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The Earth’s energy balance and its changes

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Implications for past and future temperature change

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Abstract

The energy balance is key to understand the Earth’s climate and its variations caused both by natural and anthropogenic changes in the atmospheric composition. Changes in the energy balance have been confirmed by observations and model simulations. The concept of radiative forcing has been introduced to quantify the changes of the energy flows at the top of the atmosphere through both anthropogenic and natural forcing agents. The energy balance represents fundamental physical concepts such as the conservation of energy and links radiative forcing and changes in global average temperature and heat uptake by the world’s oceans to climate sensitivity. The equilibrium climate sensitivity is defined as the equilibrium change in global average temperature for a doubling of the pre-industrial atmospheric carbon dioxide concentration. Climate sensitivity governs along with ocean heat uptake the long-term response of the climate system to changes in the Earth’s energy balance.

The aim of this thesis is to assess the constraints of the energy balance and its changes both on climate system properties such as climate sensitivity and on projections of future global temperature change. Emphasis is placed on the quantification of uncertainties attached to observations of past changes in the climate system and their effects on estimates of climate sensitivity and projected temperature change. Climate models of different complexities are employed to account for structural and parametric uncertainty. The substitution of a climate model of intermediate complexity with an artificial neural network plays a key role in this thesis.

Chapter 2 considers the mean state of the Earth’s energy balance and relates radiative indices computed with a set of state-of-the-art coupled Atmosphere-Ocean General Circulation Models (AOGCMs) to their corresponding equilibrium climate sensitivities. The simple indices were previously used to describe climate variability and changes in global temperature and include response patterns such as the land-ocean contrast, inter-hemispheric differences and the magnitude of the annual cycle. Various satellite- and reanalysis-based datasets are employed as observational reference for the regression between radiative indices and climate sensitivities, resulting in an observationally constrained estimate of the latter. The likely range and best estimate of 2.9 - 4.0°C and 3.4°C is similar to previous estimates of climate sensitivity.

The emulation of the Bern2.5D climate model of intermediate complexity with an artificial neural network is described in Chapter 3, which allows a reduction in computational costs of about three orders of magnitude. Chapter 3 introduces the framework of statistical inference in which prior information about parameters of the Bern2.5D climate model are updated with a Markov Chain Monte Carlo (MCMC) algorithm. The MCMC algorithm is based on Bayes’
Theorem and allows to infer information about the model parameters from observations of past global temperature and ocean heat uptake changes. The neural network substitute of the climate model is implemented in the MCMC algorithm and significantly increases its efficiency. The notion of constraining projections of future temperature change based on a model’s ability to reproduce past observations is tested with a cross-validation of the Bern2.5D model. Further, the ‘perfect-model’ method described in this Chapter is extended to a set of AOGCMs and it is shown that the temperature evolution during the 21st century of most AOGCMs can be well predicted with a climate model of lower complexity.

Chapter 4 examines the effect of discrepancies between different observational datasets of global temperature and ocean heat uptake change on the estimates of climate sensitivity and transient climate response. The primary source for the spread in these two quantities is likely due to differences in measurements of ocean heat uptake. The aggregation of probability density distributions derived with 12 combinations of observational datasets results in a likely range of 2.2 to 5.1°C for climate sensitivity with a mean estimate of 3.6°C. The distribution of the aggregated sensitivity estimates is found to be insensitive to a scaling of the annual observational error between –40% and +40%. Moreover, the choice of a different prior for climate sensitivity does not significantly change the likely range of the posterior climate sensitivity distribution. The estimates of decadal temperature increase during the years 2020-2029 and at the end of the 21st century are shown to be consistent with results presented in the Fourth Assessment Report (AR4) of the Intergovernmental Panel on Climate Change (IPCC).

The response of the climate system to changes in anthropogenic and natural forcing agents is driven by the total net radiative forcing, in which some of the positive and negative forcings partly offset each other. The attribution of different forcing species has been primarily assessed with optimal fingerprinting methods, which rely mostly on spatial-temporal warming patterns of natural and anthropogenic origin being different. Chapter 5 quantifies the contributions of individual forcing agents - including e.g. long-lived greenhouse gases, sulphates, tropospheric and stratospheric ozone as well as variations in solar irradiance and volcanic eruptions - to the total observed warming since the year 1850. The results are derived with the posterior parameters distributions of the Bern2.5D model presented in Chapter 4. The applied method makes few assumptions besides fundamental principles like the conservation of energy. We find that since the mid-20th century, greenhouse gases alone contributed 0.85°C with a 5-95% uncertainty of 0.6-1.1°C to the total observed change of about 0.56°C in global temperature. The observed trends are extremely unlikely (<5%) to be caused by internal variability even if current models were found to underestimate internal variability. Combining the results of Chapter 5 with estimates derived with optimal fingerprinting suggests an even higher confidence in anthropogenic causes dominating the observed warming of ocean and atmosphere.
Zusammenfassung


Methode zwischen 2.9 – 4.0°C mit einer besten Schätzung von 3.4°C, die konsistent mit früheren Studien ist.


rameterverteilungen des Bern2.5D Klimamodells aus Kapitel 4. Die präsentierte Methode trifft wenige Annahmen nebst fundamentalen Prinzipien wie der Energieerhaltung. Es wird gezeigt, dass Treibhausgase allein seit der Mitte des 20. Jahrhunderts 0.85°C mit einer 5 – 95% Unsicherheit von 0.6–1.1°C zur beobachteten Erwärmung von etwa 0.56°C in der global gemittelten Temperatur beigetragen haben. Es ist extrem unwahrscheinlich (<5%), dass die beobachteten Trends nur auf interner Variabilität begründet sind, sogar wenn die aktuellen Klimamodelle diese unterschätzen. Die Kombination der Ergebnisse in Kapitel 5 mit Schätzungen anhand der optimal fingerprinting Methode deutet auf ein noch höheres Vertrauen hin, dass der menschliche Einfluss die beobachteten Erwärmung der Ozeane und Atmosphäre dominiert.
Chapter 1

Introduction

Life is uncertain, eat dessert first
(Ernestine Ulmer)

1.1 The Earth’s Climate System

The term ‘climate’ refers to the statistical description of the mean state and variability of quantities such as land and ocean temperatures, precipitation, radiation, pressure and humidity. The Earth’s climate system is highly complex, with a myriad of processes within and between its components. Owing to their particular physical, chemical and biological properties, the climate system is commonly partitioned into the atmosphere, hydrosphere, biosphere and cryosphere. These spheres are strongly coupled to each other and interact via the exchange of energy and matter. Further, the processes within the climate system show distinct patterns of spatial and temporal variability. In this regard, the heat capacity of each sphere plays a dominant role and strongly affects the sphere’s response to changes in the climate system. The heat capacity of the ocean is about three orders of magnitude larger than the corresponding value for the atmosphere; hence the long–term response of the ocean to external heating or cooling affects the Earth’s climate on timescales of centuries to millennia, which is of importance in the context of changes in past and future greenhouse gas concentrations. An illustration of the various processes and interactions within the climate system is depicted in Figure 1.1.

Robust evidence for both naturally and anthropogenically driven changes in the climate system comes from a variety of regional–to–global scale observations, from simplified to complex climate models and from various statistical methods (Solomon et al., 2007). The environmental and socio–economic implications of a changing climate crucially depend on our understanding of the processes and timescales involved in the response of the Earth’s climate system to internal and external changes.

Recent effort focused on the formal description and quantification of uncertainties both in our process understanding and in model projections of future climate changes. The overall goal of this thesis is to investigate several aspects of climate system properties which are crucial in the global average temperature response to changes in the energy fluxes within the climate system. A special emphasis is placed on the quantification of uncertainties of our knowledge of climate system properties and future climate projections.
1.1.1 The Earth’s Energy Balance

Incoming shortwave radiation from the sun is the Earth’s primary energy source and its amount and distribution determines weather and climate on Earth. The flow of incident solar radiation exhibits periodic fluctuations caused by variations in the Earth’s orbital parameters, referred to as the Milankovitch cycles. In order to attain thermal equilibrium, the absorbed radiative energy needs to be balanced by longwave radiation emitted at the top–of–atmosphere (TOA). In the course of this balancing process of incoming and outgoing radiation, the energy flows within the climate system undergo a variety of processes which are illustrated in Figure 1.2 together with recent observational estimates during the period March 2000 to May 2004 (Trenberth et al., 2009)

About a third of the incoming solar radiation is reflected back to space by clouds, the atmosphere and the Earth’s surface. The emission of longwave radiation balances the remaining positive net energy flow. Atmospheric greenhouse gases absorb and emit themselves longwave radiation and partly send it back to the surface, yielding a global average temperature of around 16°C.

Changes in the atmospheric composition alter the radiative flows and leave their distinct “footprint” in the energy balance, which makes the energy balance an invaluable tool for the assessment of anthropogenic and natural induced climate change (Trenberth and Fasullo, 2010). In particular, the net radiation imbalance at the TOA contains valuable information about energetic changes within the climate system and a net imbalance of about 0.9 ± 0.15 Wm⁻² is suggested by observations and model simulations (Hansen et al., 2005a; Trenberth et al., 2009). Due to its large heat capacity and volume, the world ocean is by far the largest heat reservoir and
1.1 THE EARTH’S CLIMATE SYSTEM

**Figure 1.2:** The Earth’s global annual mean energy budget for the March 2000 to May 2004 period \([\text{Wm}^{-2}]\) (Fig. 1 of Trenberth et al., 2009).

dominates the heat uptake of the additional radiative forcing caused by the perturbation of the energy balance. In spite of differences and uncertainties in data retrieval and measurement techniques, a robust warming trend of the upper ocean of about 0.64 Wm\(^{-2}\) during the years 1993 to 2008 was found (Lyman et al., 2010). The energy uptake by the ocean accounts for more than 90% of the increase in the Earth’s energy (Levitus et al., 2001; Bindoff et al., 2007). The remaining part of the additional radiative energy from external and internal forcings is balanced by adjusting the temperature and thereby altering the net imbalance at the TOA. The strength of the temperature response is strongly coupled to climate sensitivity (e.g. Gregory et al., 2004a), confer also Sect. 1.1.2. By combining satellite data products and radiative transfer models, the balancing of radiative forcing by energy storage in the ocean and outgoing longwave radiation during the years 1950 to 2004 could recently be quantified (Murphy et al., 2009). In addition, the individual contributions of different forcing agents to the cumulative energy budget could be assessed.

This thesis is concerned with the implications of the observed changes of the Earth’s energy balance on the estimation of climate system properties such as climate sensitivity and future temperature projections.

### 1.1.2 Radiative Forcing and Climate Sensitivity

An important concept in understanding the response of the climate system to alterations of the equilibrium energy balance is the radiative forcing (RF). According to Ramaswamy (2001), the definition of RF is “the change in net (down minus up) irradiance (solar plus longwave; in
Wm\(^{-2}\)) at the tropopause after allowing for stratospheric temperatures to readjust to radiative equilibrium, but with surface and tropospheric temperatures and state held fixed at the unaltered values’. The concept is valid for natural and anthropogenic radiative agents including e.g. long–lived greenhouse gases, stratospheric and tropospheric ozone, the forcing caused by the direct and indirect effect of aerosols and variations in the solar irradiance. Radiative forcing accounts for the net energy flow caused by a perturbation of the atmospheric concentration of radiative agents and thus constitutes a fundamental concept in the understanding of climate change.

Figure 1.3 depicts the anthropogenic and natural radiative forcings and their 90% uncertainty ranges in 2005. The best estimate of the total net anthropogenic forcing in 2005 is 1.6 Wm\(^{-2}\) with an uncertainty of 0.6 to 2.4 Wm\(^{-2}\). Carbon dioxide, methane and tropospheric ozone are the three largest positive contributors to the anthropogenic forcing, whereas the direct and indirect aerosol effects dominate the negative contributions. In addition to the magnitude of radiative forcing, the uncertainties attached to the individual forcing agents are of great importance. While the radiative forcing from greenhouse gases is comparably well known as shown in Figure 1.3, the negative forcings from aerosols are rather uncertain, especially for the indirect effects. Despite the uncertainties in radiative forcing contributions, Figure 1.3 suggests that it is extremely likely (>95%) that the Earth experienced a positive net forcing in the year 2005.

The changes in the Earth’s climate system caused by the alteration of the equilibrium energy balance can be expressed with the following equation:

\[
\Delta F = \Delta Q + \lambda \Delta T, \tag{1.1}
\]

where the additional radiative forcing \(\Delta F\) is balanced with heat uptake by the climate system \(\Delta Q\) and increased outgoing radiation \(\lambda \Delta T\) at the TOA which is coupled to the change in global average temperature \(\Delta T\) (e.g. Knutti and Hegerl, 2008). Physical processes and feedbacks are represented in the climate feedback term \(\lambda\) which is inversely related to the equilibrium climate sensitivity, defined as the equilibrium change in global temperature \(\Delta T^{2x}\) for a doubling of the pre–industrial atmospheric carbon dioxide concentration. The relationship between the radiative forcing \(\Delta F^{2x}\) from a doubling of the pre–industrial CO\(_2\) concentration and the equilibrium temperature change \(\Delta T^{2x}\) can be derived from Equation 1.1 by setting the heat uptake \(\Delta Q\) in equilibrium to zero:

\[
\Delta T^{2x} = \frac{1}{\lambda} \Delta F^{2x}. \tag{1.2}
\]

The \(\Delta F^{2x}\)–forcing of about 3.71 Wm\(^{-2}\) is comparably well known (Myhre et al., 1998).

The notion of a first–order linear approximation of a response – in this case the change in global mean temperature \(\Delta T\) – caused by a perturbation \(\Delta F\) finds its origins in the framework of feedback analysis (e.g. Budyko, 1969; North et al., 1981; Hansen et al., 1985; Roe, 2009). Physical processes such as feedbacks from clouds, the lapse–rate or the surface albedo that either amplify (positive feedbacks) or damp (negative feedbacks) the initial perturbation can be described within the framework of feedback analysis and their strength can be computed with complex climate models (Soden and Held, 2006).
Figure 1.3: a) Global mean radiative forcings and their 90% confidence intervals in 2005 for various agents and mechanisms. b) Probability distribution of the global mean radiative forcing from all anthropogenic agents shown in a) (Fig. TS.5. of Solomon et al., 2007).
Figure 1.4 illustrates the Earth’s energy balance described in Equation 1.1. In addition to the consideration of physical processes involved in the Earth’s response to an additional radiative forcing $\Delta F$, the examination of different time scales is key to understand changes in the climate system. On short time–scales ranging from days to months, adjustment processes occur predominantly in the tropospheric and stratospheric layers of the atmosphere. Within years, decades and even millennia, the heat uptake $\Delta Q$ is almost entirely stored in the world oceans due to their large heat capacity, confer Sect. 1.1.1. The remaining part of the additional energy is balanced with increased longwave radiation due to the warmer surface temperature $\Delta T$ (Knutti and Hegerl, 2008).

Moreover, Figure 1.4 highlights the important role of climate sensitivity and ocean heat uptake in the long–term climate changes. The effort of constraining climate sensitivity has been a vital part in the Fourth Assessment Report (AR4) of the Intergovernmental Panel on Climate Change (IPCC) (Meehl et al., 2007). The combination of observational constraints from the instrumental and paleo–climate period with a variety of climate models ranging from simple energy balance models to fully coupled Atmosphere–Ocean General Circulation Models (AOGCMs) resulted in a "likely” range (>66% probability) of $2 – 4.5^\circ C$ with a best estimate of $3^\circ C$. A review of the concept of climate sensitivity, radiative forcing, its observational constraints and policy implications can be found in Knutti and Hegerl (2008).

The substitution of Equation 1.2 in the energy balance yields the following expression:

$$
\Delta T^{2x} = \frac{\Delta F^{2x} \times \Delta T}{\Delta F - \Delta Q},
$$

from which the climate sensitivity $\Delta T^{2x}$ can be derived with historical observations of the change in global temperature $\Delta T$, ocean heat uptake $\Delta Q$ and forcing reconstructions $\Delta F$. The concept of constraining climate sensitivity with observed changes in the energy balance constitutes the pivotal point of this thesis.

Recent estimates of the observational constraints described in Equation 1.3 are illustrated in Figure 1.5. The observations of the changes in global mean surface temperatures are strongly correlated, whereas measurements of global ocean heat uptake differ in their estimates of interannual and decadal variability. The datasets of global temperature and ocean heat uptake significantly differ in their temporal coverage as well.

This thesis considers the effect of discrepancies between different observational datasets on the estimates of climate sensitivity and model projections of future temperature increase.

### 1.2 The Hierarchy of Climate Models

The numerical representation of physical and bio–chemical processes in climate models provides an invaluable tool for understanding the Earth’s mean climate state and changes from the equilibrium state caused by anthropogenic and natural drivers. The term “climate model hierarchy” was already used in the IPCC’s Third Assessment Report (TAR) to describe the variety of possible climate model architectures. Characteristics of a climate model encompass its required computational resources and the level of complexity in terms of processes and interactions built in the model.
1.2 The Hierarchy of Climate Models

**Figure 1.4:** Illustration of the concept of radiative forcing, feedbacks and climate sensitivity. The additional radiative forcing $\Delta F$ is balanced between heat uptake in the climate system $\Delta Q$ and a longwave radiative response $\lambda \Delta T$. The feedback parameter $\lambda$ is inversely related to the equilibrium climate sensitivity (Fig. 1 of Knutti and Hegerl, 2008).
Figure 1.5: Observational datasets of anomalies for global–mean temperature (a) and ocean heat content to 700 meters (b). The observations are shown with respect to their corresponding time period which differs across the datasets. For those datasets whose data is not published online, the values are obtained from the National Oceanic and Atmospheric Administration (NOAA) National Climatic Data Center (NCDC) climate indicators website (http://www.ncdc.noaa.gov/bams–state–of–the–climate/2009–time–series/).
1.2 The Hierarchy of Climate Models

Simple energy balance models (EBMs) are computationally efficient representations of the Earth’s response to changes of the radiative equilibrium described in Equation 1.1. While they do not feature complex climatic processes, their first–order approximation of the climate system allows a probabilistic assessment of parameters such as climate sensitivity within large model ensembles.

Adding more processes and computational time leads to Earth System Models of Intermediate Complexity (EMICs) (Claussen et al., 2002), featuring – inter alia – representations of ocean dynamics, atmospheric processes, sea–ice and the bio–chemical carbon cycle. The Bern2.5D climate model is a representative of this model category and plays a central role in this thesis. The model is built of a zonally averaged dynamic ocean model based on the primitive equations (Stocker and Wright, 1991; Wright and Stocker, 1991). It resolves the Atlantic, Pacific, Indian, and Southern Oceans and is coupled to a zonally and vertically averaged energy and moisture–balance model of the atmosphere (Stocker et al., 1992; Schmittner and Stocker, 1999). The additional radiative forcing at the top-of-the-atmosphere (TOA) is specified as

\[ \Delta F_{TOA}(t) = \Delta F_{dir}(t) + \mu \Delta T_{atm}(t), \]

where \( \Delta F_{dir} \) is the direct radiative forcing reconstructed over the industrial period. A feedback term \( \mu \Delta T_{atm} \) accounts for climate feedbacks (Knutti et al., 2003). The model incorporates dynamical fluxes of carbon and carbon–related tracers (Marchal et al., 1998), which are however not considered in this thesis since CO\(_2\) concentrations are prescribed.

Fully coupled atmosphere–ocean general circulation models (AOGCMs) are the most complex numerical representations of our understanding of the processes governing the Earth’s climate. Besides further development in the spatial and temporal resolution in recent years, the latest generation of climate models used in the IPCC AR5 – the World Climate Research Programme’s (WCRP’s) Working Group on Coupled Modelling (WGCM) phase 5 of the Coupled Model Intercomparison Project (CMIP5) model set – implement in addition to representations of the atmosphere, ocean and sea–ice dynamics for example the carbon/nitrogen cycle, atmospheric particles such as dust and mineral aerosols and descriptions of interactive vegetation processes.

In the context of climate model hierarchies, the distinction between parametric and structural uncertainty is crucial in the quantification of uncertainty of future climate projections derived with a set of climate models (Meehl et al., 2007). The uncertainty range resulting from parametric uncertainty can be quantified with large ensembles in which the model parameters are systematically or randomly sampled. Structural uncertainty accounts for different parameterizations implemented in the models, for example for different formulations of cloud convection schemes.

The uncertainty assessment of climate models and their projections of future climate change is crucial for mitigation and adaptation measures which rely on likelihoods of various changes in the climate system. The use of different models of the model hierarchy enables a comprehensive quantification of uncertainties underlying simulations of future emission scenarios (Knutti et al., 2008b).
1.3 Statistical Methods

Similar to everyday life, uncertainty is ubiquitous in climate science, starting with the definition of climate as a statistical quantity. While the concept of uncertainty is rather intuitive for the field of climate observations, where measurements are preferably accompanied by error estimates, the description of uncertainty for climate model output is rather complex and challenging (e.g. Knutti et al., 2010).

1.3.1 Probability and Bayes’ Theorem

Key to a formal description and assessment of uncertainty is the concept of probability. Some basic rules govern the framework of probability which are not alluded to here. The conditional probability of an event $A$ given the event $B$ – expressed by $P(A \mid B)$ – is defined as

$$P(A \mid B) = \frac{P(A \cap B)}{P(B)}.$$  \hspace{1cm} (1.5)

where $P(\cdot)$ denotes the probability of a specific event and $P(A \cap B)$ refers to the situation when both events $A$ and $B$ happen simultaneously. Bayes’ Theorem can be derived from Equation 1.5:

$$P(A \mid B) = \frac{P(B \mid A) \cdot P(A)}{P(B)},$$  \hspace{1cm} (1.6)

stating that the conditional probability of $A$ given $B$ is proportional to the product of the conditional probability of $B$ given $A$ times the probability of event $A$. Bayes’ Theorem has received much attention in the past since it provides an invaluable framework to combine observational data with uncertainty estimates of climate model parameters. Denoting the parameters as $\theta$ and the prior knowledge about $\theta$ as $p(\theta)$, the information contained in the observational data $y^{\text{obs}}$ can be employed to find a posterior distribution of the model parameters:

$$P(\theta \mid y^{\text{obs}}) = \frac{P(y^{\text{obs}} \mid \theta) \cdot P(\theta)}{P(y^{\text{obs}})}.$$  \hspace{1cm} (1.7)

The likelihood function $P(y^{\text{obs}} \mid \theta)$ describes the conditional probability of the observations for a set of parameters $\theta$ and is calculated by the climate model. It can be interpreted as a scaling factor of the prior function $p(\theta)$ to get the posterior distribution $P(\theta \mid y^{\text{obs}})$.

Recently, the prior in Bayes’ Theorem in particular received much attention, mostly with regard to climate sensitivity (Frame et al., 2005; Zickfeld et al., 2010; Annan and Hargreaves, 2011). The construction of Equation 1.7 allows an iterative formulation of updating the prior information when additional and independent lines of evidence become available. In terms of climate sensitivity, Annan and Hargreaves (2006) use data of the 20th century, volcanic cooling during that period and information of the Last Glacial Maximum to compute iteratively a posterior distribution of climate sensitivity.
1.3 Statistical Methods

1.3.2 Markov Chain Monte Carlo Methods

At the center of the statistical inference about model parameters $\theta$ described by Equation 1.7 is the sampling of the posterior distribution $P(\theta|y^{\text{obs}})$. The assumption is that a finite number of samples can adequately approximate the posterior distribution. More often than not, the estimation of $P(\theta|y^{\text{obs}})$ needs complex computations and integrations in high-dimensional parameter spaces $\Omega_\theta$. Markov Chain Monte Carlo (MCMC) methods offer computationally efficient algorithms to sample from the posterior distribution. In essence, MCMC algorithms jump through the parameter space $\Omega_\theta$ and stay longer in regions of high probability. When the algorithm converges, the sample of parameter locations of the chain mimic the posterior distribution $P(\theta|y^{\text{obs}})$.

