
4 affecting chlorophyll distributions) into the upper ocean (e.g.. Paulson and Simpson, 1977; Morel
5 and Antoine, 1994; Ohlmann, 2003). All of the US models include such capability. The inclusion
6 of river input (which, in turn, effects ocean mixing locally) in OGCMs is also handled by the
7 models in a variety of ways. The models' low resolution results in the smaller seas of the Earth
8 being isolated from the large ocean basins. This requires that there be a method to exchange water
9 between an isolated sea and the ocean to simulate what in nature involves a channel or strait. The
10 various modeling groups have chosen different methods to handle the mixing of the water between
11 these seas and the larger ocean basins, and is one potential source of model differences in climate
12 simulations.

13
14
15 **Evaluation of OGCMs:** Like the atmosphere, ocean components of climate models are separately
16 evaluated, in addition to the evaluation of coupled ocean-atmosphere GCMs discussed in Chapter V
17 below. Ocean model evaluation requires specification (as input to the computer models) of
18 boundary conditions at the air-sea interface. Typically, these are specified to match observations of
19 the recent decades, and the OGCM simulation is then evaluated by comparison with observations of
20 the ocean from the same time period. OGCM experiments with specified sea surface boundary
21 conditions are at present less robust and generally exhibit more uncertainty in model performance
22 than similar experiments for the atmosphere.

23

1 *Land Surface Models*

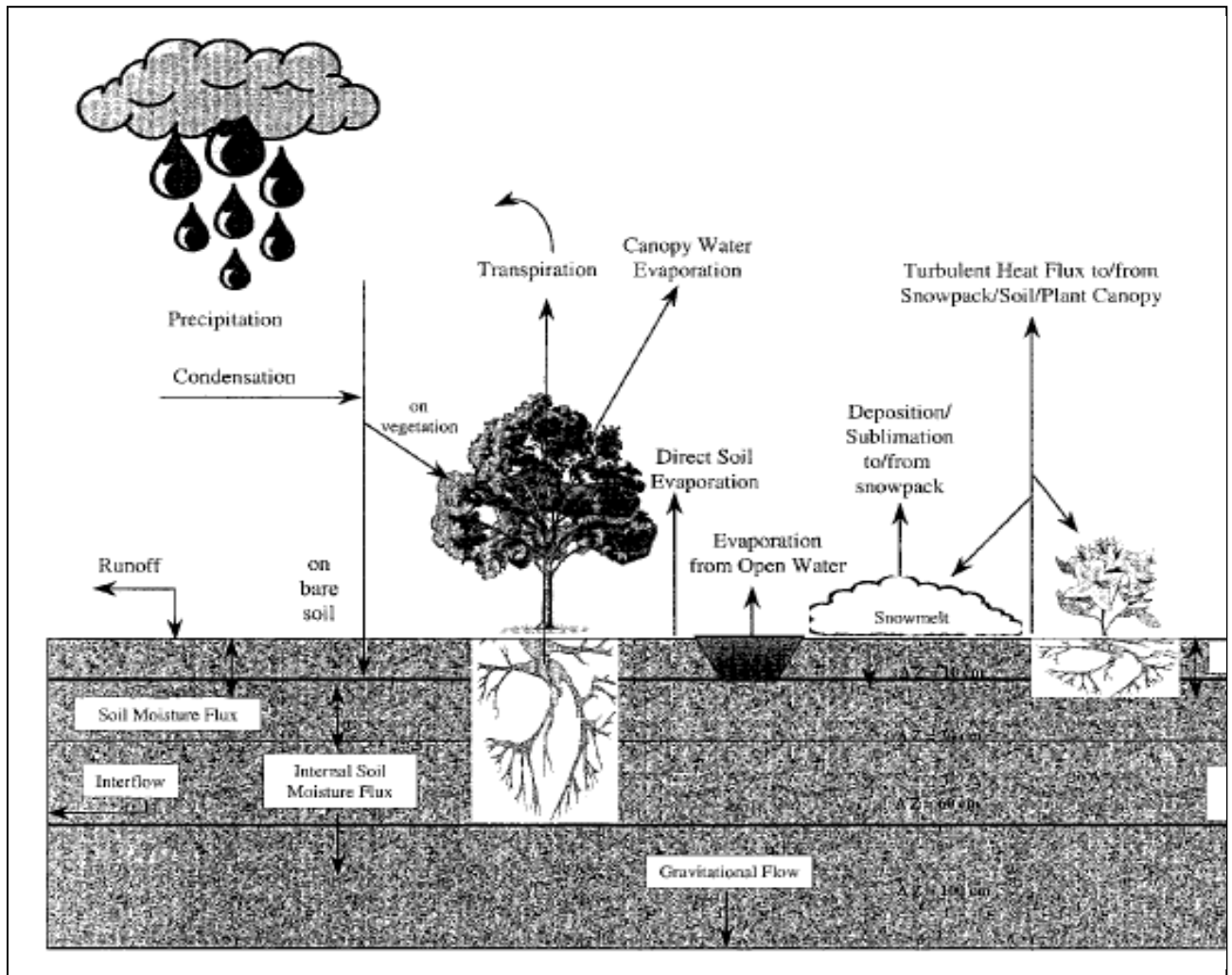
2
3 The interaction of the Earth's surface with the atmosphere is an integral aspect of the climate
4 system. At the interface, there are exchanges (fluxes) of mass and energy, notably heat, water vapor,
5 and momentum. Feedbacks between the atmosphere and the surface affecting these fluxes have
6 important effects on the climate system (Seneviratne *et al.*, 2006). Modeling the processes over
7 land is particularly challenging because the land surface is very heterogeneous and biological
8 mechanisms in plants are important. Climate model simulations are very sensitive to the choice of
9 land parameterizations (Irannejad *et al.*, 2003).

10
11 In the earliest global climate models, the land surface modeling occurred in large measure to
12 provide a lower boundary to the atmosphere that was consistent with energy, momentum and
13 moisture balances (e.g., Manabe 1969). The land surface was represented by a balance among
14 incoming and outgoing energy fluxes and a "bucket" that received precipitation from the
15 atmosphere and evaporated moisture into the atmosphere, with a portion of the bucket's water
16 draining away from the model as a type of runoff. The bucket's depth equaled soil field capacity.
17 There was little attention given to the detailed set of biological, chemical and physical processes
18 linked together in the terrestrial portion of the climate system. From this simple starting point, land
19 surface modeling for climate simulation has increased markedly in sophistication, with increasing
20 realism and inclusiveness of terrestrial surface and subsurface processes.

21
22 Although these developments have increased the physical basis of land modeling, the greater
23 complexity has at times contributed to greater differences between climate models (Gates *et al.*,
24 1995). However, the advent of systematic programs comparing land models, such as the Project for
25 Intercomparison of Land Surface Parameterization Schemes (PILPS; Henderson-Sellers *et al.*,
26 1995; Henderson-Sellers, 2006) has gradually led to greater agreement with observations and
27 among land models (Overgaard *et al.* 2006), in part because more observations have been used to
28 constrain their behavior. However, choices for adding processes and increasing realism have varied
29 between land-surface models (e.g., Randall *et al.* 2007), so convergence of simulations by current
30 models should not be expected. This section reviews the range of developments that have led to
31 contemporary simulation of land processes in climate models.

1
2 **Figure II. B** shows schematically the types of physical processes included in typical land models. It
3 is noteworthy that the schematic in **Figure II. B** describes a land model used for both weather
4 forecasting and climate simulation, an indication of the increasing sophistication demanded by both.
5 The figure also hints at important biophysical and biogeochemical processes that have gradually
6 been added to land models used for climate simulation (and continue to be added), such as
7 biophysical controls on transpiration and carbon uptake.

- 1
- 2 **Figure II. B.** Schematic of physical processes in a contemporary land model (from Chen and Dudhia, 2001).



1
2 **Vegetation:** Some of the most extensive increases in complexity and sophistication have occurred
3 with vegetation modeling in land models. An early generation of land models (Wilson *et al.*, 1987;
4 Sellers *et al.*, 1986) introduced biophysical controls on plant transpiration by adding a vegetation
5 canopy over the surface, thereby implementing vegetative control on the terrestrial water cycle.
6 These models included exchanges of energy and moisture between the surface, canopy and
7 atmosphere, along with momentum loss to the surface. Further developments included improved
8 plant physiology that allowed simulation of carbon dioxide fluxes (e.g., Bonan 1995; Sellers *et al.*,
9 1996), which lets the model treat the flow of water and carbon dioxide as an optimization problem
10 balancing carbon uptake for photosynthesis against water loss through transpiration. Improvements
11 also included implementation of model parameters that could be calibrated with satellite
12 observation (Sellers *et al.*, 1996), thereby allowing global-scale calibration.
13
14 Continued development has included more realistic parameterization of roots (Arora and Boer,
15 2003; Kleidon, 2004) and adding multiple canopy layers (e.g., Gu *et al.*, 1999; Baldocchi and
16 Harley, 1995; Wilson *et al.*, 2003). However, the latter has not been used in climate models as the
17 added complexity of multi-canopy models renders unambiguous calibration very difficult. An
18 important ongoing advance is the incorporation of biological processes that produce carbon sources
19 and sinks through vegetation growth and decay and cycling of carbon in the soil (e.g., Li *et al.*,
20 2006), although considerable work is needed to determine observed magnitudes of carbon uptake
21 and depletion.
22
23 **Soils:** The spatial distribution of soils, at least for the contiguous U.S. appears to be fairly well
24 mapped (Miller and White 1998). Most land models include only inorganic soils, generally
25 composed of mixtures of loam, sand and clay. However, high-latitude regions may have extensive
26 zones of organic soils (peat bogs), and some models have included organic soils topped by mosses,
27 which has led to decreased soil heat flux and increased surface sensible and latent heat fluxes
28 (Berringer *et al.*, 2001).
29
30 **Snow and ice:** Climate models initially treated snow as a single layer that could grow through snow
31 fall or deplete though melt (e.g., Dickinson *et al.*, 1993). More recent land models for climate

1 simulation include sub-grid distributions of snow depth (Liston, 2004) and blowing of snow (Essery
2 and Pomeroy, 2004). Snow models now may use multiple layers to represent fluxes through the
3 snow (Oleson *et al.*, 2004). Effort has also gone into including and improving effects of soil
4 freezing and thawing (Koren *et al.*, 1999; Boone *et al.*, 2000; Warrach *et al.*, 2001; Li and Koike,
5 2003; Boisserie *et al.*, 2006) though permafrost modeling is more limited (Malevsky-Malevich *et*
6 *al.*, 1999; Yamaguchi *et al.*, 2005).

7 Vegetation interacts with snow by covering it, thereby masking snow's higher albedo (Betts
8 and Ball, 1997) and retarding spring snowmelt (Sturm *et al.*, 2005). The net effect is to maintain
9 warmer temperatures than would occur without vegetation masking (Bonan *et al.*, 1992). Vegetation
10 also traps drifting snow (Sturm *et al.*, 2001), insulating the soil from subfreezing winter air
11 temperatures and potentially increasing nutrient release and enhancing vegetation growth (Sturm *et*
12 *al.*, 2001). The albedo masking is included in some land surface models, but it requires accurate
13 simulations of snow depth to produce accurate simulation of surface-atmosphere energy exchanges
14 (Strack *et al.*, 2003).

15
16 **Ice Sheets** Global sea level is rising at a rate of 30 cm/century, thanks to a combination of ocean
17 thermal expansion, melting of mountain glaciers and small ice caps, and retreat of the large ice
18 sheets of Greenland and Antarctica (Cazenave and Nerem, 2004; Church and White 2006). The rise
19 in sea level provides a common disruption and challenge to nearly every country, and the 400
20 million inhabitants who live within roughly 20 meters of elevation above sea level (Small *et al.*,
21 2000). By far the greatest uncertainty in sea level rise is associated with ice sheets. Complete
22 melting of the Greenland and West Antarctic ice sheets, which are believed vulnerable to climate
23 warming, would raise sea level by about 7 m and 5 m, respectively. During the last interglacial
24 period, roughly 125,000 years ago, these ice sheets were smaller and sea level was a few meters
25 higher than its present-day value (McCulloch and Ezat 2000, Siddall *et al.* 2003). Given the
26 potentially catastrophic impacts of sea level rise, it is essential to be able to predict how fast ice
27 sheets will melt and whether that melting, once begun, can be reversed. This is not yet possible
28 because key ice sheet dynamical processes are poorly understood and are not included in current
29 climate models. The recent IPCC assessment report (IPCC, 2007) underscores the need for
30 improved ice sheet models, but because of the early stage of model development, specifically
31 excluded rapid changes in ice flow from its 21st century sea level projections.

1
2 Ice sheets were once thought to be too sluggish to respond to climate change on time scales of less
3 than a century. However, analysis of coral reefs at several locations indicate periods, including
4 around 14,000 years ago, when sea level rose by as much as a few meters per century (Bard *et al.*,
5 1990). Recent observations suggest that ice sheets are already responding to warming. Outlet
6 glaciers in Greenland have accelerated and thinned (Rignot and Kanagaratnam, 2006), driven by
7 ocean warming and possibly by increased basal sliding. Ice shelves in the Amundsen Sea
8 embayment of West Antarctica have thinned and retreated, giving rise to acceleration of glaciers
9 tens of km upstream (Payne *et al.*, 2004). Satellites provide near-complete spatial coverage and
10 recent instruments have measured changes in total ice volume with precision that is unprecedented.
11 Surface altimetry and synthetic aperture radar interferometry measure the height of the ice surface,
12 and can be used to estimate changes in ice volume with additional information or assumptions about
13 depth (Rignot and Kanagaratnam, 2006). Surveys of the changing gravitational field provide direct
14 measurements of ice mass (Velicogna and Wahr 2006). Both indicate that the Greenland and
15 Antarctic ice sheets are losing mass. Shepherd and Wingham (2007) estimate a net loss of about
16 125 Gt/yr (which includes losses of 100 Gt/yr for Greenland and 50 Gy/yr for West Antarctica,
17 offset by a gain of 25 Gt/yr from increased snowfall in East Antarctica). The resulting contribution
18 to sea level rise is currently a modest 3.5 cm/century, but this contribution will likely increase in a
19 warming climate.

20
21 Most global climate models to date have been run with prescribed, immovable ice sheets, but
22 several modeling groups are now incorporating dynamic ice sheet models. Scientists are coupling
23 GLIMMER, an ice sheet model originally developed at the University of Bristol, to the Community
24 Climate System Model. GLIMMER will be forced with temperature, precipitation, and other
25 climate fields, and will return a modified surface elevation profile along with meltwater *freshwater*
26 fluxes. As the ice sheet thins, melting will likely increase because the surface descends to a lower
27 elevation where the temperature is higher *temperature-elevation feedback*. Meanwhile, meltwater
28 *freshwater fluxes* will freshen the upper ocean and possible modify the thermohaline circulation.
29 GLIMMER will initially be used to model the Greenland ice sheet and later will be used for
30 simulations of the Antarctic ice sheet as well as paleo ice sheets (e.g., the Laurentide ice sheet that
31 covered much of North America during the last glacial period).

1
2 Like most current-generation models, GLIMMER is based on the shallow-ice approximation, which
3 assumes that ice flow is dominated by vertical shear. This approximation is valid in slow-moving
4 ice sheet interiors but is insufficient to model fast dynamic changes near the ice sheet margin. A
5 number of physical, numerical and computational improvements are needed to provide realistic
6 projections of 21st century ice sheet changes. Among the major challenges are the following.

- 7
- 8 • Incorporate a unified treatment of stresses: both the vertical shear stresses that dominate in
9 the ice sheet interior and the longitudinal stresses that are important in ice shelves and ice
10 streams.
- 11 • Decrease grid spacing to 5 km or less to resolve small-scale features such as ice streams and
12 outlet glaciers. This may require nested or unstructured grids, as well as parallel codes that
13 scale efficiently with large numbers of processors.
- 14 • Develop improved methods of downscaling atmospheric fields, which are typically at a grid
15 spacing of 100 km or more, to the finer ice sheet grid, making sure that energy is conserved
16 in the process.
- 17 • Develop realistic parameterizations of surface and subglacial hydrology. Fast dynamic
18 processes are largely controlled by the pressure and extent of water at the base of the ice
19 sheet.
- 20 • Model the interaction of ice shelves with the ocean circulation. Ocean models, which
21 usually assumed fixed topography, must be modified to include flow beneath advancing and
22 retreating ice.

23
24 Meeting these challenges will require increased interaction between the glaciological and climate
25 modeling communities, which until recently have been largely isolated from one another.

26
27
28 **Hydrology**: The initial focus of land models was vertical coupling of the surface with the overlying
29 atmosphere. However, horizontal water flow through river routing has been available in some
30 models for some time (e.g., Sausen *et al.*, 1994; Hagemann and Dümenil, 1998), with spatial
31 resolution of routing in climate models increasing in more recent versions (Ducharne *et al.*, 2003).

1 However, freezing soil poses additional challenges for modeling runoff (Pitman *et al.*, 1999), with
2 more recent work showing some skill in representing its effects (Luo *et al.*, 2003; Rawlins *et al.*,
3 2003; Niu and Yang, 2006).

4
5 Work is also underway to couple ground-water models into land models (e.g., Gutowski *et al.*,
6 2002; York *et al.*, 2002; Liang *et al.*, 2003; Maxwell and Miller, 2005; Yeh and Eltahir, 2005).

7 Ground water potentially introduces longer time scales of interaction in the climate system in places
8 where it has contact with vegetation roots or emerges through the surface.

9
10 **Scale considerations:** Land models encompass spatial scales ranging from the size of the model
11 grid box down to biophysical and turbulence processes operating on scales the size of leaves.
12 Explicit representation of all these scales in a climate model is beyond the scope of current
13 computing systems as well as observing systems that would be needed to provide adequate model
14 calibration for global and regional climate. As indicated above, land models have been developed to
15 increase the sophistication of their climate-system simulation without becoming so complex as to be
16 intractable. Thus, for example, typical land models in climate simulation do not represent individual
17 leaves but the collective behavior of a canopy of leaves, and multiple canopy layers are generally
18 represented by a single, effective canopy.

19
20 Although model fluxes are primarily in the vertical direction, they do not represent a single point
21 but behavior in a grid box that may be many tens or hundreds of kilometers across. Initially, these
22 grid boxes were treated as homogeneous units, but starting with the pioneering work of Avissar and
23 Pielke (1989), many land models have tiled a grid box with patches of different land-use and
24 vegetation types. Although these patches may not interact directly with their neighbors, they are
25 linked by their coupling to the grid box's atmospheric column. This coupling does not allow
26 possible small-scale circulations that might occur because of differences in surface-atmosphere
27 energy exchanges between patches (Segal and Arritt, 1992; Segal *et al.*, 1997), but under most
28 conditions, the imprint of such spatial heterogeneity on the overlying atmospheric column appears
29 to be limited to a few meters above the surface (e.g., Gutowski *et al.*, 1998).

30

1 Vertical fluxes linking the surface, canopy and near-surface atmosphere generally assume some
2 form of down-gradient diffusion, though counter-gradient fluxes can exist in this region much like
3 in the overlying atmospheric boundary layer, so there has been some attempt to replace diffusion
4 with more advanced, Lagrangian random-walk approaches (Gu *et al.*, 1999; Baldocchi and Harley,
5 1995; Wilson *et al.*, 2003).

6
7 **Digital Elevation Models:** Topographic variation within a grid box is usually ignored in land
8 modeling. However, implementing detailed river-routing schemes will require accurate digital
9 elevation models (e.g., Hirano *et al.*, 2003; Saraf *et al.*, 2005). In addition, some soil water schemes
10 also include effects of land slope on water distribution (Choi *et al.*, 2007) and surface radiative
11 fluxes (Zhang *et al.*, 2006).

12
13 **Validation:** Validation of land models, especially globally, remains a problem, due to lack of
14 measurements for relevant quantities such as soil moisture and energy, momentum, moisture and
15 carbon fluxes. PILPS (Henderson-Seller *et al.*, 1995) has provided opportunity to make detailed
16 comparisons of multiple models with observations at point locations around the world with differing
17 climates, thus providing some constraint on the behavior of land models. Global participation in
18 PILPS has led to a greater understanding of differences among schemes and improvements. The
19 latest generation of land surface models exhibit relatively smaller differences (Henderson-Sellers *et*
20 *al.*, 2003) compared to previous generations. River routing can provide a diagnosis versus
21 observations of the spatially distributed behavior of a land model (Kattsov *et al.*, 2000). Remote
22 sensing has been useful for calibration of models developed to exploit it, but it has not generally
23 been used for model validation. The development of regional observing networks that aspire to give
24 Earth-system observations, such as some of the mesonets in the United States, offers promise of
25 spatially distributed observations of important fields for land models that resolve some of the spatial
26 variability of land behavior.

27
28 **Future:** Land modeling has developed in other disciplines roughly concurrently with the advances
29 implemented in climate models. Applications are wide ranging and include detailed models used
30 for water resource planning (Andersson *et al.* 2006), managing ecosystems (e.g., Tenhunen *et al.*,
31 1999), estimating crop yields (e.g., Jones and Kiniry, 1986; Hoogenboom *et al.*; 1992), simulating

1 ice sheet behavior (Peltier, 2004), and projecting land-use, such as for transportation planning (e.g.,
2 Schweitzer; 2006). As suggested by this list, there are widely disparate applications, which have
3 developed from differing scales of interest and focus processes. Land-model development in some
4 of these other applications has informed advances in land models for climate simulation, as in
5 representation of vegetation and hydrologic processes. Because land models do not include all
6 climate system processes, they can be expected in the future to engage other disciplines and
7 encompass a wider range of processes, especially as resolution increases.

9 *Sea Ice Models, including parameterizations and evaluation*

10
11 **General overview:** All the considered climate models have sea ice components that are both
12 dynamic and thermodynamic. That is, the models include the physics for ice movement as well as
13 the physics that is related to energy and heat within the ice. The differences in the various models
14 relate primarily to how complex the code for the dynamics is in determining the representation of
15 ice rheology and their use of parameters.

16
17 Two dynamical codes are in common use in ice models, the standard Hibler viscous-plastic (VP)
18 rheology (Hibler, 1979; Zhang and Rothrock, 2000) and the more complex elastic-viscous-plastic
19 (EVP) rheology of Hunke and Dukowicz (1997). The EVP method explicitly solves for the ice
20 stress tensor, while the VP solution uses an implicit iterative approach. The solutions are similar
21 (Hunke and Zhang, 1997). The NOAA-GFDL models [Delworth *et al.*, 2005] and the NCAR-
22 CCSM3 (Collins *et al.*, 2005) use the EVP rheology, while the NASA-GISS models use the VP
23 implementation. The EVP is more efficient, especially when using multiple processors.

24
25 The thermodynamics portions of the codes also vary in their implementation. Previous climate
26 models generally used the thermodynamics code of Semtner (1976). This classic sea ice model
27 includes one snow layer and two ice layers with constant heat conductivities and a simple
28 parameterization of the brine (salt) content. The NOAA-GFDL models continue to use the Semtner
29 structure with three layers but extend the code relating to brine content in the upper ice layer to be
30 represented by variable heat capacity (Winton, 2000). The NCAR-CCSM3 and NASA-GISS
31 models use variations of the Bitz and Lipscomb (1999) thermodynamics (Briegleb *et al.*, 2002).

1 The code accounts for more of the physical processes within the ice, including the melting of
2 internal brine regions and conserves energy.

3
4 The prognostic variables of the sea ice components of the separate climate models are similar to
5 their ocean counterpart, that is the NOAA-GFDL and NCAR-CCSM use velocity, temperature and
6 volume while the NASA-GISS models use velocity, enthalpy, and mass. The amounts of snow and
7 ice for the layers are also computed with each model defining the number of ice layers and ice
8 categories differently. The NOAA-GFDL models use a snow layer, two ice layers and five ice-
9 thickness categories. The NCAR-CCSM3 model has a snow layer, four ice layers, and six ice
10 categories. The NASA-GISS model includes one snow layer, three ice layers, and two ice
11 categories. There is variation among the models on how ice categories are defined, but all include a
12 "no ice" category. The resolution of the sea-ice component is the same as the ocean components of a
13 specific climate model: NASA-GISS is at a relatively low resolution of $4^{\circ} \times 5^{\circ}$, while the NOAA-
14 GFDL and NCAR-CCSM models are on the order of 1° .

15 16 **Parameterizations**

17
18 *Albedo:* As an important feedback to the atmosphere, the albedo (the proportion of incident
19 radiation reflected off a surface) of the snow and ice plays a significant role in the climate system.
20 All the sea ice component models parameterize the albedo to some extent. Figure II. C from Curry
21 *et al.* (1995) illustrates the interrelations of the sea-ice system and how the albedo is a function of
22 the snow or ice thickness, ice extent, open water, and the surface temperature, along with other
23 factors, including the spectral band of the radiance. The various models treat the different
24 contributions to the total albedo in similar ways, but vary on the details. For example, the NCAR-
25 CCSM3 sea-ice component does not include dependence on the solar elevation angle (Briegleb *et*
26 *al.*, 2002), while the NASA-GISS model does (Schmidt *et al.*, 2006). Both of these models include
27 the contribution of melt ponds (Ebert and Curry, 1993; Schramm *et al.*, 1997) The NOAA-GFDL
28 model follows Briegleb *et al.* (2002), but accounts for the differences in spectral contributions using
29 fixed ratios (Delworth *et al.* 2006).

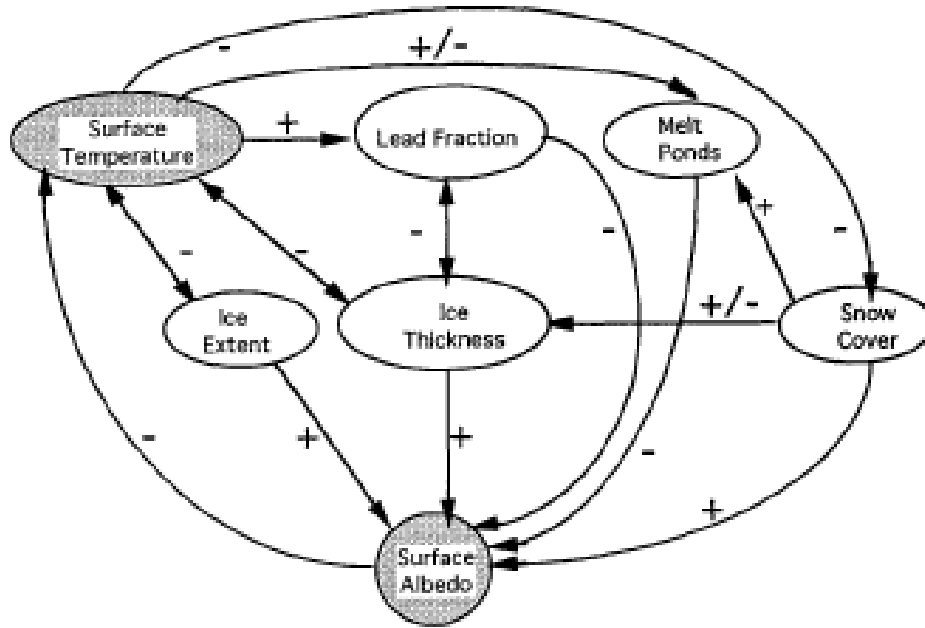


FIG. 6. Schematic diagram of the sea ice-albedo feedback mechanism. The direction of the arrow indicates the direction of the interaction. A "+" indicates a positive interaction (an increase in the first quantity leads to an increase in the second quantity) and a "-" indicates a negative interaction (an increase in the first quantity leads to a decrease in the second quantity). A "±" indicates either that the sign of the interaction is uncertain or that the sign changes over the annual cycle.

1

2 Figure II. C (from Curry *et al.* (1995)).

1
2 *Other parameterizations:* Additional parameters include reference values for defining ice salinities,
3 strengths, roughness, and drag coefficients. Details of these parameters can be found in the
4 references listed above which describe the basic sea-ice models of the various groups.
5

6 ***Component coupling and coupled model evaluation*** 7

8 We describe in the following some of the key aspects of the model development process at the three
9 U.S. groups that contributed models to the Fourth Assessment of the IPCC, with particular focus on
10 those aspects most relevant for simulation of the 20th century global mean temperature record on the
11 one hand, and the model's climate sensitivity on the other hand. We begin with some general
12 comments on the model development process.
13

14 The complexity of the climate system, and our inability to resolve all relevant processes in our
15 models, result in a host of choices for development teams to make. Differing expertise, experience,
16 and interests result in distinct development pathways for each climate model. While we eventually
17 expect to see model convergence, forced by increasing insights into the working of the climate
18 system, we are still far from that limit today in several important aspects of the models. Given this
19 level of uncertainty, multiple modeling approaches are clearly needed. Models differ in their details
20 primarily because development teams have differing ideas concerning the underlying physical
21 mechanisms relevant for the less well-understood aspects of the system.
22

23 **The NOAA Geophysical Fluid Dynamics Laboratory Model Development Path** 24

25 The Geophysical Fluid Dynamics Laboratory of NOAA conducted a thorough restructuring of its
26 atmospheric and climate models over more than five years prior to its delivery of a model to the
27 CMIP-3/IPCC database in 2004. This was performed partly in response to need for modernizing the
28 software engineering, and partly in response to new ideas in modeling the atmosphere, ocean, and
29 sea ice. The differences between the resulting models and the previous generation of climate models
30 at GFDL are sufficiently varied and substantial, that mapping out exactly why climate sensitivity
31 and other aspects of the climate simulations differ between these two generations of models would

1 be very difficult and has not been attempted. Unlike the earlier generation, the new models do not
2 use flux adjustments.

3
4 The new atmospheric models developed at GFDL for global warming studies are referred to as
5 AM2.0 and AM2.1 (GFDL Atmospheric Model Development Team, 2006). A key point of
6 departure from previous models at GFDL was the adoption of a new numerical core for solving the
7 fluid dynamical equations for the atmosphere. Much of the atmospheric development was based on
8 running the model over observed seas surface temperature and sea ice boundary conditions over the
9 period 1980-2000, with a focus on both the mean climate and the response of the atmosphere to
10 ENSO variability in the tropical Pacific. Given the basic model configuration, several subgrid
11 closures were varied to optimize aspects of the climate. Modest improvements in the midlatitude
12 wind field were obtained by adjusting a part of the model referred to as “orographic gravity wave
13 drag” which accounts for the effects of the force exerted on the atmosphere by unresolved
14 topographic features ("hills"). Substantial improvements in tropical rainfall and its response to
15 ENSO resulted from an optimization of parameters as well, especially the treatment of vertical
16 transport of horizontal momentum by moist convection.

17
18 The ocean model chosen for this development was the latest version of the Modular Ocean Model
19 developed over several decades at GFDL, notable new features in this version being a grid structure
20 better suited to simulating the Arctic ocean and a framework, that has been nearly universally
21 accepted by ocean modelers in recent years, for sub-gridscale mixing that avoids unphysical mixing
22 between oceanic layers of differing densities (Gent and McWilliams, 1990). A new sea ice model
23 includes the large-scale effective rheology that has proven itself in the past decade in several
24 models, and multiple ice thickness/lead classes in each grid box. The land model chosen was
25 relatively simple, with vertically resolved soil temperature but retaining the “bucket hydrology”
26 from the earlier generation of models.

27
28 The resulting climate model was studied, restructured, and tuned for an extended period, with
29 particular interest in optimizing the structure and frequency of the model’s spontaneously generated
30 EL Nino events, minimizing surface temperature biases, and maintaining an Atlantic overturning

1 circulation of sufficient strength. During this development phase, climate sensitivity was monitored
2 by integrating the model to
3 equilibrium with doubled CO₂ when coupled to a "flux-adjusted slab" ocean
4 model A single model modification reduced the model's sensitivity from a value of 4.0–4.5 K to
5 values between 2.5 and 3.0 K. The change responsible for this reduction was the inclusion of a new
6 model of mixing in the planetary boundary near the Earth's surface. It was selected for inclusion in
7 the model because it generated more realistic boundary layer depths and near surface relative
8 humidities. The reduction in sensitivity resulted from modifications to the low level cloud field; the
9 size of this reduction was not anticipated.

10
11 Aerosol distributions used by the model were computed off-line from the MOZART-II model as
12 described in Horowitz, *et al.*, (2003). No attempt was made to simulate the indirect aerosol effects
13 (interactions between clouds and aerosols) as the confidence in the schemes tested was deemed
14 insufficient for inclusion in the model. In the 20th century simulations, solar variations followed the
15 prescription of Lean *et al.*, (1995), while volcanic forcing was estimated from observations.
16 Stratospheric ozone was prescribed, with the Southern Hemisphere ozone hole prescribed, in
17 particular, in the 20th century simulations. A new detailed land-use history provided a time-history
18 of vegetation-types.

19
20 Final tuning of the global energy balance of the model, using two parameters in the cloud prediction
21 scheme, was conducted by examining control simulations of the fully coupled model using fixed
22 1860 and 1990 forcings. The IPCC-relevant runs of the resulting model (CM2.0) were provided to
23 the CMIP-3/IPCC archive under considerable time pressure.

24
25 The simulations of the 20th century with time-varying forcings provided to the database were the
26 first simulations of this kind generated with this model. There was no retuning of the model, and no
27 iteration of the aerosol or any other time-varying forcings, at this point.

