Chapter 2

Background and Literature Review

Following the signing of the United Nations Framework Convention on Climate Change (UNFCCC) in June 1992 (Dessler and Parson (2006)), climate change has become established as an issue of global importance. As a consequence, climate scientists have been urged by politicians and businesses to conduct policy-relevant science to inform decision makers. Inevitably, given the complexity of the system, the research community has continually modified theory and modelling methodologies to cope with the ever-changing science of climate and climate change. In striving to meet the needs of society, scientists have developed large computer simulation models of the climate system. To understand how the current (and future) generation of climate models can be used to inform decision makers requires a knowledge of the history of this rapidly evolving research area. In placing the research presented in this thesis into the wider scientific context, this chapter provides an analysis of the existing literature, relevant to the themes of the research.

Section 2.1 begins with a description of the alternative definitions of climate and then explores the development of dynamical systems theory to address climate and climate change. Section 2.2 presents a historical account for the development of models to inform climate change adaptation decisions. The section focuses on the methods and approaches adopted by various authors in the design and implementation of climate model experiments. In section 2.3, the impacts and responses of insurers to climate change are discussed in relation to the engagement of insurers with the climate research community and the use of climate model information within the insurance industry. Finally, section 2.4 documents the studies which have analysed the behaviour of the dynamical models explored in this thesis to provide insight into the treatment of uncertainty in climate modelling.

2.1 Climate as a Dynamical System

2.1.1 Defining climate and climate change

How an individual perceives the risks of climate change is fundamentally related to their understanding of the climate system. Appropriately defining climate and what constitutes a change in climate is therefore vital in enabling people to decide how to respond to climate model information. A number of years ago, Bostrom et al. (1994) presented evidence that the general public often confuses the notions of weather and climate and also misunderstands the causes of climatic change. More recently, Sterman and Sweeney (2007) described empirical evidence to suggest that low public support for mitigation policies (in the US) may have arisen due to misconceptions of how the climate evolves. Yet the contrasting perceptions of climate, and what constitutes a change in climate, within the public discourse are not well resolved even within the climate science community. After decades of research into the behaviour of the climate system, the many definitions of climate and climate change are not, and perhaps never will be, consistent across all domains of climate research.

Lorenz (1997) discusses the various working, often contradictory, definitions of climate and argues that the definition adopted for a particular application will impact the interpretation of climate variability and climate change. Many authors tend to favour a statistical temporal definition, similar to that adopted by Dymnikov and Gritsoun (2001) which states, "the climate is assumed to be the ensemble of states that the climate system (the system consisting of atmosphere, hydrosphere, cryosphere, land surface and biota) passes through during a sufficiently long time period". One therefore has to determine the modes of variability which ought to be associated with internal climate variability and infer a suitable time scale over which to define climate. For example, Lorenz (1997) states that one might decide that ENSO (El Niño Southern Oscillation) should be considered a regular feature of a stationary climate so the time-averaging period must be sufficient to account for positive and negative phases of the ENSO cycle. A climate change would then occur if ENSO events (El Niño and La Niña) became more regular and/or changed their magnitude. A typical period for analysing observations to derive climatological statistics is thirty years, consistent with the time scale advocated by the WMO (Burroughs (2003)). Thirty year datasets, representing the period 1961 to 1990, have been developed for use as a baseline for future climate projections (WMO (1996), New et al. (1999)). However climate variability is known to occur on all time scales (Schneider and Kinter III (1994), Pelletier (1997)) so the potential application for such a definition is limited. Given long-term internal variability, it is inevitable that the "climate" will be different from one thirty year period to the next, irrespective of any external forcings imposed on the climate system. Herein lies a major difficulty in using time-averaged statistics to represent the climate. The means and variances associated with a thirty year period, or indeed any other finite-time period, are dependent on the particular phases of long-term modes of climatic variability. Furthermore, in addressing the complexity of climate and investigating the methods used to provide climate information, Lucarini (2002) states that there is an element of ambiguity in the definition of climate because "the time interval over which statistics are made is not determined a priori, but is operationally chosen depending on the goal of the research".