Statistical inference strongly depends on the specification of a statistical error model relating observations $y^{\text{obs}}$ to model output $y^{\text{model}}(\theta)$ with model parameters $\theta$ and the observational error $\epsilon$. In the case of the following classic statistical model:

$$y^{\text{obs}} = y^{\text{model}}(x, \theta) + \epsilon, \epsilon \sim N(0, \Sigma),$$

where the expected mean behavior of the observations $y^{\text{obs}}$ is described by the climate model $y^{\text{model}}(x, \theta)$ with control variables $x$ and parameters $\theta$ and the normally distributed observational error $\epsilon$ with zero mean and error covariance $\Sigma$, the log-likelihood function $p(y^{\text{obs}}|\theta)$ takes the form:

$$\log(p(y^{\text{obs}}|\theta)) = \log((2\pi)^{-\frac{n}{2}}) - (y^{\text{obs}} - y^{\text{model}}(x, \theta))'\Sigma^{-1}(y^{\text{obs}} - y^{\text{model}}(x, \theta)).$$

Key to this thesis is the Metropolis–Hastings (MH) algorithm (Metropolis et al., 1953; Hastings, 1970) which is an example of a MCMC sampling algorithm and ranks among the most popular MCMC methods (Andrieu et al., 2003). The MH–algorithm jumps through the parameter space $\Omega_\theta$ and samples from the likelihood function described in Equation 1.9. At each step of the algorithm, the posterior distribution $p(\theta|y^{\text{obs}})$ and proposal distribution $q(\theta^*|\theta)$ involves sampling candidate values $\theta^*$ given the current parameter values $\theta$ according to $q(\theta^*|\theta)$ (Andrieu et al., 2003). The proposal distribution $q(\theta^*|\theta)$ commonly takes the form of a multivariate Gaussian distribution. A new parameter combination $\theta^*$ is then accepted and added to the Markov Chain with probability:

$$A(\theta^*|\theta) = \min\{1, \left[\frac{p(\theta^*|y^{\text{obs}})q(\theta|\theta^*)}{p(\theta|y^{\text{obs}})q(\theta^*|\theta)}\right]\}$$

Equation 1.10 highlights the advantage of the MH algorithm that only ratios of the posterior distribution of the model parameters need to be computed and that the normalizing constant of the target distribution is not required (Andrieu et al., 2003). The MH–algorithm is employed in this thesis to compute posterior parameter distributions of the Bern2.5D climate model of intermediate complexity.

1.3.3 Artificial Neural Networks

The origin of the field of artificial neural networks (ANNs) goes back to the year 1943 when McCulloch and Pitts formulated the concept of simplified neurons which were able to perform
computational tasks based on the characteristics of biological neurons (McCulloch and Pitts, 1943). ANNs can be trained to learn, to adapt, to generalize and to organize data (Kroese and van der Smagt, 1996) and constitute a prime example for the combination of statistics and artificial intelligence. Applications of neural networks can nowadays be found in various fields such as signal processing, data compression, optimization problems, pattern recognition and control systems.

The principle of a neural network is that of a two-stage regression or classification model (Hastie et al., 2001). Classical network topologies include feed-forward and recurrent networks. As an example, the L-layer feed-forward network is built of one input layer, (L–2) hidden layers, and one output layer. The different layers are successively connected, but there are no connections across a particular layer. The learning procedure of a neural network can be divided into two categories: supervised learning in which the network is trained by providing it with input and matching output patterns, and unsupervised learning in which an output unit is trained to respond to clusters of pattern within the input (Kroese and van der Smagt, 1996). During the learning phase, the weights connecting the different layers are continuously updated. We use the Levenberg–Marquardt algorithm (Hagan and Menhaj, 1994) for the learning procedure, which is seen as the most efficient learning algorithm for many applications due to its fast convergence.

An artificial neural network is used in this study to emulate the full Bern2.5D climate model, thereby decreasing the duration of a single model run by roughly three orders of magnitude.

1.3.4 Detection and Attribution Methods

The detection and attribution framework offers a statistical method to assess whether the observed changes in for example ocean heat content or surface air temperature can be explained by internal variability alone or by a combination of natural and anthropogenic drivers (e.g. Barnett et al., 2005). The method is based on optimal fingerprinting and takes the form of a multiple regression model (Hasselmann, 1979, 1997; Allen and Tett, 1999). The regression model takes the following form (e.g. Barnett et al., 2005):

\[ y^{\text{obs}} = Xa + u, \] (1.11)

where the vector \( y^{\text{obs}} \) is a filtered version of the observational record, matrix \( X \) contains the estimated response patterns to the external forcings that are considered, \( a \) is a vector of scaling factors that adjusts the amplitudes of those patterns, and \( u \) is a realization of unforced internal climate variability.

In essence, the response patterns to single external forcings are simulated by atmosphere–ocean general circulation models (AOGMCS) and subsequently mapped onto a post-processed version of the observational record. The error term of the multiple regression model reflects internal variability which is commonly estimated by a control-run of an AOGCM due to the lack of sufficient observational data (Stott and Kettleborough, 2002; Kettleborough et al., 2007). While the magnitude of the scaling factors in the regression model accounts for the detectability of the forcing response patterns in the observations, formal hypothesis testing on the scaling factors is used to make a statement about the forcing patterns’ attribution to the observations.
Detection and attribution studies provided invaluable insights into the contributions of different climate change drivers to the observed temperature and precipitation changes. However, the optimal fingerprint method does not necessarily take the observed changes in the Earth’s energy balance into account. A new approach to quantify contributions of different forcing components to the observed past temperature change which is not based on model simulated spatial response patterns is presented in this thesis.

1.4 Outline of the Thesis

The previous sections have highlighted the importance of the Earth’s energy balance in understanding the mean state of the climate system and its changes caused by natural and anthropogenic drivers. Any perturbation of the radiative flows within the climate system yields a particular footprint in the energy balance. Climate sensitivity is one of the key properties of the climate system governing the long–term response to both internal and external forcings. Observations of past changes of global average temperature and ocean heat uptake as well as reconstructions of historical radiative forcings provide a constraint on climate sensitivity.

The main objective of this thesis is to understand and to quantify the uncertainties attached to estimates of climate system properties and model projections of future temperature change. Hereby, different models of the climate model hierarchy are used. A probabilistic composition of the Earth’s energy budget is derived from reconstructions of historical forcings. The replacement of a climate model of intermediate complexity with a neural network emulator provides a computational framework to constrain the uncertainty attached to climate sensitivity and forcing estimates in an efficient way.

This thesis is structured in six chapters. Chapters 2 to 5 form the main body of this dissertation and consist of studies published or submitted to international peer–reviewed journals. A conclusion and outlook is presented in Chapter 6.

• Chapter 2, ”Constraints on climate sensitivity from radiation patterns in climate models” (published in Journal of Climate). In this paper, indices of surface temperature response patterns are computed for various radiation variables and are related to the climate sensitivities of the CMIP3 models. We apply numerous observational reference data sets as constraints for the regression between the radiative indices and climate sensitivities.

• Chapter 3, ”Probabilistic climate projections with an intermediate complexity model. Part I: Method and perfect model evaluation on CMIP3” (submitted to Climate Dynamics). This paper introduces a method to substitute the full Bern2.5D climate model with an artificial neural network. The replacement of the Bern2.5D model with its neural network in a MCMC algorithm is also described. The predictive capabilities of a climate model constrained to observations of past temperature and ocean heat uptake change are tested in a cross–validation study for the Bern2.5D climate model. The method allows to emulate the historical simulations of a set of CMIP3 models and to predict the CMIP3 model output for a non–intervention emission scenario during the 21st century.
• Chapter 4, ”Probabilistic climate projections with an intermediate complexity model. Part II: Application to observational datasets” (submitted to Climate Dynamics). The method presented in Chapter 3 is employed to assess the effect of different observational datasets on estimates of climate sensitivity, transient climate response and future decadal temperature increase. Further, the sensitivity of the results on the magnitude of the observational error and of the prior distribution for climate sensitivity is tested.

• Chapter 5, ”Anthropogenic and natural warming inferred from changes in Earth’s energy balance” (submitted to Nature Geoscience). The method and model parameter estimates derived in Chapters 3 and 4 are used in this paper to quantify the contributions of different forcing agents to the total observed temperature change since pre–industrial times. Similarities and differences between this approach and the detection and attribution framework are drawn.
Chapter 2

Constraints on climate sensitivity from radiation patterns in climate models
Constraints on climate sensitivity
from radiation patterns in climate models

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Abstract

The estimated range of climate sensitivity, the equilibrium warming resulting from a doubling of the atmospheric carbon dioxide concentration, has not decreased substantially in past decades. New statistical methods for estimating the climate sensitivity have been proposed and provide a better quantification of relative probabilities of climate sensitivity within the almost canonical range of 2–4.5 K; however, large uncertainties remain, in particular for the upper bound. Simple indices of spatial radiation patterns are used here to establish a relationship between an observable radiative quantity and the equilibrium climate sensitivity. The indices are computed for the Coupled Model Intercomparison Project phase 3 (CMIP3) multimodel dataset and offer a possibility to constrain climate sensitivity by considering radiation patterns in the climate system. High correlations between the indices and climate sensitivity are found, for example, in the cloud radiative forcing of the incoming longwave surface radiation and in the clear–sky component of the incoming surface shortwave flux, the net shortwave surface budget, and the atmospheric shortwave attenuation variable $\beta$. The climate sensitivity was estimated from the mean of the indices during the years 1990–99 for the CMIP3 models. The surface radiative flux dataset from the Clouds and the Earth’s Radiant Energy System (CERES) together with its top–of–atmosphere Energy Balanced and Filled equivalent (CERES EBAF) are used as a reference observational dataset, resulting in a best estimate for climate sensitivity of 3.3 K with a likely range of 2.7–4.0 K. A comparison with other satellite and reanalysis datasets show similar likely ranges and best estimates of 1.7–3.8 (3.3 K) [Earth Radiation Budget Experiment (ERBE)], 2.9–3.7 (3.3 K) [International Satellite Cloud Climatology Project radiative surface flux data (ISCCP–FD)], 2.8–4.1 (3.5 K) [NASA’s Modern Era Retrospective–Analysis for Research and Application (MERRA)], 3.0–4.2 (3.6 K) [Japanese 25–yr Reanalysis (JRA–25)], 2.7–3.9 (3.4 K) [European Centre for Medium–Range Weather Forecasts Re–Analysis (ERA–Interim)], 3.0–4.0 (3.5 K) [ERA–40], and 3.1–4.7 (3.6 K) for the NCEP reanalysis. For each individual reference dataset, the results suggest that values for the sensitivity below 1.7 K are not likely to be consistent with observed radiation patterns given the structure of current climate models. For the aggregation of the reference datasets, the climate sensitivity is not likely to be below 2.9 K within the framework of this study, whereas values exceeding 4.5 K cannot be excluded from this analysis. While these ranges cannot be interpreted properly in terms of probability, they are consistent with other estimates of climate sensitivity and reaffirm that the
current climatology provides a strong constraint on the lower bound of climate sensitivity even in a set of structurally different models.

2.1 Introduction

The earth’s climate system is almost entirely driven by shortwave radiative energy coming from the sun. Although temperature and precipitation are the most widely recognized climate variables, it is basically the radiation with its energy flows and balances within the climate system that determines the earth’s climate and thus drives its various internal processes and feedbacks. Changes in the concentration of atmospheric constituents result in a perturbation of the earth’s radiation balance; hence, the adequate representation of the radiative fluxes in the climate system is a prerequisite for any climate model. Local–to–global–scale observations of the radiative fluxes include surface (SFC) radiation measurements, for example, the Baseline Surface Radiation Network (BSRN; Ohmura et al. (1998)) and the Global Energy Balance Archive (GEBA; Ohmura and Gilgen (1991)) as well as satellite–derived data products such as ERBE (refer to Table 2.2 for expansion of dataset names; Ramanathan et al. (1989)) and the CERES experiment (Wielicki et al., 1996). The advent of improved observational datasets and comprehensive radiative transfer models recently allowed the production of the first 18–yr global gridded radiative flux profile dataset stemming from the ISCCP–FD encompassing both full– and clear–sky fluxes at five levels in the atmosphere, starting from the surface up to the top–of–atmosphere (TOA) (Zhang et al., 2004). Reanalyses are a powerful tool to combine satellite measurements and data output from numerical models and provide a comprehensive representation of the radiative fluxes in climate system. Among the most recent reanalyses are the National Aeronautics and Space Administration (NASA)’s MERRA project (available online at http://gmao.gsfc.nasa.gov/research/ merra/), the ECMWF Re–Analysis (ERA–Interim, available online at http://www.ecmwf.int/research/era/do/get/ era–interim), and JRA–25 (Onogi et al., 2007). In terms of modeling the radiative fluxes, a review of the developments in radiation budget modeling in general circulation models (GCMs) from a surface perspective over the last few decades, up to the latest generation of GCMs used in the Fourth Assessment Report (AR4) of the Intergovernmental Panel on Climate Change (IPCC) can be found in Wild (2008). A long–standing problem of AOGCMs is that they overestimate the shortwave and underestimate the longwave downward radiation at the surface (Wild, 2008).

Simple indices of surface air temperature patterns, such as the global–mean, the land–ocean contrast, the annual cycle (AC), and the interhemispheric difference (NS), were used in previous studies to describe global climate variability and change (Karoly and Braganza, 2001; Braganza et al., 2003, 2004). The observed temperature, radiation fields, and trends have been extensively used to constrain climate sensitivity and future temperature projections (Forest et al., 2002; Harvey and Kaufmann, 2002; Knutti et al., 2002; Gregory et al., 2004b; Murphy et al., 2004; Knutti et al., 2006; Knutti and Hegerl, 2008; Sanderson et al., 2008a). Here we use and extend the indices defined in Braganza et al. (2003) and look at surface and TOA radiation patterns during the period lasting from 1990 to 1999 for the multimodel dataset of the World Climate Research Programme Coupled Model Intercomparison Project phase 3 (WCRP CMIP3) and correlate them with the corresponding climate sensitivities of the dif-
different climate models. An estimate of climate sensitivity is inferred by comparing the linear relationship described above to observational reference data for the corresponding period. To relate some of the radiative indices to physical feedbacks, we compute the same indices for the total cloud cover, the column–integrated atmospheric water vapor content, and the sea ice concentration.

Despite an unprecedented effort in climate modeling and an increase in computing power and observational data, the uncertainty in predicting the response of the climate system to a doubling of atmospheric carbon dioxide levels, defined as equilibrium climate sensitivity, has not substantially decreased (Meehl et al., 2007). The AR4 estimated a likely range for climate sensitivity of 2–4.5 K, similar to the range of 1.5–4.5 K estimated in the Third Assessment Report (TAR), but with a slight increase of the lower bound. Probability distribution functions indicate non–zero probabilities for climate sensitivities outside that range (Knutti and Hegerl, 2008). While the spread of climate sensitivity derived from various multimodel ensembles mostly resulted in the range between 2 K and 4.5 K, the multi–thousand–member ensemble from Climateprediction.net (CPDN) sampled a broader range from 2 K to more than 11 K (Stainforth et al., 2005). Several studies employing the CPDN perturbed physics ensemble find a best estimate of climate sensitivity of around 3.3 K and between 3 and 3.5 K (Piani et al., 2005; Knutti et al., 2006). Despite the broad range of possible climate sensitivities suggested by the CPDN models, the best estimates still lie in the range of 2–4.5 K encompassed by the multimodel ensembles. The longstanding, main uncertainty for both equilibrium and transient runs stems from the representation of cloud feedbacks, with the spread in cloud feedbacks as computed by various GCMs being roughly 3 times larger than the one accounting for the combined water vapor– lapse–rate feedback, the radiative forcing, or the ocean heat uptake (Cess et al., 1989; Dufresne and Bony, 2008). A review of the concept of the equilibrium climate sensitivity and the methods to estimate its range can be found in Knutti and Hegerl (2008) and Allen et al. (2006).

Our goal is to account for model biases in the estimation of climate sensitivity by establishing statistically significant regressions between simulated sensitivities and model biases, and then applying observed constraints to these regressions. The focus of our efforts will be on regions and fluxes that are key in explaining the spread of GCM radiative feedbacks under climate change. This paper is structured as follows. Section 2.2 outlines the model and observational data employed in this study. It also introduces the radiative indices and the notion of constraining unmeasurable quantities in the climate system, such as the equilibrium climate sensitivity by using an intermodel correlation obtained from the radiative indices and the climate sensitivities computed by the CMIP3 multimodel dataset. These indices, the intermodel correlations to climate sensitivity, and the kernel density estimates for the latter are shown in section 2.3, where also some illustrative examples are depicted. Section 2.4 discusses some issues of uncertainty involved in our method. A summary and conclusions are presented in section 2.5.
Table 2.1: The climate models and their corresponding equilibrium climate sensitivities used in this study. Model identifications (IDs) and climate sensitivity values are taken from Table 8.2 of Randall et al. (2007). Further information on the models can be found in Table 8.1. of Randall et al. (2007).

<table>
<thead>
<tr>
<th>Model ID</th>
<th>Equilibrium Climate Sensitivity [°C]</th>
</tr>
</thead>
<tbody>
<tr>
<td>CCSM3</td>
<td>2.7</td>
</tr>
<tr>
<td>CGCM3.1(T47)</td>
<td>3.4</td>
</tr>
<tr>
<td>CSIRO–MK3.0</td>
<td>3.1</td>
</tr>
<tr>
<td>CGCM3.1(T63)</td>
<td>3.4</td>
</tr>
<tr>
<td>ECHAM5/MPI–OM</td>
<td>3.4</td>
</tr>
<tr>
<td>ECHO–G</td>
<td>3.2</td>
</tr>
<tr>
<td>FGOALS–g1.0</td>
<td>2.3</td>
</tr>
<tr>
<td>GFDL–CM2.0</td>
<td>2.9</td>
</tr>
<tr>
<td>GFDL–CM2.0</td>
<td>3.4</td>
</tr>
<tr>
<td>INM–CM3.0</td>
<td>2.1</td>
</tr>
<tr>
<td>IPSL–CM4</td>
<td>4.4</td>
</tr>
<tr>
<td>MIROC3.2(hires)</td>
<td>4.3</td>
</tr>
<tr>
<td>MIROC3.2(medres)</td>
<td>4.0</td>
</tr>
<tr>
<td>MRI–CGCM2.3.2</td>
<td>3.2</td>
</tr>
<tr>
<td>PCM</td>
<td>2.1</td>
</tr>
<tr>
<td>UKMO–HadCM3</td>
<td>3.3</td>
</tr>
<tr>
<td>UKMO–HadGEM1</td>
<td>4.4</td>
</tr>
</tbody>
</table>

2.2 Data and Methods

2.2.1 Model Data

This study employs AOGCM model output for the twentieth–century integrations obtained from the CMIP3 data archive (available online at http://www–pcmdi.llnl.gov/ipcc/about_ipcc.php). All available all–sky (as) and clear–sky (cs) radiation fields were taken into account. Because of the inconsistency of aerosol forcing agents across the CMIP3 models, as shown in Table 10.1 of Meehl et al. (2007), we did not use any aerosol data. In addition to the radiation fields, we used the monthly averaged fields of the total cloud cover (variable clt), the atmospheric water vapor (prw), and sea ice concentration (sic). To have a homogeneous set of grids and consistency with the zonal definition of the indices, the available monthly averaged fields were interpolated to a T42 grid. The models and their corresponding climate sensitivities are listed in Table 2.1.

2.2.2 Observational and Reanalysis Data Sets

As an observational dataset, we employ the 5–yr climatological radiation fields for the surface and TOA fluxes derived from CERES (Wielicki et al., 1996). Raw CERES data from the Terra FM1 instrument were used for the surface fluxes and the EBAF fields (CERES EBAF) for the
2.2 DATA AND METHODS

TOA fluxes. For the CERES surface data, clear-sky incoming and outgoing fluxes were not available, only the clear-sky net shortwave and longwave budgets. We use a modified CERES dataset that matches the TOA imbalance by Hansen et al. (2005a) (refer to section 2.4). As a satellite reference dataset for the TOA, we also use the data from the ERBE during the years 1985–1989. Because of the failure of the National Oceanic and Atmospheric Administration’s NOAA–9 satellite, we employ here the ocean–to–land energy–transport–adjusted ERBE product of Fasullo and Trenberth (2008), which incorporates also an adjustment to the outgoing longwave TOA radiation. The comprehensive radiative surface and TOA flux dataset from the ISCCP–FD (Zhang et al., 2004) is also taken into account. The ISCCP–FD dataset is the successor of the previous ISCCP–FC project and incorporates both an improved NASA Goddard Institute for Space Studies (GISS) radiative transfer model as well as more advanced satellite–retrieval algorithms. Moreover, the observations specifying the input for the radiative transfer model have also improved. Because of the surface and TOA biases in the ISCCP–FD dataset (Zhang et al., 2004) and errors in the angular distribution models of ERBE, the use of CERES data is deemed superior.

In terms of reanalysis data, the satellite data products of CERES, ERBE, and ISCCP–FD are complemented by NASA’s Global Modeling and Assimilation Office (GMAO) MERRA covering the years 1979 to present (available online at http://gmao.gsfc.nasa.gov/research/merra/intro.php) and JRA–25, which was developed at the Japan Meteorological Agency (JMA) and Central Research Institute of Electric Power Industry (CRIEPI). Six-hourly forecast radiation datasets were available for the period 1979–2009 (Onogi et al., 2007). We also use data from the ERA–40 project, which is a 45–yr reanalysis of the global atmosphere and surface conditions from September 1957 to August 2002, carried out by the ECMWF in Reading, United Kingdom (Uppala et al., 2005), and the NCEP–NCAR reanalysis starting in 1948 (Kalnay et al., 1996). Further, the ERA–Interim dataset is taken into account, which is the successor of the ERA–15 and ERA–40 reanalyses. ERA–Interim covers the period 1989 to present (available online at http://www.ecmwf.int/research/era/do/get/era–interim). This new reanalysis dataset has more extensive features than the previous datasets; that is, it includes additional cloud parameters and more pressure levels. Both the ERA–40 and ERA–Interim datasets do not contain solar clear-sky downward and upward surface fluxes. The online distribution of ERA–40 data does not contain the incoming shortwave flux at the TOA and instead the corresponding ERA–Interim field is used, which seems adequate since we consider only the mean climate state.

An overview of the observational reference datasets employed in this study is given in Table 2.2. Both the satellite-derived radiation fields and the reanalysis fields were interpolated to a T42 grid and where possible, both all-sky and clear-sky fluxes were used. The period considered are the years 1990–99 for all the observational reference datasets. The land–sea mask applied to both model and observational data is the least common denominator of the different land–sea masks of the CMIP3 climate models, which were interpolated on a T42 grid.

2.2.3 Indices

Simple indices describing global climate change using surface air temperature patterns have been investigated in previous studies (Karoly and Braganza, 2001). Braganza et al. (2003,
Table 2.2: Observational reference datasets and their corresponding periods used in this study. See text for further details and references.