28
29 Model development efforts proceeded in the interim, and a new version of the model emerged
30 rather quickly in which the numerical core of the atmospheric model was replaced by a "finite-
31 volume" code (Lin and Rood, 1996), substantially improving the wind fields near the surface. These

1 improved winds in turn resulted in improved extratropical ocean circulation and temperatures.
2 ENSO variability increased in this model, to unrealistically large values. But the efficiency of the
3 ocean code was also improved substantially, and with a retuning of the clouds for global energy
4 balance, the new model, CM2.1, was deemed to be a substantial enough improvement to warrant
5 generating a new set of runs for the database. CM2.1 when run with a slab ocean model was found
6 to have a somewhat increased sensitivity, (3.3K). However, the transient climate sensitivity, the
7 global mean warming at the time of CO₂ doubling in a fully-coupled model with 1%/yr increasing
8 CO₂, is actually slightly smaller than in CM2.0.
9 The solar, aerosol, volcanic, and greenhouse gas forcings are identical in the two models.

10

11 **The Community Climate System Model Development Path**

12

13 A new version of the Community Climate System Model, version 3 (CCSM3) has been
14 developed, and was released to the climate community in June, 2004. CCSM3 is a coupled climate
15 model with components representing the atmosphere, ocean, sea ice, and land surface connected by
16 a flux coupler. CCSM3 is designed to produce realistic
17 simulations over a wide range of spatial resolutions, enabling inexpensive simulations lasting
18 several millennia or detailed studies of continental-scale dynamics, variability, and climate change.
19 Twenty six papers documenting all aspects of the CCSM3, and runs performed with it, were
20 published in a *Journal of Climate Special Issue*, Vol 19, No 11, June 2006. Three different
21 resolutions of the model are supported. The highest resolution is the configuration used for climate-
22 change simulations, with a T85 grid for the atmosphere and land, and a grid with approximately 1°
23 resolution for the ocean and sea-ice, but finer meridional resolution near the equator. The second
24 resolution is a T42 grid for the atmosphere and land, with the 1° ocean and sea-ice resolution. There
25 is also a lower resolution version, designed for Paleoclimate studies, that has T31 resolution for the
26 atmosphere and land, and a 3° version of the ocean and sea ice.

27

28 The new version of the CCSM3 incorporates several significant improvements in the physical
29 parameterizations. The enhancements in the model physics are designed to reduce or eliminate
30 several systematic biases in the mean climate produced by previous versions of CCSM. These
31 include new treatments of cloud processes, aerosol radiative forcing, land-atmosphere fluxes, ocean

1 mixed-layer processes, and sea-ice dynamics. There are significant improvements in the sea-ice
2 thickness, polar radiation budgets, tropical sea-surface temperatures, and cloud radiative effects.
3 CCSM3 produces stable
4 climate simulations of millennial duration without ad hoc adjustments to the fluxes exchanged
5 among the component models. Nonetheless, there are still systematic biases in the ocean-
6 atmosphere fluxes in coastal regions west of continents, the spectrum of ENSO variability, the
7 spatial distribution of precipitation in the tropical oceans, and continental precipitation and surface
8 air temperatures. Work is underway to produce the next version of the CCSM, which will reduce
9 these biases further, and to extend the CCSM to a more accurate and comprehensive model of the
10 complete Earth's climate system.

11
12 The climate sensitivity of the CCSM3 has a weak dependence on the resolution used.
13 The equilibrium temperature increase due to a doubling of carbon dioxide, using a slab ocean
14 model, is 2.71C, 2.47C, and 2.32C, respectively, for the T85, T42, and T31 atmosphere resolutions.
15 The transient climate response to doubling carbon dioxide in fully coupled integrations is much less
16 dependent on resolution, being 1.50C, 1.48C, and 1.43C, respectively, for the T85, T42, and T31
17 atmosphere resolutions, see the Kiehl *et al.* paper in the *Journal of Climate Special Issue*, Vol 19,
18 No 11, June 2006, 2584–2596.

19
20 For the IPCC Fourth Assessment Report, the following CCSM3 runs were submitted for evaluation,
21 and to PCMDI for dissemination to the climate scientific community. Long, present day and 1870
22 control runs, an ensemble of eight 20th century runs, and smaller ensembles of future scenario runs
23 for the A2, A1B, and B1 scenarios, and for the 20th century commitment run, where the carbon
24 dioxide levels were kept at their 2000 values.

25 The control and 20th century runs are documented and analysed in several papers in the *Journal of*
26 *Climate Special Issue*, and the future climate change projections using the CCSM3 are documented
27 by Meehl *et al* (2006).

28

29 **The GISS Development Path**

30

1 The most recent version of the GISS atmospheric GCM, modelE, resulted from a substantial
2 reworking of the previous version, model II'. While the model physics has become more
3 sophisticated, execution by the user is simplified as a result of modern software engineering and
4 improved model documentation embedded within the code and accompanying web pages. The
5 model can be downloaded from the GISS website by outside users, and is designed to run on myriad
6 platforms ranging from laptops to a variety of multi-processor computers, partly as the result of the
7 rapidly shifting computing environment at NASA. The most recent (post-AR4) version can be run
8 on an arbitrarily large number of processors.

9
10 Historically, GISS has eschewed flux adjustment. Nonetheless, the net energy flux at the top of
11 atmosphere and surface have been reduced to near zero, by adjusting the threshold relative humidity
12 for water and ice cloud formation, two parameters that are otherwise weakly constrained by
13 observations. Near-zero fluxes at these levels are necessary to minimize drift of either the ocean or
14 the coupled climate.

15
16 To assess the sensitivity of the climate response to the treatment of the ocean, modelE has been
17 coupled to a slab-ocean model with prescribed horizontal heat transport, along with two ocean
18 GCMs. One GCM, the Russell ocean (Russell *et al.*, 1995), has 13 vertical layers and horizontal
19 resolution of 4° latitude by 5° longitude, and is mass conserving (rather than volume conserving like
20 the GFDL MOM). Alternatively, ModelE is coupled to the Hybrid Coordinate Ocean Model
21 (HYCOM), an isopycnal model developed originally at the University of Miami (Sun and Bleck,
22 2006). HYCOM has 2° latitude by 2° longitude resolution at the equator, with the latitudinal
23 spacing decreasing poleward with the cosine of latitude. A separate rectilinear grid is used in the
24 Arctic to avoid the polar singularity, and joins the spherical grid around 60 N.

25
26 Climate sensitivity to doubling of CO₂ depends upon the ocean model due to differences in sea-ice.
27 For the slab-ocean model, the climate sensitivity is 2.7 C, and 2.9 C for the Russell ocean (Hansen
28 *et al* 2005). As at GFDL and CCSM, no effort is made to match a particular sensitivity, nor is the
29 sensitivity or forcing adjusted to match 20th century climate trends (Hansen *et al* 2007). Aerosol
30 forcing is calculated from prescribed concentration, computed offline by a physical model of the
31 aerosol life cycle. In contrast to the GFDL and NCAR models, modelE includes a representation of

1 the aerosol indirect effect. Cloud droplet formation is related empirically to the availability of cloud
2 condensation nuclei, which depends upon the prescribed aerosol concentration (Menon and Del
3 Genio 2005).

4
5 Flexability is emphasized in model development (Schmidt *et al.*, 2006). ModelE is designed for a
6 variety of applications, ranging from simulation of stratospheric dynamics and the middle
7 atmosphere response to solar forcing, to projection of twenty-first century trends in surface climate.
8 Horizontal resolution is typically 4° latitude by 5° longitude, although twice the resolution is more
9 often used for studies of cloud processes. The model top has been raised from 10 mb (as in the
10 previous model II') to 0.1 mb, so that the top has less influence upon the stratospheric circulation.
11 Coding emphasizes “plug-and-play” structure, so that the model can be easily adapted for future
12 needs, such as fully interactive carbon and nitrogen cycles.

13
14 Model development is devoted to improving the realism of individual model parameterizations,
15 such as the planetary boundary layer, or sea ice dynamics. Because of the variety of applications,
16 relatively little emphasis is placed upon optimizing the simulation of specific phenomena such as El
17 Nino or the Atlantic thermohaline circulation; as noted above, successful reproduction of one
18 phenomena usually results in a sub-optimal simulation of another. Nonetheless, some effort was
19 made to reduce biases in previous versions of the model that emerged from the interaction of
20 various features of the model, such as subtropical low clouds, tropical rainfall, and variability of the
21 stratospheric winds. Some of the model adjustments were structural, as opposed to the adjustment
22 of a particular parameter: for example, the introduction of a new planetary boundary layer
23 parameterization that reduced the unrealistic formation of clouds in the lowest model level (Schmidt
24 *et al.*, 2006).

25
26 Because of their uniform horizontal coverage, satellite retrievals are emphasized for model
27 evaluation, like Earth Radiation Budget Experiment fluxes at TOA, Microwave Sounding Unit
28 channels 2 (troposphere) and 4 (stratosphere) temperatures, and International Satellite Cloud
29 Climatology Project (ISCCP) diagnostics. Comparison to ISCCP is through a special algorithm that
30 samples the GCM output to mimic data collection by an orbiting satellite. For example, high clouds
31 may include contributions from lower levels in both the model and the downward looking satellite

1 instrument. This satellite perspective within the model allows a rigorous comparison to
2 observations. In addition to satellite retrievals, some GCM fields like zonal wind are compared to
3 in situ observations adjusted by the ERA-40 reanalyses. Surface air temperature is taken from the
4 Climate Research Unit (Jones *et al.*, 1999).

6 **Common problems**

7
8 The CCSM and GFDL Development Teams met several times during this period to compare
9 experiences and discuss common biases in the two models. A topic of considerable discussion and
10 concern, for example, was the tendency for too strong an equatorial cold tongue in the Eastern
11 Equatorial Pacific and associated problems with the pattern of precipitation (often referred to as the
12 “double ITCZ problem”). It was noted in these meetings that the climate sensitivities of the two
13 models had converged to some extent from an earlier generation in which the NCAR model was on
14 the low end of the canonical sensitivity range of 1.5–4.5K, while the GFDL model had been near
15 the high end. This convergence in the global mean was considered by the teams to be coincidental;
16 it was not a consequence of any specific actions taken so as to engineer convergence, and did not
17 reflect convergence either in the specifics of the cloud feedback processes that resulted in these
18 sensitivity changes, nor in the regional temperature changes than make up these global mean values.

19
20 A procedure common to each of these three models, and to all other comprehensive climate models,
21 is a tuning of the global mean energy balance. A climate model must be in balance at the top of the
22 atmosphere and globally averaged, to within a few tenths of a W/m^2 in its control (pre-1860)
23 climate if it is to avoid temperature drifts in 20th and 21st century simulations that would obscure the
24 response to the imposed changes in greenhouse, aerosol, volcanic, and solar forcings. Especially
25 because of the difficulty in modeling clouds, but even in the clear sky, untuned models do not
26 currently possess this level of accuracy in their radiative fluxes. The imbalances are more typically
27 range up to 5 W/m^2 or more. Parameters in the cloud scheme are then altered to create a balanced
28 state, often taking care that the individual components of this balance, the absorbed solar flux and
29 emitted infrared flux, are individually in agreement with observations, since these help insure the
30 correct distribution of the heating between atmosphere and ocean. This is occasionally referred to as

1 the “final tuning” of the model, to distinguish it from the various choices made with other
2 motivations while one is configuring the model.

3
4 The need for this final tuning does not preclude the use of these models for global warming
5 simulations, in which the radiative forcing is itself of the order of several W/m^2 . Consider for
6 example, the study of Ramaswamy *et al.*, (2001) of the effects of modifying the treatment of the
7 “water vapor continuum” in a climate model. This is an aspect of the radiative transfer algorithm in
8 which there is significant uncertainty. While modifying the treatment of the continuum can change
9 the top-of-atmosphere balance by more than 1 W/m^2 , the effect on climate sensitivity is found to be
10 insignificant. The change in radiative transfer in this instance alters the outgoing infrared flux by
11 roughly 1% , and it affects the sensitivity (by altering the derivative of the flux with respect to
12 temperature) by roughly the same percentage. But a change in sensitivity of this magnitude, say
13 from 3K to 3.03K, is of little consequence given uncertainties in the cloud feedbacks. It is some
14 aspects of the models that affect the strengths of temperature-dependent feedbacks that are of
15 particular concern, not errors in mean fluxes *per se*.

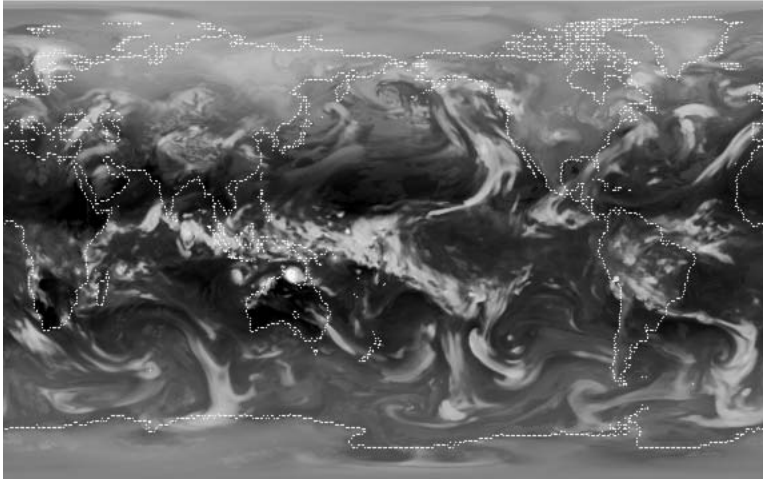
16

17 **Reductive vs. holistic evaluation of models:**

18

19 In order to evaluate models, appreciation is needed of their structure. For example, the discussion
20 of the climatic response to increasing greenhouse gases is intimately related to the question of how
21 the infrared radiation escaping to space is controlled. When summarizing the results from climate
22 models, one often speaks and thinks in terms of a simple energy balance model in which the global
23 mean infrared energy escaping to space is a single number that has a simple dependence on global
24 mean surface temperature. Water vapor or cloud feedbacks are often incorporated into such global
25 mean energy balance models with simple empirical relationships that can easily be tailored to
26 generate a desired result. In contrast, Figure II D shows a snapshot at an instant in time of the
27 infrared radiation escaping to space in the kind of atmospheric general circulation model discussed
28 in this report. The detailed distributions of clouds and water vapor simulated by the model,
29 transported by the model’s evolving wind fields, create complex patterns in space and time that, if
30 the simulation is sufficiently realistic, resemble the images seen from satellites viewing the Earth at
31 infrared wavelengths.

1 Figure II D



2
3
4
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A snapshot in time of the infrared radiation escaping to space in a version of the atmospheric model AM2 (GAMDT, 2004) constructed at NOAA's Geophysical Fluid Dynamics Laboratory. The energy emitted is largest in the darkest areas and smallest in the brightest areas. (This version of the atmospheric model has higher resolution than that used for the simulations in the CMIP3 archive (50 km rather than 200km)but other than resolution it uses the same numerical algorithm.)

1 This class of model evolves the state of the atmosphere/land system forward in time, starting from
2 some initial condition. It consists of rules that generate this state (temperature, winds, water vapor,
3 clouds, rainfall rate, water storage in the land, land surface temperature) from the preceding state, in
4 this case one half hour earlier. By this process it evolves the “weather” over the Earth. To change
5 the way in which this model’s infrared radiation reacts to increasing temperatures, one would need
6 to modify these rules.

7

8 The goal of the climate modeling enterprise is to decrease the level of empiricism and to base
9 models as much as possible on well-established physical principles. This goal is pursued primarily
10 by decomposing the climate system into a number of relatively simple processes and interactions,
11 and by focusing on the rules governing the evolution of these individual processes, rather than
12 working with more holistic concepts such as the global mean infrared radiation escaping to space,
13 the average summertime rainfall over Africa, or the average wintertime surface pressure over the
14 Arctic. These are all outcomes of the model, determined by the set of reductive rules that govern
15 the model’s evolution.

16

17 Suppose one is interested in how ocean temperatures affect rainfall over Africa. One can develop
18 an empirical, holistic, model, using observations and standard statistical techniques, in which one
19 “fits” the model to these observations. Alternatively, one can try to use a general circulation model
20 of the sort pictured above, which does not deal directly with a high level climate output such as
21 African rainfall averaged over some period, but rather attempts to simulate the inner workings, or
22 dynamics, of the climate system at a much finer level of granularity. To the extent that the
23 simulation is successful and convincing, with analysis and manipulation of the model one can hope
24 to uncover the detailed physical mechanisms underlying this causal connection. The resulting fit
25 may or may not be as good as the fit obtained with the explicitly tuned statistical model, but a
26 reductive model ideally provides a different level of confidence in its explanatory and predictive
27 power. See, for example, Hoerling, et al 2006 for an analysis of African rainfall/ocean temperature
28 relationships in a set of atmospheric GCMs.

29

30 Our confidence in the explanatory and predictive power of climate models grows based on their
31 ability to simulate many aspects of the climate system *simultaneously* with the same set of

1 physically based rules. When one evaluates a models ability to simulate the evolution of the global
2 mean temperature evolution over the 20th century, it is important to try to make this evaluation in
3 the context of the model's simultaneous capacity to simulate the seasonal cycle of the Asian
4 monsoons, for example, and it ability to generate the poleward shift of the jet stream in the Southern
5 hemisphere over the past 30 years that has impacted rainfall over southern Australia, and its ability
6 to spontaneously generate El-Nino's of the correct frequency and spatial structure and to capture the
7 effects of El Nino on rainfall and clouds. The quality of the simulation in all of these respects adds
8 confidence in the reductive rules being used to generate the simultaneous simulation of all of these
9 phenomena.

10
11 A difficulty that we will return to frequently in this report is that of relating the qualities of a climate
12 simulation to a level of confidence in the model's ability to predict climate change.

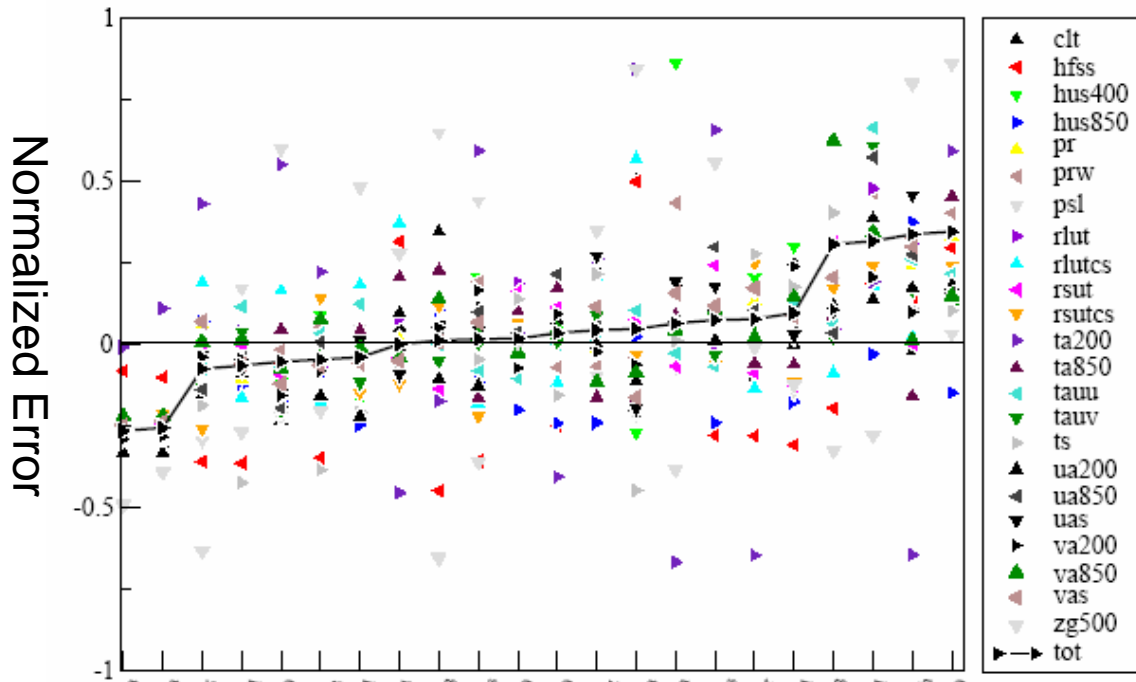
13 14 *The use of model metrics*

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16 Recently, objective evaluation of models has exploded with the wide availability of model
17 simulation results in the CMIP3 model database (Meehl, et al, 2006). One important area of
18 research is in the design of of metrics to test the ability of models to simulate well observed climate
19 features (Reichler and Kim, 2007; Gleckler, et al., 2007). It is unclear which aspects of observed
20 climate must be simulated to ensure reliable future predictions. For example, it is not clear that the
21 most realiable climate projections for temperature over North America are obtained from models
22 that simulate the most realistic present-day temperatures for North America. The projected climate
23 changes in North America may depend strongly on the changes in ocean temperature in the tropical
24 Pacific Ocean, and the manner in which the jet stream over the Pacific responds to these changes in
25 temperature. The quality of a models simulation of atmosphere-ocean cpoupling over the Pacific
26 could potentially be a more relevant metric of quality in this instance. However, metrics can
27 provide guidance about the overall strength and weaknesses of individual models as well as the
28 general state of modeling.

29
30 The use of metrics can also inform the community as why it is impossible at this time to determine
31 which is the "best" climate model. In Figure II E below, each of the colored triangles represents a

1 different metric for which each model was evaluated, for example, “ts” represents surface
2 temperature. The figure displays the relative error value for a variety of metrics, for each model,
3 represented by a vertical column above each tick mark on the horizontal axis. Values less than zero
4 represent a better than average simulation of a particular field measured by the metric, while values
5 greater than zero show models with errors greater than the average. The black triangles connected
6 by the dashed line represent the normalized sum from the errors of all 23 fields. The models were
7 then ranked from left to right based on the value of this total error. As can be seen, the models with
8 the lowest total error, tend to also score better than average in most individual metrics, however, the
9 “best” models do not score the best for every metric. For an individual application, the model with
10 the lowest total error may not be the best choice.

1
2 Figure II E – Model metrics for 23 different climate fields. Values less than 0 indicate an error less
3 than the average CMIP3 model, while values greater than 0 show values greater than the average.
4 The black triangles connected by the black line is a total score obtained by averaging all 23 fields.



Model (each model is a tick mark)

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Climate simulations discussed in this report

Three types of climate simulation are discussed in this report. They differ according to the climate forcing factors used as input to the models:

Control runs use constant forcing. (The name “control runs” originated in comparing them with the other simulation types discussed below.) The Sun’s energy output and the atmospheric concentrations of carbon dioxide and other gases and aerosols do not change in control runs. As with the other types of climate simulation, day-night and seasonal variations occur, as well as internal “oscillations” such as ENSO (see below). Other than these variations, the control run of a well-behaved climate model is expected to reach a steady state eventually.

Values of control-run forcing factors are typically set to match present-day conditions, and model output is then compared with present-day observations. Actually, the present climate is affected not only by current forcing but also by the history of forcing over time—in particular past emissions of greenhouse gases—but present-day control run output and observations are expected to agree fairly closely if models are reasonably accurate. We compare model control runs with observations in Chapter V below.

Idealized climate simulations are aimed at understanding important processes in models and in the real world. They include experiments in which the amount of atmospheric carbon dioxide increases at precisely 1% per year (about twice the present rate of increase) or doubles instantaneously. The carbon dioxide doubling experiments are typically run until the simulated climate reaches a steady state in equilibrium with the enhanced greenhouse effect. Until the mid-1990’s, idealized simulations were often employed to assess possible future climate changes including human-induced global warming. Recently, however, the more realistic time-evolving simulations defined immediately below have been used for making climate predictions. We discuss idealized simulations and their implications for climate sensitivity in Chapter IV below.

1 **Time-dependent climate forcing simulations** are the most realistic, especially for eras in which
2 climate forcing is changing rapidly such as the 20th and 21st centuries. Input for the 20th century
3 simulations includes observed time-varying values of solar energy output, atmospheric carbon
4 dioxide, and other climate-relevant gases and aerosols including those produced in volcanic
5 eruptions. Each modeling group uses its own best estimate of these factors. There are significant
6 uncertainties in many of them, especially atmospheric aerosols, so that different models use
7 somewhat different input for their 20th century simulations. We discuss these simulations in Chapter
8 V after comparing control runs with observations.

9
10 Time-evolving climate forcing is also used as input for modeling future climate change. This
11 subject is discussed in CCSP Synthesis and Assessment Product 3.2. Finally, we mention for the
12 record simulations of the distant past (various time periods ranging from the early Earth up to the
13 19th century). These simulations are not discussed in this report, but some of them have been used to
14 loosely “paleocalibrate” simulations of the more recent past and the future (Hoffert and Covey,
15 1992; Hansen *et al.*, 2006; Hegerl *et al.*, 2006).

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Chapter III – The Added Value of Regional Climate Model Simulations

Types of downscaling simulations

This section focuses on downscaling using three-dimensional models based on fundamental conservation laws, i.e., numerical models with a similar basis as GCMs. A later section of the chapter discusses an alternative approach, statistical downscaling. There are three primary approaches to numerical downscaling: limited-area models (Giorgi and Mearns, 1991; McGregor, 1997; Giorgi and Mearns, 1999; Wang *et al.*, 2004), stretched grid models (e.g., Deque *et al.*, 1995; Fox-Rabinovitz *et al.*, 2001, 2006) and uniformly high-resolution atmospheric GCMs (AGCMs) (e.g., Brankovic and Gregory, 2001; May and Roeckner, 2001; Duffy *et al.*, 2003; Coppola and Giorgi, 2005). The last approach is sometimes called “time-slice” climate simulation because the AGCM simulates a portion of the period simulated by the parent, coarser resolution GCM that supplies boundary conditions to it. The limited-area models, also known as regional climate models (RCMs), have the most widespread use. All three approaches use interactive land models, but sea-surface temperatures and sea ice are generally specified from observations or an atmosphere-ocean GCM. All three approaches are also used for purposes beyond downscaling global simulations, most especially to study climatic processes and interactions on scales too fine for typical GCM resolutions.

RCMs, as limited-area models, cover only a portion of the planet, typical a continental domain or smaller. They require lateral boundary conditions from observations, such as atmospheric analyses (e.g., Kanamitsu *et al.* 2002, Uppala *et al.* 2005), or a global simulation. There has been limited two-way coupling wherein an RCM to supplies part of its output back to the parent GCM (Lorenz and Jacob, 2005). Simulations with observation-based boundary conditions are used not only for studying fine scale climatic behavior, but also to help segregate GCM error from error intrinsic to the RCM when performing climate-change simulations (Pan *et al.*, 2001). RCMs may also use grids nested inside a coarser RCM simulation to achieve higher resolution in subregions (e.g. Liang *et al.*, 2001; Hay *et al.*, 2006). Stretched-grid models, like the high-resolution AGCMs, simulate the

1 globe, but with spatial resolution varying horizontally. Highest resolution may focus on one (e.g.
2 Deque and Piedelievre, 1995; Hope *et al.*, 2004) or a few regions (e.g., Fox-Rabinovitz *et al.*, 2002).
3 In some sense, high-resolution AGCMs are a limiting case of stretched-grid simulations where the
4 grid is uniformly high everywhere.

5
6 Highest spatial resolutions are most often several tens of kilometers, though some (e.g., Grell *et al.*,
7 2000a,b; Hay *et al.*, 2006) have simulated climate with resolutions as small as a few kilometers
8 using multiply nested grids. Duffy *et al.* (2003) have performed multiple AGCM time-slice
9 computations using the same model to simulate resolutions from 310 km down to 55 km. Such
10 approaches expose changes in climate with resolution. Higher resolution generally yields improved
11 climate, especially for fields with high spatial variability, such as precipitation. For example, some
12 studies show that higher resolution does not have a statistically significant advantage in simulating
13 large-scale circulation patterns but it does yield better monsoon precipitation forecasts and
14 interannual variability (Mo *et al.*, 2005) and precipitation intensity (Roads *et al.*, 2003).

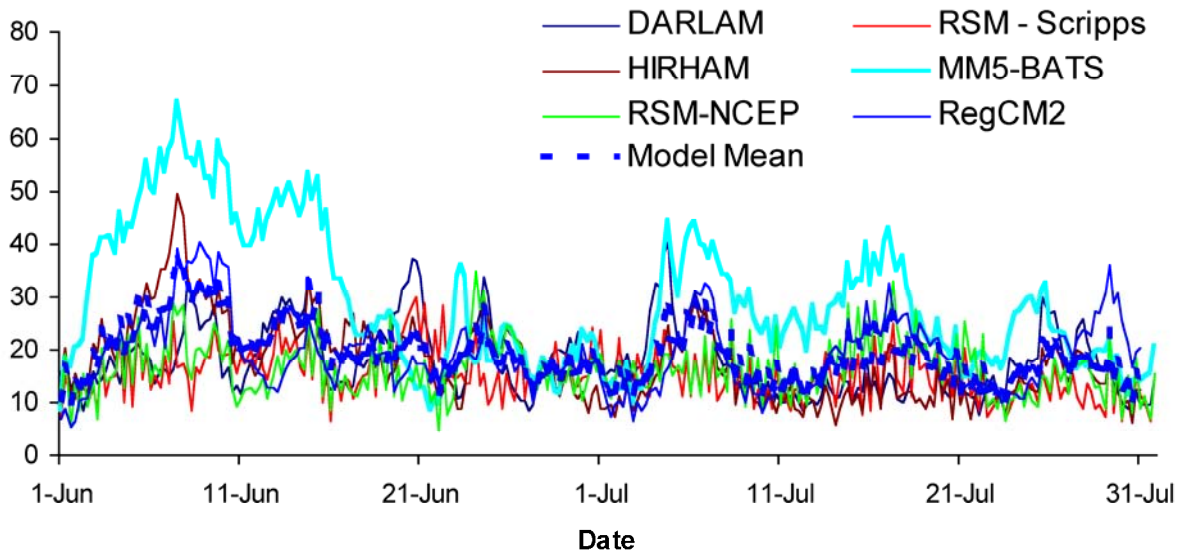
15
16 However, improvement is not guaranteed: Hay *et al.* (2006) find deteriorating timing and intensity
17 of simulated precipitation versus observations in their inner, high-resolution nests, even though the
18 inner nest improves resolution of topography. Extratropical storm tracks in a time-slice AGCM
19 may shift poleward relative to the parent, coarser GCM (Stratton, 1999; Roeckner *et al.*, 2006) or
20 lower resolution versions of the same AGCM (Brankovic and Gregory, 2001), thus yielding an
21 altered climate with the same sea-surface temperature distribution as the parent model.

22
23 Spatial resolution affects the length of simulation periods because higher resolution requires shorter
24 time steps for numerical stability and accuracy. Required time steps scale with the inverse of
25 resolution and can be one or two orders of magnitude smaller than AOGCM time steps. Since
26 increases in resolution are most often applied to both horizontal directions, this means that
27 computation demand varies inversely with the cube of resolution. Although several RCM
28 simulations have lasted 20 to 30 years (Christensen *et al.*, 2002; Leung *et al.*, 2004; Plummer *et al.*,
29 2006) and even as long as 140 years (McGregor, 1999) with no serious drift away from reality,
30 stretched-grid, time-slice AGCM and RCM simulations typically last from months to a few years.
31 Vertical resolution usually does not change with horizontal resolution, though Lindzen and Fox-

1 Rabinovitz (1989) and Fox-Rabinovitz and Lindzen (1993) have expressed concerns about the
2 adequacy of vertical resolution relative to horizontal resolution in climate models.
3
4 Higher resolution in RCMs and stretched-grid models must also satisfy numerical constraints.
5 Stretched-grid models whose ratio of coarsest to finest resolution exceeds a factor of roughly three
6 are likely to produce inaccurate simulation due to truncation error (Qian *et al.*, 1999). Similarly,
7 RCMs will suffer from incompletely simulated energy spectra and thus loss of accuracy if their
8 resolution is roughly 12 times or more finer than the resolution of the source of lateral boundary
9 conditions, which may be coarser RCM grids (Denis *et al.*, 2002, 2003; Laprise, 2003; Antic *et al.*,
10 2004, 2006; Dimitrijevic and Laprise 2005). In addition, these same studies indicate that lateral
11 boundary conditions should be updated more frequently than twice per day.
12
13 Additional factors also govern ingestion of lateral boundary conditions (LBCs) by RCMs. LBCs are
14 most often ingested in RCMs by damping of the model's state toward the LBC fields in a buffer
15 zone surrounding the domain of interest (Davies, 1976; Davies and Turner, 1977). If the buffer zone
16 is only a few grid points wide, the interior region may suffer phase errors in simulating synoptic-
17 scale waves (storm systems), with resulting error in the overall regional simulation (Giorgi *et*
18 *al.*,1993). Spurious reflections may also occur in at boundary regions (e.g., Miquez-Macho *et al.*,
19 2005). RCM boundaries should be where the driving data are of optimum accuracy (Liang *et al.*,
20 2001), but placing the buffer zone in a region of rapidly varying topography can induce surface
21 pressure errors due to mismatch between the smooth topography implicit in the coarse resolution
22 driving data and the varying topography resolved by the model (Hong and Juang 1998). Domain
23 size may also influence RCM results. If a domain is too large, the model's interior flow may drift
24 from the large-scale flow of the driving data set (Jones *et al.*, 1995). However, too small a domain
25 overly constrains interior dynamics, preventing the model from generating appropriate response to
26 interior mesoscale-circulation and surface conditions (Seth and Giorgi, 1998). RCMs appear to
27 perform well for domains roughly the size of the contiguous United States. **Figure III.A** shows that
28 the daily, root-mean-square difference (RMSD) between simulated and observed (reanalysis) 500
29 hPa heights is generally within observational noise levels (roughly 20 m).
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Spatially Averaged RMSD 500 hPa Geopotential Height 1 June - 31 July 1993



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Figure III. A. Daily root-mean-square differences (RMSD) in 500 hPa height between observations (reanalysis) and 6 models participating in the PIRCS 1b experiment (Anderson *et al.*, 2003). RMSD values averaged over the simulation domain inside the boundary-forcing zone. Also shown is the mean curve for the 6 models. (y-axis scale: meters).