As explained by Peixoto et al. (1992), definitions of climate have evolved over the past decades and many disciplines now view the climate as a complex system which includes the biosphere, cryosphere and anthroposphere. An alternative definition to the broadly adopted statistical temporal definition, originates from dynamical systems theory in which the climate is considered as the set of states consistent with fixed forcings and boundary conditions (Fraedrich (1986), Smith (2002)). A change in climate is therefore given by the changing set of possible states to which the system evolves. The definition lends itself to considering the climate as an "attractor" for weather (Palmer (1999)) so that changes in the attractor represent a change in climate (discussed further in section 2.1.3). In the real climate system, past observations of weather variables simply represent one trajectory through the set of possible states associated with the climate attractor. However, given the high-dimensionality of the climate system and the inherently complex nonlinear interactions which occur on multiple time scales, this definition is perhaps conceptually more challenging.

The IPCC provides a non-specific definition of climate in the most recent AR4 report, which encompasses many competing definitions (IPCC (2007a)):

> "Climate in a narrow sense is usually defined as the average weather, or more rigorously, as the statistical description in terms of the mean and variability of relevant quantities over a period of time ranging from months to thousands or millions of years. These quantities are most often surface variables such as temperature, precipitation, and wind. Climate in a wider sense is the state, including a statistical description, of the climate system. The classical period of time is 30 years, as defined by the World Meteorological Organization."

Multiple time scales are acknowledged in the IPCC definition because of the varied interests and motives of researchers but the lack of specificity, regarding the time scale over which climate should be considered, leads to ambiguity regarding conclusions about detection of past climate changes and projections of future climate change. The IPCC definition alludes to the dynamical systems view of the climate with reference to the "state" of the climate system but the definition provides little clarity as to what that means in practice.

Understanding how the use of alternative definitions of climate can aid or hinder climate change adaptation decisions is a theme that runs throughout the work presented in this thesis. By adopting a dynamical systems approach to conceptualising the climate system, and using the notion of an attractor, this thesis investigates the most appropriate definition of climate for use by climate modellers and decision makers in the context of climate change adaptation.

2.1.2 Is climate chaotic?

The origin of chaos theory dates back to the 19th century, and to the work of Henri Poincaré. Stewart (2009) describes how Poincaré "gazed into the abyss of chaos" with his pioneering work on the theory of dynamical systems. However, it wasn't until the 1960s, and the work of meteorologist Edward Lorenz, that chaos was formally demonstrated using a simple numerical model (Lorenz (1963)). Ever since, scientists have been grappling with the implications of chaos in the modelling and prediction of a wide variety of complex systems (e.g. Scott (1989), Dettmer (1993) and Ditto (1996)). The definition of chaos has been adapted for the many disciplines to which it is applied but the first rigorous mathematical definition of chaos was provided by Li and Yorke (1975). For a system to be considered chaotic, the rate of divergence of model trajectories must be at least exponential-on-average. The Lyapunov exponent measures the rate of divergence (or convergence) of trajectories and a chaotic system is defined as having a positive first Lyapunov exponent (Wolf (1986)). In short, a chaotic system can be thought of as a dynamic system which displays sensitive dependence to ICs (Schuster and Just (2005)) but as noted by Smith (2007), two other properties of chaotic systems are equally important; they are nonlinear and deterministic. The climate system has been shown to exhibit both deterministic and nonlinear behaviour (Hasselmann (1976)) so the notion of chaos ought to be embedded in the way we view and model the climate system. As noted by James Gleick, "the world would be a different place - and science would not need chaos - if only the Navier-Stokes equation did not contain the demon of nonlinearity" (Gleick (1988)). However, the relevance of chaos for the large-scale climate (as opposed to weather) prediction is still an area of vigorous debate (Harrison (2007)).

Lorenz (1990) states that "the climate system is unquestionably chaotic". On a time scale of weeks, chaos prohibits the predictability of exact atmospheric states (predictability of the first kind) but certain features, such as the range and expected frequency of possible states, may be highly predictable (predictability of the second kind) (Sprott (2003)). Modern weather prediction centres account for the chaotic behaviour of the atmosphere by using IC ensemble forecasting techniques largely developed in the 1990s (Palmer (1993), Toth and Kalnay (1993), Houtekamer et al. (1996)). On weather forecasting time scales boundary conditions are assumed to be constant but in predicting the evolution of the climate we are faced with the problem of extrapolating the climate system into a region where boundary conditions are changing (Stainforth et al. (2007a)). Much of the focus of the climate science community has therefore been on understanding the uncertainty associated with altered boundary conditions in the prediction of future climate states. How chaotic behaviour, arising from uncertain ICs, in the atmosphere and ocean interacts with the deterministic dynamics of the climate system, forced by changes in the boundary conditions, is not well understood (Humble (2007)) but recent developments in the theory of *spatio-temporal* chaos applied to climate modelling may provide some new insights (Climate Etc. (2011)).