<table>
<thead>
<tr>
<th>Data Set</th>
<th>Time Period</th>
</tr>
</thead>
<tbody>
<tr>
<td>Clouds and the Earth’s Radiant Energy System (CERES) (surface) and</td>
<td></td>
</tr>
<tr>
<td>Energy Balanced and Filled Equivalent (EBAF) (TOA)</td>
<td>2000 – 2005</td>
</tr>
<tr>
<td>Earth Radiation Budget Experiment (ERBE)</td>
<td>1985 – 1988</td>
</tr>
<tr>
<td>NASA’s Modern Era Retrospective–Analysis (MERRA)</td>
<td>1979 – 1999</td>
</tr>
<tr>
<td>ECMWF ERA–Interim Reanalysis (ERA–I)</td>
<td>1989 – 1999</td>
</tr>
<tr>
<td>ECMWF ERA–40 Reanalysis (ERA–40)</td>
<td>1958 – 1999</td>
</tr>
<tr>
<td>The NCEP/NCAR Reanalysis Project (NCEP)</td>
<td>1948 – 1999</td>
</tr>
</tbody>
</table>

2004) examined the correlation structure of various indices and their internal variability during the twentieth century in the context of detection and attribution of climate change. The indices are chosen to capture and represent the spatial patterns of surface air temperature change due to the enhanced greenhouse effect. The key features of temperature change include the global temperature increase, larger warming over land than over ocean, greater warming at high latitudes than at low latitudes, a reduction in the magnitude of the annual cycle of temperature over land, and a difference in the warming between the Northern and Southern Hemisphere (NH and SH, respectively) arising from differences in the effects of aerosols and ocean mixing (Karoly and Braganza, 2001). The indices, their definitions, and the abbreviations adopted in this paper are given in Table 2.3. Because of the similarities and mutual influence between temperature and radiation, the indices in this study were computed for all radiation variables, including surface and TOA fluxes. We introduce a new radiation variable called the ‘atmospheric longwave absorption and emission variable’, denoted in the following sections as $\alpha$, which is simply the difference between the outgoing longwave radiation at the TOA ($\text{LW}_{\uparrow}^{\text{TOA}}$) and the incoming longwave radiation at the surface ($\text{LW}_{\downarrow}^{\text{SFC}}$). The corresponding shortwave attenuation variable, denoted by $\beta$, is the difference between the incoming solar radiation at the TOA ($\text{SW}_{\downarrow}^{\text{TOA}}$) and the incoming shortwave radiation at the surface ($\text{SW}_{\downarrow}^{\text{SFC}}$). An overview of the radiation variables employed in this study is listed in Table 2.4.

For a deeper insight into variations in space and surface types, the indices defined globally in Braganza et al. (2003) were computed separately here for land and ocean and were divided into zonal bands defined as: northern high latitudes (NH H: 90°N – 60°N), northern mid latitudes (NH M: 60°N – 30°N), northern tropics (NH T: 30°N – 0°), southern tropics (SH T: 0° – 30°S), southern mid latitudes (SH M: 30°S – 60°S) and southern high latitudes (SH H: 60°S – 90°S) where compatible with the definition which resulted in 50 indices. The indices were computed for the mean radiation of the period between the years 1990 and 1999. An overview of the indices used in this study to estimate climate sensitivity is shown in Figure 2.1.

Both by definition and by chance, some of the indices are expected to be correlated. The 34 radiation variables and 50 indices for each of these radiation variables amount to a total of 1700 indices; thus, the correlation matrix has dimensions of 1700 x 1700 and cannot be
2.2 Data and Methods

Table 2.3: The indices, their definitions, and abbreviations used in this study.

<table>
<thead>
<tr>
<th>Index</th>
<th>Definition</th>
<th>Abbreviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>The Annual Mean</td>
<td>The area–weighted annual mean radiation flux</td>
<td>AM</td>
</tr>
<tr>
<td>The Land–Ocean Ratio</td>
<td>The ratio between the mean–field over land and the mean–field over ocean</td>
<td>LO</td>
</tr>
<tr>
<td>The Interhemispheric Difference</td>
<td>The difference between the mean Northern Hemisphere (NH) field and the mean Southern Hemisphere (SH) field</td>
<td>NS</td>
</tr>
<tr>
<td>The Annual Cycle</td>
<td>The magnitude of the annual cycle was calculated for each hemisphere by subtracting the mean winter field from the mean summer field over land. These quantities were then area–weighted by the fraction of global land surface area in the respective hemisphere and combined into a single index: ( AC = w_{NH}(JJA - DJF) + w_{SH}(DJF - JJA) )</td>
<td>AC</td>
</tr>
</tbody>
</table>

Table 2.4: Definitions of symbols representing the shortwave, longwave, and net radiative fluxes for as and cs conditions as well as for cloud radiative forcing (crf).

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \text{LW} \downarrow_{SFC}^{\text{as}} )</td>
<td>downward longwave radiation at the surface (SFC) for all–sky (as) conditions</td>
</tr>
<tr>
<td>( \text{LW} \downarrow_{SFC}^{\text{cs}} )</td>
<td>downward longwave radiation at the surface (SFC) for clear–sky (cs) conditions</td>
</tr>
<tr>
<td>( \text{LW} \downarrow_{SFC}^{\text{crf}} )</td>
<td>downward longwave radiation at the surface (SFC) cloud radiative forcing (crf), equal to: ( \text{LW} \downarrow_{SFC}^{\text{as}} - \text{LW} \downarrow_{SFC}^{\text{cs}} )</td>
</tr>
<tr>
<td>( \text{LW} \uparrow_{SFC} )</td>
<td>upward longwave radiation at the surface (SFC) for all–sky (as) conditions</td>
</tr>
<tr>
<td>( \text{LW} \uparrow_{TOA} ), ( \text{LW} \uparrow_{cs}^{TOA} ), ( \text{LW} \uparrow_{crf}^{TOA} )</td>
<td>upward longwave radiation at TOA</td>
</tr>
<tr>
<td>( \text{SW} \downarrow_{SFC}^{\text{as}} ), ( \text{SW} \downarrow_{SFC}^{\text{cs}} ), ( \text{SW} \downarrow_{SFC}^{\text{crf}} )</td>
<td>downward shortwave radiation at SFC</td>
</tr>
<tr>
<td>( \text{SW} \uparrow_{SFC}^{\text{as}} ), ( \text{SW} \uparrow_{SFC}^{\text{cs}} ), ( \text{SW} \uparrow_{SFC}^{\text{crf}} )</td>
<td>upward shortwave radiation at SFC</td>
</tr>
<tr>
<td>( \Delta \text{LW}^{SFC} ), ( \Delta \text{LW}^{SFC} ), ( \Delta \text{LW}^{SFC} )</td>
<td>net longwave radiation at SFC</td>
</tr>
<tr>
<td>( \Delta \text{SW}^{SFC} ), ( \Delta \text{SW}^{SFC} ), ( \Delta \text{SW}^{SFC} )</td>
<td>net shortwave radiation at SFC</td>
</tr>
<tr>
<td>( \Delta \text{SFC}^{SFC} ), ( \Delta \text{SFC}^{SFC} ), ( \Delta \text{SFC}^{SFC} )</td>
<td>net radiation at SFC, equal to: ( \Delta \text{SW} + \Delta \text{LW} )</td>
</tr>
<tr>
<td>( \alpha^{as} ), ( \alpha^{cs} ), ( \alpha^{crf} )</td>
<td>atmospheric longwave absorption and emission variable, equal to: ( \text{LW} \downarrow_{SFC} - \text{LW} \uparrow_{TOA} )</td>
</tr>
<tr>
<td>( \beta^{as} ), ( \beta^{cs} ), ( \beta^{crf} )</td>
<td>atmospheric shortwave attenuation variable, equal to: ( \text{SW} \downarrow_{TOA} - \text{SW} \downarrow_{SFC} )</td>
</tr>
</tbody>
</table>
visualized appropriately. An empirical orthogonal function (EOF) analysis of the correlation matrix – regarded as a spatial field – showed that 95% of the variance of the correlation matrix field can be explained by the first eight EOFs. On the one hand, this implies that the 1700 indices are highly correlated. On the other hand, the fact that at least eight EOFs are needed to explain most of the variance of the correlation matrix suggests that there is not a single pattern governing the correlations between all the indices.

2.2.4 Estimating Climate Sensitivity

The basic idea of this paper is illustrated in Fig. 2.1, where the indices for all radiation variables as computed by the CMIP3 multimodel set and their correlations to their corresponding climate sensitivities for the period 1990–99 are shown. The indices are not mutually independent, and the correlation coefficients vary from –0.89 to +0.84. We considered all correlations that are statistically significant at a 95% level. Three steps will lead to an estimate of climate sensitivity. First, a linear regression is carried out that determines the linear relationship between the index and the climate sensitivity. Subsequently, the quality of the linear relationship is quantitatively assessed via bootstrapping, giving a range of slopes between the radiative index and climate sensitivity. In the end, the index is computed for the eight observational datasets, which act as reference values. The intersection between the reference value and the bootstrapping sample gives a distribution of climate sensitivity for a particular index and a particular radiation variable.

The significance level of the correlation coefficient depends on the assumption of climate model independence. Previous studies noted that the CMIP3 multimodel ensemble constitutes an ‘ensemble of opportunity’ rather than an independent set of models (Tebaldi and Knutti, 2007; Knutti et al., 2010; Knutti, 2010; Jun et al., 2008a,b). An example of this is the fact that some models are identical except for their resolution. Hence, the assumption of model independence is not correct. Therefore, we emphasize that the distributions of climate sensitivity estimates derived here cannot be regarded as proper probability distribution functions since the prerequisite of independence of both the climate models and the indices is not fulfilled in the framework of this study.

The idea of correlating an observable variable to a predicted quantity was illustrated, for example, by Hall and Qu (2006), where they examined the case of the snow albedo feedback and noticed that large intermodel variations in the snow albedo feedback strength in climate change are well correlated with comparably large intermodel variations in the feedback strength in the context of the seasonal cycle. The high correlation leads to the conclusion that eliminating the model errors in the seasonal cycle will directly lead to a reduction in the spread of feedback strength in climate change; hence, it has the ability to reduce the spread in simulations of the climate sensitivity, to the extent that snow cover feedbacks are a major driver of these differences. A similar approach was used to constrain climate sensitivity from the seasonal cycle in surface temperature (Knutti et al., 2006). Climate sensitivity was shown to relate to aspects of present–day climatology also in several other studies (Piani et al., 2005; Sanderson et al., 2008a,b). Sanderson et al. (2008a, see Fig. 7) in particular showed that current patterns of radiation provide a constraint on climate sensitivity in the Climateprediction.net ensemble.
Figure 2.1: Overview of the correlations between the indices (ordinate) for all radiation variables (abscissa) and the equilibrium climate sensitivities. The correlation coefficients are indicated in the color bar, and only the indices that are significant at a 95% level are shown. The indices were computed from the 1990 to 1999 climatology for the CMIP3 models (see text for details). The spatial grid was divided into zonal bands as defined in section 2.2 and separated into land and ocean. The symbols of the radiation variables are given in Table 2.4.
The assumption here is that the correlation across models does not simply reflect the similarity of the models and uniformity of the underlying parameterizations but an intrinsic behavior resulting from physical processes. Of course this is difficult to prove, but support for that assumption is given by the fact that the CMIP3 models are structurally different (in contrast to the Climateprediction.net ensemble) and by the fact that the relations presented here can be understood in terms of physical processes. Moreover, the fact that high correlations are seen in different variables and regions and the consistency across the indices enhance the confidence in this method. Of course radiation indices can be changed in various ways, for example, by changing an albedo value of a land surface, which would probably not affect climate sensitivity. However, such changes are very likely to be random and uncorrelated across different models and would tend to weaken the observed correlation rather than spuriously introducing it. It is therefore very likely that the correlations indeed represent real variations in feedbacks. Note also that a strong correlation does not necessarily imply that the particular feedback is strong nor does it imply that it explains a large fraction of the climate sensitivity variation in CMIP3. A correlation may be strong, for example, in the high latitude, indicating a clear relation between the albedo feedback and climate sensitivity (Hall and Qu, 2006) even though the spread in the albedo feedback is a relatively small contribution to the spread of the total feedback in the CMIP3 models (Soden and Held, 2006).

2.3 Results

2.3.1 Relation to clouds, atmospheric water vapor and sea–ice concentration

The radiative fluxes in the climate system are functions of its physical properties e.g. those of clouds, atmospheric water vapor and sea–ice concentration. Changes in these quantities can alter the radiative fluxes and induce radiative feedbacks which can dampen or amplify the initial perturbation. Here we show the indices defined above for the total cloud cover, the column integrated amount of water vapor and sea–ice concentration and correlate them to the radiative indices in order to relate particular indices to possible feedbacks which in turn can give an insight to the correlations of the indices to climate sensitivity. These variables together with the relative humidity were used in a recent study by Fasullo (2010) who assessed the energy and water cycle feedbacks with respect to the land–ocean contrast.

The land–ocean contrast of clouds, water vapor and sea–ice is related to the land–ocean index of the radiation variables as shown Figure 2.2. On a global level we found that a high land–ocean contrast in total cloud cover in a model implies a high cloud–radiative forcing for the incoming longwave radiation (LW↓ crf T OA) and the outgoing shortwave flux at the TOA (SW↑ crf T OA). In contrast, more clouds lead to less shortwave radiation reaching the surface (SW↓ SFC as). These relations can be explained by the absorptive and reflective properties of clouds. In the tropics, Figure 2.2 indicates that a strong spatial land–ocean gradient in water vapor is related to a stronger clear–sky longwave surface flux (LW↓ SFC cs) over land than over ocean. The opposite is the case for the outgoing longwave flux at the TOA (LW↑ as T OA). The lower panel of Figure 2.2 illustrates that the sea–ice concentration is positively correlated with the land–
ocean contrast of the incoming all–sky and clear–sky shortwave surface radiation (\(\text{SW}_{\text{as}}^{\downarrow} \) and \(\text{SW}_{\text{cs}}^{\downarrow} \)) due to the reflective properties of the sea–ice surface. Overall, the correlations suggest that intermodel differences in physical properties and feedbacks induced by clouds, water vapor and sea–ice are at least partly reflected in the indices, even though a complete discussion of each of the hundreds of relations is not feasible.

### 2.3.2 Indices and Correlations

Figure 2.1 illustrates the correlations between climate sensitivity and the 50 indices in the thirty–four radiation variables used in this study which are significant at a 95% level. Since the CMIP3 data set does not include clear–sky upward longwave fluxes at the surface, the net longwave cloud–radiative forcing (\(\Delta \text{LW}^{SFC}_{\text{crf}} \)) is approximated by \(\text{LW}_{\text{cs}}^{\downarrow} - \text{LW}_{\text{as}}^{\uparrow} \). This approximation is also carried out for the reference data sets where possible. The correlation coefficients cover a range from –0.89 to +0.84 and we chose three of them in the following sections to illustrate the method of estimating climate sensitivity using a correlation between an observable radiative index and the climate sensitivity as computed by the CMIP3 models. The illustrative examples are cases where the correlation is significant and where the behavior can be understood in terms of known physical processes, i.e. where the correlation is unlikely to be purely a statistical artifact resulting from calculating a large number of correlations.

Four radiation variables dominate the correlation structure in Fig. 2.1 by exhibiting significant correlations throughout most of the indices. These variables of interest are the cloud radiative forcing of the incoming longwave radiation at the surface \(\text{LW}^{SFC}_{\text{crf}} \), the clear–sky incoming shortwave flux \(\text{SW}^{SFC}_{\text{cs}} \), the net clear–sky shortwave surface budget \(\Delta \text{SW}^{SFC}_{\text{cs}} \) and the clear–sky atmospheric shortwave attenuation \(\beta_{\text{cs}} \).
The regional partitioning of the indices highlight special regions of interest where correlations are apparent in almost all radiation variables such as the southern tropics and southern mid–latitudes along with the northern high latitudes. Some indices and their correlations appear to be governed by a particular kind of radiation, e.g., the Annual Cycle index mostly by the shortwave radiation as can be seen at the bottom part of Fig. 2.1. The Land–Ocean index and the Annual Cycle index seem to represent useful indices to connect many radiation fluxes with climate sensitivity. Moreover, the atmospheric longwave absorption and emission variable $\alpha$ and atmospheric shortwave attenuation variable $\beta$ feature significant correlations throughout almost all the indices as shown in the right part of Fig. 2.1.

2.3.3  Global Indices

The indices, their correlation coefficients to climate sensitivity and the correlation structure among the indices is illustrated for the case of the global mean indices as depicted in Fig. 2.3. The indices and their respective radiation variable are denoted in the lower panel of Fig. 2.3 at the left hand side of the symmetric correlation matrix. Red–colored blocks highlight positively correlated indices whereas blue shaded groups show negative correlations. The correlations of these indices with climate sensitivity are depicted in the upper panel. Some of the correlations among different indices may appear by chance whereas others result by definition of the indices, e.g. it is assumed that for a given radiation variable the annual mean radiation over land is correlated with the global annual mean radiation. This situation is clearly visible in the upper left corner of the correlation matrix where the Annual Mean indices in the SW ↓ SFC radiation for the entire globe (AM) and separately for land (AM land) and ocean (AM ocean) are highly correlated. Despite showing highly correlated indices, Fig. 2.3 also indicates that there are independent indices with white colored blocks. Overall, the correlation matrix in Figure 2.3 leads to the conclusion that the climate sensitivity estimates derived from the correlations of the indices in the upper panel of Fig. 2.3 are not independent. Moreover, Fig. 2.3 can be used to infer the dominant fluxes in the radiation budgets of the surface and the atmosphere. Considering again the ‘cluster’ of correlations in the AM index for the SW ↓ SFC radiation variable, Figure 2.3 shows that by moving downwards in the correlation matrix it is the SW ↓ SFC flux which governs the same indices in clear–sky shortwave attenuation variable $\beta_{cs}$.

We found that the annual–mean clear–sky shortwave radiation budget at the surface (AM × $\Delta$ SW ↓ SFC) is related to climate sensitivity with a correlation coefficient of $r = 0.84$. The same is true for the annual cycle in this radiation variable with $r = 0.76$. The correlation matrix shows that these two indices are highly correlated. The ratio in the incoming cloud–radiative forcing at the surface over land and ocean surfaces (LO × LW ↓ crf SFC) exhibits a correlation of $r = –0.65$ with climate sensitivity. This index is independent of the annual mean (AM × LW ↓ crf SFC) which is also correlated to sensitivity at $r = –0.66$.

2.3.4  Zonal Partition of the Indices

The zonal partition of the indices gives a spatial insight into the radiation patterns. Figure 2.4a) shows the indices, the radiation variables and correlations of the latter to climate sensitivity for the high latitudes. The land–ocean ratio index in the northern hemisphere is apparent
Figure 2.3: Correlation coefficients of global indices with climate sensitivity that are significant at a 95% level are shown together with the correlation matrix of the indices. The size of the circles corresponds to the magnitude of the correlation. The red shading (blue circles) denotes positive (negative) correlation coefficients.
Figure 2.4: (middle) Illustrative examples of the correlations between (left) a radiative index and the equilibrium climate sensitivity computed by the CMIP3 models for the high latitudes and (right) the correlation of the same index for the particular radiation variable of the left panel and the water vapor variable. (top) The particular index is indicated on the ordinate and the radiation variables are shown on the abscissa. (bottom) The kernel density estimates for climate sensitivity derived by bootstrapping and comparison of the linear relation between a radiative index and climate sensitivity with the observational reference datasets.
throughout almost all shortwave and longwave radiation variables. A ‘cluster’ of correlations is found for the annual cycle of the outgoing longwave radiation cloud radiative forcing at the TOA (LW$^{\uparrow}_{\text{TOA}}$) and both the all–sky and clear–sky incoming shortwave radiation at the surface (SW$^{\downarrow}_{\text{SFC}}$ and SW$^{\downarrow}_{\text{CS}}$). These correlations govern also similar correlations for the atmospheric absorption radiation variables $\alpha$ and $\beta$ in the annual cycle as seen in Figure 2.4a).

Figure 2.4b) depicts the correlation of the northern hemisphere land–ocean index of the all–sky incoming longwave surface radiation to climate sensitivity (LO $\times$ LW$^{\downarrow}_{\text{SFC}}$), the climate sensitivity estimates and the relationship between the LO $\times$ LW$^{\downarrow}_{\text{SFC}}$ index and the northern hemisphere LO index for the atmospheric water vapor. High sensitivity models tend to have a LO $\times$ LW$^{\downarrow}_{\text{SFC}}$ index smaller than 1 implying that more longwave radiation reaches the ocean surfaces than the land surfaces in the northern high latitudes. These models have also a higher amount of water vapor above the oceans as shown in the right panel of Fig. 2.4b). A higher amount of water vapor leads to an enhanced atmospheric absorption of longwave radiation hence the correlation between the LO $\times$ LW$^{\downarrow}_{\text{SFC}}$ index and climate sensitivity can be partly attributed to the longwave water vapor feedback. The comparison with the reference datasets suggests that high sensitivity models capture the LO $\times$ LW$^{\downarrow}_{\text{SFC}}$ index better and the climate sensitivity estimates are between 2.7 K and 4.5 K.

The correlations of the indices in the mid latitudes with climate sensitivity are depicted in Figure 2.5a). In the longwave regime, the cloud–radiative forcing of the incoming longwave radiation at the surface (LW$^{\downarrow}_{\text{SFC}$) shows negative correlations with climate sensitivity in the annual mean over land ($r = -0.66$), the land–ocean index ($r = -0.70$) and in the annual cycle index ($r = -0.55$). Strong negative correlations are found in the atmospheric longwave variable $\alpha$ for the land–ocean ratio. The relationship between the interhemispheric difference in the mid–latitudes for the outgoing longwave at the TOA (NS $\times$ LW$^{\uparrow}_{\text{TOA}}$) to climate sensitivity and the same index for total cloud cover is shown in Figure 2.5b). High sensitivity models show more longwave radiation escaping the TOA in the northern mid latitudes, whereas the low sensitivity model feature the opposite. The correlation coefficient between the (NS $\times$ LW$^{\uparrow}_{\text{TOA}}$) index to its respective cloud cover index is $r = -0.84$ and implies that the more clouds the models compute for the southern mid latitudes, the more longwave radiation is trapped in the climate system and the higher the (NS $\times$ LW$^{\uparrow}_{\text{TOA}}$) is. Thus, the intermodel differences in the longwave cloud feedback can be partly attributed to the correlation of the (NS $\times$ LW$^{\uparrow}_{\text{TOA}}$) index to climate sensitivity.

In the tropics, most correlations of the indices with climate sensitivity are found for the annual–mean index (AM) as illustrated in Figure 2.6. The annual cycle index (AC) shows almost no correlations. The dominating radiation variables are LW$^{\downarrow}_{\text{SFC}}$, LW$^{\downarrow}_{\text{SFC}}$, LW$^{\uparrow}_{\text{TOA}}$ and SW$^{\downarrow}_{\text{CS}}$. The strong correlations in these radiation variables induces also strong correlations in the net and atmospheric radiation budgets which include the former variables. Figure 2.6 also highlights that it is the annual–mean radiation in the ocean, and in general the radiation variables above the ocean which exhibit the most numerous correlations to climate sensitivity.

The annual mean all–sky outgoing longwave flux at the TOA in the southern ocean is correlated to climate sensitivity with a correlation coefficient of $r = 0.77$ as shown in Fig. 2.6b). The same flux is also negatively correlated to the total cloud cover in the southern tropical oceans implying that a high cloud cover increases the amount of longwave radiation in this area. This relationship suggests that high sensitivity models generally have a low total cloud cover in the
Figure 2.5: As in Fig. 2.4, but for the mid-latitudes.
Figure 2.6: As in Fig. 2.4, but for the tropics.
southern oceans and thus emit more longwave radiation to space. In this framework, the positive correlations of the clear–sky incoming surface shortwave radiation to climate sensitivity could neither be related to the total cloud amount nor the atmospheric water vapor.