1
2 Because simulations from the downscaling models may be analyzed for periods as short as a month,
3 model spin-up is important (e.g., Giorgi and Bi, 2000). During spin-up the model evolves to
4 conditions representative of its own climatology, which may differ from the sources of initial
5 conditions. The atmosphere spins up in a matter of days, so the key factor is spin-up of soil moisture
6 and temperature, which evolve more slowly. Equally important, data for initial conditions is often
7 lacking or has low spatial resolution, so that initial conditions may be only a poor approximation to
8 the model's climatology. Spin-up is especially relevant for downscaling because these models are
9 presumably resolving finer surface features than coarser models, with the expectation that the
10 downscaling models are providing added value through proper representation of these surface
11 features. Deep soil temperature and moisture, at depths of 1–2 meters, may require several years of
12 spin up. However, these deep layers generally interact weakly with the rest of the model, so shorter
13 spin-up times are used. For multi-year simulations, 3–4 years appears to be a minimal requirement
14 (Christensen, 1999; Roads *et al.*, 1999). This ensures that the upper meter of soil has a climatology
15 in further simulation that is consistent with the evolving atmosphere.

16
17 Many downscaling simulations, especially with RCMs, are for periods much shorter than two years.
18 Such simulations likely will not use multi-year spin up. Rather, these studies may focus on more
19 rapidly evolving atmospheric behavior that is governed by lateral boundary conditions, including
20 extreme periods like drought (Takle *et al.*, 1999) or flood (Giorgi *et al.*, 1996; Liang *et al.*, 2001;
21 Anderson *et al.*, 2003). Thus, they assume that the interaction with the surface, while not
22 negligible, is not strong enough to skew the atmospheric behavior studied. Alternatively, relatively
23 short regional simulations may specify, for sensitivity study, substantial changes in surface
24 evaporation (e.g., Paegle *et al.*, 1996), soil moisture (e.g., Xue *et al.*, 2001) or horizontal moisture
25 flux at lateral boundaries (e.g., Qian *et al.*, 2004).

26
27 Even with higher resolution than standard GCMs, models simulating regional climate still need
28 parameterizations for subgrid-scale processes, most notably boundary-layer dynamics, surface-
29 atmosphere coupling, radiative transfer and cloud microphysics. . Most regional simulations also
30 require a convection parameterization, though a few have used sufficiently fine grid-spacing, a few
31 kilometers, to allow acceptable simulation without one (e.g., Grell *et al.*, 2000). Often, these

1 parameterizations are the same or nearly the same as used in GCMs. However, all parameterizations
2 make assumptions that they are representing the statistics of subgrid processes, and so implicitly or
3 explicitly they require that the grid box's area in the real world would have sufficient samples to
4 justify the stochastic modeling. For some parameterizations, such as convection, this assumption
5 becomes doubtful when grid boxes become only a few kilometers in size (Emanuel 1994). In
6 addition, models simulating regional climate may include circulation characteristics, such as rapid
7 mesoscale circulations (jets) whose interaction with subgrid processes like convection and cloud
8 cover differs from the larger scale circulations resolved by typical GCMs. This factor is part of a
9 larger issue, that parameterizations may have regime dependence, performing better for some
10 conditions than others. For example, the Grell (1993) convection scheme is responsive to large-
11 scale tropospheric forcing, whereas the Kain and Fritsch (1993) scheme is heavily influenced by
12 boundary-layer forcing. As a result, the Grell scheme simulates better the propagation of
13 precipitation over the U.S. Great Plains that is controlled by the large-scale tropospheric forcing,
14 while the Kain–Fritsch scheme simulates better late afternoon convection peaks in the southeastern
15 U.S. that are governed by boundary-layer processes (Liang *et al.*, 2004). As a consequence,
16 parameterizations for regional simulation may differ from their GCM counterparts, especially for
17 convection and cloud microphysics. As noted earlier, the regional simulation in some cases may
18 have resolution of only a few kilometers and the convection parameterization may be discarded
19 (Grell *et al.*, 2000). A variety of parameterizations exist for each of these phenomena, with multiple
20 choices often available in a single model (e.g., Grell *et al.*, 1994; Skamarock *et al.*, 2005).

21
22 The chief reason for performing regional simulation, whether by an RCM, a stretched-grid model or
23 a time-slice AGCM, is to resolve behavior considered important for a region's climate that a global
24 model does not resolve. Thus, regional simulation should have clearly defined regional-scale
25 (mesoscale) phenomena targeted for simulation. These include, for example, tropical storms (e.g.,
26 Oouchi *et al.*, 2006), effects of mountains (e.g., Leung and Wigmosta, 1999; Grell *et al.*, 2000; Zhu
27 and Liang, 2007), jet circulations (e.g., Takle *et al.*, 1999; Anderson *et al.*, 2001; Anderson *et al.*,
28 2003; Byerle and Paegle, 2003; Pan *et al.*, 2004) and regional ocean-land interaction (e.g., Kim *et al.*,
29 2005; Diffenbaugh *et al.* 2004). The most immediate value, then, of regional simulation is to
30 explore how such phenomena operate in the climate system, which becomes a justification for the
31 expense of performing regional simulation. Phenomena and computational costs together influence

1 the design of regional simulations. Simulation periods and resolution are balances between
2 sufficient length and number of simulations for climate statistics versus computational cost. For
3 RCMs and stretched-grid models, the sizes of regions targeted for high-resolution simulation are
4 determined in part by where the phenomenon occurs.

5
6 In the context of downscaling, regional simulation offers the potential to include phenomena
7 affecting regional climate change that are not explicitly resolved in the global simulation. When
8 given boundary conditions corresponding to future climate, regional simulation can then indicate
9 how these phenomena contribute to climate change. Results, of course, are dependent on the quality
10 of the source of the boundary conditions (Pan *et al.*, 2001; de Elía *et al.*, 2002), though use of
11 multiple sources of future climate may lessen this vulnerability and offer opportunity for
12 probabilistic estimates of regional climate change (Raisanen and Palmer, 2001; Giorgi and Mearns,
13 2003; Tebaldi *et al.*, 2005). Results also depend on the physical parameterizations used in the
14 simulation (Yang and Arritt, 200; Vidale *et al.*, 2003; Déqué *et al.*, 2005; Liang *et al.*, 2006).
15 Advances in computing power suggest that typical GCMs will eventually operate at resolutions of
16 most current regional simulations (a few tens of kilometers), so that understanding and modeling
17 improvements gained for regional simulation can promote appropriate adaptation of GCMs to
18 higher resolution. For example, interaction between mesoscale jets and convection appears to
19 require parameterized representation of convective downdrafts and their influence on the jets
20 (Anderson *et al.*, 2007), behavior not required for resolutions that do not resolve mesoscale
21 circulations.

22
23 Because of the variety of numerical techniques and parameterizations employed in regional
24 simulation, many models and versions of models exist. Side-by-side comparison (e.g., Takle *et al.*,
25 1999; Anderson *et al.*, 2003; Fu *et al.*, 2005; Frei *et al.*, 2006; Rinke *et al.*, 2006) generally shows
26 no single model appearing as best versus observations, with different models showing superior
27 performance depending on the field examined. Indeed, the best results for downscaling climate
28 simulations and estimating climate-change uncertainty may come from assessing an ensemble of
29 simulations (Giorgi and Bi, 2000; Yang and Arritt, 2002; Vidale *et al.*, 2003; Déqué *et al.*, 2005).
30 Such an ensemble may capture much of the uncertainty in climate simulation, offering an
31 opportunity for physically based analysis of the climate changes and also the uncertainty of the

1 changes. Several regional models have performed simulations of climate change for parts of North
2 America, but at present, there have been no regional projections using an ensemble of regional
3 models simulating the same time periods with the same boundary conditions. Such systematic
4 evaluation has occurred in Europe [PRUDENCE (Christensen *et al.*, 2002) and ENSEMBLES
5 (Hewitt and Griggs 2007) projects] and is starting in North America with the North American
6 Regional Climate Change Assessment Program (NARCCAP 2007).

7 8 ***Empirical downscaling*** 9

10 Empirical, or statistical, downscaling is an alternative approach to obtaining regional-scale climate
11 information (Kettenberg *et al.*, 1996; Hewitson and Crane, 1996; Giorgi *et al.*, 2001; Wilby *et al.*,
12 2004, and references therein). It uses statistical relationships to link resolved behavior in GCMs
13 with climate in a targeted area. The size of the targeted area can be as small as a single point. So
14 long as significant statistical relationships occur, empirical downscaling can yield regional
15 information for any desired variable, such as precipitation and temperature, as well as variables not
16 typically simulated in climate models, such as zooplankton populations (Heyen *et al.*, 1998) and
17 initiation of flowering (Maak and von Storch, 1997). The approach encompasses a range of
18 statistical techniques from simple linear regression (e.g., Wilby *et al.*, 2000) to more complex
19 applications, such as those based on weather generators (Wilks and Wilby, 1999), canonical
20 correlation analysis (e.g., von Storch *et al.*, 1993) or artificial neural networks (e.g., Crane and
21 Hewitson, 1998). Empirical downscaling can be very inexpensive compared to numerical
22 simulation when applied to just a few locations or using simple techniques. This together with the
23 flexibility in targeted variables has led to a wide variety of applications for assessing impacts of
24 climate change.

25
26 There has been some side-by-side comparison of methods (Wilby and Wigley, 1997; Wilby *et al.*,
27 1998; Zorita and von Storch 1999; Widman *et al.*, 2003). These studies have tended to show fairly
28 good performance of relatively simple versus more complex techniques and to highlight the
29 importance of including moisture as well as circulation variables when assessing climate change.
30 There also has been comparison of statistical downscaling and regional climate simulation (Kidson
31 and Thompson, 1998; Mearns *et al.*, 1999; Wilby *et al.*, 2000; Hellstrom *et al.*, 2001; Wood *et al.*,

1 2004; Haylock *et al.*, 2006), with neither approach distinctly better or worse than the other.
2 Statistical methods, though computationally efficient, are completely dependent on the accuracy of
3 regional temperature, humidity and circulation patterns produced by their parent global models. In
4 contrast, regional climate simulation, though computationally more demanding, can improve the
5 physical realism of simulated regional climate through higher resolution and better representation of
6 important regional processes. The strengths and weaknesses of statistical downscaling and regional
7 modeling are thus complementary.

8
9

10 *Strengths and limitations of regional models*

11

12 We focus here on numerical models simulating regional climate without discussing empirical
13 downscaling because the wide range of applications using the latter undermines making a general
14 assessment of strengths and limitations.

15

16 The higher resolution in regional-scale simulations provides quantitative value to climate
17 simulation. With finer resolution, one can resolve mesoscale phenomena contributing to intense
18 precipitation, such as stronger upward motions (Jones *et al.*, 1995) and coupling between regional
19 circulations and convection (e.g., Anderson *et al.*, 2007). Time-slice AGCMs show intensified
20 storm-tracks relative to their parent model (Solman *et al.*, 2003, Roeckner *et al.*, 2006). Thus,
21 although regional models may still miss the most extreme precipitation (Gutowski *et al.*, 2003,
22 2007), they can give more intense events that will be smoothed in coarser resolution GCMs. The
23 higher resolution also includes other types of scale-dependent variability, especially short-term
24 variability such as extreme winds and locally extreme temperature that coarser resolution models
25 will smooth and thus inhibit.

26

27 Mean fields also appear to be simulated somewhat better on average versus coarser GCMs because
28 spatial variations are potentially better resolved. Thus, Giorgi *et al.*, (2001) report typical errors in
29 RCMs of less than 2°C temperature and 50% for precipitation for regions 10⁵–10⁶ km². Large-scale
30 circulation fields tend to be well simulated, at least in the extratropics.

31

1 As alluded to above, regional-scale simulations also have phenomenological value, simulating
2 processes that GCMs either cannot resolve or can resolve only poorly. These include internal
3 circulation features such as the nocturnal jet that imports substantial moisture to the center of the
4 United States and couples with convection (e.g., Byerle and Paegle, 2003; Anderson *et al.*, 2007).
5 These processes often have substantial diurnal variation and are thus important to proper simulation
6 of regional diurnal cycles of energy fluxes and precipitation. Some processes require resolving
7 surface features too coarse for typical GCM resolution, such as rapid topographic variation and its
8 influence on precipitation (e.g., Leung and Wigmosta, 1999; Hay *et al.*, 2006) and climatic
9 influences of bodies of water like the Gulf of California (e.g., Anderson *et al.*, 2001) and the North
10 American Great Lakes (Lofgren, 2004) and their downstream influences. In addition, regional
11 simulations resolve land-surface features that may be important for climate-change impacts
12 assessment, such as distributions of crops and other vegetation (Mearns, 2003; Mearns *et al.*, 2003),
13 though care is needed to obtain useful information at higher resolution (Adams *et al.*, 2003).

14
15 An important limitation for regional simulations is that they are dependent on boundary conditions
16 supplied from some other source. This applies to all three forms of numerical simulation (RCMs,
17 stretched-grid models, time-slice AGCMs), since they all typically require input sea-surface
18 temperature and ocean ice. Some RCM simulations have been coupled to a regional ocean-ice
19 model, with mixed-layer ocean (Lynch *et al.*, 1995, 2001) and a regional ocean-circulation model
20 (Rummukainen *et al.*, 2004) but this is not common. In addition, of course, RCMs require lateral
21 boundary conditions. Thus, regional simulations by these models are dependent on the quality of the
22 model or observations supplying the boundary conditions. This is especially true for projections of
23 future climate, suggesting that there is value in performing an ensemble of simulations using
24 multiple atmosphere-ocean global models to supply boundary conditions.

25 Careful evaluation is also necessary to show differences, if any, between the large-scale
26 circulation of the regional simulation and its driving data set. Generally, any tendency for the
27 regional simulation to alter biases in the parent GCM's large-scale circulation should be viewed
28 with caution (Jones *et al.*, 1995). RCM should not normally be expected to correct large-scale
29 circulation problems of parent model, unless there is a clearly understood physical basis for the
30 improvement. Clear physical reasons for the correction due to higher resolution, such as better
31 rendition of physical processes like topographic circulation (e.g., Leung and Qian, 2003), surface-

1 atmosphere interaction (Han and Roads, 2004) and convection (Liang *et al.*, 2006), must be
2 established. Otherwise, the regional simulation may simply have errors that counteract the parent
3 GCM's errors, which undermines confidence of projected future climate.
4
5 RCMs may also exhibit difficulty in outflow regions of the domain, especially for domains with
6 relatively strong cross-boundary flow, such as extratropical domains covering a single continent or
7 less. The difficulty appears to arise because storm systems may track across the RCM's domain at a
8 different speed than in the driving-data source, resulting in a mismatch of circulations at boundaries
9 where storms would be moving out of the domain. Also, there are always unresolved scales of
10 behavior, so the regional simulations are still dependent on the quality of their parameterizations for
11 the scales explicitly resolved. Finally, the higher computational demand due to shorter time steps
12 limits the length of typical simulations to two to three decades or less (e.g., Christensen *et al.*,
13 2002; NARCCAP, 2007), with few ensemble simulations to date.

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

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

6
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.

15
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
29 equilibrium warming in the table are obtained with the OGCM replaced by a slab ocean model.

1
2
3
4
5

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

6

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
10 for a single (Hadley Centre) model gives a 5-95 percentile range of ~2-6°C, again a three-fold span
11 (Piani et al. 2005, Knutti et al. 2006). The low end of the equilibrium sensitivity range is thought to
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°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

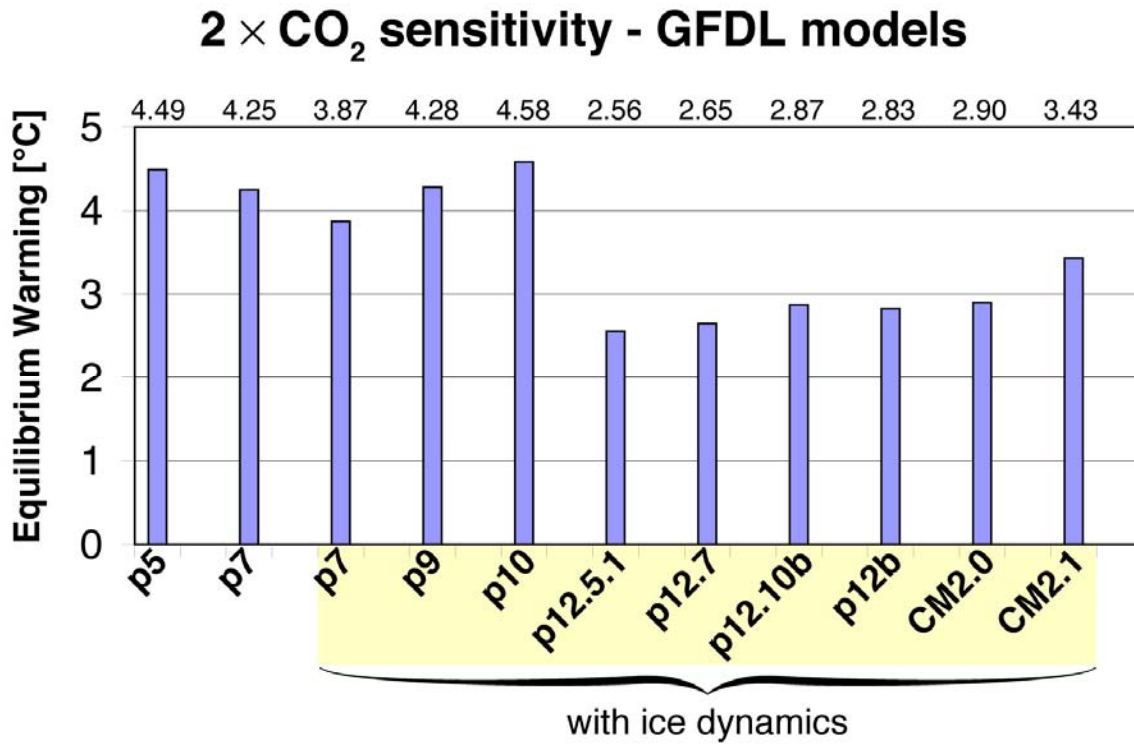
26 Climate sensitivity can be altered in a model by modifying aspects of the models that are relatively
27 poorly constrained by observations or theory. In an influential early paper, Senior and Mitchell
28 (1993, 1996) demonstrated how a seemingly minor modification to the cloud prediction scheme can
29 alter climate sensitivity. In the standard version of the model, the effective size of cloud drops is
30 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
4 Studies of the CCSM family of models provide another example of this problem. Kiehl et al.
5 (2006) found that a variety of factors are responsible for differences in climate sensitivity among the
6 models of this family. Most notably, the generally lower sensitivity of CCSM2 (evident in Table
7 IV(1)) is mainly due to a single change (relative to CSM1.4 and CCSM3) in the model's algorithm
8 for simulating convective clouds. CCSM3's formulation reflects intensive efforts to represent
9 climate processes more accurately than its predecessors CSM1.4 and CCSM2, but it is not clear
10 whether the resulting global climate sensitivity is closer to reality.

11
12 Fig. IV A below shows how equilibrium warming due to doubled atmospheric carbon dioxide
13 varied during the development of the most recent GFDL models. The dramatic drop in sensitivity
14 between model versions p10 and p12.5.1 was unexpected. It followed a reformulation of the
15 model's treatment of processes in the lower atmospheric boundary layer which, in turn, affected
16 how low level clouds in the model respond to climate change.

1



2

3

4 **Figure IV A:** Equilibrium global mean near-surface warming due to doubled atmospheric carbon
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.

1
2 Better understanding of Earth's climate sensitivity, with potential reduction in its uncertainty, will
3 require better understanding of a multitude of climate feedback processes (Bony et al. 2006). We
4 discuss two of the most important of these feedback effects below. The strengths of these feedbacks
5 are most frequently described by the resulting change in the heating of the troposphere-plus-surface
6 per degree warming of global mean temperature, in units of $W/m^2/K$.

7 8 *Cloud Feedbacks*

9
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
24 second method uses the changes in cloud radiative forcing (CRF) (Cess and Potter 1988). The CRF
25 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
27 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 $0.6 W/m^2/K$, 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.

1
2 Early GCM cloud feedback studies diagnosed positive cloud feedbacks (Hansen et al. (1984);
3 Wetherald and Manabe (1988)) using the PRP approach. In an influential work, Cess et al. (1990)
4 used the response of models to a simple warming or cooling of the oceans by 2°K as a surrogate
5 climate change and diagnosed the cloud feedbacks in 19 GCMs using the CRF approach, showing a
6 wide range of values from negative to strongly positive. Many subsequent studies with other GCMs
7 also showed large sensitivity of cloud feedbacks to the formulation of model physics (e.g., Le Treut
8 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

26 Soden and Held (2006) evaluated cloud feedbacks in 12 CMIP3 coupled models using simplified
27 PRP calculations. They showed positive cloud feedback in all models, ranging from 0.14 W/m²/K
28 to 1.18 W/m²/K. The highest values raise the equilibrium climate sensitivity from typical values of
29 2K for CO₂ doubling, a typical value in the absence of cloud feedback, to roughly 4K. Comparing
30 with the earlier studies of Cess (1990) and Coleman (2003), the spread among GCMs has become
31 somewhat smaller over the years, but it is still very substantial.

1
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.
8 (2006) and generated a negative CRF response of $-0.9 \text{ W/m}^2/\text{K}$ in the same Cess framework
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***

27
28 Analysis of the radiative feedbacks in the CMIP3 models (Soden and Held, 2006) reaffirms that
29 water vapor feedback, the increase in heat trapping due to the increase in water vapor as the climate
30 warms, is fundamental to their climate sensitivity. The strength of the water vapor feedback in these

1 models is typically close in magnitude but slightly weaker than that obtained by assuming that
2 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
20 sounding satellites, with CMIP3 20th century simulations. Both models and observations show a
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

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

3
4 The CMIP3 simulations of the water vapor climatology has also been critically analyzed (e.g.,
5 Pierce et al, 2006). Despite uncertainties in the observations, some systematic deficiencies are
6 clear, but just as for clouds, it is not straightforward to judge which kinds of deficiencies in the
7 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
17 these two effects, resulting in a net feedback ranging from 0.8-1.2 W/m²/C in the CMIP3 study of
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 21 ***Disparities In Imposed Radiative Forcing***

22
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).

1
2 The radiative forcing can be quantified in different ways, as outlined by Hansen, et al 2005. The
3 radiative response to CO₂ 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,
9 present-day forcing in GISS modelE is 1.77 W/m² when computed with fixed ocean temperatures
10 (Hansen et al. 2007), but it is 2.1 W/m² in the GFDL CM2.1 model (I. Held, personal
11 communication) using the same definition, while it is 2.6 W/m² 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/m², and the corresponding median among the climate models is higher by only 0.1 W/m².
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.

11
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
28 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/m^2 (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).

27
28 Land use changes are also uncertain, and can be of considerable significance locally, but global
29 models typically show very modest global responses, as discussed in Hegerl and Zwiers, 2007.

30

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
6 more uncertain. Given the solar reconstructions in use in the CMIP3 models, much of the early 20th
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
10 use the observed late 20th century warming to provide a sharp constraint on climate sensitivity. We
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 CO₂ 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.

31

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": κ 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*

22

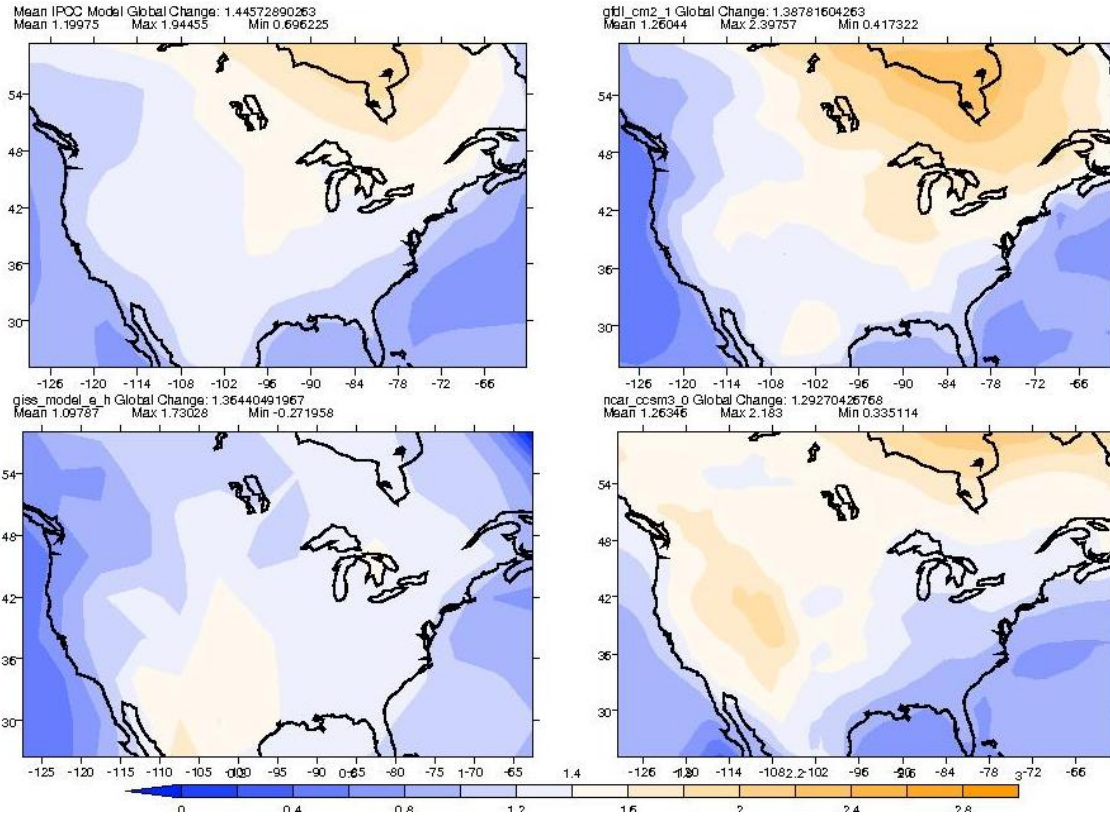
23 This chapter -- and most investigations -- emphasize the global and annual mean of surface
24 temperature change, even though practical applications of climate change science involve particular
25 seasons and locations. The underlying assumption is that local climate impacts scale with changes
26 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

1 similarity of the four maps indicates a rough agreement of "scaled" regional warming among the
2 models. The agreement occurs despite ~50% differences in globally averaged surface temperature
3 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

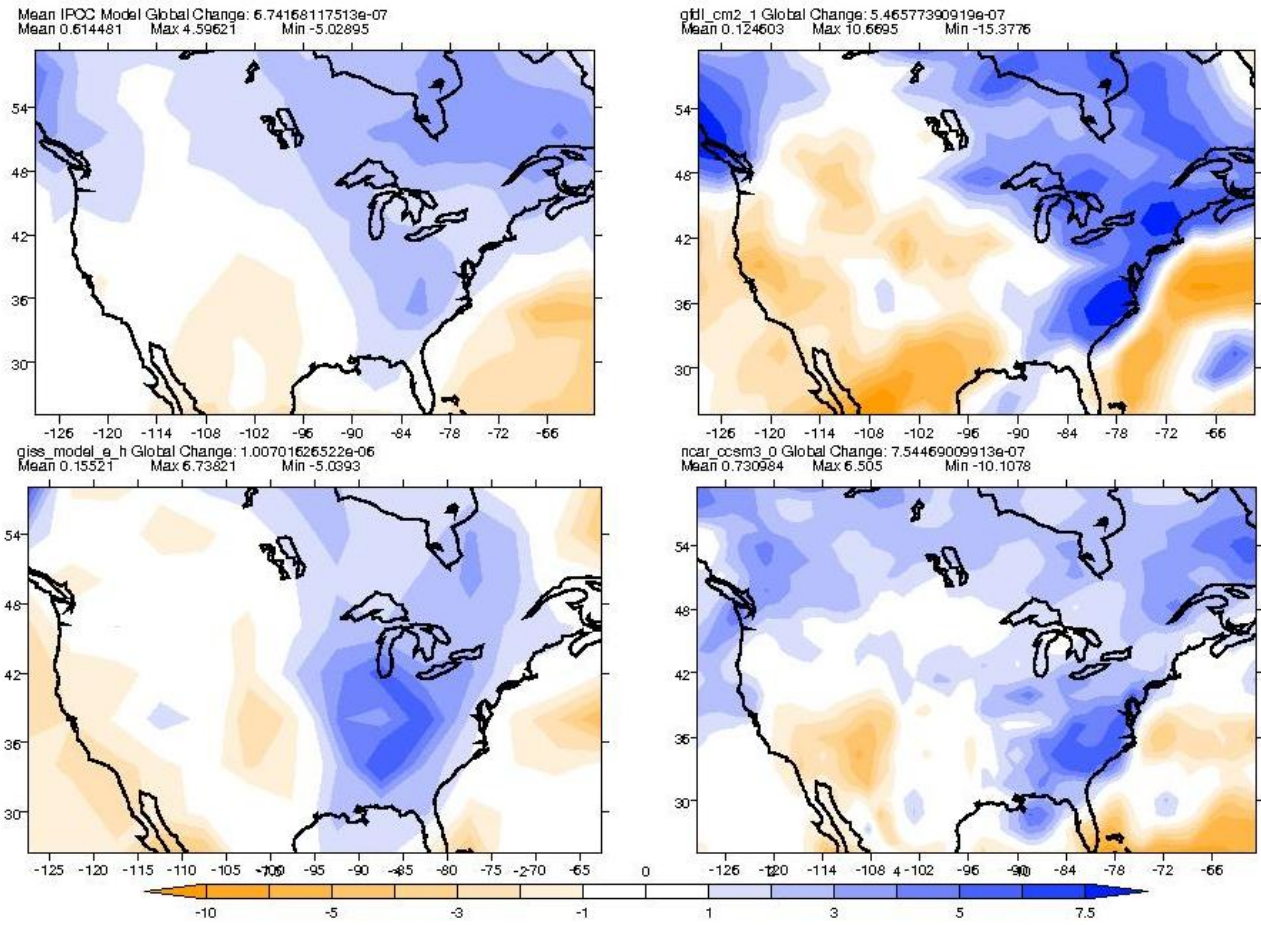


4

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

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Change in pr over North America relative to global change



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1 **Chapter V: Model simulation of major climate features**

2

3 **Mean climate**

4

5 Monthly mean near-surface temperature is well simulated by modern AOGCMs. This success
6 occurs despite the fact that nearly all models now allow the ocean and atmosphere to exchange heat
7 and water without explicitly forcing agreement with observation by artificial adjustment to air-sea
8 fluxes. Figure V A quantifies the extent of agreement between simulations by several models and
9 observations for both temperature and precipitation (the triangular points will be discussed in
10 Chapter VI below). Each model's temperature or precipitation simulation produces a single point on
11 the diagram, but in the figure, the ranges of results from all the models are shown as shaded areas.