Rial et al. (2004) discuss the complexities of the climate system and suggest that certain climatic features such as ENSO and the NAO (North Atlantic Oscillation) show signatures of chaotic behaviour. In describing the climate system as a complex system, Rind (1999) asserts that the inherent complexity of the system may impact our ability to make long-term climate projections. However, Rind (1999) comments that whilst the atmosphere is not entirely stable, the variability of atmospheric states is not chaotic. Conversely, a study by Hansen et al. (1997) using ensembles of climate simulations found that most interannual climate variability in the period 1979 to 1996 at middle and high latitudes was chaotic. Shulka (1998) argues that chaos does not imply a lack of long-term predictability in the atmosphere if the ocean temperature can be predicted. The author lists examples of geographical areas where the boundary conditions dictate the variability of atmospheric modes. Rial (2004) presents a less optimistic view for the prospects of successful long-term climate prediction. The study analyses ice core time-series' and uses a simplified model to examine the question: "do the ice core records reflect a climate system operating between order and chaos?" The author concludes the study by speculating that the earth's climate may only be weakly driven by the external forcings (e.g. solar forcing) whereas features such as abrupt warming episodes may result from the nonlinear processing of the forcing.

From a palaeoclimate perspective, Harrison (2007) argues that reductionist attempts to model the climate system, such as the attempts to model the climate using high-resolution GCMs, may be inappropriate for the climate system which is highly nonlinear and displays *emergent* behaviour. With reference to emergence, Goldenfeld and Kadanoff (1999) suggest that "microscopic" scale processes do not necessarily influence the "macroscopic" scales, so whilst uncertainty at microscopic scales may be irreducible this may not be a barrier to successful climate prediction. Harrison (2007) however, concedes that "if the macroscopic behaviour of the system is sensitively dependent upon the microscopic, then the whole system may be expected to display non-linearity and may be chaotic".

2.1.3 The climate attractor

Fundamental disagreements about the precise role of chaos in the study of climate change can often stem from the precise definition of climate, discussed in section 2.1.1. To address the potential impacts of chaotic and nonlinear behaviour in the climate system, many scientists have referred to the tools of dynamical systems theory. From the viewpoint of climate as a nonlinear dynamic system, the climate can be considered in terms of an "attractor" (Palmer (1999)). The term attractor has many definitions and has been applied in many areas of research. Milnor (1985) reviews the various working definitions of the term *attractor* and Bhattacharya (1993) states that an attractor is a region in phase space to which trajectories from different ICs converge over time. Of more relevance to the climate system is the notion of a strange attractor, which is an attractor that displays sensitivity to ICs (Ruelle (1981)) and is therefore usually chaotic; though not all strange attractors strictly display chaos (Grebogi et al. (1984)).

In a climate context, Sahay and Sreenivasan (1996) comment that "strictly speaking, the relevant phase space for weather and climate attractors would be the space of all global fields of atmospheric temperature, humidity and wind velocity and so forth." One of the first studies to investigate the existence of an attractor for the climate system was done by Nicolis and Nicolis (1984). Using isotope records from deep-sea cores the authors assessed the potential for a low-dimensional attractor by examining dynamic features of the climatic time-series and concluded that, based on their data and approaches, a low-dimensional attractor may indeed exist. In the years to follow, many studies used different methodologies to assess the potential for a low-dimensional climate attractor (Fraedrich (1986), Sahay and Sreenivasan (1996) and references therein). A number of the studies question the use of (relatively) short datasets to find approximations to a climate attractor and offer theoretical arguments to dismiss the claim that the climate can be represented by a low-dimensional attractor (Grassberger (1986); Lorenz (1991b); Zeng et al. (1992)). Whilst the characterisation of the climate as a low-dimensional climate attractor remains contested, Sahay and Sreenivasan (1996) note that one can differentiate climatic phenomena according to the spatial and temporal scales on which they display stationarity. The authors make the case for considering "local attractors", which can be dataset dependent and can be considered in the context of a large-scale "global attractor". In the work presented in this thesis, the notion of a climate attractor is not used to support either the presence of a low-dimensional or high-dimensional attractor on any particular length scale. Rather, the concept is utilised as a communication device to explore climate under climate change by analogy to simple nonlinear dynamic models. In determining the impact of altered parameters on the attractors of simple models, the assumption is that insight can be gained into the qualitative behaviour of the climate system in response to altered climate forcings.