2.3.5 Climate Sensitivity Estimates

In total, we found that 276 radiative indices correlated with climate sensitivity at a 95% significance level during the period 1990–99. The correlations among the indices, as shown in Fig. 2.3, imply that the climate sensitivity estimates are mutually dependent as well. To account for uncertainty in the linear regression between the index and climate sensitivity, we computed a sample of 1000 bootstrapping estimates of the errors of the coefficient vector in the linear regression. This results in 276 000 climate sensitivity estimates for each reference dataset (the number is smaller where not all radiation fields were available). The kernel density estimates for the eight reference datasets are depicted in Fig. 2.7. The distributions must not be regarded as probability distribution function of climate sensitivity because of the dependencies of the indices.

The climate sensitivity was estimated from the mean of the indices during the years 1990–99 for the CMIP3 models and the 5–yr climatology of the CERES and CERES EBAF data. For the best–guess estimate of climate sensitivity, we take the median of the kernel density distribution, resulting in a best guess of 3.3 K (CERES), 3.3 K (ERBE), 3.5 K (MERRA), 3.4 K (ERA–Interim), 3.6 K (JRA–25), 3.5 K (ERA–40), 3.6 K (NCEP), and 3.3 K (ISCCP–FD). The corresponding likely ranges are taken as the central 66% ranges of the kernel density distributions and are 2.7–4.0 (CERES), 1.7–3.8 (ERBE), 2.8–4.1 (MERRA), 2.7–3.9 (ERA–Interim), 3.0–4.2 (JRA–25), 3.0–4.0 (ERA–40), 3.1–4.7 (NCEP), and 2.9–3.7 K for the ISCCP–FD dataset. Aggregating the climate sensitivity estimates of the individual observational reference datasets into one sample, the best estimate of climate sensitivity is 3.4 K with a likely range of 2.9–4.0 K.

The bottom panel of Fig. 2.7 compares the likely ranges with the corresponding range of 2–4.5 K estimates by the IPCC. All estimates lie within the IPCC range except for the NCEP reanalysis, with an upper range slightly exceeding 4.5 K and the ERBE dataset with a slightly lower range. The distribution of the ERBE derived estimates contains only TOA fluxes and has because of its lower amount of correlations, a broader range than estimates derived from both surface and TOA data. For individual reference datasets, Fig. 2.7 indicates that values for the sensitivity below 1.7 K are not likely to be consistent with current observed radiation patterns within the framework of our method. This lower bound increases to 2.9 K if we aggregate the reference datasets, whereas values exceeding 4.5 K cannot be excluded from our analysis, but they are rather unlikely and appear less likely than those found, for example, in the Climateprediction.net (Stainforth et al., 2005). While these ranges cannot be interpreted properly in terms of probability, they are consistent with other estimates of climate sensitivity (Knutti and Hegerl, 2008).
Figure 2.7: (a) Kernel density estimates for climate sensitivity for various observational reference datasets. Distributions were computed using a bootstrapping sample of a linear regression between a radiative index and climate sensitivity where the correlation is significant at a 95% level. Because of different data availability among the reference datasets, the size of bootstrapping samples varies among the kernel density estimates. (b) Depiction of the median and 66% likely ranges.
2.4 Discussion

A variety of uncertainties arises in every step of our procedure. Parametric and systematic uncertainties in the CMIP3 multimodel ensemble cause errors in the radiative fluxes and thus in the radiative indices computed in this study. Moreover, the models share similar deficiencies and may not cover the full model space (Tebaldi and Knutti, 2007). Additionally, the eight observational datasets feature similar deficiencies and should not be regarded as mutually independent reference datasets. The method of deriving an estimate of climate sensitivity using a correlation of climate model patterns highly depends on the value inferred from the observational datasets, which in turn crucially depends on the uncertainty of the linear regression. Hence, the estimates of climate sensitivity are sensitive to structural biases in the observational datasets, either derived from reanalyses or satellite products, and to the correlation coefficient. Some of the issues are discussed in more detail below.

The uncertainty in the linear regression was quantitatively assessed by computing a bootstrapping sample with 1000 estimates for each correlation. The indices chosen in this study are not mutually independent, as the correlation matrix for the globally defined indices in Fig. 2.3 shows. Moreover, Huybers (2010) noted physically unexpected correlations among different feedbacks in the CMIP3 climate models that may arise from tuning and compensating errors in models. Hence, it is not possible in the framework of this study to quantitatively relate a particular index and its correlation to climate sensitivity to a particular feedback process in a climate model. By computing the indices defined here for the total cloud cover, the atmospheric water vapor, and the sea ice concentration in the model, we could show that intermodel differences in one of these quantities are related to the radiative indices and highlight the physical properties, such as the radiative absorption and reflectivity of clouds. Thus, we conclude that the radiative indices employed in this study are related to physical feedbacks, which in turn influence climate sensitivity.

The indices used in this study were in first place temperature–based and employed by Braganza et al. (2003, 2004) in a detection and attribution framework in the context of climate change. The usage of the indices as a predictor for climate sensitivity reflects the assumption that the radiative indices and their spatial distribution give insight into the radiative feedbacks and physical processes underlying the radiation patterns. The link between radiation fields and climate feedbacks has been previously assessed by the computation of radiative kernels both in multimodel and perturbed physics ensembles (Soden et al., 2008; Sanderson et al., 2009). Spatial indices of cloud amount were also shown to correlate with climate sensitivity. Volodin (2008) examined the cloud amount of the CMIP3 models and found a correlation of \( r = -0.82 \) between the equilibrium climate sensitivity and the residual of cloud amount of the tropics (28°S – 28°N) and southern temperate latitudes (56°S – 36°N). Hence, it is natural to assume that there are also spatial indices in the radiation variables itself, which are directly affected by the cloud amount and being related to the equilibrium climate sensitivity. Previous studies examined physical processes, such as the land–ocean contrast (Sutton et al., 2007; Joshi et al., 2008) and the polar amplification (Holland and Bitz, 2003) primarily for the temperature variable. Recently, Fasullo (2010) found that land–ocean contrasts in radiative fluxes and cloud amount in CMIP3 climate model ensemble are crucial in the way the energy budget equili-
brates in response to forcing. This study attempts to give some insights into these processes for the various radiation fluxes in the climate system in a qualitative way.

The zonal partitioning of the indices is designed to highlight different regions in which particular indices are related to climate sensitivity. Figure 2.6 shows that the indices both in the annual–mean longwave and shortwave radiation in the southern ocean are correlated to climate sensitivity. Bony and Dufresne (2005) found that differences in the marine boundary layer clouds are to a great extent responsible for cloud feedback uncertainties in the tropics. Studying the energy budget of the southern ocean, Trenberth (2010) found that errors in the energy budget of the Southern Hemisphere are negatively correlated to the equilibrium climate sensitivity. The correlation of $r = -0.73$ of the model sensitivity to the net downward flux at the TOA might be linked to the negative biases in cloud amount, which are together with cloud type, cloud–top height, and radiative properties one of the main reasons for the differences of TOA radiation between climate models and satellite measurements (Trenberth, 2010).

A variety of studies investigated the radiative effects of clouds and their impact on climate (e.g. Arking, 1991; Vavrus, 2004; Stephens, 2005; Soden and Held, 2006). The fact that correlations between the radiative indices and climate sensitivities are found both in full–sky and clear–sky fluxes, as shown in Fig. 2.1, highlight the influence of clouds on the radiation budget and on climate sensitivity. To account for the effect of different cloud types and other climate variables on the indices and thereby on our estimates of climate sensitivity, an extended analysis including diagnostics, for example, from the vertical pressure velocity (Bony and Dufresne, 2005) and the distinction between low–cloud and high cloud–fraction (Karlsson et al., 2008).

The climate sensitivity estimates derived here crucially depend on the accuracy of the reference datasets. To assess this sort of uncertainty, we employed various satellite–derived datasets and reanalysis–based data. At the TOA, satellite data generally performs better than other types of data, such as reanalyses (Trenberth et al., 2009). A comprehensive illustration and computation of the current best estimates of global energy flows in the climate system by comparing different satellite and reanalysis data is given by Trenberth et al. (2009). Their results are mainly based on new measurement of CERES instruments. Other satellite–derived datasets, such as the ISCCP–FD project, exhibit uncertainties of 10–15 Wm$^{-2}$ at the surface and 5–10 Wm$^{-2}$ at the TOA as well as spurious trends and discontinuities (Zhang et al., 2004; Dai et al., 2006). Trenberth et al. (2009) compared the ERA–40, the NCEP reanalysis, and the ISCCP–FD dataset and noted significant deficiencies and biases. The imbalance at the TOA between the energy absorbed and emitted by the climate system is measured by satellite data to be between –3 and 7 Wm$^{-2}$ (Loeb et al., 2009), while the current best estimate by Hansen et al. (2005a) is $0.85 \pm 0.15$ Wm$^{-2}$. Loeb et al. (2009) note that that this discrepancy is due to uncertainties in absolute calibration and algorithms. Thus, we used a modified CERES data that matches the TOA imbalance computed by Hansen et al. (2005a). Fasullo and Trenberth (2008) used this adjustment to compute the annual cycle of the energy budget of the climate system.

In a comparison of the ERA–40 and NCEP–NCAR near–surface datasets, Betts et al. (2006) found differences in the climatologies of the two different datasets along with consistent and coherent patterns of the major seasonal anomaly fields. They exhibit warm and dry seasonal biases associated with reduced precipitation and cloudiness. Prior studies noticed some deficiencies in the all–sky radiation at the TOA because of the inaccurate representation of cloud radiative properties (Allan et al., 2004). Based on their observations from multiple satel-
lite instruments, Allan et al. (2004) conclude that the all–sky radiation budget simulated by ERA–40 displays large systematic biases. Despite deficiencies in the all–sky radiation budget, the clear–sky radiation budget simulated by ERA–40 compares well with independent satellite data (Allan et al., 2004; Uppala et al., 2005).

When comparing the climate models to observations, one has to consider the fact that the model development involved some tuning toward the current climate. Hence, it is likely that the observations often fall within the range of the model indices. For example, Trenberth (2010) note that energy and moisture are conserved to order 1 Wm$^{-2}$ by the models. In an experiment where the Community Atmosphere Model, version 3 (CAM3) is tuned to fit the TOA energy budget of the ERBE and CERES data, Bender (2008) found that the climate sensitivity resulting from the two tuned version differed by 0.24 K, which is much smaller than the differences in the CMIP3 multimodel set. Because of the particular definitions of the indices, both in terms of space (e.g., the zonal slice ‘northern mid–latitudes’) and processes (e.g., the land–ocean contrast), we argue that is not possible to tune exactly these indices of the models toward observations, since most model calibration efforts focus on global–mean values, for example, on the global–mean energy budget by adjusting the albedo– or cloud–related properties. Moreover, the use of eight different reference datasets – some of them have just recently become public (e.g., MERRA) – enhances the confidence that the model–based indices can be at least partly regarded as independent of the observational datasets.

Despite the uncertainties mentioned above, the consistency of the estimates across different indices and eight reference datasets, as shown in Fig. 2.7, suggests that the range of climate sensitivity derived with the method of this study is robust. Because of the mutual correlations among the indices, some climate sensitivity estimates are accounted for several times, suggesting that the ranges depicted in Fig. 2.7 are likely to be underestimated, although the best guess of 3.4 K for climate sensitivity when the reference datasets are aggregated appears to constitute a robust quantity.

### 2.5 Conclusions

Climate change manifests itself in the perturbation of the earth’s radiation balance; hence, the accurate representation of the radiative fluxes in the climate system is a prerequisite of any climate model and observational datasets. We use indices of spatial radiation patterns to highlight both intermodel differences in modeling radiation in the group of CMIP3 models and their relation to the equilibrium climate sensitivity. Particular regions of interest are highlighted where these intermodel differences correlate to the climate sensitivity, such as the southern tropical oceans or the high latitudes. While the correlations represent a pure statistical tool to constrain both radiation fields and climate sensitivity, the behavior in different regions give insight into the possible effects of feedback processes, which are the source of uncertainty with respect to the climate sensitivity, especially the cloud feedback. Correlations between the climate sensitivity and the radiative indices are found both in all–sky and clear–sky fluxes, particularly in the tropical regions, emphasizing the importance of accurate clear–sky and cloud related feedback parameterization. These findings go along with previous studies that noted the
link between the radiative properties of clouds and the climate (Arking, 1991; Bony et al., 2004; Vavrus, 2004; Stephens, 2005; Soden and Held, 2006; Volodin, 2008).

Despite biases and deficiencies in the observational reference datasets, the analysis supports a value for climate sensitivity in the range of 2.5–5 K, and furthermore that climate sensitivities below 1.7 K are not likely to be consistent with observed radiation patterns in the current climate model structure based on individual observational reference datasets. Aggregating the eight reference datasets, we derive a likely range of climate sensitivity of 2.9–4.0 K with a median estimate of 3.4 K in agreement with previous studies that estimated the lower tail of climate sensitivity using the perturbed physics approach by Climateprediction.net. Those studies found a 5–95% probability range of 2.4–5.4 K (Murphy et al., 2004), 2.2–6.8 K (Piani et al., 2005), and a frequency distribution of the simulated climate sensitivity which ranges from 1.9 K to 11.5 K (Stainforth et al., 2005). They stress that few model versions have sensitivities less than 2 K, whereas the long tail extends to very high values. Overall, the studies highlight the low probability of a climate sensitivity below 2 K. Various methods have been derived to constrain climate sensitivity, and an overview of their probability distribution functions are depicted in Fig. 3 of Knutti and Hegerl (2008). While the range and number of probability distribution functions are large, most studies are consistent in their best estimate with the average of 3.3 K computed by the CMIP3 multi–model ensemble (Meehl et al., 2007), along with 3.3 K (Piani et al., 2005), 3.4 K (Stainforth et al., 2005) and between 3 and 3.5 K Knutti et al. (2006) for the CPDN perturbed physics ensemble. Our mean estimate of 3.4 K for the climate sensitivity fits well in this list.

The limitation here is that the number of models is rather small. On the other hand, a correlation across structurally different models is less likely to be an artifact of an oversimplified parameterization, as it may happen in a perturbed physics ensemble. The results therefore provide strong support for the lower bound of climate sensitivity seen in the CPDN ensemble; however, in contrast to those earlier studies, they are not conditional on a Hadley Centre model structure. Because of the correlation of some variables, the estimates of the climate sensitivity cannot be regarded as mutually independent. Additionally, our indices do not cover the entire space of possible correlations, for example, because of the motivated but still arbitrary zonal partitioning of the indices. Noting the range of the bias field, an improvement of the radiation fields in reanalysis datasets would better constrain climate sensitivity.

The spread of the indices highlight the need for an adequate representation of the radiation patterns in the global climate system. Our method constitutes a first, simple approach to constrain the climate sensitivity using a variety of radiation variables. While the concept of the climate sensitivity is a global approach, the computation of regional climate sensitivities could facilitate the investigation of the influence of physical feedback processes on climate sensitivity (Boer and Yu, 2003). The results of this study, particularly the derived sensitivity, should be regarded with some caution, given the biases and deficiencies in the CERES, ERBE, ISCCP–FD, MERRA, JRA–25, ERA–Interim, ERA–40, and NCEP datasets. Nevertheless, the results reaffirm that the present–day climatology provides a strong constraint on the lower bound of climate sensitivity in the current structure of GCMs.
Chapter 3

Probabilistic climate projections with an intermediate complexity model. Part I: Method and perfect model evaluation on CMIP3
3.1 Introduction

Probabilistic climate projections with an intermediate complexity model
Part I: Method and perfect model evaluation on CMIP3

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(submitted to Climate Dynamics)

Abstract

A hierarchy of climate models – ranging from simple energy balance models to fully coupled atmosphere–ocean general circulation models – has been employed to assess future climate projections under various emission scenarios. In doing so, different statistical methods such as optimal fingerprinting and ensemble–based Monte Carlo methods have been proposed to constrain climate model parameters and model projections by historical observations, which offers a quantitative treatment of uncertainty of future climate change. The advent of emulators as statistical surrogates for the computationally costly climate models allowed to increase the efficiency and ensemble size of climate model runs used in the calibration process. In this study we present a method of building a set of neural network substitutes for the Bern2.5D climate model of intermediate complexity and perform a cross–validation study of the parameter estimates and decadal temperature projections based on historical constraints. Hereby, a particular model serves as the observational reference, hence the term ‘perfect–model’. As a test for the method, we constrain the Bern2.5D model to historical temperature and ocean heat uptake simulations of a set of CMIP3 models. While the method works well within the Bern2.5D climate model, we find discrepancies in emulating some of the CMIP3 models; likely as a result of unknown forcing implementations and model drift in ocean heat uptake. Better agreement is found when the multimodel mean of the CMIP3 set is considered. On average, the method performs remarkably well in predicting transient future global temperature, providing further support for quantitative estimates of uncertainty in future projections constrained by past observed trends.

3.1 Introduction

Until about one decade ago, the assessment of prospective changes in the Earth’s climate system relied on individual climate model projections of possible future climates (Cubasch et al., 2001). In these first simulations, no likelihood or probabilities were attached to different projections (Stott and Forest, 2007; Knutti et al., 2008b). With increasing demands for a rigorous
uncertainty quantification, statistical methods were proposed to constrain climate model projections. Key in the constraining procedure is the agreement between the model output and the historical observational record. Two different approaches have mainly evolved for constraining climate predictions based on observations of past transient climate change.

The first uses large ensembles of simulations from computationally efficient climate models (e.g. Forest et al., 2002; Knutti et al., 2002; Tomassini et al., 2007; Forest et al., 2008; Sanso et al., 2008; Tomassini et al., 2009; Sanso and Forest, 2009) whereas the second employs small ensembles from state-of-the-art coupled ocean–atmosphere general circulation models (AOGCMs) (e.g. Stott and Kettleborough, 2002; Stott et al., 2006; Kettleborough et al., 2007). When compared, the two approaches are shown to give consistent ranges of future temperature changes. Stott and Forest (2007) conclude that the similarity of results demonstrates that past observed climate changes provide robust constraints on probable future climate changes despite the use of different climate models and statistical methods.

A variety of issues arise when a climate model is constrained to historical observations of changes in the climate system. The choice of the statistical error model is crucial in particular with regard to the error covariance structure accounting for internal variability. The common approach is to take the control run of an AOGCM – often the HadCM3 model (Stott and Kettleborough, 2002; Tomassini et al., 2007) – to assess the magnitude and autoregressive properties of internal variability in the climate system. Moreover, the currently available observational datasets differ in length, which is most apparent in the comparably long observational record of global mean temperature compared to only about sixty years of ocean heat uptake measurements. In addition, several datasets exist for a particular climatic variable which differ both in the methodology of data retrieval and in the actual data of the analysis (e.g. Baringer et al., 2010; Lyman et al., 2010).

The degree of independence among the datasets is not clear and partly hinders a comprehensive statistical treatment. Most of these issues and their effects on the parameter estimation process – and thereby on future climate projections – can be assessed by defining one parameter combination and its model output as the observational dataset. By definition, there is no observational error, hence the term ‘perfect-model approach’. A further advantage of this approach is that there is no need to distinguish between structural and parametric uncertainty since one considers only one climate model.

The statistical methods employed to constrain an ensemble of climate model runs to historical data requires a significant amount of computation time and simulations – for example ranging from 426 (Sanso et al., 2008) to 10,000 (Knutti et al., 2003) model runs. In the case of a Markov–Chain–Monte–Carlo (MCMC) approach, the typical chain length varies between 100,000 (Sanso and Forest, 2009) and 150,000 (Tomassini et al., 2007). Recent attempts aim at replacing parts of a climate model with a statistical surrogate. Such an emulator of a climate model can predict the model output of a specific parameter set after a training period in which the model has been run for a sample of parameter combinations.

Urban and Fricker (2010) list spline interpolation, parametric regression, artificial neural networks, and nonparametric Gaussian process regression as examples for emulators. They also note that the sampling of the parameter combinations used for the training process can have an influence on the emulator’s performance. Prior studies emulated the output of the Bern2.5D earth–system model of intermediate complexity (EMIC) with a neural network (Knutti et al.,
2003) and, respectively, of the MIT2D EMIC with Gaussian processes (Sanso et al., 2008; Sanso and Forest, 2009).

Many studies have applied a particular method to observed changes in climate, but to our knowledge none has carefully tested the method on other more comprehensive models. If the predicted future change based on the 20th century was to significantly over- or underestimate the change actually simulated by the complex model, that would cast doubt on the usefulness of the method. Indeed such perfect-model methods have been demonstrated to be powerful tools to identify oversimplified model concepts and statistical methods (Knutti et al., 2008a).

The output of the AOGCMs used in the Fourth Assessment Report (AR4) of the Intergovernmental Panel on Climate Change (IPCC) constitutes such a validation set in which the predictive capability of historical constraints on model parameters can be tested. Previous studies calibrated their climate model parameters towards the simulation of 1% per year increase in CO$_2$ concentration (Forest et al., 2008) and the quadrupling of the CO$_2$ concentration (Olivie and Stuber, 2010). However, a test of future climate projections based on the calibrated model parameters was not performed. Here, we use the AOGCMs model output for the 20th century to calibrate the Bern2.5D model parameters and test the predictive capability of the historical constraints on estimates of future temperature change for the case of a non-intervention emission scenario, for equilibrium climate sensitivity and the transient climate response.

This paper is structured as follows. Section 3.2 introduces the Bern2.5D climate model and describes the MCMC approach of constraining its model parameters. The concept of two forcing groups is also introduced which matches the radiative forcings used to drive the Bern2.5D model to the forcings of a set of AOGCMs. Section 3.3.1 shows the results of a cross-validation study in which the accuracy of the parameter and projection estimates for the Bern2.5D model is quantified. The results of the emulation of a set of AOGCMs is presented in Section 3.3.2. A discussion and conclusion is presented in Section 3.4.

### 3.2 Data and Methods

#### 3.2.1 Bern2.5D climate model

In this study we use the Bern2.5D climate model, an Earth system model of intermediate complexity. The model consists of a zonally averaged dynamic ocean model (Stocker and Wright, 1991; Wright and Stocker, 1991). It resolves the Atlantic, Pacific, Indian, and Southern Oceans and is coupled to a zonally and vertically averaged energy and moisture-balance model of the atmosphere (Stocker et al., 1992; Schmittner and Stocker, 1999). The additional radiative forcing at the top of the atmosphere (TOA) is specified as

$$\Delta F_{TOA}(t) = \Delta F_{dir}(t) + \mu \Delta T_{atm}(t), \quad (3.1)$$

where $\Delta F_{dir}$ is the direct radiative forcing reconstructed over the industrial period. A feedback term $\mu \Delta T_{atm}$ accounts for climate feedbacks and climate sensitivity (Knutti et al., 2003). The time-dependent atmospheric temperature increase is denoted by $\Delta T_{atm}$ and different climate sensitivities are obtained by varying the parameter $\mu$.

The anthropogenic radiative forcings from changes in well-mixed greenhouse gases (CO$_2$, CH$_4$, N$_2$O, SF$_6$ and 28 halocarbons including those controlled by the Montreal Protocol),
Table 3.1: Parameters of the Bern2.5D climate model \((\theta = (\theta_1,\ldots,\theta_{12}))\) considered in this study with the sampling distributions used both to train the neural network substitutes (Sec. 3.2.4) and as prior distributions in the MCMC algorithm (Sec. 3.2.5).