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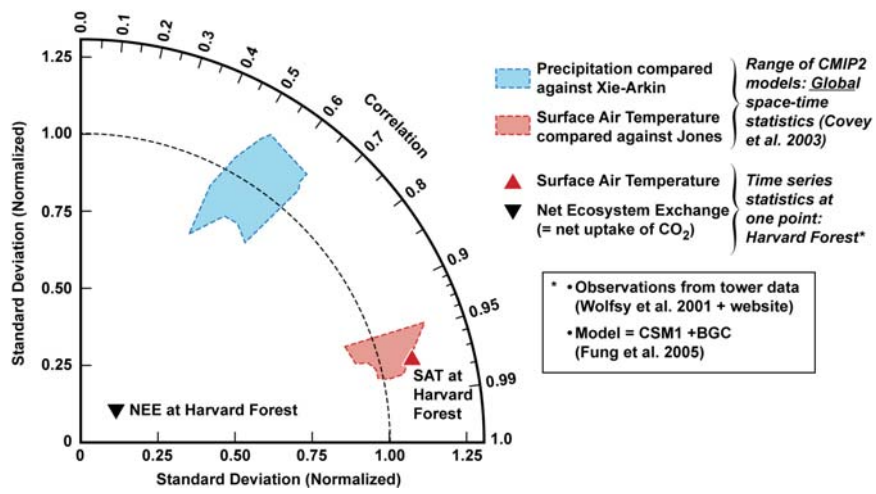


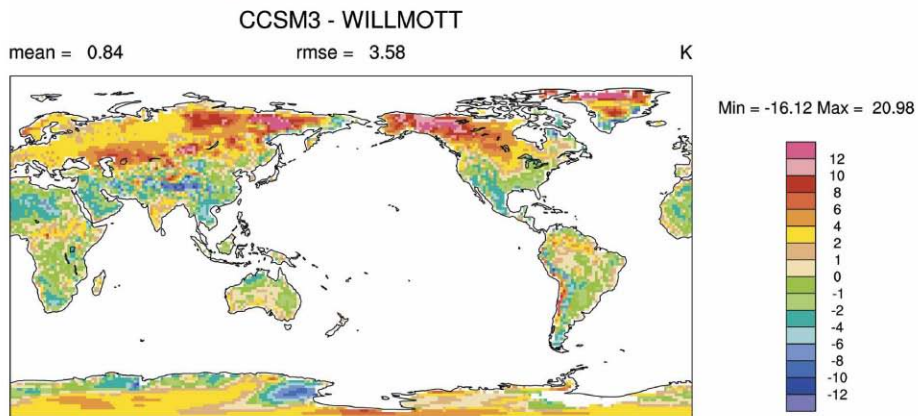
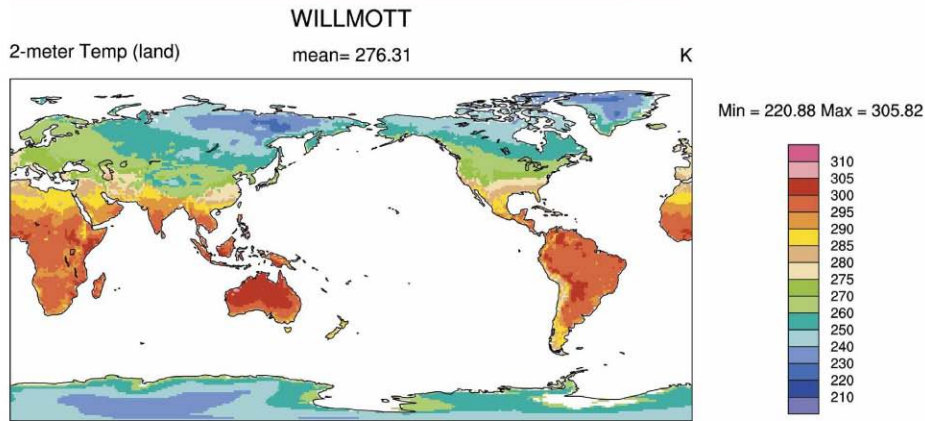
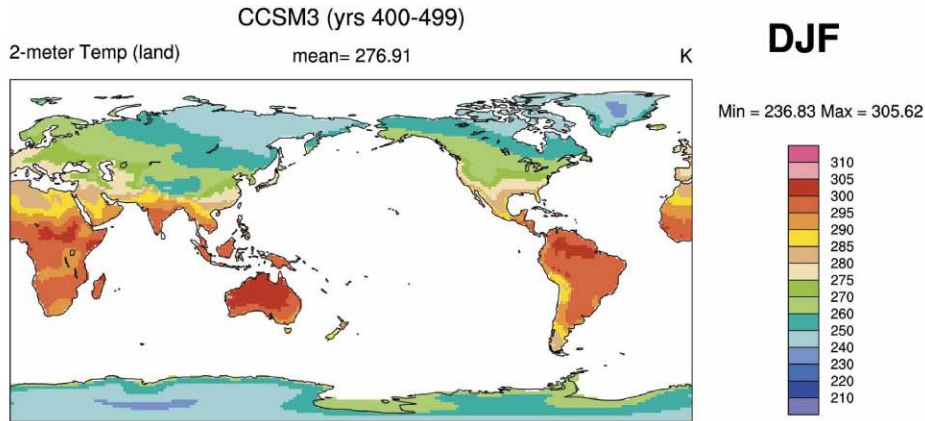
Figure V. A. Taylor Diagram of CMIP3 models

1 This type of diagram (Taylor 2001) displays the overall space-time correlation between simulated
2 and observed variables as an angular coordinate. A 100% perfect correlation would place a point
3 along the horizontal direction to the right, while zero correlation would place a point along the
4 upward vertical direction. Looking at the red-shaded area that depicts the range of near-surface
5 temperature simulations, one sees a remarkable 95–98% correlation with observations. The second
6 independent (radial) coordinate in the diagram gives the ratio of simulated to observed amplitude
7 for the variations that are being correlated. A value of 1.0 indicates perfect agreement of the
8 amplitudes. In this coordinate system, complete agreement between simulation and observation in
9 both dimensions would place a point where the dashed semicircle and the horizontal line intersect.
10 The distance from this point to the actual point for any given model is proportional to the combined
11 root-mean-square model error in both space and time dimensions. Temperature points for all of the
12 models lie very close to complete agreement with observation—indeed nearly within the
13 uncertainty range of the observations themselves (Covey *et al.*, 2003).

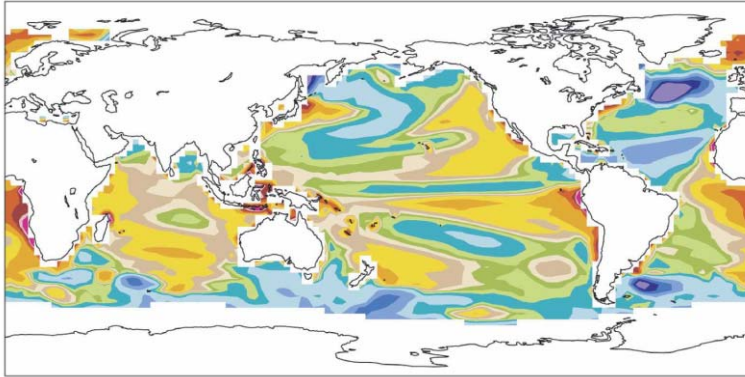
14
15 For monthly mean precipitation, AOGCM simulations are considerably less precise than for
16 temperature. The figure shows that overall space-time correlation between models and observations
17 is ~50–60%. Qualitative examination of latitude-longitude maps shows that AOGCMs generally
18 reproduce the observed broad patterns of precipitation amount and year-to-year variability (A. Dai,
19 2006: Precipitation characteristics in eighteen coupled climate models, *J. Climate*, in press). The
20 most prominent error is that models without flux adjustment fail to simulate the observed
21 northwest-to-southeast orientation of a large region of particularly heavy cloudiness and
22 precipitation in the Southwest Pacific Ocean (the Southwest Pacific Convergence Zone or SPCZ).
23 Instead, these models produce an unrealistic set of Inter-Tropical Convergence Zones in two
24 parallel lines straddling the Equator: a “double ITCZ” pattern. The double-ITCZ error has been
25 frustratingly persistent in climate models despite much effort to correct it. The average day-night
26 cycle of temperature and precipitation in AOGCMs exhibits general agreement with observations,
27 although simulated cloud formation tends to start too early in the day. Another discrepancy between
28 models and observations appears upon sorting precipitation into light, moderate and heavy
29 categories. Models reproduce the observed extent of moderate precipitation (10-20 mm/day) but
30 underestimate the extent of heavy precipitation and overestimate the extent of light precipitation

1 (Dai 2006). Additional model errors appear when precipitation is studied in detail for particular
2 regions, e.g. within the US (Ruiz-Barradas, A., and S. Nigam, 2007).
3
4 Taking examples from two of the US model families discussed in Chapter IV, one finds that
5 AOGCM-simulated and observed maps of surface temperature and even precipitation appear rather
6 similar at first sight. Constructing simulated-minus-observed “difference maps,” however, reveals
7 monthly and seasonal mean temperature and precipitation errors up to $\sim 10^{\circ}\text{C}$ and 7 mm / day
8 respectively at some points (Figs V B, W. Collins *et al.*, 2006; and V C Dellworth *et al.*, 2006).

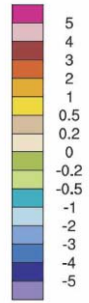
1 Figure V.B 1–4. CCSM3 annual mean simulated-minus-observed sea surface temperature [°C]
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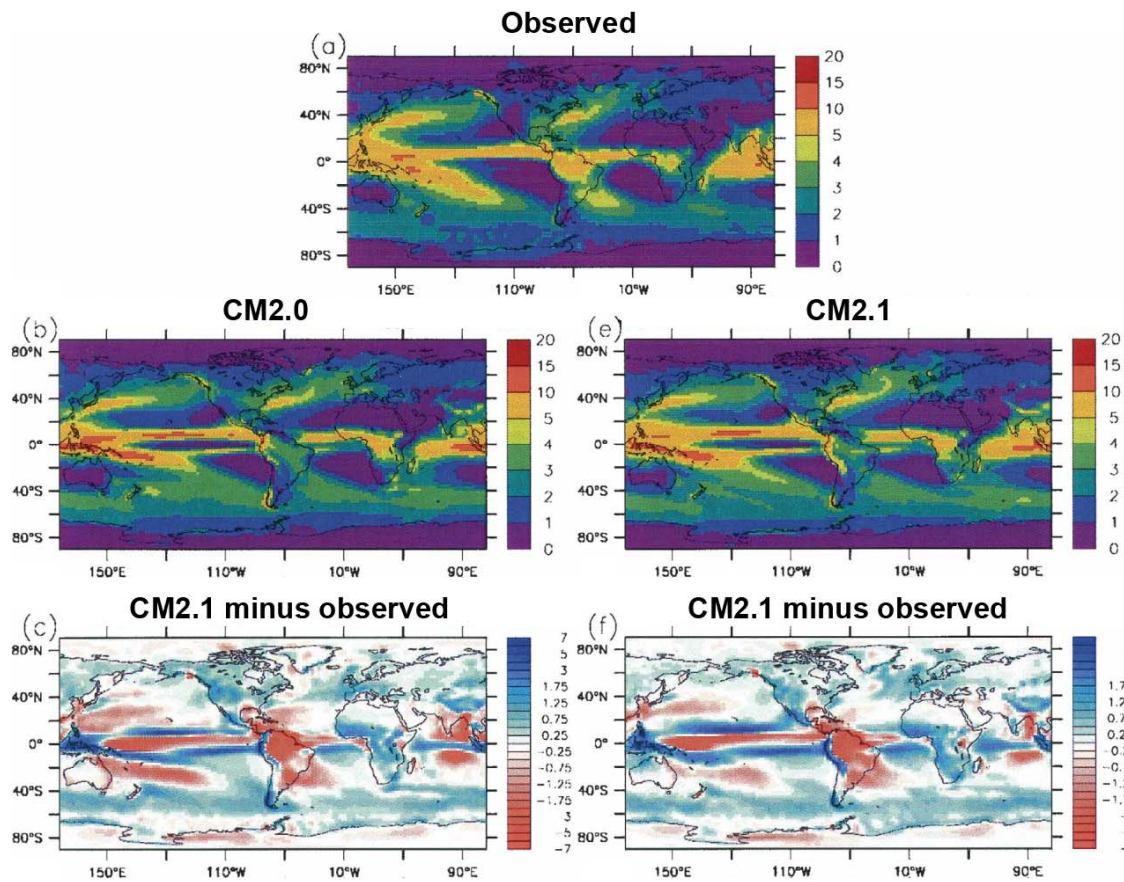
Min = -9.26 Max = 13.47



1

1
2 The CCSM3 temperature difference maps exhibit the largest errors in the Arctic (note scale change
3 in last frame), where continental wintertime near-surface temperature is overestimated. AOGCMs
4 find this quantity particularly difficult to simulate because, for land areas near the poles in winter,
5 models must resolve a strong temperature inversion (warm air overlying cold air).
6

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4 **Figure V. C 1-5. Observed and model-simulated precipitation [mm/day]**

5 The GFDL precipitation difference maps reveal significant widespread errors in the tropics, most notably in
6 the ITCZ region discussed above and in the Amazon River basin, where precipitation is underestimated by
7 several millimeters per day.

8

1 Similar precipitation errors appear in the following table of CCSM3 results Table V 1.

2

3 Table V 1 CCSM3 Precipitation by region(Collins, et al, 2006)

4

Region	CCSM3-simulated precip	Error
Southeast USA (30-40°N, 80-100°W)	2.4 mm/day	-24%
Amazon basin (10°S-10°N, 60-80°W)	4.5 mm/day	-28%
Southeast Asia (10-30°N, 80-110°E)	3.1 mm/day	-24%

5

6 AOGCM precipitation errors have serious implications for “Earth system” models with interactive
7 vegetation, because such models use the simulated precipitation to calculate plant growth (see
8 Chapter VI below). Errors of the magnitude shown above would produce an unrealistic distribution
9 of vegetation in an Earth system model, e.g. by spuriously deforesting the Amazon basin.

10

11 In summary, modern AOGCMs generally simulate large-scale mean climate with considerable
12 accuracy, but the models are not reliable for aspects of mean climate in some regions, especially
13 precipitation.

14

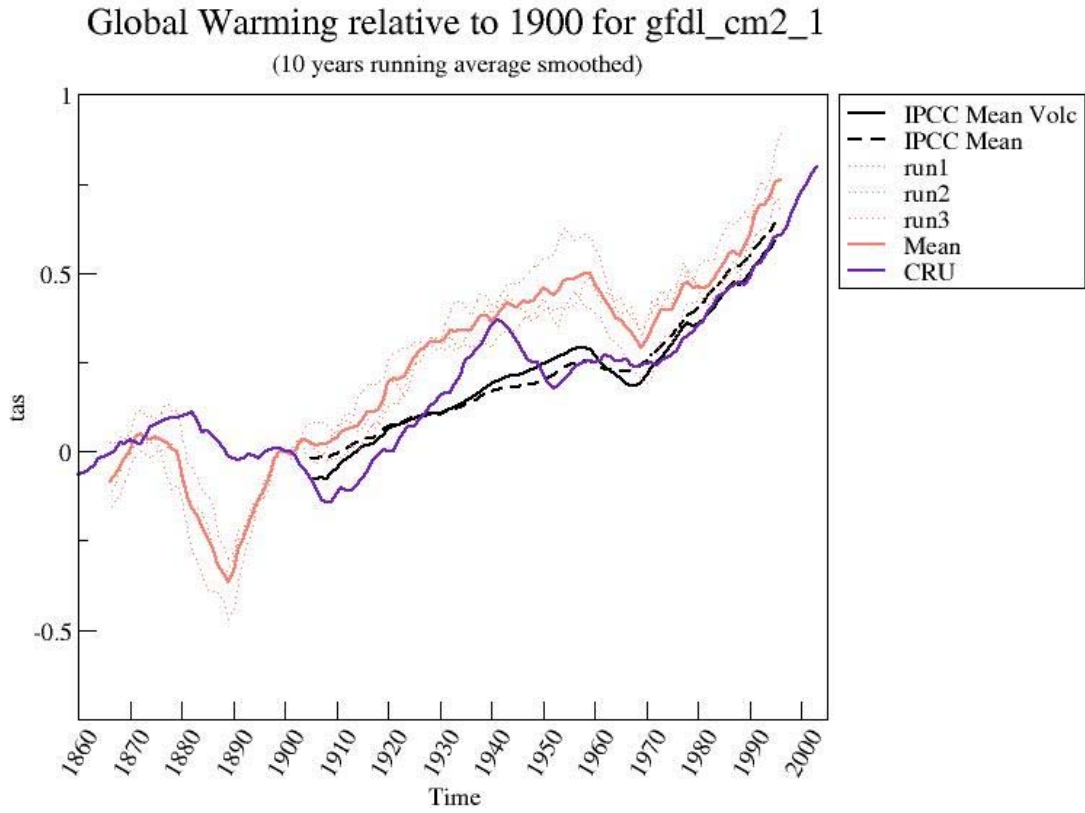
15 **20th century trends**

16

17 Modern AOGCMs are able to simulate not only the time-average climate but also changes (trends)
18 of climate during over the past century or more. For example, Figure V D shows results from the
19 three US models and “average” CMIP3 models. All parts of the figure display the same curves of
20 annual mean globally averaged near-surface temperature as observed by the UK Climatic Research
21 Unit (CRU), as well as simulated by the average over all CMIP3 models and the average over only
22 those CMIP3 models that included the effects of volcanic eruptions. Results from individual US
23 models are shown both for separate ensemble members (dotted lines) and for the average over all
24 ensemble members (continuous lines). Separate ensemble members were run under a variety of
25 initial conditions. The precise initial conditions, especially deep ocean temperature and salinity, are
26 not known for 1860; the spread among the dotted-line curves thus indicates uncertainty in model-
27 simulated temperature arising from our lack of knowledge of initial conditions.

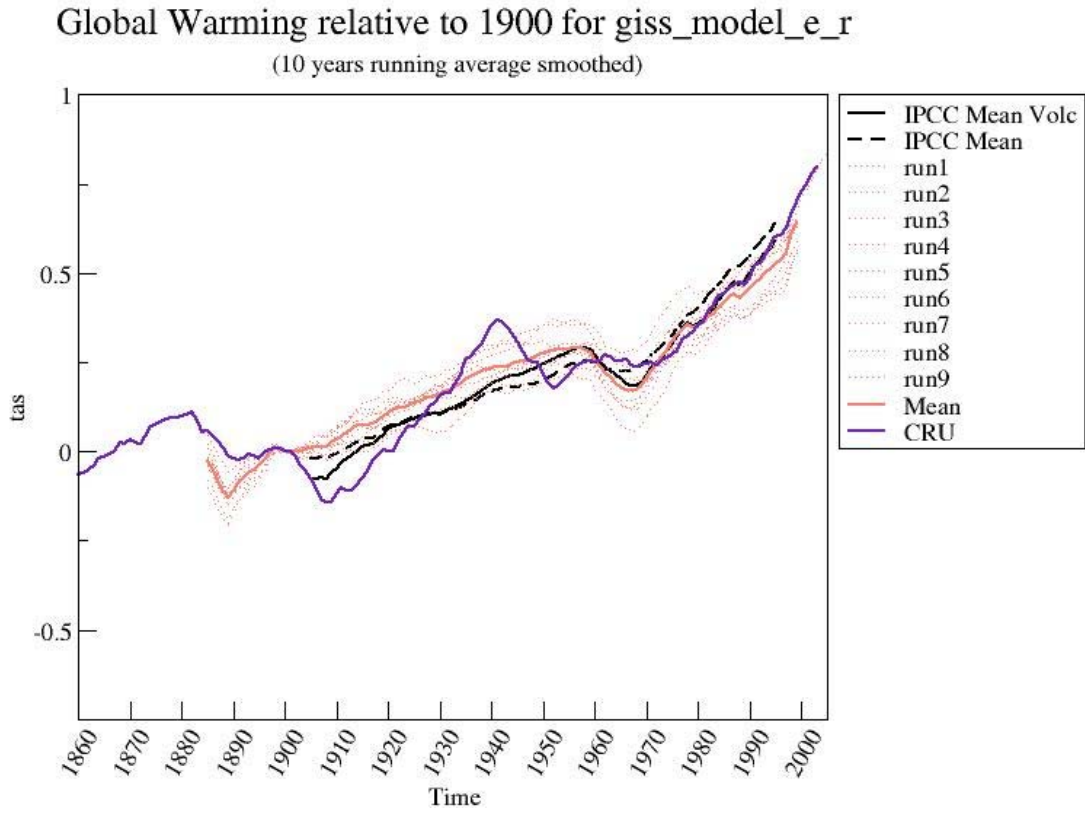
1
2 These results demonstrate that modern climate models typically exhibit good agreement with
3 observed near-surface temperature trends for the global mean (Min and Hense, 2006). Global
4 warming during the past few decades is successfully simulated by the models only if they include
5 anthropogenic emissions of greenhouse gases and aerosols. Min and Hense, (in press) show the
6 same is true for most individual continents. Observed trends in climate extremes such as heat-wave
7 frequency and frost-day occurrence are also simulated with basic reliability by the latest generation
8 of AOGCMs (Tebaldi et al., in press).

- 1 Figure V D 1. Twentieth century globally averaged surface temperature simulation from GFDL
- 2 CM2.1



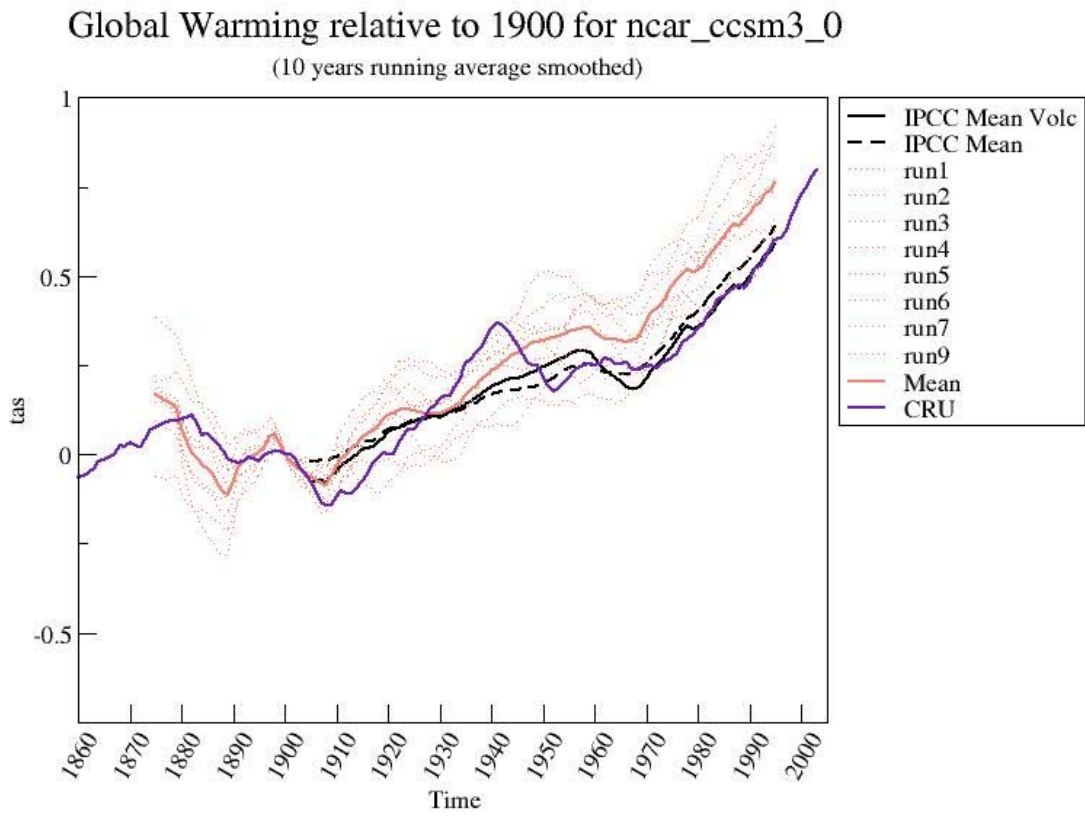
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- 1 Figure V D 2 Twentieth century globally averaged surface temperature simulation from GISS
- 2 Model E-r



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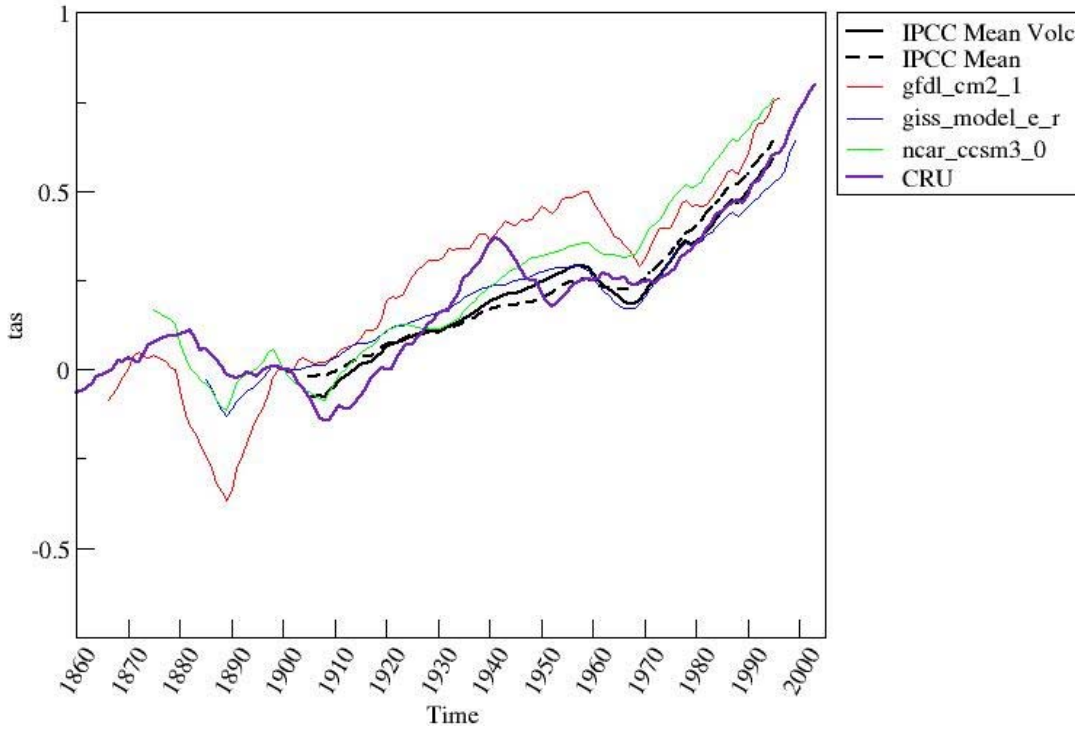
1 Figure V D 3 Twentieth century globally averaged surface temperature simulation from CCSM3



2

- 1 Figure V D 4 Twentieth century globally averaged surface temperature simulation from the three
- 2 US CMIP3 models and the average of all CMIP3 models that include volcanic effects

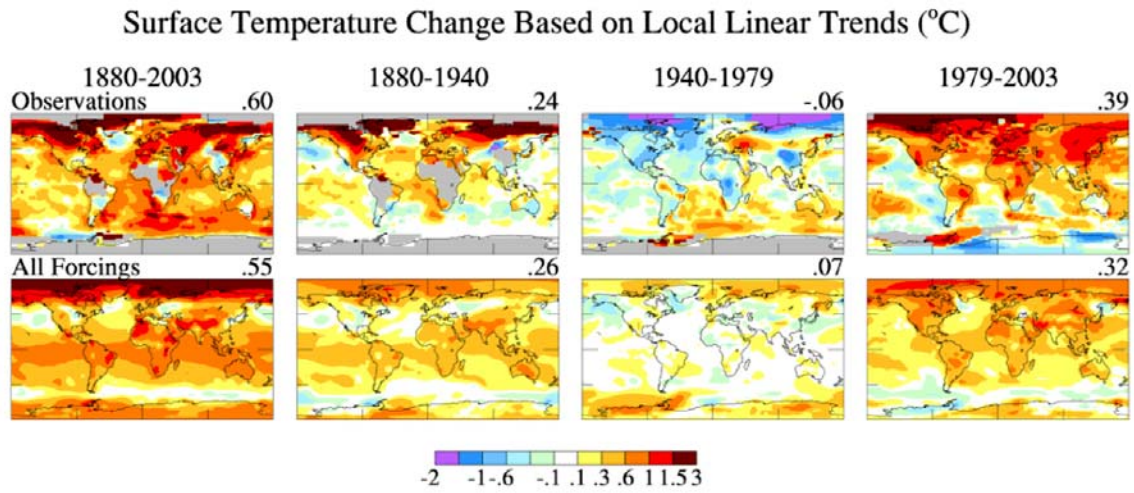
Global Warming relative to 1900 for American models
(10 years running average smoothed)



3

1
2 At smaller scales the model simulation of trends can be less accurate. For example, model-
3 simulated trends do not consistently match the observed lack of 20th century warming in the Central
4 US (Kunkel et al., in press). The evolution of large-scale patterns, however, can be simulated with
5 fair detail by modern climate models. For example, the longitude-latitude map of trends from GISS
6 modelE agrees reasonably well with the observed spatial distribution Fig V E (Hansen *et al.*, 2006) .
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Figure V. E. The figure shows general agreement between the model and observations not only for the overall period 1880-2003, but also for the segments 1880–1940 and 1979–2003, which encompass periods of early and late 20th century warming.

1 Amplification of warming and cooling at high northern latitudes is the most obvious feature in the
2 observations. For the period 1940–1979, the model simulates only a small change in global mean
3 temperature in agreement with observations, but it fails to simulate the strong north polar cooling
4 observed for this period. As a result, the model-simulated global mean temperature change (upper
5 right corner of each frame) for 1940–1979 is slightly positive rather than slightly negative as
6 observed. For both 20th century warming periods, the model simulates but underestimates the high-
7 latitude amplification of global warming.

8
9 Finally, the CCSM3 simulates 4.7 cm of global mean sea level rise during the 20th century (Meehl
10 *et al.* 2006). The actual value of sea level rise is 3–5 times as large, but the model does not include
11 melting glaciers and ice sheets, and therefore it simulates only the part of sea level rise due to
12 expansion of ocean water from heating.

13
14 A number of specific climate phenomena in addition to near-surface temperature, precipitation and
15 sea level are discussed in the following sections. These are important for practical applications of
16 climate models because they directly affect near-surface temperature and precipitation patterns (and
17 thereby indirectly affect the evolution of sea level, together with many other features of climate).

18
19

20 *Annular Modes*

21
22 The primary mode of Arctic interannual variability is the Arctic Oscillation (Thompson and
23 Wallace 1998), which is also referred to as the Northern Annual Mode (NAM) and which is related
24 to the North Atlantic Oscillation (Hurrell 1995). The primary mode of Antarctic interannual
25 variability is the Southern Annular mode (SAM) (Thompson and Wallace 2000), also known as
26 Antarctic Oscillation. Coupled global climate models have shown skill in simulating the NAM
27 (Fyfe *et al.* 1999, Shindell *et al.* 1999, Miller *et al.* 2006), although in some cases too much of the
28 variability in sea level pressure is associated with the NAM in these models (Miller *et al.* 2006).
29 Global climate models also realistically simulate the SAM (Fyfe *et al.* 1999, Cai *et al.* 2003, Miller
30 *et al.* 2006), although some details of the SAM (e.g. amplitude and zonal structure) show

1 disagreement between global climate model simulations and reanalysis data (Raphael and Holland
2 2006; Miller et al. 2006).

3 In response to increasing concentrations of greenhouse gases and tropospheric sulfate
4 aerosols in the 20th century, the multi-model average exhibits a positive annular trend in both
5 hemispheres, with decreasing sea-level pressure (SLP) over the poles and a compensating increase
6 in mid-latitudes (Miller et al. 2006). However, the models underestimate the coupling of
7 stratospheric changes (from volcanic aerosols) to annular variations at the surface, and may not
8 simulate the appropriate response to increasing GHGs (Miller et al. 2006)) and changes in
9 stratospheric ozone (Arblaster and Meehl, 2006).

10 .

11

12 *Ocean structure and circulation*

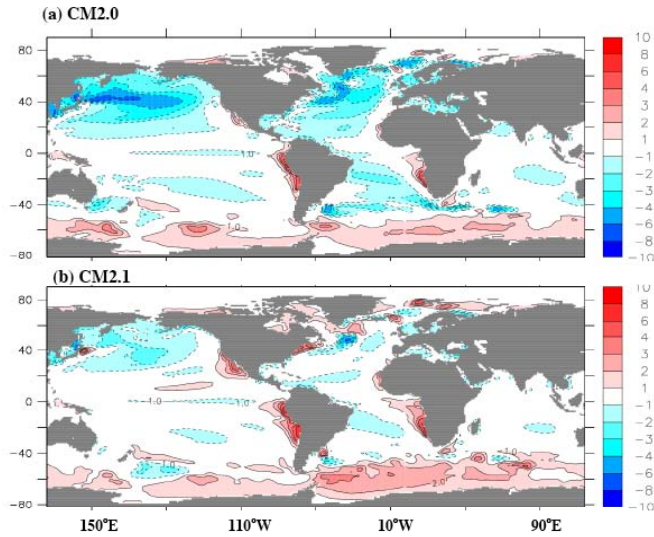
13

14 A set of ocean characteristics or metrics (sea surface temperature, ocean heat uptake, meridional
15 overturning and ventilation, sea level variability and global sea level rise) is used to describe the
16 realism of the ocean in the climate models.

17

18 *Sea surface temperature:* The sea surface temperature (SST) plays a critical role in the
19 determination of the climate and the predictability of the changes. In general, when the simulated
20 fields of SST are compared to observational fields there is improvement in the models'
21 representation of the mean SST Figure V F(Delworth *et al.*, 2006) compares the CM2.0 and CM2.1
22 mean SST field averaged over a period of 100 years to the Reynolds SST observational
23 climatology. With an improved atmospheric core and a different viscosity parameter value, the later
24 version (CM2.1) of the GFDL climate model produces a reduced cold bias in the northern
25 hemisphere.