2.1.4 Ergodic theory, intransitivity and climate

In the history of chaotic and nonlinear dynamic systems research, other concepts and tools have been key to developments in considering chaos in real-world problems. For climate research, ergodic theory has provided a conceptual basis for defining climate and interpreting the dynamics of the climate system. Ergodic theory stems from the study of statistical mechanics, dating back to the nineteenth century and the pioneering work of Ludwig Boltzmann on the development of the ergodic hypothesis (Boltzmann (1871), Boltzmann (1872)). Yet it wasn't until the late 1920s that George D. Birkhoff and John von Neumann established mathematical proofs of the "ergodic theorem" and "mean ergodic theorem" respectively (Birkhoff (1931), von Neumann (1929)). Research on the application of ergodic theory was subsequently extended to the discipline of nonlinear dynamics theory, notably in the work of Ruelle (1976). Eckmann and Ruelle (1985) describes ergodic theory in basic terms as the theory that for a dynamical system, "a time average equals a space average". There are a number ways of expressing ergodicity in relation to the climate system and climate modelling. Schneider et al. (2000) states that a system can be considered ergodic if an ensemble of "replicates" averaged at a point in time produces the same statistics as that produced from an infinite time average of one member from the ensemble. The results presented in this thesis utilise the definition described by Sprott (2003):

> "The ergodic hypothesis (Ruelle (1976)) asserts that the probability distribution is the same for many iterations of a single orbit (time average) and for a high-order iteration of many orbits with a range of random initial conditions (ensemble average)"

The ergodic assumption has become an accepted, though rarely acknowledged, feature of many studies analysing past climates and projecting future climates with computer simulation models. In using past observations and forecast simulations to understand climate, von Storch and Zwiers (1999) consider climate as a realisation of a continuous stochastic process, stating that without the ergodic assumption, "the study of the climate would be all but impossible". Yet, by viewing the climate system as a cascade of hierarchical sub-systems, Peicai et al. (2003) conclude that climate processes are not ergodic.

Monin (1986) states that an ergodic system is one in which "during the course of time, the trajectory representing [the system's] evolution in the corresponding phase space goes around all points of this space". In this description, Monin (1986) is describing "transitive" behaviour, stating that an ergodic system displays transitivity. There is clearly disagreement regarding the extent to which the climate system can or cannot be considered ergodic and the relevant literature is dominated by the related concept of transitivity. A *transitive* system is one in which a trajectory can pass through all of the possible system states whilst an *intransitive* system is one in which a trajectory will only pass through a subset of all possible system states; the subset is determined by the initial state and once established, will persist forever (Lorenz (1968))[1]. Whether or not the climate system as a whole is ergodic may be important in developing a comprehensive theory of the climate system but in this thesis, the presence (or absence) of ergodicity is determined in relation to the time scales of interest for adaptation decision making; the precise mathematical definition of ergodicity and the axioms of proof are not studied in detail.

In 1968, Lorenz asked, "how about the real atmosphere? Is it transitive?" concluding "we do not know" (Lorenz (1968)). Lorenz (1990) explored this notion with the aid of a simple nonlinear model and he deduced that the climate system is unlikely to be intransitive due to seasonal forcing changes that move the system into chaotic (or near chaotic) regions of parameter space facilitating the transition to new climates; rendering the system transitive. A more refined concept, almost-intransitivity, describes a system which is transitive over an infinite time but appears intransitive on shorter finite time scales (Lorenz (1968)). Lorenz (1970) discusses this concept in relation to climate and sees it as an "attractive hypothesis" for a system which has processes operating on different time scales such as sea ice and continental snow cover. In a review of early climate modelling studies, Schneider and Dickinson (2000) comment on

[1]Detailed definitions of transitivity and intransitivity are provided in the glossary.

the difficulty of understanding the origin of climate changes in a system that may be almost intransitive. The authors state that the assumption of climate being transitive is unfounded, and the climate may change as a consequence of internal or external influences, or some combination of both. Schneider and Dickinson (2000) therefore conclude that in the absence of transitivity, a definition of climate as a time-mean, rather than an ensemble average, is beneficial. In the years to follow, various studies were unable to resolve the issue of whether or not the climate system is transitive of otherwise, leading to Lorenz' conclusion in 1976; "we have no means at present of determining whether the atmosphere-ocean-system is transitive or intransitive" (Lorenz (1976)). The possibility that climatic changes can be attributed not only to external forcing changes but also the integration of subsystems of the climate (i.e. internally induced changes) poses significant challenges for the climate modelling community and is still an area of contention as recognised more recently by McGuffie and Henderson-Sellers (2005) who state:

> "Should the climate turn out to be almost intransitive, successful climate modelling will be extremely difficult."