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Distribution</th>
<th>Mean</th>
<th>Std dev</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Climate sensitivity (\left[ ^\circ \text{C} \right] ) ((\theta_1))</td>
<td>Uniform</td>
<td>1</td>
<td></td>
<td>1–8</td>
</tr>
<tr>
<td>Vertical ocean diffusivity (10^{-5} \text{m}^2\text{s}^{-1} ) ((\theta_2))</td>
<td>Uniform</td>
<td>1</td>
<td></td>
<td>1–10</td>
</tr>
<tr>
<td>Transfer Coefficient (\text{Wm}^{-2}\text{K}^{-1} ) ((\theta_3))</td>
<td>Normal</td>
<td>10</td>
<td>2.5</td>
<td></td>
</tr>
<tr>
<td>Greenhouse gas forcing scale ((\theta_4))</td>
<td>Normal</td>
<td>1</td>
<td>0.05</td>
<td></td>
</tr>
<tr>
<td>Stratospheric (\text{O}_3) forcing scale ((\theta_5))</td>
<td>Normal</td>
<td>1</td>
<td>0.335</td>
<td></td>
</tr>
<tr>
<td>Tropospheric (\text{O}_3) forcing scale ((\theta_6))</td>
<td>Normal</td>
<td>1</td>
<td>0.215</td>
<td></td>
</tr>
<tr>
<td>Direct aerosol forcing scale ((\theta_7))</td>
<td>Lognormal</td>
<td>1</td>
<td>0.375</td>
<td></td>
</tr>
<tr>
<td>Indirect aerosol forcing scale ((\theta_8))</td>
<td>Uniform</td>
<td>1</td>
<td></td>
<td>0–2.5</td>
</tr>
<tr>
<td>Organic and black carbon forcing scale ((\theta_9))</td>
<td>Lognormal</td>
<td>1.163</td>
<td>0.69</td>
<td></td>
</tr>
<tr>
<td>Stratospheric water vapor forcing scale ((\theta_{10}))</td>
<td>Lognormal</td>
<td>1.163</td>
<td>0.69</td>
<td></td>
</tr>
<tr>
<td>Volcanic forcing scale ((\theta_{11}))</td>
<td>Lognormal</td>
<td>0.9</td>
<td>0.379</td>
<td></td>
</tr>
<tr>
<td>Solar forcing scale ((\theta_{12}))</td>
<td>Normal</td>
<td>1</td>
<td>0.335</td>
<td></td>
</tr>
</tbody>
</table>

stratospheric and tropospheric \(\text{O}_3\), the direct forcing of black and organic carbon, stratospheric \(\text{H}_2\text{O}\) due to \(\text{CH}_4\) changes, and the direct and indirect effects of aerosols are individually prescribed from reconstructions for the years 1765–2000 (Joos et al., 2001). Variations in solar irradiance and radiative forcing by volcanoes are taken from Crowley (2000).

The model is forced with annual radiative forcings from the forcing agents listed above. We implement scaling factors into the model in order to account for the uncertainty in different forcing agents (Forster et al., 2007). The parameter distributions of the scaling factors are taken from Tomassini et al. (2007) and standard deviations of the prior distributions are derived from the assumption that the uncertainties given by IPCC in the Third Assessment Report represent a range of one standard deviation (Houghton et al., 2001). The lower bound of the indirect aerosol forcing scale is shifted down to zero. A gaussian prior distribution is assumed where the uncertainties are given in percent, and a log–normal distribution is used where the uncertainty is given as a factor (Knutti et al., 2003). An overview of the parameters sampled in the model is given in Table 3.1.

One may argue that newer estimates of radiative forcing are somewhat more narrow and should be considered (Forster et al., 2007). However, there are two reasons why we did not do this here. First, the implementation of the forcings in the different models is often unclear, and may not always be consistent with the latest evidence of bottom up forcing estimates. Second, and more importantly, such probabilistic studies with energy balance models performed since 2002 have pointed to inconsistencies between bottom up estimates of forcings and those inferred from the observed warming (Anderson et al., 2003; Knutti et al., 2002, 2003; Lohmann et al., 2010). So there is some danger that the new direct estimates of aerosol radiative forcing may inadvertently be biased by earlier indirect estimates. Therefore, we deliberately use somewhat broader estimates to avoid any potential double counting. The main
Table 3.2: Different forcing groups used in this study, corresponding to different forcing parameters in the Bern2.5D climate model (Tab. 3.1)

<table>
<thead>
<tr>
<th>Group / θ</th>
<th>θ1</th>
<th>θ2</th>
<th>θ3</th>
<th>θ4</th>
<th>θ5</th>
<th>θ6</th>
<th>θ7</th>
<th>θ8</th>
<th>θ9</th>
<th>θ10</th>
<th>θ11</th>
<th>θ12</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ia</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Ib</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Ic</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Id</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>X</td>
<td>X</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Ie</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>X</td>
<td>✓</td>
<td>✓</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>IIa</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>IIb</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>IIc</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>

results however are not affected by those choices. The largest source of forcing uncertainty is the indirect aerosol effect which is treated as a feedback rather than a forcing in the AR4 report.

3.2.2 Forcing Groups

A goal of this study is to constrain the Bern2.5D EMIC to the model output of a set of CMIP3 models. However, the treatment of the radiative forcing agents in the CMIP3 ensemble (Sec. 3.2.3) is very inhomogeneous (see Table 10.1 of Meehl et al., 2007). We define eight different forcing groups (FGs) to ensure that the appropriate corresponding forcing agents are used in the simulations of the 20th century. The groups are divided into two main groups according to the treatment of volcanic forcing and are listed in Table 3.2. Forcing Group I (FG I) does not include the effect of volcanic eruptions, in contrast to Forcing Group II (FG II) which includes the effect. Besides the distinction of the treatment of volcanic forcing, the group members differ in that they treat other forcings such as organic and black carbon, indirect aerosol and tropospheric ozone differently. The three physical parameters – climate sensitivity, vertical ocean diffusivity and the transfer coefficient for sensible heat – are sampled in all groups. Each forcing group member corresponds to a particular CMIP3 model. The classification is defined in Table 3.3.

3.2.3 CMIP3 Ensemble

A subset of the fully coupled atmosphere–ocean general circulation models of the World Climate Research Programme’s (WCRP’s) Coupled Model Intercomparison Project phase 3 (CMIP3) is used in this study as observational reference data. The forcing scenarios are chosen to be the 20c3m scenario for the historical period until the year 2000, continued by the Special Report on Emission Scenarios (SRES) A2 scenario for the twenty–first century (Nakicenovic and Swart, 2000). Some models provide the 20c3m but not the A2 scenario.

Due to drifts in global surface–air and ocean temperature, we use the drift–removed global mean temperature data of Figure 10.4 of (Meehl et al., 2007) where available and a post–
Table 3.3: Subgroup of CMIP3 fully coupled atmospheric–ocean general circulations models considered in this study. The concept of forcing groups is introduced in Section 3.2.2 and corresponds to the treatment of different radiative forcing agents in the simulations.

<table>
<thead>
<tr>
<th>Model ID</th>
<th>Forcing Group</th>
<th>SRES A2</th>
<th>Equilibrium Climate Sensitivity (°C)</th>
<th>Transient Climate Response (°C)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CGCM3.1(T47)</td>
<td>Ia</td>
<td>✔</td>
<td>3.4</td>
<td>1.9</td>
</tr>
<tr>
<td>CCSM3</td>
<td>IIa</td>
<td>✔</td>
<td>2.7</td>
<td>1.5</td>
</tr>
<tr>
<td>CNRM–CM3</td>
<td>Ib</td>
<td>✔</td>
<td>✗</td>
<td>1.6</td>
</tr>
<tr>
<td>CSIRO–Mk3.0</td>
<td>Ic</td>
<td>✔</td>
<td>3.1</td>
<td>1.4</td>
</tr>
<tr>
<td>FGOALS–g1.0</td>
<td>Id</td>
<td>✗</td>
<td>2.3</td>
<td>1.2</td>
</tr>
<tr>
<td>GFDL–CM2.0</td>
<td>IIa</td>
<td>✔</td>
<td>2.9</td>
<td>1.6</td>
</tr>
<tr>
<td>GISS–AOM</td>
<td>Ia</td>
<td>✗</td>
<td>✗</td>
<td>✗</td>
</tr>
<tr>
<td>GISS–EH</td>
<td>IIc</td>
<td>✗</td>
<td>2.7</td>
<td>1.6</td>
</tr>
<tr>
<td>GISS–ER</td>
<td>IIc</td>
<td>✔</td>
<td>2.7</td>
<td>1.5</td>
</tr>
<tr>
<td>MIROC3.2 (medres)</td>
<td>IIc</td>
<td>✔</td>
<td>4.0</td>
<td>2.1</td>
</tr>
<tr>
<td>MIROC3.2 ( hires)</td>
<td>IIc</td>
<td>✗</td>
<td>4.3</td>
<td>2.6</td>
</tr>
<tr>
<td>MRI–CGCM2.3.2</td>
<td>IIb</td>
<td>✔</td>
<td>3.2</td>
<td>2.2</td>
</tr>
<tr>
<td>UKMO–HadCM3</td>
<td>Ie</td>
<td>✔</td>
<td>4.4</td>
<td>2</td>
</tr>
</tbody>
</table>

processed ocean heat content data including a drift removal technique previously employed by Domingues et al. (2008). The drift–removed ocean heat content data is only available for 13 AOGCMs and constrains the CMIP3 models to those in Table 3.3. Table 3.3 shows the different model identifications, their corresponding forcing group (Sec. 3.2.2), the availability of the SRES A2 scenario, the equilibrium climate sensitivity (ECS) and the transient climate response (TCR). The identification of the forcing group for each model corresponds to Table S1 of the Supplementary Material of Domingues et al. (2008).

The time period of interest is chosen to be the 20th century for global mean temperature anomaly and the years 1950 to 1999 for ocean heat content anomaly, both to mimic the nature of currently available observational datasets and to have a time period covered by the entire CMIP3 set. Figure 3.1 shows the model output of the set of CMIP3 model as well as the timeseries of the multimodel mean and intermodel standard deviation.

### 3.2.4 Neural Network Substitute

Artificial neural networks (ANNs) are computational models based on units called neurons. ANNs can be trained to learn, to adapt, to generalize and to organize data (Kroese and van der Smagt, 1996). Applications of neural networks can nowadays be found in various fields such as signal processing, data compression, optimization problems, pattern recognition and control systems.

The principle of a neural network is that of a two–stage regression or classification model (Hastie et al., 2001). Classical network topologies include feed–forward and recurrent net-
Figure 3.1: Global mean temperature (a) and ocean heat content up to 700 meters (b) anomalies of the CMIP3 models listed in Tab. 3.3. The multimodel mean and standard deviation timeseries are also shown. Note the different time periods.
works. As an example, the L–layer feed–forward network is built of one input layer, (L–2) hidden layers, and one output layer. The different layers are successively connected, but there are no connections across a particular layer. The learning procedure of a neural network can be divided into two categories: supervised learning in which the network is trained by providing it with input and matching output patterns, and unsupervised learning in which an output unit is trained to respond to clusters of pattern within the input (Kroese and van der Smagt, 1996). During the learning phase, the weights connecting the different layers are continuously updated. We use the Levenberg–Marquardt algorithm (Hagan and Menhaj, 1994) for the learning procedure, which is the most efficient learning algorithm for our application due to its fast convergence.

Figure 3.8 in the Appendix outlines the training procedure of the neural network substitute of the Bern2.5D climate model in detail. The basic idea is to train a 3–layer feed–forward neural network built of 10 nodes with a 5000 member ensemble of truncated timeseries input separately for the global mean temperature, ocean heat uptake to 700 meters and the 1% to double CO\textsubscript{2} simulation. The training is carried out for each forcing group individually. The neural networks are computed with the MATLAB Neural Network Toolbox. The trained neural networks can subsequently be employed as a substitute for the Bern2.5D model.

The performance of the neural networks is tested on a set of 500 independent parameter combinations which were not used in the training procedure. Figure 3.2 shows the standard deviation of the network error defined as difference between the true global mean temperature (ocean heat uptake respectively) and the neural network prediction. The error is shown for those time periods which are similar to the observational datasets and which are covered by all the CMIP3 models. For comparison, the standard deviation across the CMIP3 models is also shown. Note that the CMIP3 standard deviation are based on anomalies with respect to the entire time period, whereas the network error are based on the comparison of absolute temperature and ocean heat uptake values.

In terms of global–mean temperature, the error of the neural networks is smaller than the CMIP3 standard deviation during the entire time period and is of the same magnitude as the observational errors. In general, the networks for FG I perform better than FG II since they do not include the effect of volcanic forcings on global mean temperature and ocean heat uptake. The network error for ocean heat uptake is around 3–4·10\textsuperscript{22} (6–7·10\textsuperscript{22}) J for FG I (FG II). The small standard deviation in the CMIP3 ocean heat uptake arises from the fact the anomalies are considered. Figure 3.2 suggests that the error introduced by the replacement of the full Bern2.5D EMIC is well within the simulated and observed uncertainty in interannual variability.

Figure 3.9 in the Appendix shows the mean squared error of the networks as a function of the training epoch and highlights that the learning has converged and overfitting has been avoided.

### 3.2.5 Markov Chain Monte Carlo Algorithm

In the framework of parameter estimation, Bayes Theorem allows to update prior information about model parameters \( p(\theta) \) to a posterior distribution \( p(\theta|y^{\text{obs}}) \), given observational data \( y^{\text{obs}} \) and the likelihood function \( p(y^{\text{obs}}|\theta) \). In the case of the following classic statistical model:

\[
y^{\text{obs}} = y^{\text{model}}(x, \theta) + \epsilon, \quad \epsilon \sim N(0, \Sigma),
\]

\( y^{\text{obs}} \) represents the observed data, \( y^{\text{model}} \) is the model prediction, \( \theta \) are the model parameters, \( \epsilon \) is the error term, and \( N(0, \Sigma) \) is a normal distribution with mean 0 and covariance matrix \( \Sigma \).
3.2 Data and Methods

Figure 3.2: Annual standard deviation of the emulator error and the standard deviation across the CMIP3 models for global mean temperature (a) and ocean heat content up to 700 meters (b) anomalies.

where the expected mean behavior of the observations $y^{\text{obs}}$ is described by the climate model $y^{\text{model}}(x, \theta)$ with control variables $x$ and parameters $\theta$ and the normally distributed observational error $\epsilon$ with zero mean and error covariance $\Sigma$, the log–likelihood function $p(y^{\text{obs}}|\theta)$ takes the form:

$$
\log(p(y^{\text{obs}}|\theta)) = \log((2\pi)^{-\frac{N}{2}}) - (y^{\text{obs}} - y^{\text{model}}(x, \theta))^\top \Sigma^{-1} (y^{\text{obs}} - y^{\text{model}}(x, \theta)).
$$

(3.3)

Markov chain Monte Carlo (MCMC) methods use the likelihood function defined above to sample from the posterior distribution $p(\theta|y^{\text{obs}})$. The Metropolis–Hastings algorithm (MH) (Metropolis et al., 1953; Hastings, 1970) is an example of such an MCMC sampling algorithm and ranks among the most popular MCMC methods (Andrieu et al., 2003). The MH algorithm jumps through the parameter space spanned by $\theta$ and a step of the invariant posterior distribution $p(\theta|y^{\text{obs}})$ and proposal distribution $q(\theta^*|\theta)$ involves sampling candidate value $\theta^*$ given the current value $\theta$ according to $q(\theta^*|\theta)$ (Andrieu et al., 2003). The new parameter $\theta^*$ is then accepted with probability:

$$
A(\theta^*|\theta) = \min\{1, \frac{p(\theta^*|y^{\text{obs}})q(\theta|\theta^*)}{p(\theta|y^{\text{obs}})q(\theta^*|\theta)}\}
$$

(3.4)

Thus, the advantage of the MH algorithm is that only ratios of the posterior distribution of the model parameters need to be computed and that the normalizing constant of the target distribution is not required (Andrieu et al., 2003).
In order to increase the efficiency of the MH algorithm, a neural network substitute of the Bern2.5D model is used (Sect. 3.2.4). The full statistical model incorporating the error in the statistical surrogate ($\mu$) and observational error ($\epsilon$) can be written as:

$$y_{\text{obs}} = y_{\text{model}}(x, \theta) + \epsilon + \mu, \epsilon \sim N(0, \Sigma), \mu \sim N(0, \Psi).$$  

(3.5)

The error distribution of $\mu$ is assumed to be normal with a standard deviation taken from Figure 3.2 which is determined with a set of 500 independent Bern2.5D model simulations.

The goal of this study is to test the notion of constraining climate model parameters and projections when historical model output is given. In a cross-validation study, the observational error $\epsilon$ is by definition zero and only the error from the neural network substitute $\mu$ is left in Equation 3.5. In Section 3.3.2, the Bern2.5D model is constrained to the output of the CMIP3 models listed in Table 3.3. In order to include the structural uncertainty of the CMIP3 ensemble, as well as the error introduced by internal unforced variability not simulated by the energy balance model, the common observational error $\epsilon$ is replaced by the standard deviation across the CMIP3 models which is also depicted in Figure 3.2. If the CMIP3 structural model uncertainty were negligible, the standard deviation across CMIP3 would simply be the interannual unforced variability. It is important to include this component, since a small fraction of the observed signal could simply be natural variability rather than a response to external forcing. As shown in Huber and Knutti (2011b), the main conclusions do not strongly depend on the choice of error model. When emulating the CMIP3 ensemble, the standard deviation of the total error is defined as the square-root of the sum of the squared neural network error and the squared structural uncertainty in the CMIP3 ensemble:

$$\sigma = \sqrt{\sigma(\text{CMIP3})^2 + \sigma(\text{Neural} - \text{Network})^2}.$$  

(3.6)

Since the Bern2.5D EMIC lacks the representation of internal variability, a 11–year (5–yr) running mean is used for global averaged temperature (ocean heat uptake) when the Bern2.5D model output is compared to the CMIP3 simulations.

In terms of computational implementation of the Metropolis–Hastings algorithm, we use the MATLAB MCMC toolbox by Marko Laine and Haiko Haario (Haario et al., 2006) (available at http://www.helsinki.fi/~mjlaine/mcmc/).

### 3.3 Results

#### 3.3.1 Cross–validation

A set of 100 perfect-models with known parameter combinations and corresponding model output is used to test the accuracy of the perfect-model method. FG Ia (6 parameters) and IIC (12 parameters) are chosen as representatives of the two forcing groups. The inaccuracy $\epsilon$ of the Bern2.5D substitute is assumed to be gaussian with standard deviation $\sigma$ taken from Figure 3.2. The calibration period for global mean temperature are the years 1850 to 2010 and 1950 to 2010 for global mean ocean heat uptake to 700 meters, respectively. For each FG, the Markov chain has a length of 50,000. The posterior distribution for the parameters does not significantly differ for longer chains.
Figure 3.3 shows the 5 – 95% and 17 – 83% percentiles together with the median values for the error distribution in climate sensitivity, vertical ocean diffusivity, the transfer coefficient and the nine forcing scaling factors. For both FGs, climate sensitivity and ocean diffusivity are slightly underestimated. The likely range of the error in climate sensitivity is around 3 K. The scaling factors for greenhouse gases, stratospheric and tropospheric ozone, volcanic and solar forcing can be well estimated for FG II. There are large errors for the organic and black carbon and stratospheric water vapor scaling factors. But although the uncertainty in these factors is large, their corresponding radiative forcing is only a minor contribution to the total forcing.

The error in the decadal temperature prediction between 2020–29 is likely to lie within –0.05°C and 0.07°C for FG Ia and –0.13°C and 0.11°C for FG IIc. The lower panel of Figure 3.3 indicates that the median error slightly underestimates the temperature increase during 2090–99. In the case of FG IIc, the 5 – 95% error range is −1.4°C to 1.2°C.

The set of perfect–models used for this cross–validation includes parameter combinations at the lower and upper bound of the training set. The performance for parameter values near the center of the range is better. Thus, we argue that the distributions in Figure 3.3 is a conservative estimate of the error in the parameter estimation.

### 3.3.2 Application to CMIP3 climate models

Here, the Bern2.5D model is constrained to the CMIP3 model output depicted in Figure 3.1. The length of the MCMC chains is 150,000 to ensure convergence. The posterior distributions are based on combined temperature and ocean heat content anomalies.

Figure 3.4 shows an example of posterior parameter distributions in the case of observational constraints of the CCSM3 model. The most likely climate sensitivity estimate of 2.76°C with a likely range of 2.6°C to 4°C is close to the CCSM3 model’s sensitivity of 2.7°C. The global mean temperature and ocean uptake simulations of CCSM3 provide only minor constraints on the transfer coefficient, greenhouse gas and stratospheric and tropospheric ozone forcing scaling factors. The posterior mean of the direct aerosol forcing is about twice the prior mean. The likely reason for this high direct aerosol forcing factor is the compensation of the negative forcing from the missing indirect aerosol effect in the CCSM3 model. The timeseries of the direct indirect aerosol effect are identical, so only the total aerosol effect, i.e. the sum of the two, is constrained. The posterior distribution of the Bern2.5D model parameters can be used to emulate the timeseries of 20th temperature anomaly which are shown in Figure 3.5 for each CMIP3 model individually. The red lines show the temperature anomalies for the mean of the posterior distribution. The CMIP3 models strongly differ in their interannual variability which is not included in the Bern2.5D Model. The calibrated Bern2.5 model follows the general temperature evolution simulated by the CMIP3 models. For the CMIP3 models which include the volcanic effects, the Bern2.5D mimics the cooling of global mean temperature following a volcanic eruption. There are some periods with a mismatch between a CMIP3 and the Bern2.5D model emulation, i.e. the Bern2.5D model cannot emulate the negative temperature trend during the years 1900 to 1950 in the FGOALS–g1.0 model. However, other aspects of this model have also been found to be unrealistic compared to observations.

Figure 3.6 shows the posterior probability density functions (pdfs) of equilibrium climate sensitivity and transient climate response. The width of the distributions is dependent on the
Figure 3.3: Error distributions (true–predicted) of the Bern2.5D model parameters and decadal temperature predictions. The distributions are based on a set of 100 independent Bern2.5D model runs with known parameters of the forcing groups Ia and IIc.
3.3 Results

Figure 3.4: Prior and posterior distributions of the Bern2.5D model parameters when constrained to the global mean temperature and ocean heat uptake model output of the CCSM3 climate model.
Figure 3.5: Emulation of 20th century global mean temperature anomalies for the set of CMIP3 models with the Bern2.5D neural network substitute. The reference period is the entire 20th century. The emulation is based on the posterior distributions of Bern2.5D model parameters derived with the MCMC algorithm and CMIP3 model data of Figure 3.1. The red solid lines denote the mean Bern2.5D emulation and the shading the 5–95% uncertainty range.
size of the error terms $\mu$ and $\epsilon$ representing the neural networks inaccuracy and the structural uncertainty. Some pdfs suggest rather large sensitivities, e.g. for CGCM3.1(T47) and CNRM–CM3. For the CNRM–CM3 model, this might be due to the strong temperature increase during the second part of the 20th century as seen in Figure 3.5. The transient climate response and climate sensitivity are related in a non–linear way and low climate sensitivities in Figure 3.6a tend to have low transient climate responses in Figure 3.6b.