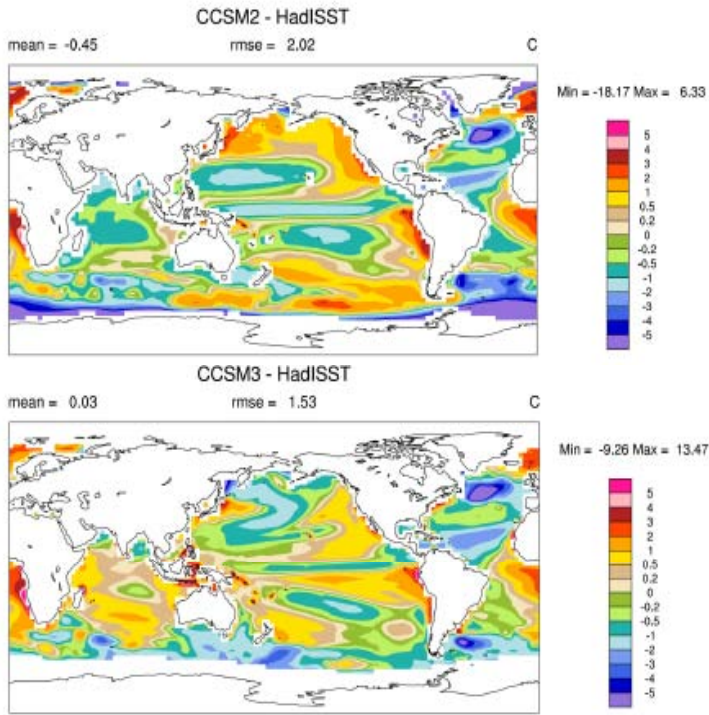
1 Figure V F Maps of errors in simulation of annual mean sea-surface temperature (SST). Units are
2 K. The errors are computed as model minus observations, where the observations are from the
3 ReynoldsSST data (provided by the NOAA-CIRES Climate Diagnostics Center, Boulder, Colorado,
4 USA, from their Web site at <http://www.cdc.noaa.gov/>). (a) CM2.0 (using model years 101-200).
5 (b) CM2.1 (using model years 101-200). Contour interval is 1K, except that there is no shading for
6 values between 1 K and +1 K.



7

1
2 The CCSM3.0 model also has improved its simulation of SST primarily in the handling of the
3 processes associated with the mixed layer of the upper ocean waters (Danabasoglu *et al.*, 2005).
4 The improvement in the representation of the SST is apparent especially in the eastern tropical
5 Pacific (see Figure V G). An inter-model comparison of the 50 year global SST trend for each
6 model is shown in Figure V H. The SST trends range from a low of 0.1°C/50yrs to a high of about
7 0.6°C/50yrs, with the observational trend estimate given as about 0.43°C/50yrs. The figure also
8 shows that within a group, the estimates significantly vary. This distribution of values in SST trends
9 shows that improvements in any model's representation of SST are dependent on both advances in
10 the ocean and atmospheric components.

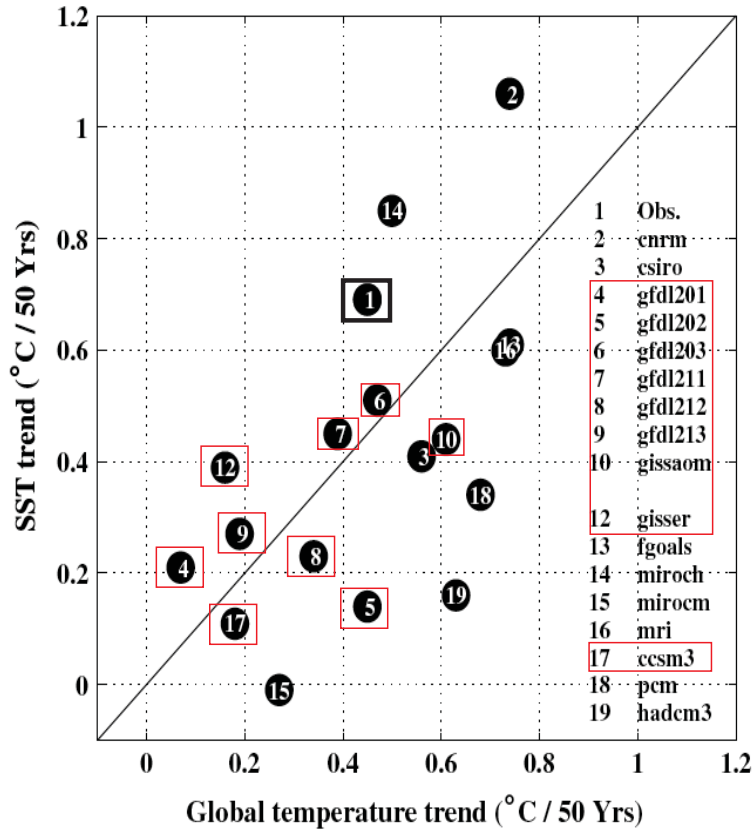
1 Figure V G Differences in annual-mean surface temperature between CCSM2 and the HadISST
2 data set (Rayner *et al.* 2003) (top); corresponding differences for CCSM3 (bottom) (Collins, et al,
3 2005).
4



5

1 Figure V H Scatter plot of the SST trends averaged in the central and eastern tropical Pacific (9 S–9
 2 N and 90–180 W), and global mean surface temperature trends. Correlation of the model results is
 3 0.58, of higher magnitude than the 95% significance level of 0.46. The 1:1 line is drawn for clarity.
 4 The red boxes denote US Climate models and the black box is the relationship computed from
 5 observations. (Zhang & McPhaden, 2006)

6



7

1 *Meridional overturning circulation and ventilation:* The circulation process related to the
2 transportation heat and freshwater throughout the global oceans is referred to as thermohaline
3 circulation. The Atlantic portion of this process is called the Atlantic meridional overturning
4 circulation (AMOC). Tropical and warm waters flow northward via the Gulf Stream and North
5 Atlantic Current. The southward flow occurs when water is sub-ducted in the regions of the
6 Labrador Sea and Greenland Seas and occurs when the freshening of the surface waters become
7 denser and flow down the slope to deeper depths. Similar processes occur at locations in the
8 Southern Ocean. Ventilation is the process by which these dense surface waters are carried into the
9 interior of the ocean. The important climate parameter is the rate at which this process occurs, the
10 so-called "ventilation rate". It has been suggested that this pattern of circulation if it becomes
11 weaker (i.e. less warmer water flowing towards Europe) will impact the climate. It is thus important
12 to understand how well the ocean component simulates the observed estimates of these overturning
13 processes.

14
15 *Schmittner et al.* [2005] examined the performance of the models in reproducing the observed
16 meridional overturning in 4 of the 5 US models. The authors examined a small ensemble set of
17 simulations to quantify the uncertainty in the models' representation of 20th century AMOC
18 transports. To make their estimate, they evaluated the global temperature (T), the global salinity (S),
19 the pycnocline depth (D), the surface temperature and surface salinity in the Atlantic (SST, SSS),
20 and calculations of the overturning at 3 locations ~in the Atlantic. Their results suggest that
21 temperature is simulated the most successfully on the large scale and that the overturning transports
22 at 24°N are close (~18Sv) to the observed measurements (~15.8Sv). However, the maximum mean
23 overturning transports in these models are too high (23.2, 31.7, 27.7, and 30.9 Sv: *Schmittner et al.*
24 [2005] and 21.2 Sv from *Bryan et al.* [2006]) than the observed value (17.7 Sv). Table V 2 shows a
25 reduced version of Table 1 from *Schmittner et al.* [2005] that shows the root mean errors (RMS) for
26 the various quantities as compared to observations. The authors do not attempt to explain why the
27 models are different from each other and from observations, rather, that there is a broad range in the
28 value of these metrics for a set of climate models.

1

2 Table V 2 Model Errors

Model	T_{global}	S_{global}	D_{global}	SST_{NAtl}	SSS_{NAtl}	D_{NAtl}	AMOC _{24N} (15.8) (SV)
GFDL-2.0	0.20	0.43	0.57	0.34	0.53	0.75	0.16 (18.3)
GISS- AOM	0.66	0.75	2.29	0.43	0.79	3.48	0.22 (19.2)
GISS-EH	0.31	0.76	1.57	0.61	1.12	1.85	0.34 (21.1)
GISS-ER	0.69	0.82	2.06	0.65	1.11	2.40	0.13 (17.9)

3 From Schmittner et al. [2005] Table 1. RMS Errors for the Individual Models; RMS errors are
4 normalized by the standard deviation of the observations unless otherwise stated. *Schmittner et al.*
5 2005; "Observation-based estimates of the AMOC at 24 N from *Ganachaud and Wunsch* [2000]
6 *and Lumpkin and Speer* [2003], at 48 N from *Ganachaud* [2003], and its maximum value in the
7 North Atlantic from *Smethie and Fine* [2001] *and Talley et al.* [2003], as well as temperature,
8 salinity, and pycnocline depth observations from the World Ocean Atlas 2001 [*Conkright et al.*,
9 2002] are used to evaluate the climate models."

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The global overturning circulation can also be quantified by also examining the realism of the transports through the Drake Passage. The passage, between the tip of South America and the Antarctic Peninsula provides a constrained passage to measure the flow between two large ocean basins. The observed mean transport is around 135 Sv. *Russell et al.* [2006] estimate the flow in the passage for a subset of the climate models (Table V 3). There is a wide range in the simulated mean values. The interaction between the atmospheric and ocean component models appears to be important in reproducing the observed transport. The strength and location of the zonal wind stress correlates with how well the transport reflects observed values.

1

2 TABLE V 3

Model	ACC (Sv)	$d\rho/dy$ (kg m^{-3})	Total τ_x 10^{12} N	Max τ_x (N m^{-2})	Lat of max τ_x
Observational estimate	135	0.58	6.5	0.161	52.4
GISS-ER	266	0.62	4.3	0.107	46.0
GISS-AOM	202	0.38	2.9	0.166	43.5
GFDL-CM2.1	135	0.58	6.1	0.162	51.0
GFDL-CM2.0	113	0.56	4.5	0.149	46.0
GISS-EH	-6	0.43	3.6	0.096	46.0

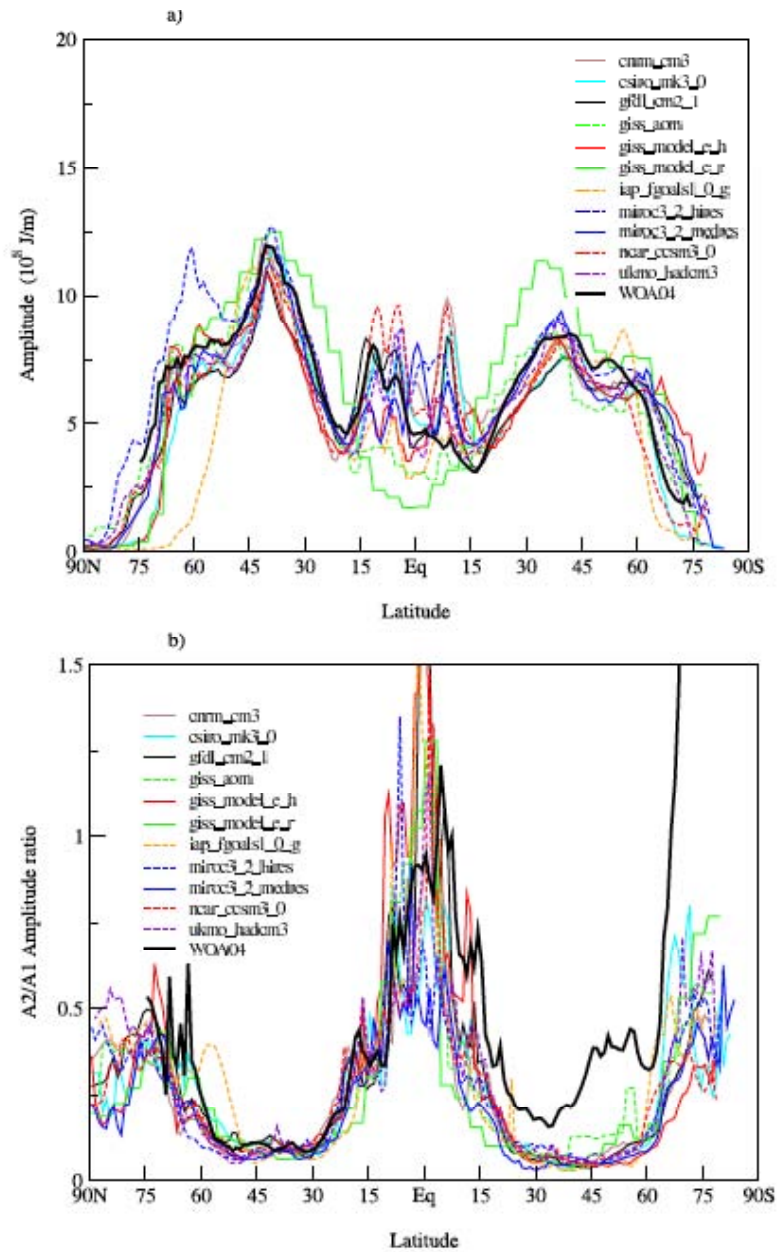
3 **Reduced From Table 1 Russell et al. [2006]** Various parameters related to the strength of the
4 ACC. The ACC transport is the integral of the zonal velocity across the Drake Passage at 69°W.
5 The density gradient ($d\rho/dy$) is the zonally averaged density difference between 65° and 45°S. The
6 total ACC-related wind stress (τ_x total) is the integral of the zonal wind stress over the Drake
7 Passage channel (54°–64°S). The maximum westerly wind stress (τ max) is the maximum of the
8 zonally averaged wind stress that is located at the latitude given by Lat τ max. The observed ACC
9 strength is from *Cunningham et al.* (2003). The observed density gradient is calculated from the
10 World Ocean Atlas 2001 (*Conkright et al.* 2002). The observed wind data are from the NCEP long-
11 term mean (*Kistler et al.* 2001). NA indicates data not archived at PCMDI

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2
3 *Northward Heat Transport:* A common metric used to quantify the realism in ocean models is the
4 northward transport of heat. This integrated quantity (from top to bottom and across latitude bands)
5 gives an estimate of how heat moves within the ocean and is important in balancing the overall heat
6 budget of the Earth. The calculations for the ocean's northward heat transport in the current
7 generation of climate models show that the models reasonably represent the observations (*Delworth*
8 *et al.* 2006, *Collins et al.* 2006, and *Schmidt et al.* 2006). The current models have significantly
9 improved over the last generation in the Northern Hemisphere. Comparisons of the simulated values
10 to the observed values for the North Atlantic are within the uncertainty of the observations. In the
11 Southern Hemisphere, the comparisons in all the models are not as good, with the Indian Ocean
12 transport estimates contributing to a significant part of the mismatch.

13
14 *Heat Content:* Related to the heat transport is the ocean's heat content itself. This can be thought of
15 how realistically the models reproduce the uptake of heat. An evaluation of the temporally evolving
16 ocean heat content in the suite of climate models for the AR4 shows the models abilities to simulate
17 the zonally integrated annual and semi-annual cycle in heat content. In the middle latitudes
18 [*Gleckler et al.* 2006], the models do a reasonable job while there is a broad spread of values for the
19 tropical and polar regions. This analysis showed that the models replicate the dominant amplitude
20 of the annual cycle along with its phasing in the mid-latitudes [Fig V I]. At high latitudes, the
21 comparisons with observations are not as consistent. While the annual cycle and global trend are
22 reproduced, analyses of the models [e.g. *Hansen et al.* 2005] show that they do not simulate the
23 decadal changes in estimates made from observations [*Levitus et al.* 2001]. Part of the difficulty of
24 comparisons at high latitudes and at long periods is the paucity of observational data [*Gregory et al.*
25 2004].

1 Figure V I 1

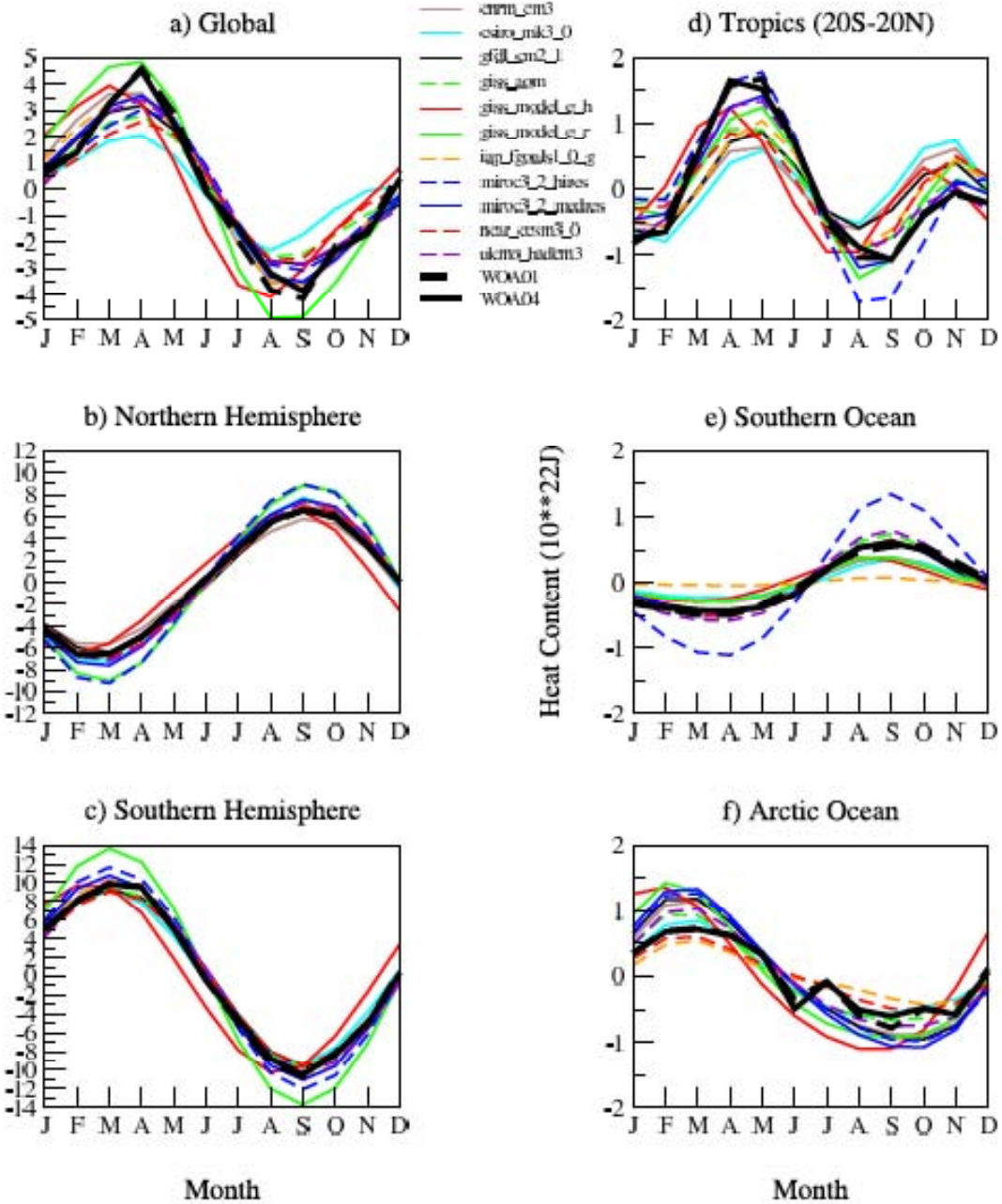
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4 **From Glecker *et al.* 2006 .Figure 1.** Observed (WOA04) and simulated zonally integrated ocean heat content (0–250
5 m): (a) annual cycle amplitude (10^8 J/m^2) and (b) semiannual/annual (A2/A1).

1 Figure V I 2



2

3 From Glecker *et al.*, 2006, Figure 3. Annual cycle of observed (WOA04) and simulated basin average global ocean
4 heat content

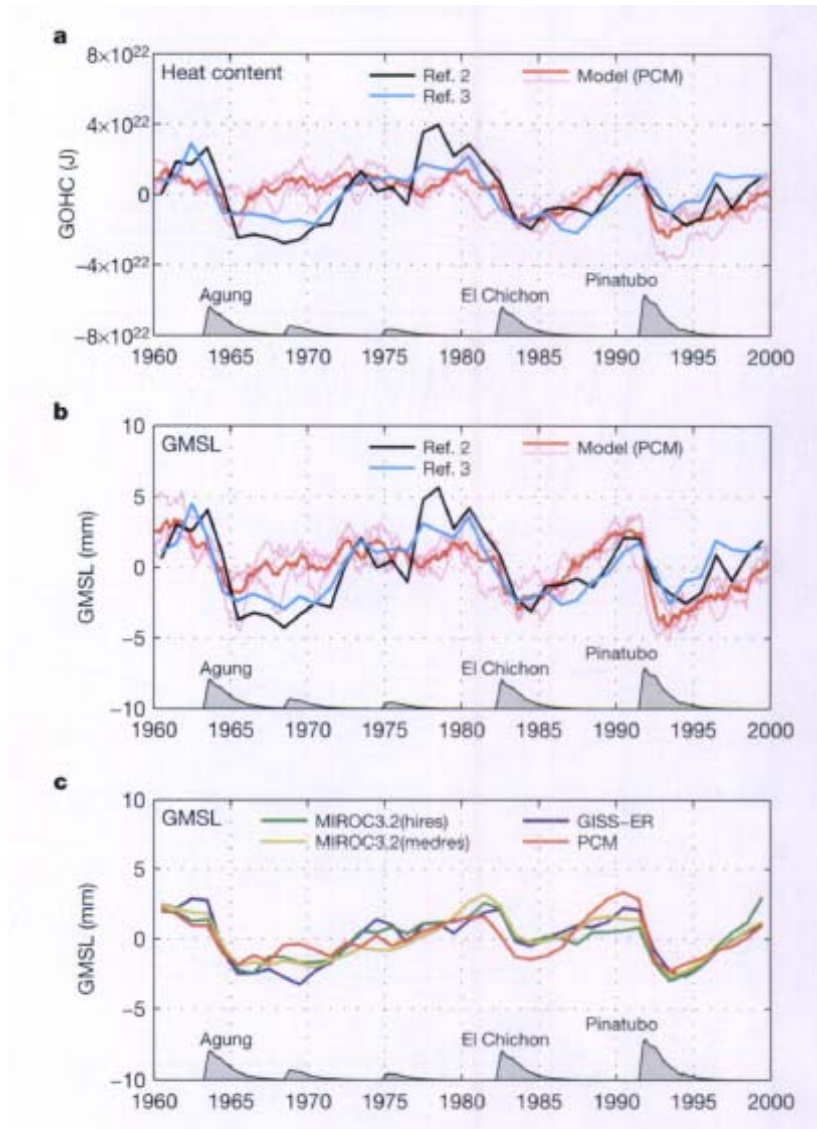
5 (0–250 m). Units are $10^{22}J$. Arctic Ocean is defined as north of 60 N, and Southern Ocean is south of

6 60 S.

1
2 *Global mean sea level rise*: Two separate physical processes contribute to the sea level rising: 1) the
3 thermal expansion of the ocean from an increase in the heat uptake by the ocean (steric component)
4 and 2) the addition of freshwater from precipitation, continental ice melt, and/or river runoff (the
5 eustatic component). The current ocean component of all the models except the GISS models,
6 conserve volume. In practice, the first component can be easily computed from a model's primary
7 variables. The second contribution maybe considered as a freshwater flux into the ocean. The
8 various ocean models handle the process in different ways. With the addition of a free surface in the
9 current generation of ocean models, the freshwater flux into the oceans can be included directly
10 [Griffies *et al.* 2001]. In other cases, the mass or freshwater contribution is computed by quantities
11 estimated by land/ice sheet components of the climate model [e.g. Church *et al.*, 2005, Gregory *et*
12 *al.*, 2006]. In general, the state-of-the-art climate models underestimate the combined global mean
13 sea level rise as compared to tide gauge and satellite altimeter estimates while the rise for each of
14 the separate components is within the uncertainty of the observed values. The reason for this is an
15 open research question and may relate to either observational sampling or not correctly accounting
16 for the all the eustatic contributions. The steric component to the global mean sea level rise is
17 estimated to be 0.40 ± 0.05 mm/yr from observations [Antonov *et al.* 2005]. The models simulate a
18 similar, but somewhat smaller rise [Gregory *et al.*, 2006, Meehl *et al.* 2005]. There are also
19 significant differences in the magnitudes of the decadal variability between the observed and the
20 simulated sea level or SSH. It must be noted, however, that progress is been made over the previous
21 generation of climate models. When atmospheric volcanic contributions are included, for example,
22 ocean models of the current generation capture the observed impact on the ocean (a decrease in the
23 global mean sea level). Figure V J from Church *et al.* 2006 gives an example of a few models and
24 their de-trended estimate of the historic global mean sea level that shows the influence of including
25 the additional atmospheric constituents in changing the steric height of the ocean.

1 Figure V J

2



3

Figure 2 | Observed and modelled GOHC and GMSL for the period 1960–2000. The response to volcanic forcing, as indicated by the differences between the pairs of PCM simulations for GOHC (a) and the GMSL (b) is shown for the ensemble mean (bold line) and the three ensemble members (light lines). The observational estimates^{2,3} of GOHC and GMSL are shown by the black and blue bold lines. For a and b, all results are for the upper 300 m only and have been detrended over the period 1960–2000. c, The ensemble mean (full depth) GMSL for the GISS-ER, MIROC3.2(hires), MIROC3.2(medres) and the PCM models (after subtracting a quadratic) are shown.

4

1 **C. Simulation of specific climate dynamical features**

2

3 *Extratropical storms*

4 Climate models have developed from numerical weather prediction models whose performance has
5 been primarily judged on their ability to forecast mid-latitude weather. The success of these models
6 in their simulation of midlatitude cyclones and anticyclones has resulted in the continuous growth in
7 the value of numerical weather prediction. The ability of general circulation models to generate
8 realistic statistics of midlatitude weather has also been central in the development of climate
9 modeling. This is not only because midlatitude weather is important in its own right, but also
10 because these storms are the primary mechanism by which heat, momentum, and water vapor are
11 transported by the atmosphere, making their simulation crucial for the simulation of the atmospheric
12 climate.

13

14 Indeed, it can be thought of as the defining feature of Atmospheric General Circulation Models
15 (AGCMs) that they compute midlatitude eddy statistics and the associated eddy fluxes through
16 explicit computation of the life cycles of individual weather systems and not through some
17 turbulence or closure theory. It may seem very inefficient to compute the evolution of individual
18 eddies when primarily interested in the long term statistics of the eddies, but it has been the clear
19 judgment of the community for decades that the explicit simulation of these eddies in climate
20 models is far superior to the attempts that have been made to date in developing closure theories for
21 the eddy statistics. The latter theories typically form the basis for EMICs (Earth System Models of
22 Intermediate Complexity), which are far more efficient computationally than GCMs, but provide
23 less convincing simulations.

24

25 Two figures illustrate the quality of the simulations of midlatitude eddy statistics that coupled
26 AOGCMs of the horizontal resolution used in AR4 are capable of generating. Shown for the GFDL
27 CM2.1 in Fig. V K 1 is the wintertime variance of the north-south component of velocity at 300 hPa
28 (in the upper troposphere) and in Fig. V K 2 the wintertime poleward eddy heat flux, or the
29 covariance between temperature and north-south velocity, at 850mb (in the lower troposphere).
30 When analyzing eddy statistics it is often useful to filter the flow fields to retain only those time
31 scales, roughly 2-10 days, associated with midlatitude weather systems, but the two quantities

1 chosen here are dominated by these time scales to a sufficient degree that they are relatively
2 insensitive to filtering. Here we have simply removed the monthly means before computing
3 variances. In each case, the eddy statistics are compared to the estimates of the observed statistics
4 obtained from the NCEP-NCAR reanalysis (B.Wyman, personal communication).

5
6 In winter, Northern Hemisphere storms are organized into two major oceanic storm tracks over the
7 Pacific and Atlantic oceans. Historically, it has been found that atmospheric models of resolutions
8 of about 200-300 kms are typically capable of simulating the midlatitude storm tracks with
9 comparable realism to that shown in the figure. The eddy amplitudes are often a bit weak and often
10 displaced slightly equatorward, especially in Southern hemisphere summer (although the model
11 shown here has a weaker Southern hemisphere bias than most models). In models with resolution
12 coarser than 200-300kms, the simulation of the midlatitude storm tracks typically deteriorates
13 significantly (see for example, Boyle 1993). It is thought to be important for the general
14 improvement in model simulations described in Chapter 1 that most of the models in the CMIP3
15 database are now utilizing this 200-300km resolution. While finer resolution results in better
16 simulations of the structure of midlatitude storms, including the structure of warm and cold fronts as
17 well as the interaction between these storms and coastlines and mountain ranges, the improvements
18 in the midlatitude climate on large scales tend to be less dramatic and systematic. Other factors
19 besides horizontal resolution are considered to be important for the details of storm track structure,
20 including the distribution of tropical rainfall, which is sensitive to the closure schemes utilized for
21 moist convection, interactions between the stratosphere and the troposphere, which are sensitive to
22 vertical resolution. Roeckner *et al* (2006) illustrate the importance of vertical resolution for the
23 midlatitude circulation and storm track simulation.

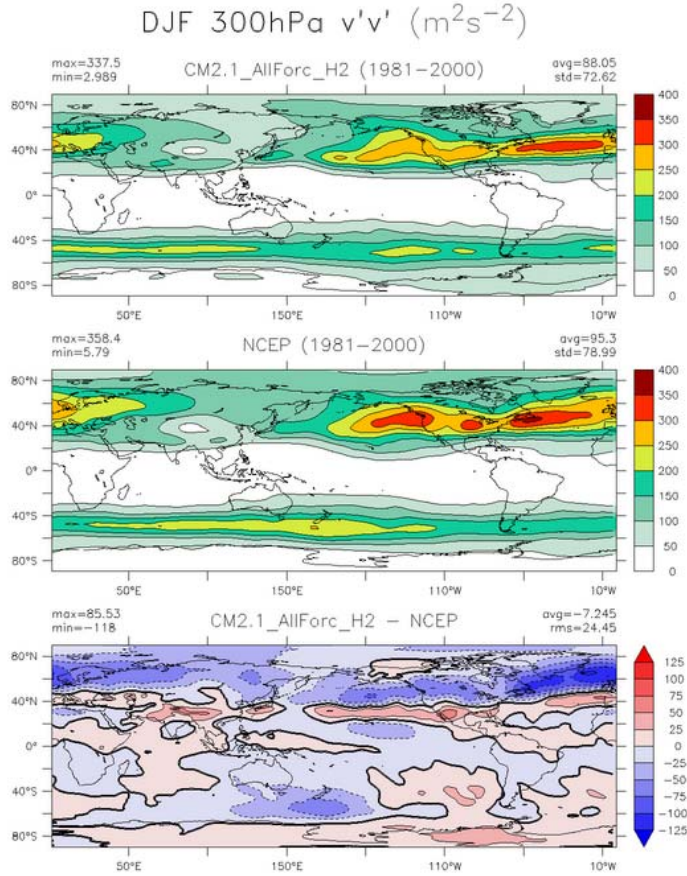
24
25 A more detailed look at the ability of the AR4 models to simulate the space-time spectra of the
26 observed eddy statistics is provided by Lucarini, *et al*,(2006). These authors view the deficiencies
27 noted, which vary in detail from model to model, as serious limitations to the credibility of the
28 models. But, as indicated in Chapter 1, our ability to translate measures of model biases into useful
29 measures of model credibility is limited, and the implications of these biases in the space-time
30 spectra of the eddies is not self-evident. Indeed, in the context of the simulation of the eddy
31 characteristics generated in complex turbulent flows in the laboratory (e.g., Dimotakis , 2005) the

1 quality of these atmospheric simulations, closely based on fluid dynamical first principles, should
2 probably be thought of as one of the most impressive characteristics of current models.

3
4 As an example of a significant model deficiency that can plausibly be linked to limitations in the
5 credibility of the climate projections, note that the Atlantic storm track, as indicated by the
6 maximum in velocity variance in Fig 5.1, is too zonally oriented, the observed stormtrack having
7 more of an southwest-northeast tilt. This particular deficiency is common in the CMIP-3 models
8 (van Ulden and van Oldenborgh, 2006) and is related to the difficulty in simulating the phenomenon
9 of blocking in the North Atlantic with the correct frequency and amplitude. Van Ulden and van
10 Oldenborgh make the case that this bias is significant for the quality of regional climate projections
11 over Europe.

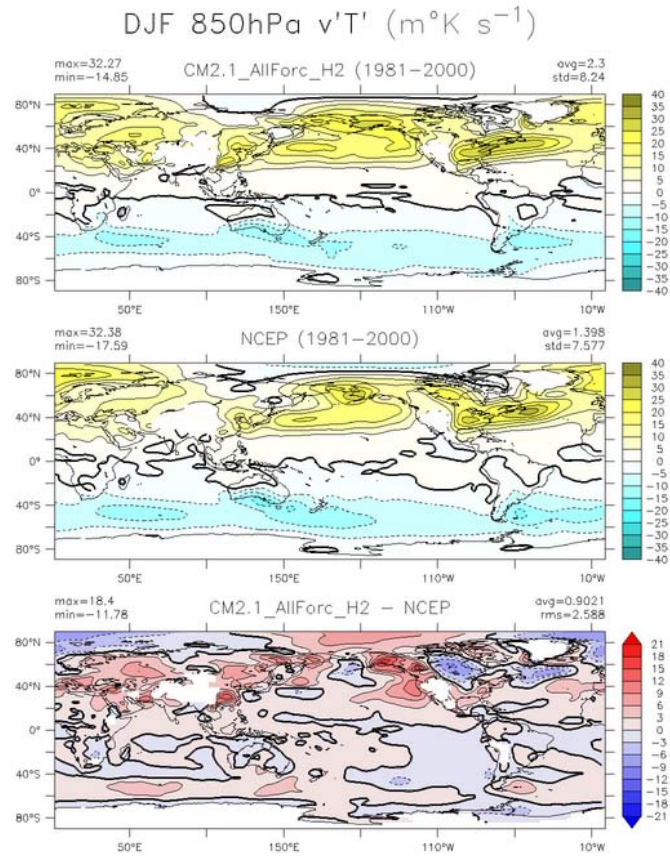
12 .