2.2 Developing Climate Models to Inform Policy

2.2.1 Historical context

Over the past few decades the capabilities of climate modelling centres has increased dramatically and the uptake in the use of climate model output to inform adaptation decisions has grown as a consequence. In the late 1960s the first GCM, which combined atmosphere, ocean and cryosphere processes, was developed by the NOAA Geophysical Fluid Dynamics Laboratory (Manabe and Bryan (1969)). However, it wasn't until the mid to late 1970s that modelling centres became sufficiently advanced to produce more realistic representations of the Earth's climate system (e.g. Manabe et al. (1975), Bourke et al. (1977)). The main focus of early numerical modelling efforts was to use GCMs to produce globally consistent weather forecasts. Long-term climate projections were rarely performed due to the computational demands and limited access to supercomputers.

Edwards (2010) describes how computer simulation models have evolved since their emergence in the 1960s and explains why initial experiments tended to focus on radiative transfer. The author describes the work of Svente Arrhenius, Guy Callendar, Gilbert Plass and other eminent scientists in estimating the climate sensitivity: the warming associated with a doubling of CO_2 concentrations from their pre-industrial levels. Whilst the variable remains uncertain, it has provided a foundation for experiments to investigate the impact of an increase in the atmospheric concentrations of CO_2 to inform policy in mitigating anthropogenic CO_2 emissions. Estimating the climate sensitivity became a central goal of the climate science community and has led to much disagreement amongst scientists. Arrhenius (1896) calculated the climate sensitivity using a 2-D radiative transfer model, and solved the model equations by hand, obtaining an estimate of $5 - 6°C$. The first GCM to simulate the effects of doubled CO_2 resulted in a $2.9°C$ warming (Manabe and Wetherald (1975)). More recently, a multi-thousand member perturbed parameter ensemble[2] (PPE) experiment utilising distributed computing, climate*prediction*.net, obtained a range between 1.9 and $11.5°C$ (Stainforth et al. (2005)); discussed further in section 2.2.3. The latest IPCC report judged that the most likely range for the climate sensitivity was between 2 to $4.5°C$ (Solomon et al. (2007)), informed from a number of modelling studies conducted in preparation for the IPCC report. Despite major advances in system understanding and computational capacity, the median estimate of climate sensitivity remains at approximately $3°C$ and the uncertainty has not been constrained.

Climate models have evolved from relatively simple energy balance, atmosphere only models (North et al. (1981)) to highly complex, fully coupled interactive climate system models (Karl and Trenberth (2003)). The development of climate modelling capabilities has been coupled to the developing political agenda and the increasing demands placed on modelling centres to address key policy questions. The first questions regarding the impacts of anthropogenic GHG emissions on the climate system were mostly scientific in nature until the 1980s when society and

[2] Also referred to as a perturbed-physics ensemble

politicians becamse increasingly concerned about the impacts of global warming, resulting in the foundation of the UNFCCC (Dessler and Parson (2006)). The political dialogue culminated in the formation of the IPCC in 1988 and complex numerical climate models became the primary tool for informing IPCC projections of the impacts of anthropogenic climate change. As the shift in policy focus has moved increasingly towards questions regarding impacts at regional and local scales rather than mitigation policy questions on global scales, the expectations placed on climate modelling centres has become evermore demanding. The next section discusses the efforts of climate modellers to address questions concerned with climate change adaptation.

2.2.2 Climate model information for adaptation

The term “adaptation” is widely used in many research fields and the relevant definition is dependent on the application of interest. For the purposes of this thesis, the definition used is that adopted by the IPCC and defined in Smit et al. (1999):

> “Adjustments in ecological-social-economic systems in response to actual or expected climatic stimuli, their effects or impacts.”

A certain degree of adaptation to climate change is likely to be autonomous; spontaneous adaptation that will occur without direct intervention of a public agency (Smit et al. (2001)). The content of this thesis is relevant to autonomous adaptation where decisions require an appreciation of relevant climatic uncertainties but the primary focus is on the needs of policymakers in the insurance industry who are interested in planned adaptation to climate change.