A comparison of the mean estimates and 5 – 95% uncertainty ranges of the two quantities with the true CMIP3 values is illustrated in Figures 3.6c and 3.6d. Most true sensitivity values lie in the 5 – 95% range of the estimates except for the FGOALS–g1.0 and CGCM3.1(T47) model. The ensemble–mean sensitivity of 3.1°C is overestimated by 0.7°C, whereas the mean estimate of the ensemble–mean TCR is very close to the true value. Figure 3.6d suggests that the estimated transient climate response based on the CMIP3 output of the 20th century differs from the actual TCR of the CMIP3 models by less than 0.5°C in most cases. Those results suggest that the uncertainty range for TCR given in IPCC AR4, a 10-90% range of 1.0 – 3.0°C is likely to be too large. Consistent with earlier studies, the results also demonstrate that the transient climate response is more strongly constrained by the observed warming so far (e.g. Allen et al., 2000; Knutti and Tomassini, 2008; Stott and Forest, 2007; Frame et al., 2005).

Note that the interpretation of the mean of all pdfs is not straightforward. If for example each of the CMIP3 models had a very different sensitivity or transient response, but the prediction for each would be very accurate, then the mean pdf would still be very wide. While the median is useful to indicate whether the Bern2.5D prediction is biased high or low on average, the range of the multi model mean pdf is not representative for accuracy with which the temperature for the SRES A2 scenario, the transient climate response or climate sensitivity of an individual CMIP3 model is approximated. Alternatively, the method could be applied to the mean of all models, but that would strongly reduce the internal variability and would therefore also not be a representative test for the real world.

The CMIP3 model output for the SRES A2 scenario allows to test the Bern2.5D model predictions based on the calibration to the CMIP3 simulations of the 20th century. In terms of the multimodel mean prediction, Figure 3.7 shows the mean plus and minus one standard deviation of the Bern2.5D prediction and the CMIP3 model set both for the calibration and prediction period. Only nine of the models in Table 3.3 computed the SRES A2 scenario, whereas all models produced output for the calibration period. Panel 3.7a highlights that the mean behavior of the CMIP3 set can be reproduced during the calibration period. Despite errors in the parameter estimates for climate sensitivity, the CMIP3 multimodel–mean prediction can be predicted with the mean of the Bern2.5D predictions until the the end of the 21st century.

The decadal temperature predictions at the end of the 21st century (2090–99) with respect to the years 1961–1990 are shown in Figure 3.7b for each CMIP3 model individually. The true predictions are depicted. Due to the overestimation of the climate sensitivity for the CGCM3.1(T47) and the CNRM–CM3 model, the predictions of the Bern2.5D neural network substitute are too high. For the CCSM3, CSIRO–Mk3.0, GISS–ER and UKMO–HadCM3 models, the median estimate of decadal global mean temperature increase is close to the increase computed by the respective model.

Despite discrepancies in predicting the future temperature evolution of some CMIP3 models, Figure 3.7 suggests that on average, the method proposed here does not appear to over–
Figure 3.6: Probability density functions of climate sensitivity (a) and transient climate response (b) of the CMIP3 models. Panels c) and d) show the 5 – 95% and likely ranges together with the median estimate and true CMIP3 values (coloured dots). The ensemble-mean estimates take only the estimate for those CMIP3 models with published climate sensitivity and transient climate response into account.

or underestimate future warming compared to AOGCMs. However, this result is based on the rather small ensemble of nine CMIP3 models with simulations of the SRES A2 scenario. One should note that the implementation of the different radiative forcings is rather unclear for many CMIP3 models, and drift in the model control state lead to difficulties in using the forcing induced heat uptake as a constraint. Another point to reiterate is that this method does not calibrate the Bern2.5D model to simulate future scenarios by using data from the 21st century or the 1%/yr CO$_2$ scenarios as for example in Meinshausen et al. (2011a) and Meinshausen et al. (2011b) but uses only the time period for which observations are available as constraint. The prediction for the 21st century is thus a real prediction conditional on the 20th century, the closest test for the method to be applied to real observations.

3.4 Discussion and Conclusion

The results and conclusions of this study are based on the replacement of the full Bern2.5D climate model with a neural network substitute. This replacement features a trade-off between efficiency and accuracy of the model output. The error introduced by the neural network substitute is probabilistically quantified by computing the distribution of annual errors for a set of independent Bern2.5D model runs which were not used in the training process. The runtime of the model for a given forcing scenario is reduced by nearly three orders of magnitude. Figure 3.2 highlights that the strength of the volcanic forcing and its induced drop in global mean temperature induces the largest uncertainty in the neural network emulator. Without volcanic
forcing considered, the neural network almost perfectly replaces the full Bern2.5D model. Such high prediction skill of the neural network is of course largely due to the lack of interannual variability in the Bern2.5D climate model.

In terms of the setup and training procedure of the neural network, the performance of the neural networks as measured by the mean squared error is depicted in Figure 3.9 of the Appendix. The number of training epochs is limited to twelve iterations to prevent overfitting. Figure 3.9 shows that all networks show a mean squared error below 0.1°C at the end of the training procedure. Knutti et al. (2003) demonstrated that the increase in network performance in small with more than 500 training samples and a network size of more than 5 nodes. Thus, we conclude that our current setup with 10 nodes and 5000 training points is sufficient to emulate the Bern2.5D model output accurately within a residual error similar to internal variability. We argue that the neural network substitute is adequate for the purpose of this study.

The likely range of the error estimates of climate sensitivity of about –2 to 1°C for FG IIc is slightly larger than the likely range of climate sensitivity of 2 – 4.5 K assessed in the past (Meehl et al., 2007) based on multiple constraints. Since the error distribution of Figure 3.3 is based on a set of parameters with a wide sampling distribution – including unlikely parameter combination when compared to observations and parameters combination close to the sampling limits – we argue that the parameter estimates might be more robust than Figure 3.3 implies. In terms of the uncertainty in future temperature increase, the 5 – 95% and likely ranges of the error estimate of Figure 3.3 for the forcing group with volcanic forcings are smaller than the absolute ranges of current temperature projections as compiled in Figure 10.28 and 10.29 of Meehl et al. (2007). However, the latter are partly based on optimal fingerprinting results and include internal variability, whereas the results here only estimate the externally forced temperature response.

The goal of this study was to apply the perfect–model method to a set of CMIP3 climate models. The most prominent difference between the Bern2.5D EMIC and the fully–coupled AOGCMs of the CMIP3 ensemble is the level of complexity built in the models. The introduction of two forcing groups with their respective members attempted to ensure that a CMIP3
model and the Bern2.5D model include the same forcing agents, except for forcing agents such as sea–salt which are not included in the Bern2.5D model. It can be assumed that their effect on parameter constraints and climate projections are not significant. We showed that the general temperature characteristics of the CMIP3 models during the 20th century can be reproduced with the Bern2.5D EMIC when its parameters are constrained to the CMIP3 temperature and ocean heat uptake timeseries.

A reason for the mismatch between climate sensitivity estimates derived from historical CMIP3 simulations might originate in the drifts in both global mean temperature and ocean heat uptake data which might still be apparent despite the post–processing, seen for example in the negative temperature trend during the first half of the 20th century in the FGOALS–g1.0 model. Further, structural differences between the CMIP3 models and the Bern2.5D EMIC such as in the representation of feedbacks (e.g. clouds) can induce errors in the parameter estimation. In order to filter the interannual variability of the CMIP3 models we used a running mean to compare the CMIP3 output to the Bern2.5D model. Tomassini et al. (2007) took a different approach and added an error term in the covariance matrix of the likelihood function which was derived from the autoregressive properties of an AOGCM control run.

In terms of future temperature projections we found that despite errors in individual climate sensitivity estimates, the evolution of global–mean temperature under the SRES A2 scenario can be reproduced reasonably during the 21st century for most models as shown in Figure 3.7. Since the Bern2.5D model has not been evaluated against or calibrated to the set of CMIP3 models in its model development, we argue that within the perfect–model approach employed here the parameter constraints and climate projections of CMIP3 can be interpreted like an independent set of ‘observations’, on which the model and method can be evaluated.

Such a perfect model test is not a complete guarantee that the method will work on observations (Huber and Knutti, 2011b), but it is an important step in establishing confidence in the method. If the perfect model test fails on CMIP3, it is almost guaranteed to fail for the real world as well. We therefore argue that such test should be used more often to test reduced complexity models and statistical methods that infer parameters or constrain the future climate response.

3.5 Acknowledgments

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3.6 Appendix 1: Training Procedure and Performance of the Neural Networks

Figure 3.8 illustrates the training procedure for the Bern2.5D neural network substitute. The annual output of a typical Bern2.5D model simulation with historical forcings and the SRES A2 scenario for the 21st century consists of different diagnostics during the years 1765 to 2099. During the training process, each timeseries was truncated to a timeseries consisting of 178 data points. Periods with large interannual variability, for example after a volcanic eruption, were sampled more densely. A 3–layer feed–forward neural network with 10 nodes was separately built for global mean temperature, ocean heat uptake to 700 meters and the timeseries of the 1% to double CO\textsubscript{2} simulation from which the transient climate response is derived.

From a large Bern2.5D model ensemble, 5000 parameter combinations – satisfying certain boundary conditions such as meridional overturning within the observational range – were used as training data for each forcing group separately. Thus, the input matrix for the neural network consisted of a 5000 x \(n_\theta\) data matrix where \(n_\theta\) denotes the number of model parameters \(\theta\) and the output data was represented by a 5000 x 178 data matrix. The length of the truncated timeseries and the ensemble size of the training set were chosen to achieve reasonable computational performance.

The performance of the neural networks measured by the mean squared error is shown in Figure 3.9 for global mean temperature and ocean heat uptake to 700 meters. The networks without volcanic forcing treatment generally perform better than the ones including volcanic effects. The training iterations were constrained to 12 epochs to avoid overfitting. In terms of temperature, the mean squared error is roughly 0.001°C (FG I) and 0.01°C (FG II). The corresponding numbers for ocean heat uptake are 0.5·10\textsuperscript{22}J (FG I) and 1.2·10\textsuperscript{22}J (FG II). Overall, Figure 3.8 shows that 6 to 10 training epochs are sufficient to train the neural network.
Figure 3.8: Illustration of the training procedure of the Bern2.5D model neural network substitute. I) The CMIP3–Forcing Groups are described in Sect. 3.2.2. These groups denote particular forcing parameter combinations which are implemented in the Bern2.5D climate model. The 12 sampling parameters are described in Table 3.2 for each forcing group individually. II) 5500 Bern2.5D model simulations are computed for each of the 8 CMIP3 Forcing Groups. 5000 runs are used to train the neural network and 500 simulations are employed in the evaluation of the network’s performance. III) Three different feed–forward neural networks with one hidden layer and each having 10 neurons are trained separately for global mean temperature, ocean heat uptake to 700 meters and the forcing scenario 1% to double pre–industrial atmospheric carbon dioxide concentrations. 178 unequally spaced training points are selected from each model simulations, resulting in a 5000x178 input matrix.
3.6 Appendix 1: Training Procedure and Performance of the Neural Networks

![Graphs showing the performance of neural networks for global mean temperature and ocean heat uptake to 700 meters for different forcing groups.](image)

**Figure 3.9:** Performance of the neural networks for global–mean temperature and ocean heat uptake to 700 meters of the Bern2.5D model during 12 training epochs for the different forcing groups.
Chapter 4

Probabilistic climate projections with an intermediate complexity model. Part II: Application to observational datasets
4.1 Introduction

Probabilistic climate projections
with an intermediate complexity model
Part II:
Application to observational datasets

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(submitted to Climate Dynamics)

Abstract

Observations of the Earth’s climate system play an important role in the climate model
development and model evaluation process. They constitute a constraint on climate model
parameters and projections of future climate changes. Here we investigate the effect of dif-
ferent global observational datasets of transient surface air temperature and ocean heat uptake
down to 700 meters on the estimates of equilibrium climate sensitivity, transient climate re-
sponse and projections of global–mean temperature change under a specific non–intervention
emission scenario. We find that differences in the observations of ocean heat uptake are a
large source of uncertainty in the estimates of climate sensitivity and future climate projec-
tions. Aggregating climate sensitivity estimates from twelve combinations of observational
datasets results in a likely range of 2.2°C to 5.1°C for climate sensitivity with a mean of 3.6°C.
Using a different prior for climate sensitivity and scaling the annual observational error does
not significantly alter the posterior distribution of climate sensitivity. The estimated ranges of
temperature increase at the end of the 21st century for combinations of observational datasets
confirm previous best estimates and uncertainties presented in the Intergovernmental Panel on
Climate Change (IPCC) Fourth Assessment Report (AR4).

4.1 Introduction

The quantification of uncertainties in climate system properties such as the equilibrium climate
sensitivity (ECS) – defined as the equilibrium increase in global–mean temperature for a dou-
bling of the pre–industrial atmospheric CO₂ concentration – and in future climate projections
for emission scenarios has been a vital part in the assessment of the climate system’s response
to past and future radiative forcings (Stott and Forest, 2007; Knutti et al., 2008b). The combi-
nation of different observational datasets, statistical methods and a variety of climate models
resulted in comprehensive uncertainty estimates for global–mean temperature increase under
different forcing scenarios (Meehl et al., 2007). Every estimate of a future climate trajectory
is hereby conditional on the assumption underlying the method and model. These assump-
tions encompass – among others – the choice of prior distributions of the model parameters, the treatment of time–varying forcing, the model used for the projections ranging from simple energy balance models to fully coupled general circulation models (AOGCMs) and the observational dataset to which the climate model may be calibrated (Forest et al., 2002; Knutti et al., 2002; Frame et al., 2005; Stott et al., 2006). A synthesis of probabilistic estimates and non–probabilistic ranges of global–mean temperature change during the 21st century for 6 marker scenarios based on different climate models and statistical methods used for the projections is presented in Knutti et al. (2008b).

At the center of the quantification of parameter and projection uncertainty based on observations is a goodness–of–fit statistic which weights a particular climate model according to its ability to reproduce a given observational record. This matching procedure highlights the importance of the choice of observational datasets in the parameter estimation process. For example, this goodness–of–fit statistic is employed in optimal fingerprinting (Allen and Tett, 1999; Forest et al., 2002) or in Markov Chain Monte Carlo algorithms (Tomassini et al., 2007, 2009). Often, a combination of surface temperature and ocean heat uptake measurements are used as observational constraints. For example, Tomassini et al. (2007) used the observations of Jones and Moberg (2003) for global–mean temperature and the dataset of Levitus et al. (2005) for ocean heat uptake down to 700 meters. The sensitivity of projections of global–mean temperature increase and sea–level rise on the choice of ocean heat uptake measurements was previously assessed by Sokolov et al. (2010) who concluded that the projections of sea–level rise strongly depend on the particular ocean heat content observations.

The observational datasets differ in their data retrieval methods and in reconstruction and interpolation techniques (Baringer et al., 2010). In their assessment of currently available observational dataset, Baringer et al. (2010) note a strong independence of the methods used to derive three datasets of global temperature including the National Aeronautic’s and Space Administration (NASA) GISS product (Hansen et al., 2001), the Met Office Hadley Centre HadCRUT3 (Brohan et al., 2006) and the National Oceanic and Atmospheric Administration’s (NOAA) dataset (Smith et al., 2008). Further, biases in the instruments used to monitor the global climate can lead to artefacts in the observations such as the sudden decrease in global–mean temperature after the year 1945 apparent in the surface temperature record (Thompson et al., 2008). While observations of global–mean temperature strongly correlate, there are significant differences across observations of global–mean ocean heat content change, e.g. see Figure 4.1. For example, Gouretski and Reseghetti (2010) just recently reassessed the biases in the expendable bathythermograph data (XBT). Moreover, the sparse data coverage of ocean temperatures requires statistical infilling techniques (Gregory et al., 2004b; AchutaRao et al., 2006). A summary of recent advances in global temperature and ocean heat uptake observations is presented in Baringer et al. (2010).

Here, we account for the uncertainty in the estimates of climate system properties and future climate projections caused by the spread in observations of global–mean temperature and ocean heat uptake by using four global–mean temperature and ocean heat uptake observational datasets and combinations of those to constrain the parameters and future climate projections of the Bern2.5D Earth System Model of Intermediate Complexity (EMIC). The method follows Huber and Knutti (2011a) where a MCMC algorithm, the model calibration and the neural network substitute of the Bern2.5D climate model are described.
This paper is structured as follows. Section 4.2 introduces the Bern2.5D EMIC and the method to constrain its parameters with a neural network substitute of the full climate model. Estimations of climate sensitivity, transient climate response and future decadal temperature changes under a specific forcing scenario are presented in Section 4.3. The robustness of the estimates as a function of the magnitude of the observational error is also illustrated in Section 4.3. A discussion and conclusion is presented in Section 4.4.

4.2 Data and Methods

4.2.1 Bern2.5D climate model

We use the Bern2.5D earth system model of intermediate complexity which is built of a zonally averaged dynamic ocean model (Stocker and Wright, 1991; Wright and Stocker, 1991). The ocean basins of the Atlantic, Pacific, Indian, and Southern Oceans are resolved and are coupled to a zonally and vertically averaged energy and moisture–balance model of the atmosphere (Stocker et al., 1992; Schmittner and Stocker, 1999). Climate feedbacks are represented by a feedback term that can be varied to obtain different climate sensitivities. The prescribed historical natural and anthropogenic radiative forcing timeseries used to drive the climate model are identical Knutti et al. (2003) and include forcing reconstructions from Crowley (2000) and Joos et al. (2001).

The implementation and prior distributions of scaling factors in the Bern2.5D climate model, which account for the uncertainty in different forcing agents, are described in Huber and Knutti (2011a). In total, twelve parameters are sampled in the model: three physical parameters including climate sensitivity, vertical ocean diffusivity and the transfer coefficient for sensible heat as well as nine forcing scaling parameters accounting for forcing uncertainty e.g. of greenhouse gases, direct and indirect aerosols, volcanic eruptions and variations in solar irradiance (Forster et al., 2007).

4.2.2 Observational Data

As observational references for global–mean surface air temperature we use the HadCRUT3 dataset of the Met Office Hadley Centre\(^1\), the GISS Surface Temperature Analysis (GISTEMP) of the National Aeronautics and Space Administration\(^2\), data of the National Oceanic and Atmospheric Administration (NOAA) National Climatic Data Center (NCDC)\(^3\) as well as data from Jones and Moberg (2003). Annual error distributions are only available for the HadCRUT3 and Jones and Moberg (2003) data. In order to include the GISTEMP and NCDC into the probabilistic calculations, the two available error estimates are averaged and applied to these two datasets.

For ocean heat uptake, we use the data of Levitus et al. (2009), Domingues et al. (2008), Ishii and Kimoto (2009) and Palmer et al. (2007). The latter two datasets were obtained from

\(^{1}\)available at http://www.metoffice.gov.uk/hadobs/hadcrut3/index.html

\(^{2}\)http://data.giss.nasa.gov/gistemp/

\(^{3}\)http://www.ncdc.noaa.gov/cmb–faq/anomalies.html
CHAPTER 4: PROBABILISTIC CLIMATE PROJECTIONS PART II: APPLICATION TO OBSERVATION DATASETS

the NOAA Climate Indicators website⁴ and were previously used in Baringer et al. (2010). Observational error estimates are only available for Levitus et al. (2009) and Domingues et al. (2008) and are averaged and applied to the datasets of Ishii and Kimoto (2009) and Palmer et al. (2007).

We subtract the mean value of each data product to obtain the timeseries with respect to the entire observational time periods since the datasets feature different reference periods. Figure 4.1 illustrates the observational data used to constrain the Bern2.5D climate model. The temperature observations show a high interannual correlation whereas the datasets of ocean heat uptake display both differences in the trend and in interannual variability. Most of the ocean heat uptake observations show a slight decrease until the mid of the 1970s followed by an increase in heat uptake afterwards. Since every pair of temperature and ocean heat uptake dataset represents a plausible observation of the Earth’s climate system, a total of 16 dataset combinations are available for model calibration. The datasets are of course not independent as they are partly based on the same station records or ocean temperature profiles. In particular, the HadCRUT3 and the Jones and Moberg (2003) datasets are strongly related. However, the set of 16 different combinations probably represents the best available set to sample the range of observational uncertainty.

4.2.3 Bern2.5D Neural Network Substitute

In order to increase the efficiency of the parameter estimation process, we use the neural network substitute of the Bern2.5D EMIC which is described in Huber and Knutti (2011a). A 3–layer feed–forward neural network built of 10 nodes was trained with 5000 truncated timeseries of the Bern2.5D model output. A network is trained separately for global–mean temperature, ocean heat content to 700 meters with historical and future projections under the SRES A2 emission scenario (Nakicenovic and Swart, 2000) and the temperature increase under a simulation with annual 1% increase to double CO₂ concentration from which the transient climate response can be derived.

The annual error distribution of the neural network defined as the standard deviation of the difference between the neural network prediction and the true value is shown in Figure 4.2. The distribution is based on a set of 1000 independent Bern2.5D timeseries with known parameter combinations. For comparison, the standard deviation of a set of observations and an estimate of internal variability based on the control runs of the model set of the World Climate Research Programme’s (WCRP’s) Coupled Model Intercomparison Project phase 3 (CMIP3) are also depicted. A linear and a cubic fit are removed from the control runs of global mean temperature and the net radiation imbalance at the top–of–atmosphere, respectively to remove model drift. The error distribution of internal variability is sampled from moving–window segments of the control runs of the particular length of an observational dataset.

In terms of global–mean temperature, the magnitude of the neural network error of around 0.1°C is similar to observational errors and internal variability. The network error in ocean heat uptake to 700 meters is slightly larger than the observational reference values of Levitus et al. (2009) and Domingues et al. (2008) and ranges between 7–8·10²² J. Since the reference set

4.2 Data and Methods

Figure 4.1: Observational datasets of anomalies for global–mean temperature (a) and ocean heat content to 700 meters (b). The observations are shown with respect to their corresponding time period which differs across the datasets.
Figure 4.2: Standard deviation of the neural network error distributions for global–mean temperature (a) and ocean heat uptake to 700 meters (b). The distributions are derived from a set of 1000 independent Bern2.5D model runs with known parameter combinations. The figure shows anomalies with respect to 1881 to 2004 for temperature and 1955–2002 for ocean heat uptake. The estimates of internal variability are based on the control runs of the CMIP3 models.

of 1000 Bern2.5D model runs also includes parameter combinations at the lower and upper boundary of the training set, we conclude that the error distribution in Figure 4.2 is a conservative measure of the neural networks accuracy in emulating the Bern2.5D model.

4.2.4 Markov Chain Monte Carlo Algorithm and Statistical Error Model

Markov Chain Monte Carlo (MCMC) algorithms are Bayesian methods to update prior information about some parameters $p(\theta)$ to a posterior distribution $p(\theta|y^{obs})$, given observational data $y^{obs}$. Key to the MCMC algorithm is the likelihood function $p(y^{obs}|\theta)$ which weighs a parameter combination according to its capability to reproduce the observational dataset.