- 1 **Figure V K 1:** Top: variance of north-south velocity at 300hPa as simulated by the GFDL CM2.1
- 2 model in years 1981-2000 of one realization of the 20C3M simulation, as contributed to the CMIP3
- 3 database. Units are m^2/s^2 . Middle: The same quantity as obtained from the NCEP-NCAR
- 4 reanalysis (ref). Bottom: model minus observations.



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 2 **Figure V K 2:** Top: covariance of north-south velocity and temperature at 850hPa as simulated by
 3 the GFDL CM2.1 model in years 1981-2000 of one realization of the 20C3M simulation, as
 4 contributed to the CMIP3 database. Units are Km/s. Middle: The same quantity as obtained from
 5 the NCEP-NCAR reanalysis (ref). Bottom: model minus observations.



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Monsoons

The word `monsoon' derives from the Arabic word for season, and a monsoonal circulation is distinguished by its seasonal reversal after the sun crosses the equator into the new summer hemisphere. Rain is largest, if not entirely restricted, to the summer within monsoonal climates, when continental rainfall is supplied mainly by evaporation from the nearby ocean. This limits the reach of monsoon rains to the distance over which moisture can be transported onshore (Prive and Plumb 2007). Variations in the spatial extent of the monsoon from year to year determine which inland regions experience a drought.

Historical theories for the monsoon emphasize the influence of the contrast between land and ocean (Webster et al. 1998). Land responds more quickly to solar heating than the ocean, where heating is mixed over a deeper layer. Air is driven by this temperature contrast toward the warm land, where it ascends and precipitates moisture before returning offshore. Conversely, land cools more rapidly during winter when the sun is in the opposite hemisphere, and this drives air offshore toward the warmer ocean where it rises. While a coastal sea breeze is also driven by the temperature contrast between land and ocean, the monsoon is distinguished by its continental scale. The onshore flow is so extensive that it is deflected by the earth's rotation. Over the Arabian Sea, for example, surface air flows toward the east and northeast during the Northern Hemisphere summer, rather than traveling directly north toward the Asian continent.

While the monsoon takes its name from a language spoken by traders

1 around the Arabian Sea, this circulation reaches far beyond the
2 periphery of the Indian Ocean, and local cultures have their own words
3 for the monsoon: for example, Mei-yu in China, Chang-ma in Korea, and
4 Bai-yu in Japan. Over a billion people are dependent upon the arrival
5 of the monsoon rains for water and irrigation for agriculture. The
6 Asian monsoon during NH summer is the most prominent example of the
7 monsoon circulation, dominating global rainfall during this
8 season. However, the seasonal reversal of winds and summer rainfall
9 maximum also indicate monsoon circulations in West Africa and the
10 Amazon basin. In addition, during NH summer, air flows off the eastern
11 Pacific Ocean toward Mexico and the American southwest, while over the
12 Great Plains of the United States, moisture from the Gulf of Mexico
13 brings an annual peak in rainfall. Thus, the climate in these regions
14 is also described as monsoonal.

15

16 Because of the geographic extent of the Asian monsoon, the fidelity of
17 climate model simulations is weighed according to metrics from a
18 variety of regions. Kripalani et al. (2007) judged that three-quarters
19 of the eighteen analyzed coupled models (including the GFDL CM2.0 and
20 2.1 models, along with the NCAR PCM and GISS modelE-R) match the
21 timing and magnitude of the summertime peak in precipitation over East
22 Asia between 100 and 145E and 20 to 40N that is evident in the NOAA
23 NCEP Climate Prediction Center Merged Analysis of Precipitation (CMAP,
24 Xie and Arkin 1997). However, only half of these models (including
25 both GFDL CGCMs) were able to reproduce the observed spatial
26 distribution of monsoon rainfall, and its extension along the coast of
27 China toward the Korean peninsula and Japan. Considering a broader
28 range of longitude (40-180E) that includes the Indian subcontinent,
29 Annamalai et al. (2007) found that only six of eighteen CGCMs
30 (including both GFDL models) were significantly correlated with the
31 observed spatial pattern of CMAP precipitation during June through

1 September. These six models also included a realistic simulation of
2 ENSO variability, which is known to influence interannual variations
3 in the Asian summer monsoon. Kitoh and Uchiyama (2007) computed the
4 spatial correlation and root-mean-square error of simulated
5 precipitation over a similar region and found the GFDL models in the
6 top tercile with a spatial correlation exceeding 0.8, while the GISS
7 modelE-R correlation was just under 0.5.

8
9 During NH winter, the Asian surface winds are directed offshore: from
10 the northeast over India, and the northwest over East Asia. The two
11 American models included in the comparison of the simulated East Asian
12 winter monsoon by Hori and Ueda (2006), GFDL CM2.0 and GISS modelE-R,
13 generally reproduce the observed spatial distribution of sea level
14 pressure and 850 mb zonal wind.

15
16 In response to increasing greenhouse gases, models project increasing
17 summer precipitation during the 21st century (Kripalani et al. 2007
18 Kimoto 2005). However, the circulation strength in both winter and
19 summer is expected to weaken (Kimoto 2005, Ueda et al. 2006),
20 consistent with simple physical arguments by Held and Soden (2006).
21 The latter is also consistent with a study of previous generation
22 models where interannual fluctuations in low-latitude rainfall
23 increased, indicating increasingly severe seasonal departures from the
24 mean (Ramanen 2002).

25
26 Observed variability of the West African monsoon is related to
27 variations of ocean temperature in the Gulf of Guinea. The drying of
28 the Sahel during the late 20th century, and the attendant
29 societal impacts, is related to the inland extent of the monsoonal
30 circulation. Cook and Vizy (2006) found that slightly over half of
31 the 18 analyzed coupled models reproduced the observed maximum in

1 precipitation over land during June through August. Of these models,
2 only six reproduced the anti-correlation between Gulf of Guinea ocean
3 temperature and Sahel rainfall. The GISS modelE-H and both GFDL
4 models were among the most realistic.

5
6 It is unresolved whether the late-20th century Sahel drought is due to
7 natural or human influences. Hoerling et al. (2006) surveyed the
8 average response of eighteen coupled model to conclude that
9 anthropogenic forcings during this period account for only a small
10 fraction of rainfall variations observed in the Sahel. In contrast,
11 Biasutti and Giannini (2006), contrast Sahel rainfall between
12 simulations with observed 20th century forcings (such as greenhouse
13 gas and aerosol concentrations), nineteenth century (pre-industrial)
14 conditions, and increasing greenhouse gases. They suggest that the
15 observed late 20th century trend was externally forced, predominately
16 by anthropogenic aerosols. This conclusion is based upon the average
17 behavior of the models considered. It is supported in particular by
18 the GFDL and GISS models. It is currently unclear how to resolve these
19 contrasting conclusions, because they are based upon different methods
20 and comparisons of models. Both studies agree that the Sahel drought
21 is the result of ocean warming in the Gulf of Guinea, compared to the
22 NH subtropical Atlantic. What remains unresolved is whether forcing by
23 greenhouse gases and aerosols has changed the contrast in ocean
24 temperature between these two regions.

25
26 Rainfall over the Sahel and Amazon are anti-correlated: when the Gulf
27 of Guinea warms, rainfall is generally reduced over the Sahel but
28 increases over South America. Amazon rainfall also depends upon the
29 eastern equatorial Pacific, and during an El Nino, rainfall is reduced
30 in the Nordeste region of the Amazon. Li et al. (2006) compare the
31 hydrological cycle of eleven CGCMs over the Amazon during the

1 late 20th and twenty-first centuries. Based upon a comparison to
2 CMAP rainfall, the GISS modelE-R is among the best, with the GFDL
3 CM2.1 and NCAR CCSM3 models similarly ranked. Despite this fidelity,
4 the models make disparate predictions for the 21st century.
5 In the GISS modelE-R, the equatorial Pacific warms more in the west,
6 resembling a La Nina event. This, together with warming in the Gulf
7 of Guinea, is associated with an increase in Amazon rainfall. While
8 the NCAR CCSM3 predicts a comparable increase, the GFDL CM2.1 exhibits
9 a decrease and lengthening of the Amazon dry season.

10
11 The studies of Li et al. (2006) along with Ammamalai et al. (2007) note
12 that future changes in the South American and Asian monsoons are
13 intimately tied to the response of El Nino in the 21st
14 century. Expected temperature changes in the eastern equatorial
15 Pacific are discussed in ENSO section. Here, we note that a consensus
16 is yet to emerge, adding to uncertainty in monsoon projections.

17
18 The ability of climate models to simulate NH summer rainfall over the
19 US Great Plains and Mexico was summarized by Ruiz-Barradas and Nigam
20 (2006). Among the American models, the GISS modelE-H matches the
21 annual cycle of precipitation over the Great Plains and Mexico most
22 closely. It is also one of two models to simulate interannual
23 variations in precipitation that are significantly correlated with
24 observed variability during the second half of the 20th century.

25 The observed predominance of moisture import from the Gulf of Mexico
26 compared to local evaporation is most closely reproduced by the NCAR
27 PCM. Moisture import is excessive in the GISS modelE-H, whereas as
28 evaporation contributes too large a fraction in the GFDL CM2.1.

29
30 Initial evaluations of the monsoon simulated by the most recent
31 generation of climate models have emphasized the seasonal time scale.

1 However, subseasonal variations, such as break periods when the
2 monsoon rains are temporarily interrupted, are crucial to forecasts
3 and the impact of the monsoon upon water supply. Simulation of the
4 diurnal cycle, and the local hour of rainfall, is also important to
5 the partitioning of rainfall between runoff and transpiration, and
6 these are important topics for future model evaluation. Transports of
7 moisture by regional circulations beneath the resolution of the model
8 (such as low-level jets along the Rockies and Andes and tropical
9 cyclones) contribute to the onshore transport of moisture. In
10 general, the models show success at simulating the gross seasonal
11 features of the various monsoon circulations, but variations on
12 smaller spatial and time scales that are important to specific
13 watersheds and hydrological projections need to be evaluated.

14

15 *Tropical storms*

16

17 Tropical storms (hurricanes in the Atlantic and typhoons in the Pacific and Indian Oceans) are of
18 too small a scale to be reliably simulated in the class of global climate models currently used for
19 climate projections. There is hope for qualitatively useful simulations of the climatology of
20 incipient tropical depressions, however. The work of Vitart and Anderson (2001) is an example of
21 evidence for significant information content concerning tropical storm-like vortices in simulations
22 with models of this type, using the model's ability to simulate the effects of El Nino on Atlantic
23 storm frequency as a guide.

24

25 The recent 20km resolution simulation with an atmospheric model over prescribed ocean
26 temperatures by Oouchi et al (2006) is indicative of the kinds of modeling that will be brought to
27 bear on this problem in the next few years. Experience with tropical storm forecasting suggests that
28 this resolution should be adequate for describing many aspects of the evolution of nature tropical
29 storms, and possibly the generation of storms from incipient disturbances, but probably not tropical
30 storm intensity.

31

1 An alternative very promising approach is described by Knutson et al (2007), in which a regional
2 model of comparable resolution (18 km) is used in a downscaling framework to simulate the
3 Atlantic hurricane season. Given the observed year-to year variations in the large-scale structure of
4 the atmosphere over the Atlantic ocean, the model is capable of simulating the year-to-year
5 variations in hurricane frequency over a 30-year period with a correlation of 0.7-0.8 and also
6 captures the observed trend towards greater hurricane frequency over this period in the Atlantic.
7 These results suggest that models of this resolution may be able to provide a convincing
8 downscaling capability for tropical storm frequency projections into the future, although these
9 projections will still rely on the quality of the global model projections for changes in sea surface
10 temperature, atmospheric stability, and vertical shear. The behavior of the El Nino Southern
11 Oscillation into the future will be a key element affecting changes in those aspects of the large-scale
12 structure of the atmosphere over the Atlantic that control tropical storm formation and tracks.

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16 *Polar climates*

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18

19 Changes in polar snow and ice cover affect the Earth's albedo and thus the amount of insolation
20 heating the planet (e.g., Holland and Bitz 2003, Hall 2004, Dethloff *et al.* 2006). Concern has also
21 emerged about potential melting of glaciers and ice sheets in Greenland and Antarctica that could
22 produce substantial sea-level rise (Arendt *et al.* 2002, Braithwaite and Raper 2002, Alley *et al.*
23 2005). Polar regions thus require accurate simulation for projecting future climate change and its
24 impacts.

25 Polar regions present unique environments and, consequently, challenges for climate
26 modeling. The obvious are processes involving frozen water. While not unique to polar regions,
27 they are more pervasive there. These processes include seasonally frozen ground and permafrost
28 (Lawrence and Slater 2005, Yamaguchi *et al.* 2005) and seasonal snow cover (Slater *et al.* 2001),
29 which can have significant sub-grid heterogeneity (Liston 2004), and clear-sky precipitation,
30 especially in the Antarctic (King and Turner 1997, Guo *et al.* 2003). Polar radiation also has
31 important characteristics that test the ability of models to handle extreme geophysical behavior,

1 such as longwave radiation in clear, cold environments (Hines *et al.* 1999, Chiacchio *et al.* 2002,
2 Pavlonis *et al.* 2004) and cloud microphysics in the relatively clean polar atmosphere (Curry *et*
3 *al.* 1996, Pinto *et al.* 2001, Morrison and Pinto 2005). In addition, polar atmospheric boundary
4 layers can be very stable (Duynderke and de Roode 2001, Tjernström *et al.* 2004, Mirocha *et al.*
5 2005), and stable boundary layers remain an important area for model improvement.

6 Confidence in climate model projections of future climate is greatly increased if it can be
7 shown that climate models can accurately simulate the current climate state, and much effort has
8 gone into this type of analysis (e.g. Collins *et al.* 2006, Delworth *et al.* 2006). In particular climate
9 models should be able to reproduce both long-term and short-term variations in climate including
10 daily, seasonal, interannual, and decadal variability. For polar regions, much of the assessment of
11 simulated interannual variability has focused on the primary modes of polar interannual variability,
12 the Northern and Southern Annular Modes. Assessment of simulated annular modes appears in
13 Section B. of this chapter.

14 Less attention has been given to the ability of global climate system models to simulate
15 shorter-duration climate and weather variability in polar regions. Uotila *et al.* (2007) and Cassano
16 *et al.* (2007) evaluated the ability of an ensemble of 15 global climate-system models to simulate
17 the daily variability in sea level pressure in the Antarctic and Arctic. In both polar regions, it was
18 found that the 15-model ensemble was not able to reproduce the daily synoptic climatology, with
19 only a small subset of the models accurately simulating the frequency of the primary synoptic
20 weather patterns identified in global reanalysis data sets. The U.S. models discussed in detail in
21 Chapter 2 of this report spanned the same range of accuracy as non-U.S. models, with GFDL and
22 NCAR GCM versions part of the small, accurate subset. Vavrus *et al.* (2006) assessed the ability
23 of seven global climate models to simulate extreme cold-air outbreaks in the Northern Hemisphere,
24 and found that the spatial pattern of the outbreaks was accurately reproduced in the models,
25 although some details differed.

26 Attention has also been given to the ability of regional climate models to simulate polar
27 climate. In particular, the Arctic Regional Climate Model Intercomparison Project (ARCMIP)
28 (Curry and Lynch 2002) engaged a suite of Arctic regional atmospheric models to simulate a
29 common domain and period over the western Arctic. Rinke *et al.* (2006) evaluated the spatial and
30 temporal patterns simulated by 8 ARCMIP models, and found that the model ensemble agreed well
31 with global reanalyses, despite some large errors for individual models. Tjernstrom *et al.* (2005)

1 evaluated near-surface properties simulated by 6 ARCMP models. In general surface pressure, air
2 temperature, humidity, and wind speed were all well simulated, as were radiative fluxes and
3 turbulent momentum flux. Tjernstrom *et al.* (2005) found that turbulent heat flux was poorly
4 simulated, and that over an entire annual cycle the accumulated turbulent heat flux simulated by the
5 models was an order of magnitude larger than the observed turbulent heat flux (Fig. PA-1). In both
6 Tjernstrom *et al.* (2005) and Rinke *et al.* (2006), the U.S. models performed about the same as their
7 European counterparts.

8 Although simulations of polar climate display agreement with observed behavior, as
9 indicated above, there remains room for improvement. In global models, polar simulation may be
10 affected by errors in simulating other regions of the planet, but much of the difference from
11 observations and uncertainty about projected climate change stems from current limitations in polar
12 simulation. These limitations include missing or incompletely represented processes and poor
13 resolution of spatial distributions.

14 As with other regions, model resolution affects simulation of important processes. In the
15 polar regions, surface distributions of snow depth vary markedly, especially when snow drifting
16 occurs. Improved snow models are needed to represent such spatial heterogeneity (e.g., Liston
17 2004), which will continue to involve scales smaller than resolved for the foreseeable future. Frozen
18 ground, whether seasonally frozen or occurring as permafrost, presents additional challenges.
19 Models for permafrost and seasonal freezing and thawing of soil are being implemented in land
20 surface models (see Chapter 2, Land Surface Models). Modeling soil freeze and thaw continues to
21 be a challenging problem as characteristics of energy and water flow through the soil affect
22 temperature changes, and such fluxes are poorly understood (Yamaguchi *et al.* 2005).

23 Frozen soil affects surface and subsurface hydrology, which influences the spatial
24 distribution of surface water with attendant effects on other parts of the polar climate system such as
25 carbon cycling (e.g., Gorham 1991, Aurela *et al.* 2004), surface temperature (Krinner 2003), and
26 atmospheric circulation (Gutowski *et al.* 2007). The flow of fresh water into polar oceans
27 potentially alters their circulation, too. Surface hydrology modeling typically includes limited, at
28 best, representation of subsurface water reservoirs (aquifers) and horizontal flow of water at both
29 the surface and below surface. These features limit the ability of climate models to represent
30 changes in polar hydrology, especially in the Arctic.

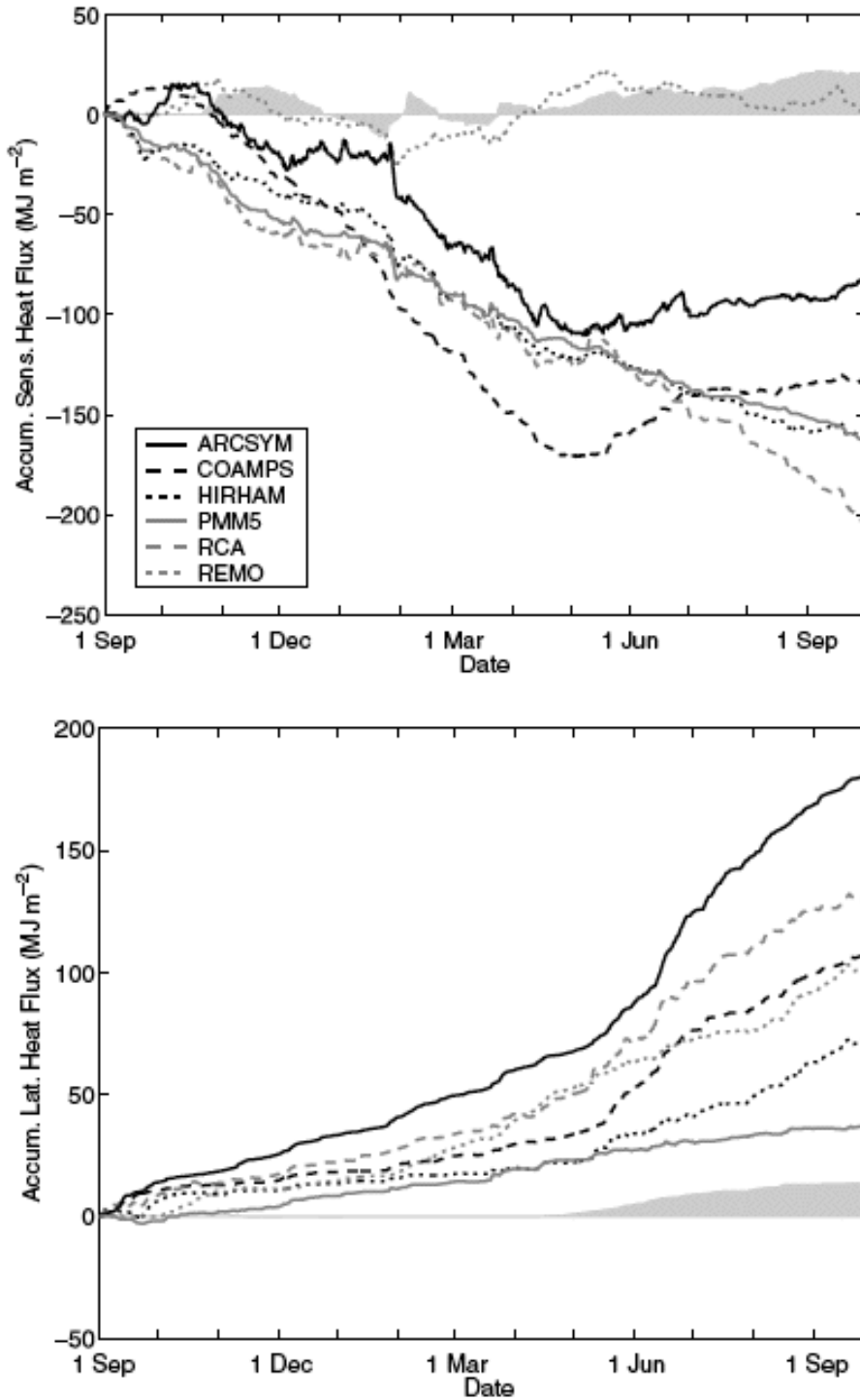
1 Vegetation has been changing in the Arctic (Callaghan *et al.* 2004) and projected warming,
2 which may be largest in regions where snow and ice cover retreat, may produce further changes in
3 vegetation (e.g., Lawrence and Slater 2005). Current models use static distributions of vegetation,
4 but dynamic vegetation models will be needed to account for changes in land-atmosphere
5 interactions influenced by vegetation.

6 A key concern in climate simulations is how projected anthropogenic warming may alter ice
7 sheets on land, whose melting could raise sea levels substantially. At present, climate models do not
8 include ice-sheet dynamics and thus cannot account directly for how ice sheets might change,
9 possibly changing heat absorption from the sun and atmospheric circulation in the vicinity of the ice
10 sheets.

11 How well each of the processes above is represented in climate simulation depends in part
12 on model resolution. Distributions of snow, ice sheets, surface water, frozen ground and vegetation
13 have important spatial variation on scales smaller than the resolutions of typical contemporary
14 climate models. Finer resolution is thus needed. Part of this need may be satisfied by regional
15 models simulating just a polar region. Because both the northern and southern polar regions are
16 within circumpolar atmospheric circulations, their synoptic coupling with other regions is more
17 limited than is the case with midlatitude regions, where the westerlies rapidly move synoptic
18 systems in and out of a region (e.g., Wei *et al.* 2002), which could allow polar-specific models that
19 focus on ant/arctic processes, in part to improve modeling of surface-atmosphere exchange
20 processes (Fig. V L). While each of the above processes have been simulated in finer scale, stand-
21 alone models, their interactions as part of a climate system also need to be simulated and
22 understood.

23

1 Fig. V L. Cumulative fluxes of surface sensible heat (top panel) and latent heat (bottom) at the
2 SHEBA site from six models simulating a western Arctic domain for Sept. 1997 – Sept. 1998 for
3 ARCMIP. SHEBA observations are the gray vertical bars; model identifications are given by the
4 key in the upper panel. Adapted from Tjernstrom *et al.* (2005).



5

1 **Sea ice** plays a critical role in the exchange of heat, mass, and momentum between the ocean and
2 atmosphere and any errors in the sea-ice system will contribute to errors in the other components.
3 Two recent papers [*Holland and Raphael 2006* and *Parkinson et al. 2006*] quantify how the
4 current models simulate the sea-ice process of the climate system. Very limited observations make
5 any evaluation of sea ice difficult. The primary observation available is sea ice concentration. In
6 some comparisons, sea ice extent (ice concentration greater than 15%), is used. Satellites have
7 made it possible for a more complete data set of observations for the past few decades. Prior to
8 satellite measurements becoming available, observations of ice extent were fewer. Other quantities
9 that might be evaluated include ice thickness. Such comparisons are difficult because of the limited
10 number of observations and will not be discussed.

11
12 *Ice Concentration and extent:* Both of these studies indicate that the seasonal pattern in ice growth
13 and decay in the polar regions for all the models is reasonable [*Holland and Raphael 2006*] (**Figure**
14 **V M**). However, there is a large amount of variability between the models in their representation of
15 the sea ice extent in both the northern and southern hemispheres. Generally, the models do better in
16 simulating the Arctic region than in their simulation of the Antarctic region as shown with **Figure V**
17 **N**]. An example of the complex nature of reproducing the ice field is given in *Parkinson et al.*
18 [2006]. They found that all the models showed an ice-free region in winter to the west of Norway,
19 as seen in observational data, but all the models also produced too much ice north of Norway. They
20 suggest that this is because the North Atlantic Current is not being simulated correctly. In a
21 qualitative comparison, Hudson Bay is ice covered in winter in all the models correctly reproducing
22 the observations. The set of models are not consistent in their "fidelity" between the Northern and
23 Southern regions and maybe due, partly, to how the parameters are defined in the sea ice models.

24
25 *Holland and Raphael [2006]* examined the variability in the Southern Ocean sea ice extent
26 extensively. As an indicator of the ice response to large scale atmospheric events, they compared a
27 set of IPCC AR4 climate models sea ice response to the atmospheric index, the Southern Annular
28 Mode (SAM) for the April-June (AMJ) period (Table V 4). The models show that the ice variability
29 does respond modestly to the large scale atmosphere forcing but less than limited observations
30 show. Two of the models also exhibit the out-of-phase buildup of ice between the Atlantic and
31 Pacific sectors (the Antarctic Dipole) to some degree.

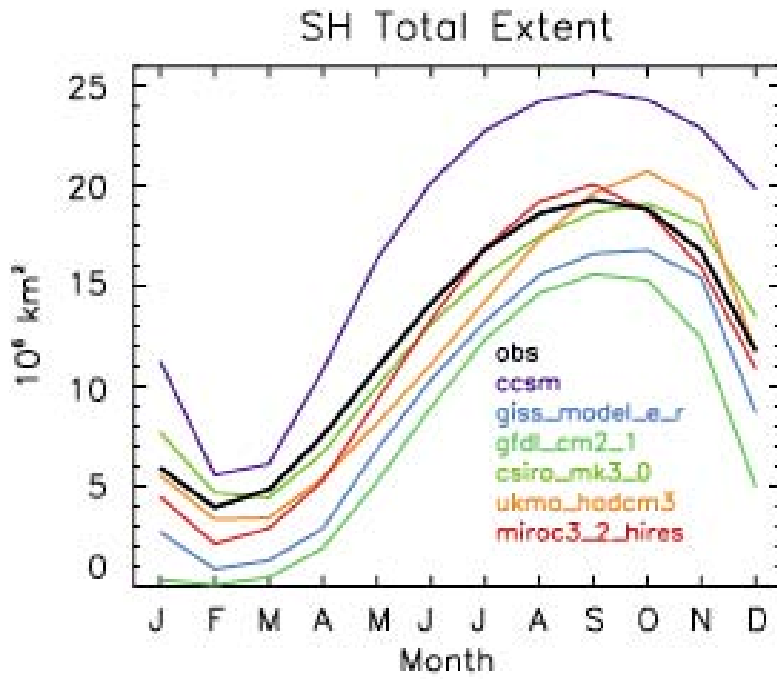
1
 2 **Table V 4**
 3
 4 **MODIFIED FROM Table 1 *Holland and Raphael* [2006]** Correlations of the leading mode of sea
 5 ice variability and the southern annular mode (SAM) for the observations and model simulations

	AMJ SAM and high-pass filtered fields	AMJ SAM and detrended fields
Observations	0.47	0.47
CCSM3	0.40	0.44
GFDL-CM2.1	0.39	0.19
GISS-ER	0.30	0.20

6 Bold values are significant at the 95% level accounting for the autocorrelation of the timeseries
 7

1 Figure V M

2

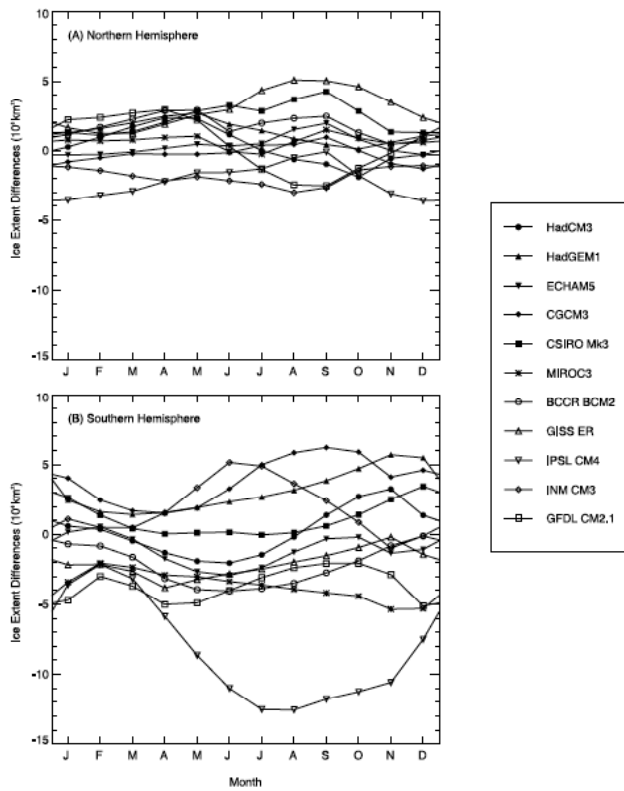


3

4 From *Holland and Raphael 2006*. Fig. 1 The annual cycle of southern hemisphere ice extent

5 defined to be the area of ice with concentrations greater than 15%

1 Figure V N



2
3 **From Parkinson *et al.* 2006: Figure 4.** Difference between the modeled 1979–2004 monthly
4 average sea ice extents and the satellite-based observations (modeled minus observed), for each of
5 11 major GCMs, for both the (a) Northern Hemisphere and (b) Southern Hemisphere.

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Modes of variability

The Madden-Julian Oscillation: (MJO) is a characteristic pattern in the tropical atmosphere. It has taken on special prominence in research on simulating the tropical atmosphere. This phenomenon consists of large-scale eastward propagating patterns in humidity, temperature, and atmospheric circulation which strengthen and weaken tropical rainfall as they propagate around the Earth in roughly 30-60 days. This pattern often dominates intraseasonal (within season) variability of tropical precipitation on time scales longer than a few days, creating such phenomena as 1-2 week breaks in Asian monsoonal rainfall and weeks with enhanced hurricane activity in the Eastern North Pacific and the Gulf of Mexico. Inadequate prediction of the evolution of these propagating structures is considered one the main impediments to more useful extended-range weather forecasts in the tropics, and improved simulation of this phenomenon is considered by some a litmus test for the credibility of climate models in the tropics

Recent surveys of model performance indicate that simulations of the MJO remain inadequate. For example, Lin *et al* (2006), in a study of many of the models in the CMIP-3 models, conclude that "... current GCMs still have significant problems and display a wide range of skill in simulating the tropical intraseasonal variability", while Zhang *et al.* (2005) in another multi-model comparison study, state that "... commendable progress has been made in MJO simulations in the past decade, but the models still suffer from severe deficiencies ...". Nearly all models do capture the essential feature of the pattern, with large-scale eastward propagation and with roughly the correct vertical structure. But the propagation is often too rapid and the amplitudes too weak. As an example of recent work, Klein (2007?) studies whether two of the US IPCC models can maintain a pre-existing strong MJO pattern when initialized with observations (from the TOGA-COARE field experiment), with limited success. Controlled experiments have suggested that for models to simulate MJO, the instability of the atmosphere must be allowed to accumulate to a certain amount before convective storms are triggered, and sufficient mesoscale stratiform heating from convective systems should exist in the upper troposphere (Wang and Schlesinger 1999). These processes are however poorly understood in current climate models.

1
2 The difficulty in simulation of the MJO is related to the multi-scale nature of the phenomenon: the
3 propagating pattern is itself of large enough scale that it should be resolvable by climate models, but
4 the convection and rainfall modulated by this pattern, and feeding back and energizing it, occur on
5 much smaller, unresolved, scales. In addition to this dependence on the parameterization of tropical
6 convection, a long list of other effects has been shown by models and/or observational studies to be
7 important for the MJO. These include the pattern of evaporation generated as the MJO propagates
8 through convecting regions, feedback from cloud-radiative interactions, intraseasonal ocean
9 temperature changes, the diurnal cycle of convection over the ocean, as well as the vertical structure
10 of the latent heating, including especially the proportion of shallow cumulus congestus clouds and
11 deep convective cores in the different phases of the oscillation (Lin *et al.* 2004).