In this study we use the following statistical model:

$$y^{obs} = y^{model}(x, \theta) + \epsilon + \mu + \tau, \epsilon \sim N(0, E), \mu \sim N(0, M), \tau \sim N(0, T), \quad (4.1)$$
where the expected mean behavior of the observations $y_{\text{obs}}$ is described by the climate model $y_{\text{model}}(x, \theta)$ with control variables $x$ and parameters $\theta$. The error model consists of a sum of an observational error term $\epsilon$ and a term $\mu$ describing the neural networks inaccuracy in emulating the full Bern2.5D model. The uncertainty associated with internal variability is denoted by $\tau$. The statistical error model is similar to Huber and Knutti (2011a). We assume that the error terms are normally distributed with zero mean and covariance matrices $E$, $M$, $T$. We define the observational annual standard deviation of the observational datasets as $\sigma_\epsilon$ and the other error terms accordingly as $\sigma_\mu$ and $\sigma_\tau$. The values of the error terms are shown in Figure 4.1. The standard deviation of the total error is defined as:

$$\sigma_{\text{total}} = \sqrt{\sigma_\epsilon^2 + \sigma_\mu^2 + \sigma_\tau^2}. \quad (4.2)$$

Since the Bern2.5D EMIC does not feature interannual variability, we use a 11–year running mean for temperature and 5–year running mean for ocean heat uptake data. Due to the smoothing of the data with a running mean, the off–diagonal elements of the covariance matrices $E$, $M$ and $T$ are assumed to be zero. An earlier study with the same model used annual values with an error covariance matrix but came to very similar results (Tomassini et al., 2007). Further, we did not consider cross–covariance between the three error terms due to the use of a running mean both in observations and annual errors. The length of the chains was chosen to 150,000 in order to ensure convergence. In terms of computational implementation of the Metropolis–Hastings algorithm, we use the MATLAB MCMC toolbox developed by Marko Laine and Haiko Haario (Haario et al., 2006) (available at http://www.helsinki.fi/ mjlaine/mcmc/).

### 4.3 Results

#### 4.3.1 Illustration of a Posterior Distribution

As illustration of the constrained Bern2.5D model parameters, Figure 4.3 shows the prior and posterior parameter distributions when the global–mean temperature data of the HadCRUT3 and ocean heat uptake data from Levitus et al. (2009) are applied as observational constraints. Figure 4.3 highlights that the observations provide constraints on some parameters such as climate sensitivity, vertical ocean diffusivity, the indirect aerosol and volcanic forcing, whereas the posterior distribution for other parameters including the stratospheric and tropospheric ozone, direct aerosol and stratospheric water vapor forcing factors are almost identical to the prior distribution. For these two observational reference datasets, the likely range (central 66% of the distribution) of climate sensitivity is $2.6 – 5.4^\circ C$ with a median (mean) of $3.8^\circ C$ ($4.0^\circ C$). The addition of the neural network error results in a somewhat wider distribution of parameter estimates compared to the case where only observational errors and internal variability are considered.

The substitution of the full Bern2.5D EMIC with a neural network allows to emulate the evolution of global–mean temperature and ocean heat uptake during the 20th century for each parameter combination of the Markov Chain efficiently. The probabilistic Bern2.5D model timeseries and the observational constraints are shown in Figure 4.4. The Bern2.5D model cannot reproduce the interannual and decadal variability of the observations but follows the
Figure 4.3: Posterior distributions for the Bern2.5D model parameters with the observational constraints of HadCRUT3 and Levitus et al. (2009). The black dashed lines show the prior parameter distributions whereas the solid blue lines depict the posterior distributions.
4.3 Results

![Graph of Global Mean Temperature Anomaly and Global Mean Ocean Heat Content](image)

**Figure 4.4:** Emulation of the observational datasets (black) with the Bern2.5D model (red) using the posterior distributions shown in Figure 4.3 derived from the HadCRUT3 temperature dataset and the ocean heat uptake observations by Levitus et al. (2009). The shading denotes the ± one standard deviations and the solid lines correspond to the mean estimate.

Figure 4.4 shows the comparison between observational datasets and the Bern2.5D model predictions for global mean temperature anomaly and ocean heat content. The emulation results are derived from the HadCRUT3 temperature dataset and ocean heat uptake observations by Levitus et al. (2009). The shaded areas represent ± one standard deviation from the mean estimate.

The general trend of the observations is well captured by the model. However, there are discrepancies, such as the flattening of ocean heat uptake in the observations between 2000–2009 and the peak and subsequent drop in surface temperature between 1935 and 1955, which are not reproduced by the Bern2.5D model. These features may be due to data artefacts or limitations in the model.

### 4.3.2 Estimates of Climate Sensitivity and Transient Climate Response

The pairwise combination of temperature and ocean heat uptake observations results in 16 estimates for climate sensitivity and transient climate response, which are illustrated in Figure 4.5.

Panel 4.5a highlights that the probability density function (pdf) of climate sensitivity strongly depends on the choice of observational constraint. The climate sensitivity estimates differ both in their estimate of the most likely sensitivity and in their distribution. The choice of ocean heat...
uptake dataset is likely to be the primary source of differences among the climate sensitivity estimates. For example, all sensitivity estimates derived from Domingues et al. (2008) tend towards high sensitivities with a large spread in the estimates.

The aggregation of 12 posterior sensitivity distributions in one estimate of climate sensitivity results in a 5–95% (17–83%) range of 1.7 – 6.5°C (2.2 – 5.1°C) with a mean and most likely estimate of 3.6°C and 2.6°C, respectively. The dataset of Jones and Moberg (2003) is not included in this estimate since it is a predecessor the HadCRUT3 data product.

Despite differences in the estimates of equilibrium climate sensitivity (ECS), we find rather similar estimates for transient climate response (TCR) as shown in Figure 4.5b. TCR and ECS are related in a nonlinear way and low TCRs correspond to low ECSs. The sensitivity of TCR to changes in ECS weakens for high values of ECS (Meehl et al., 2007), which is the reason for the more similar pdfs of Figure 4.5b. We find a 5 – 95% (17 – 83%) range of 1.3 – 2.3°C (1.5 – 2.1°C) with a mean and most likely estimate of 1.8°C and 1.9°C respectively for the aggregated estimates.

### 4.3.3 Climate Projections under the SRES A2 scenario

Each of the posterior densities of the various dataset combinations gives a probabilistic temperature projection under the SRES A2 scenario (Nakicenovic and Swart, 2000). The probability density functions (pdfs) of the decadal temperature predictions of the near-term future (years 2020 to 2029) and at the end of the 21st century between 2090–99 with respect to the years 1980 to 1999 are depicted in Figure 4.6. As reference estimates, the temperature projections of Figure 10.28 of Meehl et al. (2007) are also shown, which include probability distributions.
of Wigley and Raper (2001), Knutti et al. (2003), Stott et al. (2006), Furrer et al. (2007) and a normal distribution fitted to the CMIP3 climate models. Figure 4.6a shows that the temperature increase of the near–term future is very unlikely to be below 0.5°C and to exceed about 0.9°C. The individual spread of the estimates is similar. The 5 – 95% (17 – 83%) ranges for the aggregated posterior densities are 0.56 – 0.82°C (0.62 – 0.77°C). The median and mean are 0.69°C. The standard deviation of the neural network error in predicting the decadal temperature change is 0.12°C.

The spread across the estimates for the end of the 21st century temperature increase is found to be larger due to differences in the estimates of climate sensitivity. The shapes of the individual pdfs follow the estimates of TCR. The average mean temperature increase across the dataset combinations is 3.5°C. The 5 – 95% (17 – 83%) ranges for the aggregated estimates are 2.2 – 4.5°C (2.7 – 4.0°C). The estimates presented here are a more narrow in the projections of near–term temperature increase compared to the reference datasets, because the energy balance model only projects the forced response. The AOGCM based results of Stott et al. (2006) and Furrer et al. (2007) include natural variability which is a significant contribution on those timescales. The spread in the estimates of the temperature change between 2090 and 2099 are similar for all methods. The median prediction of 3.4°C derived from the aggregated estimates is close to the reference estimates of the IPCC. All 5 – 95% quantiles overlap in the region between 3°C and 4°C. The standard error of the neural network Bern2.5D substitute in predicting the temperature increase between the years 2090 to 2099 is 0.16°C and comparably small with respect to the magnitude of the projected warming.

4.3.4 Scaling of the Observational Error

The results of the previous sections depend on the choice of error model in the MCMC algorithm. Figure 4.7 shows the effect of scaling the annual error on the climate sensitivity estimates and the decadal temperature increase at the end of the 21st century. We scale the annual error from –75% to +75% and perform a Markov chain of length 80,000 for each case. The mean estimates of the two quantities are depicted in the upper two panels for each of the 16 dataset–combinations individually. Figure 4.7a highlights that the mean climate sensitivity estimate strongly depends on the choice of observational reference data. In particular, the ocean heat uptake estimates of Domingues et al. (2008) lead to rather high sensitivities as shown in Figure 4.5a. Low sensitivities are derived with the Ishii and Kimoto (2009) observations. An increase of the annual error between 0% – 50% however has only a minor effect of the mean sensitivity estimates. The mean sensitivity estimates tend to increase for strong reductions in the magnitude of the annual error. Presumably, the sudden increase in sensitivity for an error reduction of –60% is due to an early convergence of the Markov Chain resulting in a narrow posterior distribution close to the initial values of the MCMC algorithm. The temperature increase at the end of the 21st century also depends on the magnitude of the annual error. Figure 4.7b suggests that a reduction of the error increases the mean estimate of global–mean temperature increase. More importantly however, an increase in the error results in similar estimates.

While the individual climate sensitivity estimates strongly depend on the choice of observational constraint, the distribution of the aggregated posterior densities is almost constant between an error scaling –40% to +40% as seen in Figure 4.7c. In particular, the mean climate
Figure 4.6: Probability density functions of decadal global–mean temperature change under the SRES A2 scenario for the periods 2020–2029 (a) and 2090–99 (b) compared to the years 1980 to 1999. The estimates for the 16 observational dataset combinations are shown in blue and the aggregated estimates in black. The data of Figure 10.28 of Meehl et al. (2007) is shown in red. The lower panel of (b) illustrates the 5 – 95% percentiles and the median estimate.
sensitivity is around 4°C in that range of observation uncertainty. The tails are most affected when the annual error is reduced. The mean estimate and the 5% and 17% quantiles of global–mean temperature increases during the years 2090–99 slightly increase for a decrease of the annual error as shown in Figure 4.7d.

We conclude from these sensitivity tests that the magnitude of the errors and uncertainties in the statistical error model do not strongly affect the results and conclusions of this study.

### 4.3.5 Role of Prior Climate Sensitivity Distribution

A direct influence of a parameters’ prior distribution on the estimates of the posterior distribution is predicted by Bayes’ Theorem and can affect the estimates of climate system properties such as climate sensitivity and projections of future climate change (e.g. Frame et al., 2005; Annan and Hargreaves, 2011). Independently derived observational constraints can be combined to incrementally update a prior distribution, i.e. data from the last glacial maximum, the temperature evolution during the 20th century and the climate system’s response to volcanic eruptions (Annan and Hargreaves, 2006). We define a gamma distribution with a shape parameter of 4.3 and scale parameter of 0.95 (see Figure 4.8) as an alternative prior distribution for climate sensitivity to the uniform climate sensitivity of the standard case (Huber and Knutti,
Figure 4.8: Dependency of the climate sensitivity and decadal temperature increase estimates between the years 2090 and 2099 with respect to the period 1980 to 1999 on the choice of prior distribution for climate sensitivity. The standard case uses an uniform distribution between 1 – 8°C and is compared to a Gamma distribution with a shape parameter of 4.3 and scale parameter of 0.95.

2011a). Such a prior distribution could be supported for example from paleoclimate data of the Last Glacial Maximum (Knutti and Hegerl, 2008).

Figure 4.8 shows the sensitivity of the estimates of climate sensitivity and decadal temperature change at the end of the 21st century for the uniform and gamma distribution for the aggregated estimates of the different dataset combinations. The posterior climate sensitivity derived from the uniform prior has a slightly higher mean estimate of 3.6°C compared to 3.4°C based on the gamma prior distribution. The uniform prior leads to a higher upper bound of the likely range of 2.2 – 5.1°C compared to 2.3 – 4.5°C computed with the gamma prior, whereas the estimates of the lower bound of climate sensitivity are similar for the two prior distributions. The effect of the two different prior distributions on the temperature change during the years 2090–99 is therefore more pronounced for high warming estimates than for moderate temperature changes as shown in Figure 4.8b. However, the influence of the prior is not very strong for the aggregated climate sensitivity estimates based on all observational datasets, mainly because climate sensitivity values above 6–7°C are considered very unlikely in any case.
4.4 Discussion and Conclusion

The replacement of the full Bern2.5D EMIC with a neural network substitute decreased the computational time for a simulation of historical and future global–mean temperature and ocean heat uptake by three orders of magnitude (Huber and Knutti, 2011a). The error induced by this substitution is probabilistically quantified in Huber and Knutti (2011a) and in Figure 4.1 of this study. The error is of the same magnitude as the spread across currently available observational datasets and internal variability. Thus, the enhanced error due to the introduction of the model substitute in the likelihood function results in a somewhat broader range of climate sensitivity estimates presented in Figure 4.5.

In this study we quantified the effect of the choice of observational dataset on the estimates of climate sensitivity, transient climate response and future temperature change under the SRES A2 scenario for the Bern2.5D EMIC. Four current global–mean temperature and ocean heat uptake datasets were taken into account resulting in 16 estimates of ECS, TCR and future temperature increase. We found that different ocean heat uptake measurements lead to significant differences in the pdfs of equilibrium climate sensitivity and transient climate response.

We consider the estimates derived from aggregation of twelve dataset–combinations as the ‘best–guess’ estimates. The estimate accounts for uncertainty in past radiative forcing, climate system properties and discrepancies across observations of global temperature and ocean heat uptake change. Each dataset–combination is regarded as equally likely.

Similar to the argument of Knutti et al. (2002, 2008b) that observations of global–mean warming trends represent a poor constraint on climate sensitivity, the assumed uniform prior between 1°C and 8°C for climate sensitivity allows rather high climate sensitivities. The best–guess estimate of the likely range of climate sensitivity are 2.2°C to 5.1°C with a median of 3.3°C derived from the aggregated posterior densities.

For a more informative (and maybe more reasonable) prior assumption, the likely range is 2.3 – 4.5°C, very similar to the corresponding values of 2 – 4.5°C (3°C) by the Fourth Assessment Report (AR4) of the Intergovernmental Panel on Climate Change (IPCC).

Our mean estimate of the transient climate response of 1.8°C is slightly higher than the value of 1.58°C derived by Knutti and Tomassini (2008) using observations from Jones and Moberg (2003) and Levitus et al. (2005) yet smaller than the estimates by Stott et al. (2006) who employed three AOGCMs and optimal fingerprinting. The 5 – 95% range of 1.3–2.3°C for TCR estimated here is nearly identical to that obtained by Gregory and Forster (2008) and Forest et al. (2006) which are also based on the 20th century warming and radiative forcing. However, very large values of TCR for the Bern2.5D EMIC could not be included in the training procedure of the neural network since non–linear effects such as the shut down of the thermohaline circulation appear for strong and fast increases in global–mean temperature. Nevertheless, the uncertainty in TCR is probably smaller than the 10-90% range of 1.0 – 3.0°C given in IPCC AR4.

Projections of long–term temperature change strongly depend on the climate model, statistical methods and observational data (Knutti et al., 2008b; Meehl et al., 2007). In terms of the choice of the climate model, Stott et al. (2006) applied the same fingerprint scaling method to three AOGCMs and found varying estimates for end of 21st century temperature projections.
They also considered variations in future natural forcing which is not accounted for in this study. The Bern2.5D model does not feature interannual variability which is reflected in the narrow distribution for near–term temperature change in Figure 4.6. Moreover, the Bern2.5D model version used in this study does not incorporate carbon cycle uncertainties. When a carbon–cycle feedback uncertainty is included in the model, the upper limit of the uncertainty range in the SRES A2 scenario is increased (Knutti et al., 2003). Figure 4.6 highlights that the range of projections of global–mean temperature change at the end of the 21st century using different observational dataset combination covers the uncertainty ranges of other reference studies where the latter are indicative of the sensitivity of the projections on the choice of climate model and statistical method.

The estimates of the Bern2.5D model parameters and projections are tested against the sensitivity of the magnitude of the annual error in the likelihood function for the case of the aggregated estimates. Figure 4.7 suggest that the mean estimate of climate sensitivity and transient climate response of 3.6°C and 1.8°C, respectively are a robust in the range of an error scaling factor of −40% to +40%.

While models of reduced complexity obviously have limitations and are unable to resolve small scales, the results here provide insight into which factors determine the overall uncertainty in short term and long term warming, and how different assumptions affect the results. The main results are remarkably robust and support the conclusions of previous studies and IPCC AR4 that warming for scenarios with emissions above current levels will likely exceed the observed warming over the 20th century.

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Chapter 5

Anthropogenic and natural warming inferred from changes in Earth’s energy balance
Anthropogenic and natural warming inferred from changes in Earth’s energy balance

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Abstract

The energy balance is key to understand the Earth’s climate and its variations caused by natural and anthropogenic changes in the atmospheric composition. Despite abundant observational evidence for changes in the energy balance (Domingues et al., 2008; Murphy et al., 2009; Trenberth et al., 2009), the formal detection and attribution of the observed warming to human influence has so far relied mostly on spatio–temporal warming patterns of natural and anthropogenic origin being different. Here we demonstrate a strong constraint on the anthropogenic warming based on the observed changes in the global energy balance combined with known changes in radiative forcing. We find that since the mid–20th century, greenhouse gases alone contributed 0.85°C with a 5-95% uncertainty of 0.6–1.1°C to the total observed change of about 0.56°C in global temperature. The observed trends are extremely unlikely (<5%) to be caused by internal variability even if current models were found to strongly underestimate internal variability. The method employed here makes few assumptions besides fundamental principles on the conservation of energy and provides information on attribution complementary to optimal fingerprinting. Combining the two approaches suggests an even higher confidence in anthropogenic causes dominating the observed warming of ocean and atmosphere.

5.1 Introduction

The optimal fingerprint detection and attribution framework provides a rigorous, statistical method to quantify the contributions of different external forcings and internal variability to the observed climate changes (Barnett et al., 2005). In essence, it is based on a regression of the observations onto model simulated patterns and relies on the spatio–temporal response patterns from different forcings being clearly distinct. The assumptions are that climate models simulate the spatial patterns reasonably well and that regional responses from different forcings can be scaled and combined linearly. The global energy budget is not necessarily conserved and observed changes in the energy budget are not considered. Previous studies showed that observed patterns of surface-air temperature provide a constraint on the human contribution to the observed warming (Hegerl et al., 2007). Here we demonstrate that the global energy balance provides a further strong, comprehensive and physically motivated constraint.
In equilibrium, the Earth emits as much energy by outgoing longwave radiation at the top–of–atmosphere as it receives shortwave radiation from the sun. Robust evidence for recent deviations from that equilibrium comes from a variety of observations and model simulations (Solomon et al., 2007; Trenberth et al., 2009). The most likely value of the current net radiative forcing $F$ is estimated at 1.6 W/m$^2$, compensated by additional outgoing longwave radiation $\lambda T$ and energy uptake of the planet $Q$:

$$F = Q + \lambda T. \quad (5.1)$$

Due to its large heat capacity, the ocean accounts for more than 85% of the energy content change $Q$ in the climate system (Levitus et al., 2005). A robust ocean warming trend is evident despite sparse data and uncertainties and biases in ocean observations (Domingues et al., 2008; Lyman et al., 2010). The feedback parameter $\lambda$ is inversely related to climate sensitivity (Knutti and Hegerl, 2008).

We use a massive ensemble of the Bern2.5D climate model of intermediate complexity (Knutti et al., 2002; Stocker et al., 1992), driven by bottom up estimates of historic radiative forcing $F$, and constrained by a set of observations of the surface warming $T$ since 1850 and heat uptake $Q$ since 1955 (see Methods). The SRES A2 (Nakicenovic and Swart, 2000) emission scenario is used as one illustration of a non intervention scenario. The radiative forcing timeseries (Crowley, 2000; Joos et al., 2001) are shown in Figure 5.1 along with the probabilistic model output based on the constrained model parameters (Huber and Knutti, 2011b). The energy balance model has no interannual variability but is able to reproduce the observed global trend of past temperature and ocean heat uptake. Uncertainties in surface warming, ocean heat uptake and in all individual radiative forcing components are considered (see Methods).

### 5.2 Results

Figure 5.2a shows the contribution of different forcing species to the accumulated forcing since the year 1850. The partitioning of the net cumulative forcing into ocean heat uptake and outgoing longwave radiation is illustrated in Figure 5.2ab. Between 1850 to 2010, the climate system accumulated a total net forcing energy of $140 \cdot 10^{22}$J with a 5-95% uncertainty range of 95 to $197 \cdot 10^{22}$J, corresponding to an average net radiative forcing of roughly 0.54 (0.36–0.76) Wm$^{-2}$. The additional energy input is balanced in nearly equal parts by ocean heat uptake and outgoing longwave radiation. About 83% of the accumulated energy from carbon dioxide forcing alone of $164 \ (151–178) \ 10^{22}$J is offset by the combined negative direct and indirect effect of aerosols. However, there are large uncertainties for the radiative forcing of aerosols, in particular for the indirect effect. The negative forcings of stratospheric ozone, black and organic carbon as well as the positive forcings of stratospheric water vapor and nitrous oxide play only a minor role in the cumulative forcing budget. The positive and negative non–CO$_2$ forcings are also of similar magnitude. For an A2 scenario, the historic cumulative forcing would be doubled in the next 33 (28–38) years and tripled in 52 (45–60) years.

The model results for 1950 to 2004 are shown in Figures 5.2c and 5.2d and compare very well with recent observational estimates (Murphy et al., 2009), partly as a result of calibrating the model to the observed total ocean and surface warming. While the estimates for most
Figure 5.1: a) Radiative forcings from historical reconstructions and the SRES A2 scenario for different forcing agents. Emulation of two observational datasets: the Met Office Hadley Centre observations dataset of global–mean temperature (b) and ocean heat uptake to 700 meters of Levitus et al. (2009) (c) with the Bern2.5D climate model. The grey shading denotes the 5 – 95% uncertainty range.
forcing agents are similar, we infer a larger energy flux from variations in solar irradiance as a result of the particular forcing reconstruction used. If anything our estimate of the solar contribution is likely to be overestimated (see Methods). Ocean heat uptake for 3000m depth is also larger in the model but is only constrained using data to 700m depth. In addition, uncertainties in ocean heat uptake are large, differences between various reconstructions are significant (Baringer et al., 2010). The near constant ocean temperature over the past five years are not simulated by the model and its causes remain unclear (Lyman et al., 2010).

The probabilistic contributions of individual forcing agents to past and future decadal changes in global temperature are shown in Figure 5.3. We assume that all forcing agents have equal efficacy, in contrast to studies using more complex models (Hansen et al., 2005b). The probabilistic ranges presented here account for uncertainties in the observations, radiative forcing, internal variability and model inadequacy (see Methods). The simulated mean temperature increase 2000–2009 compared to 1850–1859 is 0.82°C with a 5–95% uncertainty range of 0.72 to 0.93°C. The estimate is similar to the observed value of 0.79°C. Greenhouse
gases contributed with 1.31°C (0.85–1.76°C) to the increase, i.e. 159% (106–212%) of the total warming. The cooling effect of the direct and indirect aerosol forcing is about -0.85°C (-1.48 to -0.30°C). The warming induced by tropospheric ozone and solar variability are of similar size of roughly 0.2°C. The contributions of stratospheric water vapor and ozone, volcanic eruptions as well as organic and black carbon are small.