12
13
14 A picture seems to be emerging that the difficulty in simulation may not be due to a single model
15 deficiency but a result of the complexity of the phenomenon, given this long list of factors thought
16 to be significant. In several of the multi-model studies, such as Lin *et al.* (2006) a few of the models
17 do perform well, but without a clearer understanding of how these factors combine to generate the
18 observed characteristics of the MJO, it is difficult to maintain a good simulation as the model is
19 modified for other reasons, and it is difficult to transfer one model's successful simulation to other
20 models. It also remains unclear whether the models with superior MJO simulations should be given
21 extra weight in multi-model studies of climate change in the tropics.

22
23
24 **The El Nino – Southern Oscillation (ENSO)** El Nino was named originally in the 19th century by
25 Peruvian sailors to note the early arrival of a warm current from equatorial latitudes (Philander
26 1990). Every few years, a springtime northerly current arrives prematurely around Christmas (Yu
27 and McPhaden 1999), bringing heavy rains to coastal Peru and a temporary decline in the anchovy
28 harvest. By the mid 20th century, scientists recognized that this local anomaly was in fact part of a
29 disruption to the atmospheric circulation across the entire Pacific basin. During El Niño,
30 atmospheric mass migrates west of the dateline as part of the Southern Oscillation, reducing surface
31 pressure and drawing rainfall into the central and eastern Pacific (Rasmussen and Wallace 1983).

1 Together, El Niño and the Southern Oscillation, often abbreviated in combination as ENSO, are the
2 largest source of tropical variability observed during recent decades.

3
4 Changes along the equatorial Pacific have been linked to global disruptions of climate (Ropelewski
5 and Halpert 1987). During an El Niño event, the Asian monsoon is typically weakened, along with
6 rainfall over eastern Africa, while precipitation increases over the American southwest. El Niño
7 raises the surface temperature as far poleward as Canada, while changes in the North Pacific Ocean
8 are linked to decadal variations in ENSO (Trenberth and Hurrell 1994). In many regions far from
9 the eastern equatorial Pacific, accurate projections of climate change in the twenty-first century
10 depend upon the accurate projection of changes to El Niño. Moreover, the demonstration that
11 ENSO alters climate across the globe indicates that even changes to the *time-averaged* equatorial
12 Pacific during the 21st century will influence climate far beyond the tropical ocean. For example, a
13 long-term warming of the eastern equatorial Pacific relative to the surrounding ocean will favor a
14 weaker Asian monsoon, even in the absence of changes to the size and frequency of El Niño events.

15
16 Incident sunlight is largest on the equator, but in the eastern Pacific, the ocean is colder than at
17 neighboring latitudes. Because of the Earth's rotation, easterly winds along the equator cool the
18 surface by raising cold water from below, which offsets heating by the absorption of sunlight (e.g.
19 Clement *et al* 1996). In contrast, warm water extends deeper to the west so upwelling has little
20 effect upon the surface temperature of the West Pacific, where the warmer ocean is consistent with
21 the strong, equatorial solar heating. The westward increase of temperature along the equator is
22 associated with a decrease in atmospheric pressure, reinforcing the easterly Trade winds.

23
24 Theoretical arguments offer conflicting projections of tropical Pacific climate during the twenty-
25 first century. One projection is for the equatorial temperature contrast to increase, so that the
26 average state more closely resembles La Niña, marked by unusually cold ocean temperatures and
27 enhanced upwelling in the East Pacific, the opposite to El Niño (Clement *et al* 1996; Cane *et al*
28 1997). According to this argument, an increase in net radiation into the ocean resulting from an
29 increase in greenhouse gas concentration is partially offset by the upwelling of cold water. This
30 compensation is stronger in the east than in the west, where the surface layer of warm water extends
31 to greater depth. There is evidence for an observed trend toward a La Niña state (Cane *et al* 1997),

1 but the trend remains ambiguous because of the large decadal variations in the ENSO cycle.
2 Another theory is based upon the origin of upwelling water along the equator within descending
3 surface water in higher latitudes. Liu *et al* (1998) suggest that as these higher latitudes warm, the
4 temperature of the upwelling water will increase, reducing its ability to offset radiative warming at
5 the surface. A third theory suggests that as the tropical atmosphere becomes more stable in response
6 to surface warming, the tropical circulation will weaken (Knutsen and Manabe 1998; see also Meehl
7 and Washington 1996). This will draw less cold water to the surface, preferentially warming the
8 East Pacific. Until recently, many coupled ocean-atmosphere models projected larger warming of
9 the East Pacific and a drift of mean conditions toward an ENSO state.

10
11 Below, we summarize the most recent model comparisons, emphasizing those studies carried out as
12 part of the IPCC AR4. Our conclusions are based upon model behavior from a worldwide collection
13 of coupled ocean-atmosphere models, although we illustrate many of the scientific issues using
14 models from American laboratories. The coupled models are designed for prediction of global
15 climate over decades and centuries and are not tuned to optimize their simulation of ENSO *per se*,
16 unlike many of the more simple dynamical and statistical models currently used for operational
17 forecasts of ENSO over a period of several months. Nonetheless, we find that the global models as a
18 group exhibit realistic simulations of present-day seasonal variations and ENSO variability, and
19 represent a marked improvement compared to previous generations of coupled models. However,
20 among the most realistic models, there is little consensus on the anticipated change to either the
21 mean state of the tropical Pacific (particularly the east-west difference in ocean temperature along
22 the equator) or the amplitude and frequency of ENSO variability. This introduces uncertainty in the
23 projected climate response within regions throughout the globe influenced by El Niño.

24
25 In general, coupled models developed for the CMIP3 are far more realistic than those of a decade
26 ago, when ENSO variability was comparatively weak, and some models lapsed into permanent El
27 Niño states (Neelin *et al.*, 1992). Even compared to the models assessed more recently by ENSIP
28 and CMIP2 (Latif *et al.*, 2001; AchutaRao and Sperber 2002), ENSO variability of ocean surface
29 temperature is more realistic, although sea level pressure and precipitation anomalies show little
30 recent improvement (AchutaRao and Sperber 2006). Part of this progress is the result of increased
31 resolution of the equatorial ocean circulation that has accompanied inevitable increases in

1 computing speed. Table V 5 shows the horizontal and vertical resolution of the seven American
 2 coupled models whose output was submitted to AR4.

3

4 Table V 5

5

6 Spacing of grid points at the equator in the American coupled models developed for AR4. Except
 7 for the GISS models, spacing of grid points generally increases away from the equator outside of
 8 the domain of ENSO, so that resolution is highest on the equator.

9

10 Model: Longitude Latitude Vertical Levels

11

12 GFDL CM2.0 1 1/3 50

13 GFDL CM2.1 1 1/3 50

14 GISS AOM 5 4 13

15 GISS modelE-H 2 2 16

16 GISS modelE-R 5 4 13

17 NCAR CCSM3 1.125 0.27 27

18 NCAR PCM 0.94 0.5 32

19

20

21

22 Along the equator, oceanic waves that adjust the equatorial temperature and currents to changes in
 23 the wind are tightly confined to within a few degrees of latitude. To simulate this adjustment, the
 24 ocean state is calculated at points as closely spaced as 0.27 degrees of latitude in the NCAR
 25 CCSM3. NCAR PCM has half degree resolution, while both GFDL models have equatorial
 26 resolution of one-third of a degree. This degree of detail is a substantial improvement compared to
 27 previous generations of models. In contrast, the GISS AOM and modelE-R calculate equatorial
 28 temperatures at grid points separated by four degrees of latitude. This is broad compared to the
 29 latitudinal extent of cold temperatures observed within the eastern Pacific (the 'cold tongue' region),
 30 which are the result of a narrow band of cold water rising to the surface along the equator. In the
 31 coarse resolution models, changes to the upward flow are spread over the dimensions of the grid

1 box, which is broader than the observed upwelling. The cooling effect of this rising water is spread
2 over a larger area, so that the amplitude of the resulting temperature fluctuation at the surface is
3 weakened. In fact, both the GISS AOM and modelE-R models have unrealistic ENSO variations
4 that are much smaller than observed (Hansen *et al* 2007). This minimizes the influence of their
5 simulated El Nino and La Nina events on climate outside the equatorial Pacific, and we will not
6 discuss these two models further in this section.

7
8 In comparison to previous generations of global models, where ENSO variability was typically
9 weak, the AR4 coupled models generally simulate El Nino near the observed amplitude, or even
10 above (Neelin *et al* 1992; AchutaRao and Sperber 2006). The latter study compared sea surface
11 temperature (SST) variability within the tropical Pacific calculated under pre-industrial conditions.
12 Despite its comparatively low two-degree latitudinal grid spacing, the GISS modelE-H among the
13 American models most closely matches observed SST variability since the mid-19th century,
14 according to the HadISST v1.1 data set (Rayner *et al* 2003). The NCAR PCM also exhibits El Niño
15 warming close to the observed magnitude. This comparison is based upon spatial averages within
16 three longitudinal bands, and GISS modelE-H along with the NCAR models exhibit their largest
17 variability in the eastern band as observed. However, GISS modelE-H underestimates variability
18 since 1950, when the NCAR CCSM3 is closest to observations (Joseph and Nigam 2006). While the
19 fidelity of each model's ENSO variability depends upon the specific data set and period of
20 comparison (c.f. Capotondi *et al.*, 2006; Merryfield 2006, van Oldenborgh *et al.*, 2005), the general
21 consensus is that the GISS modelE-H, both NCAR models, and GFDL CM2.0 have roughly the
22 correct amplitude, while variability is too large by roughly one-third in the GFDL CM2.1. While
23 most models (including GISS modelE-H and both NCAR models, but excluding the GFDL models)
24 exhibit the largest variability in the eastern band of longitude, none of the AR4 models match the
25 observed variability at the South American coast, where El Nino was originally identified
26 (AchutaRao and Sperber 2006; Capotondi *et al.*, 2006). This is possibly because the longitudinal
27 spacing of the model grids is too large to resolve coastal upwelling, and its interruption during El
28 Niño (Philander and Pacanowski 1981). Biases in the atmospheric model, including underestimate
29 of the persistent stratus cloud decks along the coast, may also contribute (Mechoso *et al.*, 1995).
30
31 El Niño occurs every few years, albeit irregularly. The spectrum of anomalous ocean temperature

1 shows a broad peak between two and seven years, and there are multi-decadal variations in event
2 frequency and amplitude. Almost all of the AR4 models have spectral peaks within this range of
3 time scales. Interannual power is broadly distributed within the American models, as observed, with
4 the exception of the NCAR CCSM3 which exhibits strong biennial oscillations.

5
6 While the models generally simulate the observed magnitude and frequency of events, reproduction
7 of their seasonality is more elusive. Anomalous warming typically peaks late in the calendar year,
8 as originally noted by South American fisherman. Among American models, this seasonal
9 dependence is simulated only by the NCAR CCSM3 (Joseph and Nigam 2006). Warming in the
10 GFDL CM2.1 and GISS modelE-H are nearly uniform throughout the year, while warming in the
11 NCAR PCM is largest in December but exhibits a secondary peak in early summer. The mean
12 seasonal cycle along the equatorial Pacific also remains a challenge for the models. Each year, the
13 east Pacific cold tongue is observed to warm during NH spring and cool again late in the calendar
14 year. The GFDL CM2.1 and NCAR PCM1 have the weakest seasonal cycle among the American
15 models, while GISS modelE-H, GFDL 2.0 and NCAR CCSM3 are closest to the observed
16 amplitude (Guilyardi 2006). Among the worldwide suite of AR4 models, the amplitude of the
17 seasonal cycle of equatorial ocean temperature generally varies inversely with the strength of the
18 ENSO cycle.

19
20 Anticipation of twenty-first changes to El Nino remains uncertain, because of a lack of consensus
21 among the models. Among fifteen models forced by increasing carbon dioxide, three exhibit
22 statistically significant increases in amplitude, while five exhibit a decrease, compared to their
23 variability under pre-industrial conditions (Merryfield, 2006). Even when only the most realistic
24 models are surveyed (including the GFDL CM2.1), identified according to a detailed examination
25 of their mechanisms of variability (described below), no consensus emerges. No significant change
26 in event period is found either (Guilyardi 2006). These trends are inferred based upon the response
27 to a doubling or quadrupling of carbon dioxide, compared to a pre-industrial climate. This forcing is
28 strong compared to forcing over the 20th century in which one might hope to infer trends in El Nino
29 from the observational record. The occurrence of the two largest El Nino events late in the 20th
30 century has been attributed to increasing greenhouse gas concentrations (Trenberth and Hoar 1997;
31 Knutsen and Manabe 1998), although this remains unsettled because of large variations in the

1 tropical Pacific within the multi-decadal instrument record (Rajagopalan *et al.*, 1997).

2

3 Changes in the climate of the tropical Pacific (as opposed to trends in El Niño variability) are also
4 inconsistent (van Oldenborgh *et al* 2006). Of particular interest is the relative warming along the
5 equator, because this is related to the strength of the tropical circulation, which creates regional
6 changes throughout the globe. The ostensible consensus among the most recent generation of
7 models (including both American and international modeling centers) is that the eastern Pacific will
8 warm by about a half degree Celsius more compared to the west (see Figure 10.16 of Meehl *et al.*
9 2007).

10 This is small compared to the currently observed difference of a few degrees. When only the most
11 realistic models are surveyed (including the two GFDL models), the warming is nearly uniform
12 across the Pacific (van Oldenborgh *et al.* 2005). This behavior is consistent with a previous
13 generation of global models, surveyed as part of CMIP2 (Collins *et al.* 2005). When the model
14 predictions were weighted by the realism of each model, the multi-model average warming was
15 nearly uniform, with only a small probability of greater warming in the east. In summary, warming
16 along the equatorial Pacific is expected to be uniform or slightly larger to the east, but this contrast
17 is on the order of differences among the models. This translates into an uncertainty in the climate in
18 regions outside the tropical Pacific affected by ENSO.

19

20 The lack of consensus among model projections for the 21st century may result from the
21 combination of physical mechanisms contributing to observed variability, and the difficulty of
22 simulating them individually along with their relative importance. There is evidence that the
23 importance of certain mechanisms changed in the middle of the 1970's (Wang 1995), so it is unclear
24 what the correct emphasis should be. In addition, positive feedbacks, inferred from the observations,
25 may exacerbate unrealistic features in the models, contributing further to model error.

26

27 Several studies have assessed the mechanisms contributing to variability among the AR4 models.
28 Confidence in the models' projection of climate within the tropical Pacific during the twenty-first
29 century depends upon accurate simulation of mechanisms of variability observed at present. El Niño
30 occurs when the upwelling of cold water to the surface is interrupted within the equatorial eastern
31 Pacific and South American coast. This can occur because the rate of upwelling decreases, or

1 alternatively because the temperature of the upwelling water increases. This subsurface temperature
2 is related to the depth of the thermocline, within which the water temperature falls off sharply with
3 depth. During El Niño, the thermocline deepens, so that upwelling water originating in the cold
4 water below now begins its rise within the relatively warm layer above (Wyrki 1975). In addition,
5 the slowing of the easterly Trade winds reduces the rate of upwelling (Bjerknes 1969), which at the
6 surface reduces the export of water from the cold tongue toward the West Pacific. Within the
7 weaker surface current, water has more time to be warmed by the sun and overlying atmosphere. El
8 Niño is a coupled phenomenon because the winds that change the upwelling of cold water to the
9 surface depend upon the ocean temperature itself. Because the easterlies are driven partly by the
10 temperature contrast between the cold east Pacific and the warmer ocean west of the dateline,
11 warming in the east reinforces the slackening of the easterly Trade winds.

12
13 The coupling between ocean temperature and equatorial winds is typically inferred by regressing
14 wind stress upon temperature averaged within the ENSO domain. The observed wind anomaly is
15 westerly and strongest slightly to the west of a warm ocean anomaly, as expected based upon simple
16 theoretical models (Gill 1980; Lindzen and Nigam 1987, Yu and Neelin 1997). The model wind
17 anomalies are typically displaced farther west than observed, and are excessively confined to the
18 equator (Capotondi *et al.*, 1987). The NCAR PCM regression is roughly half the observed strength,
19 while among the American models, the NCAR CCSM3 and GFDL CM2.1 come closest to
20 observations (Van Oldenborgh *et al.*, 2005). The GISS modelE-H exhibits reasonable coupling in
21 the Central Pacific, but almost no coupling toward South America.

22
23 The converse response of SST to wind anomalies is diagnosed by evaluating various terms in the
24 equation for the evolution of ocean temperature (van Oldenborgh 2005; Capotondi *et al.*, 2006).
25 Changes in the temperature of upwelling water are observed to be important in the eastern Pacific
26 (Capotondi *et al.*, 2006). This feedback is reproduced by the GFDL CM2.0 and NCAR CCSM3
27 models, although with somewhat low amplitude, possibly because the climatological upwelling is
28 weak. (The model output necessary for this diagnosis was not available for the GFDL CM2.1,
29 NCAR PCM, and GISS modelE-H.) While a decrease in the rate of upwelling is crucial to observed
30 warming in the Central Pacific, this feedback is weak in the GFDL CM2.0, and absent in the NCAR
31 CCSM3. The ocean feedback to wind anomalies is also diagnosed by regressing the evolution of

1 ocean temperature upon various mechanisms represented within the ocean heat budget (van
2 Oldenborgh *et al.*, 2005). The NCAR PCM has very strong feedbacks of upwelling rate and
3 temperature in response to wind anomalies, which compensate for its weak wind response to
4 anomalous SST. The GFDL CM2.1 generally reproduces the observed regression relations. In
5 contrast, van Oldenborgh *et al.* (2005) note that regression analysis of GISS modelE-H is noisy and
6 difficult to interpret. It is not clear at this point how GISS modelE-H compensates for its weak wind
7 response to ocean temperature anomalies in order to create ENSO temperature variability near the
8 observed magnitude and location. This lack of transparency calls its projection of future changes
9 into question.

10
11 In general, GFDL2.1 is consistently ranked among American models as the most realistic
12 simulation of El Nino (van Oldenborgh *et al.*, 2005; Guilyardi 2006; Merryfield 2006). This is
13 based not only on its surface temperature variability (which in fact is slightly too high), but on its
14 faithful simulation of the observed relationship between ocean temperature and surface wind, along
15 with the wind-driven ocean response. While SST in many models is consistently dominated either
16 by anomalies of upwelling strength or else temperature, these processes alternate in importance over
17 several decades within the GFDL CM2.1 as observed (Guilyardi 2006). Since the 1970's, the
18 upwelling temperature has been the predominant feedback (Wang 1995).

19
20 While GFDL CM2.1 predicts a reduced ENSO amplitude in response to increased greenhouse
21 forcing, there is no consensus even among the most highly regarded models. Philip and Van
22 Oldenborgh (2006) find that while both upwelling feedbacks amplify as the greenhouse gas
23 concentration increases, damping processes (due to cloud radiation, for example) also become more
24 effective. A robust prediction of future El Niño amplitudes requires both the upwelling feedback
25 and damping along with their relative amplitude to be simulated consistently, which remains a
26 challenge.

27
28 El Niño events are related to climate anomalies throughout the globe. Models with more realistic
29 ENSO variability generally exhibit an anti-correlation with the strength of the Asian summer
30 monsoon (e.g. Annamalai *et al.*, 2006), while 21st century changes to Amazon rainfall have been
31 shown to depend upon projected trends in the tropical Pacific (Li *et al.*, 2006). El Niño has a long-

1 established relation to North American climate (Horel and Wallace 1981), assessed in the AR4
2 models by Joseph and Nigam (2006). This relation is strongest during NH winter, when the tropical
3 anomalies are largest. Anomalous circulations driven by rainfall over the warming equatorial
4 Central Pacific radiate atmospheric disturbances into mid-latitudes that are amplified within the
5 North Pacific storm track (Sardeshmukh and Hoskins 1988; Held *et al.*, 1989; Trenberth *et al.*,
6 1998). To simulate the influence of ENSO upon North America, the models must simulate realistic
7 rainfall anomalies and in the correct season in order that the connection is amplified by the
8 wintertime storm tracks. The connection between equatorial Pacific and North American climate is
9 simulated most accurately by the NCAR PCM model (Joseph and Nigam 2006). In the GFDL
10 CM2.1, North American anomalies are too large, consistent with the model's excessive El Niño
11 variability within the equatorial Pacific. The connection between the two regions is realistic if the
12 model's tropical amplitude is accounted for. In the GISS model, anomalous rainfall during ENSO is
13 small, consistent with the weak tropical wind stress anomaly cited above. The influence of El Niño
14 over North America is nearly negligible in this model. The weak rainfall anomaly is presumably a
15 result of unrealistic coupling between the atmospheric and ocean physics. When SST is instead
16 prescribed in this model, rainfall calculated by the GISS model E AGCM over the American
17 southwest is significantly correlated with El Niño as observed.

18
19 Realistic simulation of El Niño, and its global influence, remains a challenge for coupled models,
20 because of the myriad processes contributing and their changing importance in the observational
21 record. Key aspects of the coupling between the ocean and atmosphere, the relation between SST
22 and wind stress anomalies, for example, are the result of complicated interactions between the
23 resolved model circulations, along with parameterizations of the ocean and atmospheric boundary
24 layers and moist convection. Simple models identify parameters controlling the magnitude and
25 frequency of El Niño, such as the wind anomaly resulting from a change in SST (e.g., Zebiak and
26 Cane 1987; Fedorov and Philander 2000), offering guidance to improve the realism of fully coupled
27 GCM's. However, in a GCM, the coupling strength is emergent rather than prescribed, and it is
28 often unclear *a priori* how to change the coupling. Nonetheless, the improved simulations of the
29 ENSO cycle compared to previous generations (AchutaRao and Sperber 2006) suggest that
30 additional realism can be expected in the future. This optimism arises in part from the extensive and

1 unprecedented model comparisons carried out as part of the AR4, where the flaws identified in
2 current models may point toward future solutions.

3

4 *Multi-decadal variability*

5

6 The Earth's climate varies naturally on multi-decadal scales due to the internal dynamics of the
7 system. These changes are apparent from accurate measurements taken over decades to centuries.
8 From the 1950s onward, an unprecedented volume of observations has been collected that
9 contributes to the understanding of the changes to our climate. The satellite era, beginning in the
10 late 1960's has further expanded the available data and contributed greatly to the set of
11 measurements that are used in this area of research. Further, retrospective research efforts are able
12 to deduce earlier changes to the climate through the analyses of climate indicators such as tree rings
13 and ice cores.

14

15 To understand the long period changes in the Earth's climate system, scientists primarily use a set of
16 indices that reduce a large amount of data to a small set of time series. For example, in the tropical
17 Pacific, an index referred to as "Nino 3" is the average sea surface temperature (SST) between 5°N-
18 5°S and 150°W-90°W, and indicates variations associated with El Nino and the climate of the
19 tropical Pacific. Other indices, such as the North American Oscillation Index, use sea surface
20 pressure differences at two locations, one in Iceland and one near the Azores (Jones et al. 1997,
21 Hurrell 1995) to examine large-scale shifts in atmospheric pressure systems. Long period
22 measurements of precipitation, such as over the Sahel (20°N-10°N, 20°W-10°E) (Janowiak 1988)
23 also are used understand decadal variability. These analyses can be used to assess the realism of
24 internal or natural variability of the climate models. In addition to whether actual events have been
25 modeled correctly, the climate models are evaluated also in terms of whether the statistical
26 properties of the observed variability are well represented. Previous sections have described some
27 of the low frequency behavior of the climate models (e.g. ENSO, annular modes, polar climates, ice
28 models).

29

30 All the models have their own unique intrinsic or natural variability due to the various model design
31 decisions that have been made. The models also tend to differ regionally in their simulation skill.

1 For example, some are better at simulating the North Atlantic, while others have more skill in the
2 tropics. Often, this regional skill is serendipitous and emerges unexpectedly from attempts to
3 improve simulation of processes that operate globally. A set of examples are given to provide an
4 overview of the general abilities of the current climate models to reproduce decadal and longer
5 variability.

6

7 In the Arctic, during the last century, there have been two long period warm events, one between
8 1920 and 1950 and another beginning after 1979. Wang et al. (2007) evaluated a set of IPCC
9 Fourth Assessment models as to the models' ability are to reproduce the amplitudes of air
10 temperature variability of the mid-century. The CCSM3 and GFDL-CM2 models contain similar
11 variance with the observational variance in the Arctic region. Other models under-represented the
12 natural variability.

13

14 Multi-decadal variability in the North Atlantic is characterized by the Atlantic Multidecadal
15 Oscillation (AMO) index which represents a spatial average of SST (Enfield et al. 2001). Kravtsov
16 and Spannagle (2007) analyzed SST from a set of current generation climate models. Their analysis
17 attempts to separate the variability that is associated with internal fluctuations of the ocean from that
18 associated with changes in the atmospheric component due to anthropogenic contributions. By
19 isolating the multi-decadal period of several regions in the ensemble SST series through statistical
20 methods, they found that models, on average, correlate well with the AMO (Figure 7, 8 from
21 Kravtsov and Spannagle, 2007).

22

23 In the mid-latitude Pacific region, the decadal variability is generally under-represented in the ocean
24 (e.g. volume transports as described by Zhang and McPhaden, 2006, Figure 3), with some of the
25 models approaching the amplitudes seen in the observations. Examination of complicated
26 feedbacks between the atmosphere and ocean at the decadal and longer scales show that the while
27 the climate models generally reproduce the pattern in SST related to the Pacific Decadal Oscillation
28 (PDO), observed correlations between the PDO and tropical SST are not seen in the models (e.g.
29 Alexander et al. 2006).

30

1 One of the most difficult areas to simulate is the Indian Ocean, because of competing effects of
2 warm water inflow through the Indonesian archipelago, ENSO, monsoons, etc). The processes
3 interact to varying degrees, challenging a model's ability to simulate all aspects of the system with
4 the observed relative emphasis. An index used to understand the Indian Ocean's variability is the
5 Indian Ocean Dipole pattern that combines information about the SST and wind stress fields of the
6 Indian Ocean (Saji et al., 1999). While most of the models evaluated by Saji et al. (2006) were able
7 to simulate the Indian's Ocean response to local atmospheric forcing on short time periods (semi-
8 annual), the longer period events such as the ocean's response to ENSO changes in the Pacific, were
9 not simulated well.

12 *Extreme events*

14 Flood-producing precipitation, drought, heat waves, and cold waves have severe impacts on North
15 America. Flooding resulted in average annual losses of \$3.7 billion during 1983-2003
16 (<http://www.flooddamagedata.org/>). Losses from the 1988 drought were estimated at \$40 billion
17 and the 2002 drought at \$11 billion. The heat waves in 1995 resulted in 739 excess deaths in
18 Chicago alone (Whitman *et al.*, 1997). It is probable that a large component of the overall impacts
19 of climate change will arise from changes in the intensity and frequency of extreme events.

21 The modeling of extreme events poses special challenges since they are, by definition, rare in
22 nature. Although the intensity and frequency of occurrence of extreme events are modulated by the
23 state of the ocean and land surface and by trends in the mean climate state, internal variability of the
24 atmosphere plays a very large role and the most extreme events arise from the chance confluence of
25 unlikely conditions. Their very rarity makes statistical evaluation of model performance less robust
26 than for the mean climate. For example, if one wanted to evaluate the ability of a model to simulate
27 heat waves as intense as the 1995 event in Chicago, there are only a few episodes in the entire 20th
28 century that approach or exceed that intensity (Kunkel *et al.*, 1996). For such rare events, there is
29 substantial uncertainty in the real risk, varying from once every 30 years to once every 100 years or
30 more. Thus, a model that simulates such events at a frequency of once every 30 years may be

1 performing adequately, but it cannot be distinguished in its performance from a model simulating
2 such an event at a frequency of once every 100 years.

3
4 Although one might expect that a change in mean climate conditions will apply equally to changes
5 in the extremes, this is not necessarily the case. Using as an example the 50 state record low
6 temperatures, the decade with the largest number of records is the 1930's, yet winters during this
7 decade averaged as the third warmest since 1890; in fact, there is no significant correlation between
8 the number of records and U.S. wintertime temperature (Vavrus *et al.*, 2006). Thus, the severest
9 cold air outbreaks in the past have not necessarily been coincident with cold winters. Another
10 examination of model data showed that the future changes in extreme temperatures differed from
11 changes in the mean temperature in many regions (Hegerl *et al.*, 2004). This means that climate
12 model output must be analyzed explicitly for extremes by examining daily (or even finer) resolution
13 data, a resource-intensive effort.

14
15 The evaluation of model performance with respect to extremes is hampered by incomplete data on
16 the historical frequency and severity of extremes. A study by Frich *et al.*, (2002) described a set of
17 indices suitable for performing global analyses of extremes and presented global results. However,
18 many areas were missing due to lack of suitable station data, particularly in the tropics. It has
19 become common to use some of these indices for comparisons between models and observations.
20 Another challenge for model evaluation is the spatially-averaged nature of model data, representing
21 an entire grid cell, while station data represent point observations. For some comparisons, it is
22 necessary to average the station data over areas representing a grid cell.

23
24 There are several approaches toward the evaluation of model performance of simulation of
25 extremes. One approach examines whether a model reproduces the magnitude of extremes. For
26 example, a daily rainfall amount of 100 mm or more is expected to occur about once every year in
27 Miami, once every 6 years in New York City, once every 13 years in Chicago, and once every 200
28 years in Phoenix. To what extent is a model able to reproduce the absolute magnitudes and spatial
29 variations of such extremes? A second approach examines whether a model reproduces observed
30 trends in extremes. Perhaps the most prominent observed trend in the U.S. is an increase in the

1 frequency and intensity of heavy precipitation, particularly during the last 20–30 years of the 20th
2 century. Another notable observed trend is an increase in the length of the frost-free season.

3
4 In some key respects, it is likely that the model simulation of temperature extremes is less
5 challenging than of precipitation extremes, in large part due to the scales of these phenomena. The
6 typical heat wave or cold wave covers a relatively large region, of the order of several hundred
7 miles or more, or a number of grid cells in a modern climate model. By contrast, heavy precipitation
8 can be much more localized, often extending over regions of much less than 150 km, or less than
9 the size of a grid cell. Thus, the modern climate model can directly simulate the major processes
10 causing temperature extremes while heavy precipitation is sensitive to the parameterization of
11 subgrid scale processes, particularly convection (Chapter 2; Emori *et al.*, 2005; Iorio *et al.*, 2004).

12 13 **Droughts, particularly over North America and Africa**

14
15 Recent analysis indicates that there has been a globally-averaged trend toward greater areal
16 coverage of drought since 1972 (Dai *et al.*, 2004). A simulation by the HadCM3 model
17 reproduces this dry trend (Burke *et al.*, 2006) only if anthropogenic forcing is included. A
18 control simulation indicates that the observed drying trend is outside the range of natural
19 variability. The model, however, does not always correctly simulate the regional
20 distributions of areas of increasing wetness and dryness.

21
22 The simulation of specific regional features remains a major challenge for models. Globally, one of
23 the most significant observed changes is the shift to more frequent and more severe droughts in the
24 Sahel region of Africa since about 1970. Lau *et al.*, (2006) find that only eight CGCMs produce a
25 reasonable Sahel drought signal, while seven CGCMs produce excessive rainfall over the Sahel
26 during the observed drought period. Even the model with the highest prediction skill of the Sahel
27 drought could only predict the increasing trend of severe drought events but not the beginning and
28 duration of the events. Hoerling *et al.* (2006) also finds that the AR4 models fail to simulate the
29 drying and furthermore uses the model results to suggest that the observed drying was not due to
30 anthropogenic forcing. However, two GFDL models are successful in reproducing the drying and
31 analysis of those models suggests that the drying is of anthropogenic origin (Held *et al.* 2005).

1 Biasutti and Giannini (2006) interpret these results as an indication that the drying was a
2 combination of decadal-scale internal variability superimposed on longer timescale changes
3 associated with anthropogenic forcing. The differences between modeled and observed regional
4 patterns may then be due to the randomness of natural variability, but may also result from
5 inadequate representation of regional processes and feedbacks.

6
7 **Excessive rainfall leading to floods** Several different measures of excessive rainfall have been
8 used in analyses of model simulations. A common one is the annual maximum 5-day
9 precipitation amount, one of the Frich *et al.* (2002) indices. This has been analyzed in
10 several recent studies (Kiktev *et al.* 2003; Hegerl *et al.* 2004; Tebaldi *et al.* 2006). Other
11 analyses have examined thresholds of daily precipitation, either absolute (e.g. 50 mm per
12 day in Dai 2006) or percentile (e.g. 4th largest precipitation event equivalent to 99th
13 percentile of the 365 daily values as in Emori *et al.* 2005). Recent studies of model
14 simulations produced for the IPCC AR4 provide information on the performance of the
15 latest generation of models.