The individual contributions to the observed temperature increase of about 0.55°C since the 1950s are illustrated in Figure 5.3c. Our total estimate of 0.51°C (0.45-0.57°C) is close to the observed temperature change. The largest positive contribution of 0.85°C (0.57-1.13°C) is from greenhouse gases and compares well with the values estimated by optimal fingerprint studies (Stone et al., 2007; Stott et al., 2001; Tett et al., 1999) (See Supplementary Material). Expressed as fraction of the total warming, greenhouse gases contributed 166% (120-215%). The net cooling from the direct and indirect aerosol forcing is -0.45°C (-0.78 to -0.16°C), thereby offsetting -44% (-73 to -28%) of the greenhouse induced warming. It is thus extremely likely (>95% probability) that the greenhouse gas induced warming since the mid-20th century was larger than the observed rise in global average temperatures, and extremely likely that anthropogenic forcings were by far the dominant cause of warming. The natural forcing contribution since 1950 is near zero.

Similar to earlier studies (Knutti et al., 2002; Meinshausen et al., 2009), such constrained ensembles can be used for probabilistic temperature projections of future emission scenarios. The contributions to the total warming for the mid of the 21st century by different radiative forcings are illustrated in Figure 5.3d. Under the SRES A2 scenario the temperature change by 2050-2059 of 1.29 (0.94–1.60)°C compared to the 2000s is almost entirely due to increasing greenhouse gas forcing. The cooling effect of aerosols and other negative forcing agents as well as of other positive forcing agents depend on the particular choice of the scenario, and the A2 case is simply one illustrative case. However, it demonstrates the overwhelming contribution of greenhouse gases, and CO2 in particular, for non-intervention scenarios. The warming induced by CO2 will also persist for at least a thousand years as a result of the slow ocean carbon uptake, far longer than the warming from most other forcing agents (Solomon et al., 2009). This emphasizes the need to focus on CO2 in mitigating climate change. The projections under the SRES A2 scenario based on this method is very similar to estimates from a range of different climate models and statistical methods (Huber and Knutti, 2011b).

The basis for our energy balance model and a crucial step in determining the contributions of anthropogenic and natural (solar and volcanic) forcings to the observed changes is the internal unforced variability of global temperature and energy content. Figure 5.4 compares the observed trends in global average temperature and energy content over the past 50 years with the distribution of 50 year linear trends derived from unforced control–runs in the World Climate Research Programme’s (WCRP) phase 3 Climate Model Intercomparison Project (CMIP3) (Meehl et al., 2005). The bottom panels shows the upper 95% quantiles of the distribution for all timescales, along with the corresponding values for the observed surface temperature (from 2009 backwards) and ocean heat uptake to 700 meters (from 2007 backwards). For global surface temperature it is extremely unlikely (<5% probability) that internal variability contributed more than 26±12% and 18±9% the observed trends over the last 50 and 100 years, respectively. Even if models were found to underestimate internal variability by a factor of three, it is extremely unlikely that internal variability could produce a trend as large as observed. This is
Figure 5.3: a) Contributions of anthropogenic and natural forcings to total simulated and observed global temperature change. b–d) Contributions of individual forcing agents to the total decadal temperature change for three time periods. Errorbars denote the 5 – 95% uncertainty range. The grey shading shows the estimated 5 – 95% range for internal variability based on the CMIP3 climate models. Observations are shown as dashed lines.
5.2 RESULTS

Figure 5.4: a,b) Distribution of linear trends for surface temperature and total energy content from unforced control simulations (grey stackings) and observations (red lines) during 1956 to 2007. c,d) upper 95% percentile as in a,b estimated for each CMIP3 model (grey). Observations are shown in red. In panel b,d), observations of the ocean heat uptake to 700 meters are compared to the net radiation imbalance of the CMIP3 models. The total energy content of the Earth is difficult to measure but is about 40% higher than the 700m heat uptake which is indicated in panels b,d as dotted lines.

consistent with reconstructions over the last millennium indicating relatively small temperature variations that can mostly be explained by solar and volcanic forcing (Hegerl et al., 2006). The ocean warming is similarly anomalous but observations are more uncertain and the evaluation of model variability is more difficult.

The International Panel on Climate Change (IPCC) states in its Fourth Assessment Report (AR4) (Solomon et al., 2007) that “most of the observed increase in global average temperatures since the mid–20th century is very likely due to the observed increase in anthropogenic greenhouse gas concentrations”, that “it is likely that increases in greenhouse gas concentrations alone would have caused more warming than observed”, and that “it is extremely unlikely that global climate change of the past 50 years can be explained without external forcing, and very likely that it is not due to known natural causes alone”. Those results were predominantly driven by optimal fingerprinting studies.

Here we have shown that for global temperature the fundamental principle of conservation of energy, combined with knowledge about the evolution of radiative forcing provides a
complementary approach to attribution. Our results are strongly constrained by global observations and are robust when considering uncertainties in radiative forcing, the observed warming and in climate feedbacks. Each of the thousands of model simulations is a consistent realization of the ocean atmosphere energy balance. The resulting distribution of climate sensitivity (1.7-6.5°, 5-95%, mean 3.6°) is also consistent with independent evidence derived from paleoclimate archives (Knutti and Hegerl, 2008). Using a more informative prior assumption does not significantly alter the conclusions (see Supplementary Material). Our results show that it is extremely likely that at least 74% (±12%, 1σ) of the observed warming since 1950 was caused by anthropogenic radiative forcings, and less than 26% (±12%) by unforced internal variability. Of the forced signal during that particular period, 102% (90-116%) is due to anthropogenic and 1% (−10 - 13%) due to natural forcing. The discrepancy between the total and the sum of the two contributions (14% on average) arises because the total ocean heat uptake is different from the sum of the responses to the individual forcings. Even for a reconstruction with high variability in total irradiance, solar forcing contributed only about 0.07° (0.03-0.13°) to the warming since 1950 (see Fig. 5.3c). The combination of those results with attribution studies based on optimal fingerprinting, with independent constraints on the magnitude of climate feedbacks, with process understanding, as well as paleoclimate evidence leads to an even higher confidence about human influence dominating the observed temperature increase since preindustrial.

5.2.1 Methods

We use the Bern2.5D earth system model of intermediate complexity which is based on a zonally averaged dynamic ocean model. The ocean basins of the Atlantic, Pacific, Indian, and Southern Oceans are resolved and are coupled to a zonally and vertically averaged energy and moisture-balance model of the atmosphere (Schmittner and Stocker, 1999). The prescribed historical natural and anthropogenic radiative forcings used to drive the climate model are based on Crowley (2000) and Joos et al. (2001) and are identical to Knutti et al. (2003).

The implementation and prior distributions of scaling factors in the Bern2.5D climate model, which account for the uncertainty in different forcing agents, are described in detail in Huber and Knutti (2011a). In total, twelve parameters are sampled in the model: three physical parameters including climate sensitivity, vertical ocean diffusivity and the transfer coefficient for sensible heat as well as nine forcing scaling parameters accounting for forcing uncertainty e.g. of greenhouse gases, direct and indirect aerosol effects, volcanic eruptions and solar variations.

The replacement of the full Bern2.5D with a neural network substitute is described in Huber and Knutti (2011a). A 3–layer feed–forward neural network built of 10 nodes is trained with 5000 timeseries of the Bern2.5D model output. A network is trained separately for global–mean temperature, ocean heat content to 700 meters and the temperature increase under a 1% to double CO₂ compared to pre–industrial atmospheric concentrations. In terms of global temperature, the annual error of the neural network is of the order of 0.1°C which is of the same magnitude as the error of current observational datasets and internal variability.

In Huber and Knutti (2011b), the Bern2.5D model is constrained to a set of observational datasets including the HadCRUT3 dataset of Met Office Hadley Centre, the GISS Surface
Temperature Analysis (GISTEMP) of the National Aeronautics and Space Administration and data of the National Oceanic and Atmospheric Administration (NOAA) National Climatic Data Center (NCDC). Ocean heat uptake observations include datasets of Levitus et al. (2009), Domingues et al. (2008), Ishii and Kimoto (2009) and Palmer et al. (2007). Each combination of these datasets constitute a plausible observational constraint. Best–guess estimates for the climate model parameters are derived from the aggregation of the posterior distributions from the individual dataset combinations.

The twelve model parameters in the Bern2.5D model are constrained with a Markov Chain Monte Carlo Algorithm (MCMC) described in Huber and Knutti (2011a). The full climate model is replaced with its NN substitute to decrease the computational time of the algorithm. Within the parameter estimation process, uncertainties from observations, unforced internal variability and the neural network substitute are taken into account. At the core of the MCMC algorithm is the comparison of the model output for a given parameter combination with the observational datasets, thereby weighing the model parameters and their output according to their ability to reproduce past trends of global-mean surface-air temperature and ocean heat uptake to 700 meters (Huber and Knutti, 2011a,b).

The contributions of the individual forcing species to the total temperature change is computed with nine single–forcing neural networks with a network for each of the nine forcing agents, e.g. greenhouse gases and aerosols. Climate sensitivity, vertical ocean diffusivity and the transfer coefficient for sensible heat are sampled in each single–forcing network. All NNs perform better than 0.01°C which is about one magnitude smaller than the observed interannual variability of global–mean temperature. Since the Bern2.5D climate model does not feature interannual variability, the temperature evolution is basically determined by climate sensitivity and vertical ocean diffusivity which are sampled in each single–forcing NN. The single–forcing temperature contributions can subsequently be computed from the joint posterior distribution of the parameters. Here, we take the aggregated posterior distribution of the individual dataset combinations.

5.3 Supplementary Material

5.3.1 Comparison with Optimal Fingerprinting

Figure 5.5 shows the comparison of the contributions from greenhouse gases, other anthropogenic agents and natural components to the observed temperature difference between 1990s and 1900s for our energy balance model and five estimates based on optimal fingerprinting. The optimal fingerprinting values were taken from Figure 9.9 of Meehl et al. (2007) and the methods are described e.g. in Stott et al. (2006). While most of these reference estimates based on optimal fingerprinting are derived with fully coupled ocean-atmosphere general circulation models, there has been also an approach to optimal fingerprinting with simple energy balance models (Stone and Allen, 2005).

For the greenhouse gas attributable warming, the estimate based on the energy balance model agrees well with the results of the optimal fingerprint studies and the uncertainty ranges are of similar size. We find a generally larger and more uncertain estimate of the contribution
Figure 5.5: Contribution from greenhouse gases (a), other anthropogenic drivers (b) and natural forcings (c) to observed global mean surface temperature changes between 1990s and 1900s. The results derived by the energy balance model are shown in colours and are compared to previous estimates based on optimal fingerprinting. The data is taken from Figure 9.9 of Meehl et al. (2007). The errorbars denote the 5 – 95% uncertainty range. Observations of three global mean surface air temperature datasets are shown as dashed lines.

of other anthropogenic forcings to the total temperature change, mostly due to uncertainties in the aerosol forcing. Our mean estimate of the contribution of natural drivers is larger than the reference estimates, partly due to the choice of a solar forcing reconstruction with relatively large decadal variations.

5.3.2 Role of Prior Distribution for Climate Sensitivity

The standard setup includes a uniform prior distribution between 1 – 8°C for climate sensitivity (Huber and Knutti, 2011b). Here we test the sensitivity of the results on the prior assumption about climate sensitivity and choose a gamma distribution with shape and scale parameters of 4.3 and 0.95. The effect of the two priors on decadal temperature projections at the end of the 21st century is assessed in Huber and Knutti (2011b). The prior and posterior distributions of the aggregated estimate of twelve combinations of observational datasets are illustrated in Figure 5.6. The two climate sensitivity estimates have similar lower bounds, whereas the posterior sensitivity derived with the uniform prior has a slightly higher upper tail. The corresponding posterior likely ranges (central 66% of the distribution) are 2.2 – 5.1°C based on the uniform prior and 2.3 – 4.5°C derived with the gamma prior. The corresponding mean sensitivities are 3.6°C and 3.4°C respectively.

Panels b) and c) of Figure 5.6 illustrate the effect of the prior choice on the individual forcing contributions to the total temperature change. The effect is small on the mean estimates of the contributions. The 5 – 95% uncertainty range for the attribution of greenhouse gases and aerosols is slightly smaller for the case of a gamma prior, however, the effect on the contributions of the total anthropogenic and natural contributions is negligible.
Figure 5.6: a) Posterior climate sensitivity estimates for a uniform and gamma prior. The effect of the prior choice on the individual forcing contributions to the total temperature change is illustrated in panels b,c) for two time periods. The left bars denotes the estimates derived from a uniform climate sensitivity prior, whereas the right bars correspond to the estimates based on a gamma prior.
Chapter 6

Conclusions and outlook

6.1 Conclusions

This thesis aims at understanding the way the Earth’s energy balance and its changes constrain both climate system properties such as climate sensitivity and future temperature projections. A variety of radiation variables as well as global average temperature and ocean heat uptake are considered. The results are based on different models of the climate model hierarchy including the Bern2.5D climate model of intermediate complexity and the set of CMIP3 models used in the Intergovernmental Panel on Climate Change (IPCC) Forth Assessment Report (AR4).

- Radiation patterns and climate sensitivity

Any perturbation of the Earth’s energy balance results in distinctive response patterns, for example a more pronounced warming of the land masses compared to the ocean and a reduction of the annual cycle in the high latitudes. The statistical description of these response patterns as simple indices was previously used to assess global climate variability and change (Karoly and Braganza, 2001; Braganza et al., 2003). Since global surface air temperature is closely related to the flow of energy within the climate system, the temperature based indices are computed for different radiation variables both for shortwave and longwave radiation fluxes in Chapter 2. The equilibrium climate sensitivity depends on the magnitude of different physical feedbacks such as cloud–feedback or lapse–rate feedback, which in turn are dependent on the radiative fluxes. We established statistically significant regressions between the climate sensitivities of a set of state–of–the–art climate models and model biases in the radiative indices. High correlations are found in the cloud radiative forcing of the incoming longwave surface radiation and the net shortwave surface budget. By constraining the radiative indices with a set of observational datasets, our best estimate of the likely range of climate sensitivity is $2.9 – 4.0 ^\circ C$ with a mean of $3.4 ^\circ C$. The distribution of climate sensitivity is similar to other estimates derived with different observations and statistical methods. The results presented in Chapter 2 highlight both the need for an adequate representation of radiative fluxes in climate models and accurate observations of the Earth’s energy balance. Moreover, further process understanding is needed to fully explain the correlations between radiative indices and climate sensitivity.
• **Emulating an energy balance model**
  
  Due to their efficient use of computational resources, climate models of reduced complexity are readily employed to account for uncertainty in the estimates of climate system properties such as climate sensitivity. Key to this uncertainty assessment is the process of constraining the climate model parameters to observations of historical climate change, mostly to changes of temperature and ocean heat uptake. However, a significant number of model runs is needed in the statistical methods computing the posterior parameter distributions. In Chapter 3 we describe the substitution of the Bern2.5D climate model of intermediate complexity with a neural network. The run–time for a single model run could be reduced by 3 orders of magnitude. The Bern2.5D substitute consists of a 3–layer feed–forward neural network with ten nodes. The network is trained with 5000 truncated timeseries of the Bern2.5D model output accounting for uncertainty in three physical parameters – climate sensitivity, vertical ocean diffusivity and the transfer coefficient of sensible heat – and nine scaling parameters describing the uncertainty in radiative forcing of different forcing components, e.g. long–lived greenhouse gases and sulphate. The error of the network in predicting the annual timeseries of global average temperature and ocean heat uptake was probabilistically quantified and is of the same magnitude as interannual variability and observational uncertainty.

• **Parameter Estimation with the Markov Chain Monte Carlo (MCMC) Algorithm**
  
  Bayes’ Theorem provides an invaluable, statistical framework to use observational data to update prior information about model parameters. Key to the statistical inference about model parameters is the likelihood function which defines the probability of the observations for a given set of parameters. In Chapters 3, 4 and 5, we use a Markov Chain Monte Carlo (MCMC) algorithm to sample from the joint posterior distribution of the model parameters of the Bern2.5D climate model. We employ the Metropolis–Hastings algorithm which ranks among the most popular MCMC methods. For this algorithm, a large ensemble of parameter combinations – and thereby model runs – are necessary during the algorithm. The replacement of the full Bern2.5D model with a neural network substitute plays a key role in this thesis. By combining the MCMC algorithm with the Bern2.5D emulator, a posterior distribution of the model parameters can be computed in 1–2 hours.

• **Emulating a set of complex climate models with a climate model of reduced complexity**
  
  The fully coupled atmosphere–ocean general circulation models of the World Climate Research Programme’s (WCRP) Coupled Model Intercomparison Project phase 3 (CMIP3) were the most comprehensive, numerical representations of numerous physical and bio–chemical processes in the climate system at the time of the Fourth Assessment Report (AR4) of the Intergovernmental Panel on Climate Change (IPCC). Chapter 3 outlines the attempt to emulate a set of CMIP3 models with the Bern2.5D model by regarding the CMIP3 simulations of global temperature and ocean heat uptake as observational constraints on the Bern2.5D model. We find that the general evolution of global temperature during the 20th century can be well reproduced for most CMIP3 models (see Fig.
However, we find discrepancies between the climate sensitivity estimated with the Bern2.5D model and the true climate sensitivities of some CMIP3 models. Drifts in the simulations of global temperature and ocean heat uptake and an inhomogeneous representation of historical radiative forcings within the CMIP3 set are likely to be the primary sources of error in the parameter estimation process. Despite discrepancies in emulating some CMIP3 climate models, the multi–model mean prediction of future temperature change during the 21st century under the SRES A2 non–intervention scenario can be accurately predicted with the Bern2.5D model as illustrated in Figure 3.7.

**Constraints of different observational datasets on climate sensitivity and climate projections**

The weighting of a large ensemble of climate model runs based on the ability of individual ensemble members to reproduce past climate change constitutes an important step towards the statistical quantification of uncertainty in climate system properties and projections. However, various data products differ in their estimates of historical changes in the climate system, in particular for changes in ocean heat uptake. The method developed in Chapter 3 provides an efficient tool to test the effect of different observations of global mean temperature and ocean heat uptake on the estimates of climate sensitivity and future temperature change. Probability density functions of climate sensitivity and transient climate response are presented in Chapter 4 for 16 combinations of four temperature and four ocean heat uptake datasets. Aggregating the different estimates, we find a likely range of 2.2 – 5.1°C with a mean of 3.6°C for climate sensitivity which is slightly higher than the likely range of 2 – 4.5°C estimated in the IPCC AR4. We argue that the broader range of our climate sensitivity estimates partly originates in the addition of the neural network substitute error in the parameter estimation process which allows rather high sensitivities still to agree with the observational constraints. Figure 4.7. in Chapter 4 highlights that the differences in the observations of past ocean heat uptake are likely to be the primary source for differences in the climate sensitivity estimates. While the estimates of climate sensitivity and future decadal temperature increase at the end of the 21st century for a given set of observations depend on the magnitude of the sum of observational and neural network error, our ranges of the aggregated probability density functions of the two quantities is almost constant within a scaling of –40% to +40% of the error (see Fig. 4.7).

**Anthropogenic and natural contributions to total past temperature change**

In the past decade, the assessment of the contributions of different forcing agents – including both anthropogenic and natural drivers – relied primarily on optimal fingerprinting studies. These studies basically employ a regression of the observations onto model simulated patterns. While optimal fingerprinting constitutes a sound and rigorous statistical tool, the method does not necessarily take observed changes in the Earth’s energy balance into account. In Chapter 5, we use the joint posterior distribution of the Bern2.5D model parameters to probabilistically quantify the contributions of different forcing components to the total observed temperature change. Moreover, the likely share of internal variability on the trend in global temperature during the last 50 and 100 years is assessed
from control runs of the CMIP3 models. We find that at least 74% (±12%) of the observed warming since 1950 was caused by anthropogenic and natural forcings, and less than 26% (±12%) by unforced internal variability. Further, greenhouse gases alone contributed 0.85°C with a 5 – 95% uncertainty range of 0.6 – 1.1°C to the total observed change of about 0.56°C in global temperature. The effect of a different prior for climate sensitivity on the conclusions of Chapter 5 is small. The results take observations of changes in the Earth’s energy balance into account and are consistent with estimates derived with optimal fingerprinting, suggesting an even higher confidence in anthropogenic causes dominating the observed warming of ocean and atmosphere.

6.2 Outlook

This thesis combines a variety of observational data products with model simulated data as well as Bayesian statistics with artificial neural networks which are one of numerous machine learning methods. In particular, the substitution of a climate model of intermediate complexity with a neural network allows to perform both hardware– and software–intensive computations. This approach offers many new applications of which some are outlined below.

- **Machine Learning and Statistical Emulators**
  
  Artificial neural networks are just one of various machine learning algorithms which are concerned with mimicking, training, and learning processes from data distributions. Machine learning includes many different approaches such as decision tree learning, evolutionary programming, gaussian processes and bayesian networks. Different approaches were tested to emulate the Bern2.5D model, including Random Forest and Ant Colony Optimization. However, due to the possibility to emulate full timeseries and high computational efficiency, the use of artificial neural networks was deemed superior for our purposes. The field of statistical emulators provides vast possibilities for climate modeling, particularly with regard to the efficient use of computational resources and adequate data for statistical analysis. The trade–off between sufficient data and accuracy is at the core of the question how and if a climate model can be replaced by statistical emulator. Applications of emulators could be anticipated in the substitution of entire parameterizations in highly complex climate models, especially if the processes show high linearity.

- **Seamless Prediction**
  
  This thesis considers climate models of two stages of the climate model hierarchy: the Bern2.5D model of intermediate complexity and the fully–coupled general circulation models of the CMIP3 ensemble. The particular choice of complexity incorporated in a climate model depends on the problem considered. However, there is only on true climate system. Seemless prediction is a newly emerging idea trying to fill the gaps in the model hierarchy and between weather and climate (Palmer et al., 2008). The seemless prediction approach aims at using a model family for climate predictions across a range of timescales and spatial resolution.
• **RCP Emission Scenarios**

The commonly used SRES scenarios of future atmospheric concentrations of greenhouse gases, sulphate and other radiatively active species will be replaced by the Representative Concentration Pathways (RPCs) in the IPCC Fifth Assessment Report (AR5). The set of RCPs should be “compatible with the full range of stabilization, mitigation and baseline emission scenarios available in the current scientific literature” (Moss et al., 2008). The method developed in Chapter 3 provides a simple tool to compute the future temperature change under the RCP scenarios. Moreover, the multimodel mean response of the CMIP5 models could be assessed considering the results depicted in Figure 3.7, given the information about the representation of forcing agents in the CMIP5 models.

• **Representation of the Carbon Cycle**

The results of Chapters 3, 4 and 5 are based on a version of the Bern2.5D climate model without a representation of a dynamic carbon cycle. While the results are robust for historical simulations of global temperature and ocean heat uptake, the carbon cycle has an influence on the trajectories during the 21st century and on longer timescales. Thus, the calculations of the RCP scenarios should ideally be computed with a Bern2.5D model version accounting for the carbon–cycle climate feedback uncertainty.

• **Effect of additional observations on uncertainty estimates**

The climate system responds to the total net forcing and the effects of the canceling of positive and negative forcings – e.g. greenhouse gases and aerosols – have been assessed in previous studies. However, the radiative forcing of greenhouse gases has long–range effects on the Earth’s energy balance, ranging from centuries to millennia. During the next couple of decades, the signal of anthropogenic induced climate change is expected to be better detectable and attributable due to the additional data. Hereby, both the optimal fingerprinting approach and the method presented in Chapter 5 could be employed to constrain the contribution of individual radiative forcing agents to the observed temperature change. Moreover, the observational data of the coming decades provides a strong constraint on the transient climate response since the temperature change during this period is presumably governed by radiative forcing from greenhouse gases.
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