16 There is a general tendency for models to underestimate very heavy precipitation. This is
17 shown in a comparison between satellite (TRMM) estimates of daily precipitation and model-
18 simulated values within the 50S-50N latitude belt (Dai 2006). The TRMM observations derive 7%
19 of the total precipitation from very heavy rainfall of 50 mm or more per day, in contrast to only 0-
20 2% for the models. For the frequency of very heavy precipitation of 50 or more mm per day, the
21 TRMM data show a frequency of 0.35% (about once every 300 days), whereas it is 0.02-0.11%
22 (once every 900 to 5000 days) for the models. A global analysis of model simulations showed that
23 the models produced too little precipitation in events exceeding 10 mm per day (Sun *et al.* 2006).
24 Examining how many days it takes to accumulate 2/3's of the annual precipitation, the models
25 generally show too many days compared to observations over North America, although a few
26 models are close to reality. In contrast to the general finding of a tendency toward underestimation,
27 a study (Hegerl *et al.* 2004) of two models (HadCM3 and CGCM2) indicates generally good
28 agreement with the observed annual maximum 5-day precipitation amount over North America for
29 HadCM3 and even somewhat of an overestimation for CGCM2.

1 This model tendency to produce rainfall events less intense than observed appears to be due
2 in part to the low spatial resolution of global models. Experiments with individual models show that
3 increasing the resolution improves the simulation of heavy events. For example, the 4th largest
4 precipitation event in a model simulation with a resolution of approximately 300 km averaged 40
5 mm over the conterminous U.S., compared to an observed value of about 80 mm. When the
6 resolution was increased to 75 km and 50 km, the 4th largest event was still smaller than observed,
7 but by a much smaller amount (Iorio *et al.* 2004). A second factor that is important is the
8 parameterization of convection. Thunderstorms are responsible for many intense events, but their
9 scale is smaller than the size of model grids and thus they must be indirectly represented in models
10 (Chapter 2). One experiment showed that changes to this representation improves model
11 performance and, when combined with high resolution of about 1.1 deg latitude, can produce quite
12 accurate simulations of the 4th largest precipitation event on a globally-averaged basis (Emori
13 2005). Another experiment found that the use of a cloud-resolving model imbedded in a global
14 model eliminated the underestimation of heavy events (Iorio *et al.* 2004). A cloud-resolving model
15 eliminates the need for a parameterization of convection, but is very expensive to run. These sets of
16 experiments indicate that the problem of heavy event underestimation may be significantly reduced
17 in the future as increases in the computer power allows simulations at higher spatial resolution and
18 perhaps eventually the use of cloud-resolving models.

19 The improved model performance at higher spatial resolutions provide motivation for use of
20 regional climate models when only a limited area is of interest, such as North America. The spatial
21 resolution of these models is sufficient to resolve the major mountain chains; some of these models
22 thus display considerable skill in areas where topography plays a major role in the spatial patterns.
23 For example, they are able to reproduce rather well the spatial distribution of the magnitude of the
24 95th percentile of precipitation (Leung *et al.* 2003), the frequency of days with more than 50 mm
25 and 100 mm (Kim and Lee 2003), the frequency of days over 25 mm (Bell *et al.* 2004), and the
26 annual maximum daily precipitation amount (Bell *et al.* 2004) over the western U.S. Kunkel *et al.*
27 (2002) found that an RCM's simulation of the magnitude of extreme events over the U.S. varied
28 spatially and depended on the duration of the event being examined; there was a tendency for
29 overestimation in the western U.S. and good agreement or underestimation in the central and
30 eastern U.S.

1 Most studies of observed precipitation extremes suggest that such extremes have increased
2 in frequency and intensity during the latter half of the 20th century. A study by Tebaldi *et al.*, (2006)
3 indicates that models generally simulate a trend towards a world characterized by intensified
4 precipitation, with a greater frequency of heavy-precipitation and high-quantile events, although
5 with substantial geographical variability. This is in agreement with observations. Wang and Lau
6 (2006) find that the CGCMs simulate an increasing trend in heavy rain over the tropical ocean.

7 8 **Heat and cold waves**

9 Analysis of simulations produced for the IPCC AR4 by seven climate models indicates that they
10 reproduce the primary features of cold air outbreaks (CAOs), with respect to location and
11 magnitude (Vavrus *et al.*, 2006). In their analysis, a CAO is an episode of at least 2 days duration
12 during which the daily mean winter (December-January-February) surface temperature at a
13 gridpoint is 2 standard deviations below the gridpoint's winter mean temperature. Maximum
14 frequencies of about four CAO days/winter are simulated over western North America and Europe,
15 while minimal occurrences of less than one day/winter exist over the Arctic, northern Africa, and
16 parts of the North Pacific. The GCMs are generally accurate in their simulation of primary features,
17 with a high pattern correlation with observations and the maximum number of days meeting the
18 CAO criteria around 4 per winter. One favored region for CAOs is in western North America,
19 extending from southern Alaska into the upper Midwest. Here, the models simulate a frequency of
20 about 4 CAO days per year, in general agreement with the observed values of 3-4 days. The models
21 underestimate the frequency in the southeastern United States: mean simulated values range from
22 0.5 to 2 days *versus* 2 to 2.5 days in observations. This regional bias occurs in all the models and
23 reflects the inability of GCMs to penetrate Arctic air masses far enough southeastward over North
24 America.

25 The IPCC AR4 model simulations show a positive trend for growing season, heat waves and
26 warm nights and a negative trend for frost days and daily temperature range (maximum minus
27 minimum) (Tebaldi *et al.* 2006). They indicate that this is in general agreement with observations,
28 except that there is no observed trend in heat waves. The modeled spatial patterns have generally
29 larger positive trends in western North America than in eastern sections. For the U.S., this is in
30 qualitative agreement with observations which show that the decreases in frost-free season and frost
31 days are largest in the western U.S. (Kunkel *et al.* 2004; Easterling *et al.* 2002).

1 Analysis of individual models provides a more detailed picture of model performance. In a
2 simulation from the PCM (Meehl *et al.* 2004), the largest trends for decreasing frost days occurs in
3 the western and southwestern USA (values greater than -2 days per decade), and trends near zero in
4 the upper Midwest and northeastern USA, in good agreement with observations. The biggest
5 discrepancy between model and observations is over parts of the southeastern USA where the
6 model shows trends for decreasing frost days and the observations show slight increases. This is
7 thought to be a partial consequence of the two large El Nino events in the observations during this
8 time period (1982–83 and 1997–98) where anomalously cool and wet conditions occurred over the
9 southeastern USA and contributed to slight increases of frost days. The ensemble mean from the
10 model averages out effects from individual El Nino events, and thus the frost day trends reflect a
11 more general response to the forcings that occurred during the latter part of the 20th century. An
12 analysis of short-duration heat waves simulated by the PCM (Meehl and Tebaldi, 2004) indicates
13 good agreement with observed heat waves for North America. In that study, heat waves were
14 defined by daily minimum temperature. The most intense events occurred in the southeast U.S. for
15 both the model simulation and observations. The overall spatial pattern of heat wave intensity in
16 the model matched closely with the observed pattern. In a four-member ensemble of simulations
17 from the HadCM3 (Christidis *et al.* 2005), the model shows a rather uniform pattern of increases in
18 the warmest night for 1950-1999. The observations also show a global mean increase, but with
19 considerable regional variations. In North America, the observed trends in the warmest night vary
20 from negative in the south-central sections to strongly positive in Alaska and western Canada,
21 compared to a rather uniform pattern in the model. However, this discrepancy might be expected,
22 since the observations probably reflect a strong imprint of internal climate variability that is reduced
23 by ensemble averaging of the model simulations.

24 An analysis of the magnitude of temperature extremes for California in a regional climate
25 model simulation (Bell *et al.* 2004) show mixed results. The hottest maximum in model is 4°C less
26 than observations, while coldest min is 2.3°C warmer. The number of days $>32^{\circ}\text{C}$ is 44 in the
27 model compared to an observed value of 71. This could result from the lower diurnal temperature
28 range in the model (15.4°C observed vs. 9.7°C simulated). While these results are better than the
29 driving GCM, the RCM results are still somewhat deficient, perhaps reflecting the very complex
30 topography of the region of study.

31

1 Models display some capability to simulate extreme temperature and precipitation events, but there
2 are differences from observed characteristics. They typically produce global increases in extreme
3 precipitation and severe drought, and decreases in extreme minimum temperatures and frost days, in
4 general agreement with observations. There is a general, though not universal, tendency to
5 underestimate the magnitude of heavy precipitation events. Regional trend features are not always
6 captured. Since the causes of observed regional trend variations are not known in general and such
7 trends could be due in part to stochastic variability of the climate system, it is difficult to assess the
8 significance of these discrepancies.
9
10

1 **Chapter VI – Future Model Development**

2

3 *Cloud-resolved models*

4

5 Cloud resolving models (CRMs) have spatial resolutions of less than a few kilometers. CRMs can
6 therefore explicitly calculate many atmospheric systems that are on sub-grid scales of AGCMs
7 (Randall *et al.* 2005). These include the mesoscale organizations in squall lines, updrafts and
8 downdrafts, and cirrus anvils. The CRMs also allow calculation of cloud properties and cloud
9 amount with more realistic dynamical conditions, and thus their impact on radiative transfer.
10 Because of improved resolution, CRMs can also better simulate the spatial distribution of
11 precipitation and convective enhancement of the surface fluxes, which are important to describe the
12 interaction of the atmosphere with the land and ocean surfaces.

13

14 CRMs are variations of models designed for mesoscale storm and cumulus convection simulations.
15 At CRM scales, hydrostatic balance is no longer universally valid. CRMs are therefore formulated
16 with non-hydrostatic equations in which vertical accelerations are calculated. Tripoli (1992)
17 contains a good review of the various model formulations used to simulate non-hydrostatic
18 meteorological dynamics.

19

20 Similar to AGCMs, CRMs also contain empirical relationships to calculate the impact of sub-grid
21 scale processes. These relationships however have different roles from those in AGCMs. First,
22 because CRMs capture a larger portion of the size spectrum of the meteorological systems, the
23 impact of the empiricism is less important in CRMs. For example, cumulus parameterizations for
24 deep tropical convection are no longer needed in CRMs. Second, since CRMs better resolve
25 atmospheric dynamics, cloud processes can be formulated based on more realistic physical
26 conditions.

27

28 CRMs can therefore accommodate more sophisticated microphysical and precipitation processes
29 than AGCMs. One-moment bulk microphysical schemes (mass concentration only) with two-class
30 liquid (cloud water and rain) and three-class ice (cloud ice, snow and graupel/hail) are commonly
31 used in CRMs. This level of sophistication is rare in AGCMs and, in any case, unlikely to be useful

1 given the absence of the needed detail in the small scale flow field. Some CRMs have started to use
2 explicit bin-microphysical schemes. These schemes solve the stochastic kinetic equations for the
3 size distribution functions of water droplets (both cloud droplets and raindrops) and different ice
4 particle habitats (i.e., columnar, plate-like, dendrites, snowflakes, graupel and frozen drops).
5 Because of better size information, these schemes can more realistically calculate the nucleation or
6 activation processes of clouds, along with more accurate calculation of conversion processes among
7 different cloud habitats (Tao 2007).

8
9 Subgrid scale processes in CRMs are calculated by using turbulence models. The majority of CRMs
10 use either simple first-order closure to diagnostically compute the turbulent diffusion strength, or
11 the one-and-a-half order closure to prognostically calculate the turbulent kinetic energy which is
12 then used to determine turbulent diffusion coefficients. Prognostic methods typically take into
13 account the thermodynamic stability, deformation, shear stability, diffusion, dissipation, moist
14 processes and transport of sub-grid energy (Klemp and Wilhelmson 1978). Other CRMs use higher
15 order turbulence closures (Krueger 1988).

16
17 Radiative transfer in the atmosphere and surface fluxes of heat and moisture in CRMs are computed
18 using algorithms similar those in AGCMs. Because of better spatial resolution atmospheric fields
19 such as clouds and precipitation, CRMs calculate these parameters more accurately than AGCMs.

20
21 High resolution of CRMs, however, is at the expense of model domain size and integration length.
22 Current computing infrastructure, with the exception of the Japanese Earth Simulator, only allows
23 CRMs to simulate the atmosphere of less than a few thousand kilometers. Most previous CRM
24 studies were carried out only for two-dimensional slices of the atmosphere, an assumption that
25 somewhat compromises the fidelity of three-dimensional convective cloud simulations. Few CRM
26 simulations are carried out for longer than a year. CRMs with explicit bin-microphysics or high
27 order turbulence closures have been integrated only for a few days.

28
29 Research with CRM falls into two categories. In the first one, CRMs are used to investigate the time
30 evolution of cloud systems by specifying realistic initial conditions. This type of study enables
31 deterministic understanding of convection initiation, cold pools, surface fluxes and their direct

1 comparison with aircraft and other high resolution observation. The simulations are however only
2 valid for a few hours. In the second category, CRMs are used to study the properties of cloud
3 ensembles by specifying external forcing fields. This approach allows statistical description of
4 multiple cloud types with different life cycles (Tao 2007).

5
6 Although CRMs are advantageous over ACGMs in describing moist processes, they also face
7 unique challenges when utilized in forecasting mode. CRM results are often very sensitive to the
8 specification of initial conditions and external forcing conditions. They are also sensitive to the
9 physical algorithms in them. There are still large uncertainties in the CRM cloud microphysics,
10 including prediction of ice particle concentrations, falling speed calculation of cloud habitats, initial
11 broadening of cloud droplet spectra in warm clouds, details of hydrometeor spectra evolution,
12 quantitative simulations of entrainment rates (Cotton 2003). The high sensitivity of model results
13 makes it difficult to rigorously validate CRMs.

14
15 Several field programs, such as the DOE ARM program, have enabled collection of observational
16 data that are essential to evaluate CRMs (Zhang *et al.* 2001; Tao *et al.* 2004). Results from these
17 programs will facilitate the improvement of model physics. On the other hand, a global model
18 approaching CRM resolution has been developed and has been integrated on the Earth Simulator
19 with spatial resolution of 7 kilometers (Miura *et al.* 2005). There is another paradigm for multiscale
20 problems that will be likely attempted in the next decade. This is the nesting of coupled regional
21 models of the atmosphere and the ocean within global coupled GCMs. Progress on these fronts will
22 guide where climate models should go in the future.

23 24 25 ***Biogeochemistry***

26
27 **The Carbon Cycle** Libes [1992] defined biogeochemistry as "the science that studies the
28 biological, chemical, and geological aspects of environmental processes". At present, three-
29 dimensional climate models are usually limited to the physical climate system: atmosphere, land,
30 ocean, and sea ice. However, the physical climate system and biogeochemical processes are tightly
31 coupled. For example, changes in climate affect the exchange of atmospheric CO₂ with the land

1 surface and ocean, and changes in CO₂ fluxes affect Earth's radiative forcing and thus the physical
2 climate system. Some recently developed AOGCMs have included the carbon cycle and confirmed
3 the potential for strong feedback between it and global climate (Cox *et al.*, 2001; Friedlingstein *et*
4 *al.*, 2001; Govindasamy *et al.*, 2005). The next generation of AOGCMs is expected to include the
5 carbon cycle and possibly interactive atmospheric aerosols and chemistry. Such models would
6 predict time-evolving atmospheric concentrations of CO₂, etc., using anthropogenic emissions
7 rather than assumed concentrations as input.

8
9 Models that include the global carbon cycle must account for the processes shown in **Figure VI.1**.
10 Boxes represent the carbon reservoirs and arrows show the direction and magnitude of the fluxes.
11 The present-day atmosphere holds about 750 Petagrams of carbon atoms in the form of CO₂.
12 (“Petagrams of carbon” is abbreviated PgC; note that 1 Petagram = 10¹⁵ grams = 10⁹ metric tons.) A
13 roughly equal amount of carbon is contained in land vegetation and about twice as much in soils.
14 The ocean is by far the largest reservoir of carbon with about 40,000 PgC. The largest flows of
15 carbon in the system are photosynthetic uptake of ~120 PgC / year by terrestrial ecosystems (gross
16 primary productivity or GPP), plant respiration which releases ~60 PgC / year back to the
17 atmosphere (hence the remainder—net primary production or NPP—is ~60 PgC / year), and
18 heterotrophic (soil) respiration which releases ~60 PgC / year. In the upper ocean, photosynthesis by
19 marine organisms incorporates carbon at the rate of ~50 PgC / year, about 4/5 of which is
20 reconverted to CO₂ and related inorganic carbon molecules by respiration. The remaining ~10 PgC /
21 yr of organic matter sinks into deep ocean, a process sometimes called the “biological pump.” This
22 organic matter is oxidized and eventually returns to the surface ocean via a combination of both
23 convective / turbulent mixing and the “solubility pump” (the latter so named because it involves
24 sinking of cold water, with high levels of dissolved inorganic carbon, near the poles).

25
26 The present-day global carbon cycle is not in equilibrium because of fossil fuel burning and other
27 anthropogenic carbon emissions. These must of course be included in models of climate change, but
28 such a calculation is not easy because human-induced changes to the carbon cycle are small
29 compared to the large natural fluxes discussed above. Fossil fuels are estimated to contain about
30 4,000 PgC. During the 1990's, fossil fuel emissions averaged ~6 PgC / year and carbon release from
31 land cover change (e.g. deforestation) averaged ~2 PgC / year, providing a net anthropogenic source

1 of ~8 PgC / year to the atmosphere. Terrestrial and ocean ecosystems together absorbed about half
2 of this flux, i.e. ~4 PgC / year, with the net uptake of carbon by the terrestrial biosphere and the net
3 flux of CO₂ into the ocean each estimated as ~2 PgC / year. The rest (~ 4 PgC/ year) accumulated in
4 the atmosphere, appearing as an increasing concentration of atmospheric CO₂.

5
6 The globally averaged carbon reservoirs and fluxes shown in **Figure VI .1** are consistent with
7 estimates from a variety of sources, but substantial uncertainties attach to the numbers (e.g. often a
8 factor > 2 uncertainty for fluxes; see Prentice *et al.* 2001). Additional uncertainty applies to
9 regional, seasonal and interannual variations in the carbon cycle. Evaluation of climate-carbon cycle
10 models is therefore problematic: for many aspects of a simulation it is not clear what the “right
11 answer” is.

12 13 *Recent three-dimensional climate-carbon modeling studies*

14
15 The feedbacks between the physical climate system and the carbon cycle are represented plausibly,
16 but with substantial differences, in different AOGCM / carbon-cycle models. Cox *et al.* (2000)
17 obtained a very large positive feedback, with global warming reducing the fraction of anthropogenic
18 carbon absorbed by the biosphere and thus boosting the model’s simulated atmospheric CO₂;
19 Friedlingstein *et al.* (2001) obtained a much weaker feedback. Thompson *et al.* (2004)
20 demonstrated that making different assumptions about the land biosphere within a single model
21 gave markedly different feedback values. Using the same model, Govindasamy *et al.* (2005) noted
22 a positive correlation between the magnitude of carbon cycle feedback and the sensitivity (q.v.) of
23 the physical climate system.

24
25 A recent study examined carbon cycle feedbacks in eleven coupled AOGCM / carbon-cycle models
26 using the same forcing (Friedlingstein *et al.*, 2006). There was unanimous agreement among the
27 models that global warming will reduce the fraction of anthropogenic carbon absorbed by the
28 biosphere, but the magnitude of this feedback varied widely among the models (Fig VI .2), leading
29 to additional global warming (when the models included an interactive carbon cycle) ranging
30 between 0.1 to 1.5 °C. Eight models attributed most of the feedback to the land biosphere, while
31 three attributed it to the ocean.

1
2 These results demonstrate extreme sensitivity of climate model output to assumptions about carbon-
3 cycle processes. To reduce the consequent uncertainties in model predictions of the future, it will be
4 necessary to thoroughly compare model output with real-world observations for present day
5 conditions. Studies that span a broad range of ecosystems and climate regimes, including both and
6 global remote sensing by satellites and local in situ measurements, are beginning to be integrated
7 with diagnosis and improvements of the models. For example, the CCSM Biogeochemistry
8 Working Group has recently begun intercomparison of three different biogeochemistry sub-models
9 within the CCSM (climate.ornl.gov/bgcmip).

10
11 **Other biogeochemical cycles** Methane (CH₄) is a potent greenhouse gas and part of the carbon
12 cycle. Also, CO₂-fertilized ecosystems are limited by the availability of nutrients such as nitrogen
13 and phosphorous, so changes in their availability are important to the carbon cycle through changes
14 in plant nutrient availability (Field *et al.* 1995; Schimel 1998; Nadelhoffer *et al.* 1999; Shaw *et al.*
15 2002; Hungate *et al.* 2003). Future climate-carbon models will probably represent these variables.
16 The few models that do so now show less plant growth in response to increasing atmospheric CO₂
17 (Cramer *et al.* 2001, Oren *et al.* 2001, Nowak *et al.* 2004). Incorporation of other known limiting
18 factors such as acclimation of soil microbiology to the higher temperatures (Kirschbaum, 2000;
19 Tjoelker, *et al.*, 2001), and other elemental cycles such as the sulfur cycle (which affects aerosol
20 and cloud properties), will also be important in developing comprehensive Earth system models.

21
22 ***Land Cover and land management practice changes***

23
24 Generally, climate-carbon models do not include the effects land cover and land management
25 changes on natural ecosystems. Land cover change is often accounted for simply by prescribing
26 estimates for the historical period (e.g., Houghton, 2003) and the IPCC SRES scenarios for the
27 future. These estimates do not include practices such as crop irrigation and fertilization. Many
28 models with “dynamic vegetation” do not actually simulate crops; they allow only natural
29 vegetation to grow. Deforestation, land cultivation and related human activities will probably be
30 included in at least some future AOGCMs, enabling assessment of total anthropogenic effects on
31 the global climate and environment (Ramankutty *et al.* 2002, Root and Schneider 1993).

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Ocean Biogeochemistry

With respect to the ocean, we are concerned with how global warming impacts the marine environment including changes in the carbon content of the ocean and feedbacks to the atmosphere. Also of importance are the effects of modified ocean temperature, salinity and circulation patterns on the ocean's biota. Implementation of ocean biogeochemistry processes into AOGCMs is still in the development stage (e.g. CCSM Biogeochemistry Working Group Meeting Report, Mar. 2006, and GFDL Earth System Model, <http://gfdl.noaa.gov/~jpd/esmdt.html>) but is expected to proceed rapidly (Doney *et al.* 2004) to improve simulation of the ocean carbon cycle under various scenarios.

One challenge to this effort is the complexity of the ocean's ecosystems. Complexity is added with each organism that fixes nitrogen, denitrifies, calcifies, or silicifies because each adds additional parameterizations and variables to the system (Hood *et al.* 2006). There needs to be sufficient complexity in the biological models to capture the variability of the system as observed. In addition, models should include processes that are important over time periods substantially greater than a year (Rothstein *et al.* 2006) in addition to much shorter periods. However, Earth system models cannot be so complex that their computational cost precludes their actual use, and adding complexity to the biogeochemistry models may lead to a decrease in their predictive ability because the inability to constrain the model with the available data (Hood *et al.* 2006). Thus, as with other component models such as those simulating clouds and convection, the development of ocean (and land) BGC models for incorporation into physical climate models involves a trade-off between realism and tractability.

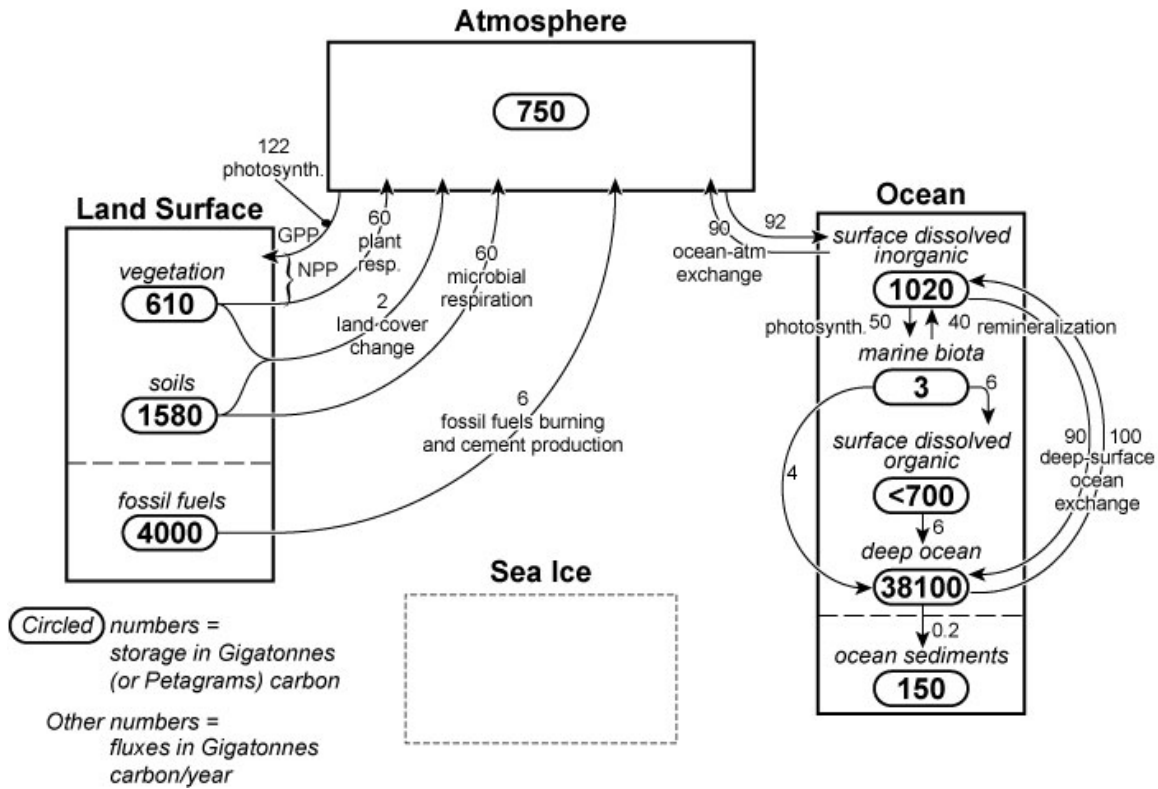
The current strategy of climate modeling groups to address ocean carbon and biogeochemistry includes systematic comparison of different models in the Ocean Carbon-Cycle Model Intercomparison Project (OCMIP) under auspices of the International Geosphere-Biosphere Programme (IGBP). The most recent phase of OCMIP involved 13 groups—including several from the USA—implementing a common biological model in their different GCMs (Najjar *et al.* 2006). The common biological model includes five prognostic variables: inorganic phosphate (PO_4^{2-}),

1 dissolved organic phosphorus (DOP), dissolved oxygen (O_2), dissolved inorganic carbon ($CO_2 +$
2 $HCO_3^- + CO_3^{2-}$) and total alkalinity (the acid / base buffering capacity of the system).
3 Intercomparison of the models revealed significant differences in simulated biogeochemical fluxes
4 and reservoirs. A biogeochemistry model's realism of any particular simulation is closely tied to the
5 dynamics of the simulation's circulation model. The US climate modeling groups are building upon
6 this community effort to incorporate biogeochemistry into the ocean component of the models.

7

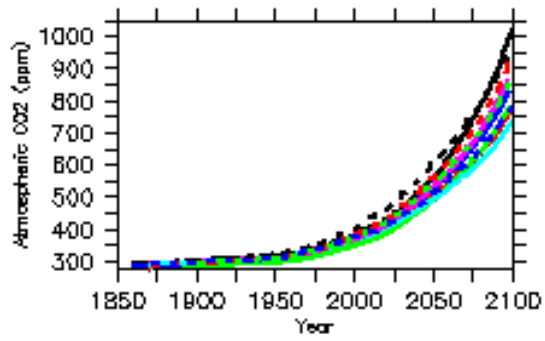
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The Global Carbon Cycle as seen by an AOGCM



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8 **Figure VI 1:** The global carbon cycle from the point of view of existing physical climate system
9 models (coupled AOGCMs). The four boxes represent atmosphere, land-surface, ocean and sea-
10 ice—the major components of AOGCMS. Earth System Models will evolve from AOGCMS by
11 incorporating the relevant biogeochemical cycles into the four-box framework (with the sea-ice
12 component not being a reservoir of carbon). Numbers shown are average values for the 1990s.
13 Small (≤ 1 PgC / year) fluxes such as carbon runoff from land to ocean and methane fluxes are not
14 shown, except for burial of ~ 0.2 PgC / year in ocean bottom sediments. Burial in ocean sediments
15 removes carbon from the AOGCM four-box domain;



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7 **Figure VI .2:** Time series of atmospheric CO₂ temperature from eleven different AOGCM / carbon
8 cycle models (from Friedlingstein et al. 2006, Figure 1(a))

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Chapter VII - Example Applications of Climate Model Results

Dryland Crop Yields

The effects of weather and climate on crops are complicated and not fully understood. Numerous models that simulate crop growth have been developed. These models parameterize many physiological processes. The present generation of state-of-the-art crop models typically steps through the growth process at a daily resolution and utilizes as input a number of meteorological variables that usually include maximum and minimum temperature, precipitation, solar radiation, and potential evapotranspiration. A key characteristic of these models is that they have been developed for application to a point location and have been validated based on point data, including meteorological inputs. Thus, the use of these models for assessment of climate change impacts on crop yields confronts a mismatch between the spatially-averaged climate model grid box data and the point data expected by the crop models. Also, biases in climate model data can have unknown effects on crop model results because the dependence of crop yields on meteorological variables is highly non-linear. The typical applications study circumvents these difficulties by avoiding the direct use of climate model output using some form of statistical downscaling. One approach developed during the early days of climate change assessments is still used today. In this approach, sometimes dubbed the “delta” method, the climate model output is used to determine the future change in climate with respect to the present-day climate, typically a difference for temperature and a percentage change for precipitation. Then, these change functions are applied to historical daily climate data for input to the crop model. In a second approach, the climate model data is used to adjust statistical characteristics of the observed data. Then, daily weather data for future periods are artificially produced using weather generators. In a recent study, Zhang (2005) used this approach to estimate Oklahoma wheat yields for a future simulation from HadCM3. These methods do not transmit certain climate model-simulated changes that do not affect basic statistical characteristics but might affect yields (a change to longer wet and dry spells without a change in total precipitation). Thus, additional uncertainty is introduced by such downscaling.

1 ***Small watershed flooding***

2 This application faces many of the same issues as for dryland crop yields. For example, the
3 models used for simulating runoff in small watersheds have been validated using point station data.
4 In addition, runoff is a highly non-linear function of precipitation and the occurrence of flooding is
5 particularly sensitive to the exact frequency and amount of precipitation for the most extreme
6 events. As noted in Section V.H, climate models often under-estimate the magnitude of extremes.
7 The ubiquitous “delta” method is also often used in such applications. Recently, Cameron (2006)
8 determined percentage changes in precipitation from climate model simulations and applied these to
9 a stochastic rainfall model to produce precipitation time series for input to a hydrologic model.

10
11 ***Urban heat waves***

12 This estimation of changes in heat wave frequency and intensity can be accomplished using
13 only near-surface temperature, a state variable. In addition, heat waves are large-scale phenomena
14 and near-surface temperature is rather highly correlated over the scale of grid box size. Biases
15 remain an issue, but that can be circumvented by using percentile-based definitions of heat waves.
16 Meehl and Tebaldi (2004) used output from the National Center for Atmospheric Research/U.S.
17 Department of Energy Parallel Climate Model (PCM) for 2080-2099 to calculate percentile-based
18 measures of extreme heat; they found that heat waves will increase in intensity, frequency, and
19 duration. If mortality estimates are desired, then biases are an issue because existing models
20 (Kalkstein and Green 1997) used location-specific absolute magnitudes of temperature to estimate
21 mortality. However, in this case, there are other factors that should be considered, such as
22 adaptation (e.g. Davis et al. 2002).

23
24
25 ***Water Resources in the Western U.S.***

26 The possibility that climate change may adversely affect the limited water resources of the
27 mostly arid and semi-arid western U.S. poses a threat to the prosperity of that region. A group of
28 university and government scientists, under the auspices of the Accelerated Climate Prediction
29 Initiative (ACPI), conducted a coordinated set of studies that represented an end-to-end assessment
30 of this issue (Barnett et al. 2004). A suite of carefully selected climate simulations were performed
31 by the Parallel Climate Model (Dai et al. 2004; Pierce et al. 2004). These were then used to drive a

1 regional climate model to provide higher resolution data (Leung et al. 2004), both for direct
2 assessment of effects on water resources and for use in impacts models. Finally, time series of
3 model data at a daily resolution were used in a set of studies to assess water resources impacts
4 (Steward et al. 2004; Payne et al. 2004; VanRheenen et al. 2004; Dettinger et al. 2004; Knowles and
5 Cayan 2004; Christensen et al. 2004) and other environmental impacts (Brown et al. 2004; Pierce
6 2004). This project is noteworthy because of the close coordination between the production of the
7 model simulations and the needs of the impacts modeling. Those performing the impacts studies
8 had the opportunity of influence the model simulations and the type of model output that was made
9 available. It is also a good example of the use of very detailed, high temporal resolution model
10 data, rather than simple change functions between the present and the future. Overall, this
11 assessment indicated that future climate change will likely create major challenges for water
12 resource management, even under the rather modest changes produced by the low climate
13 sensitivity PCM.

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