Given the desire for reliable and accurate information on future climate states, there is an obvious role for climate models to be used as a tool for guiding advice to decision makers. However, the climate model projections used to address policy questions relating to climate change mitigation often lack the detail necessary to address policy questions related to climate change adaptation. Stainforth et al. (2007b) recognises the differences in the demands placed on climate modelling centres noting that mitigation decisions can be driven by global scale projections whilst adaptation decisions benefit from regional and local scale information. Burton et al. (2002) highlights the issue of a mismatch in the resolution of global climate model projections and adaptation measures which are usually local or site specific.

In an attempt to bridge the scale divide, a number of statistical and dynamical downscaling techniques have been developed. Giorgi and Mearns (1991) present an early review of the various approaches being adopted by modelling groups, identifying ‘nested-models’ as a promising methodology for exploring regional climate impacts. In the following years, statistical downscaling approaches were favoured and many studies implemented such techniques for a large number of applications (Heyen et al. (1996), Schubert and Henderson-Sellers (1997), New and Hulme (2000), Wilby et al. (2004)). Huth (1999) states that the essence of statistical downscaling is to "seek statistical relationships between the variables simulated well by GCMs, which are treated as predictors, and those required by impacts researchers, treated as predictands". More recently, with the benefit of improved computational capacity, dynamical models representing sub-global domains have been employed in the hope of improving regional-scale predictions (Kundzewicz et al. (2006), Meier (2006), Christensen et al. (2007a)).

A number of studies have compared the benefits and limitations associated with statistical and dynamical approaches to modelling regional climates and the successes and failures of each approach depend strongly on the specific variables of interest, the geographical location and time scale (Mearns et al. (1999), Murphy (1999)). However, in many cases, the dominant source of disagreement between regional results is the driving GCM which leads to considerable uncertainty in the projections of regional impacts (Fowler et al. (2007)). A study by Kendon et al. (2010) concludes that in general, exploration of uncertainty using model ensembles should be focused on sampling GCM uncertainty rather than RCM uncertainty. Section 2.2.3 examines the methods which have been employed to explore uncertainty in the model projections of climate change.

2.2.3 Handling model uncertainties

Uncertainty can be separated into two broad categories; epistemic and aleatoric uncertainty. Aleatoric uncertainty arises due to "natural, unpredictable variation in the performance of the system under study" and epistemic uncertainty results from "a lack of knowledge about the behaviour of the system that is conceptually resolvable" (Daneshkhah (2004)). Climate change prediction has to cope with both types of uncertainty and considerable effort has been focussed on trying to reduce epistemic uncertainty by improving the ability of climate models to represent the climate system.

In order to provide model output to inform policy, Stainforth et al. (2007a) describes three distinct sources of uncertainty which must be considered: (1) forcing uncertainty from forcings considered external to the climate system; (2) IC uncertainty relating to the initialisation of a model run/ensemble; and (3) model imperfection resulting from insufficient and incomplete understanding and limited capability to model the climate system. Stainforth et al. (2007a) separates the third source of uncertainty into two types; (i) model uncertainty (or parametric uncertainty) describing the uncertainty about what parameter values and parameterisations to include; and (ii) model inadequacy (or structural uncertainty) which refers to the fact that no set of parameter values, parameterisation schemes and ICs would create a model which is "isomorphic" to the real system. Whilst a number of studies have stressed the need to consider IC uncertainty in long-term climate projections (Pielke (1998), Palmer (1999), Collins (2002), Giorgi (2005)), climate modelling experiments have tended to ignore IC uncertainty on longer time scales in favour of exploring forcing uncertainty and model imperfections (Meehl et al. (2007b)).

In a systematic attempt to explore model uncertainty, Murphy et al. (2004) created a 53 member PPE of the HadAM3 model coupled to a mixed-layer ocean to estimate a probability density function (PDF) for the climate sensitivity. Having identified 29 key parameters controlling sub-grid scale atmospheric and surface processes, the parameters were perturbed one at a time relative to the standard version of the GCM (Pope et al. (2000)). In a more comprehensive exploration of model parametric uncertainty, Stainforth et al. (2005) performed the first multi-thousand-member grand ensemble of GCM simulations, again using the HadAM3 model coupled to a mixed-layer ocean. The PPE utilised distributed computing technology available from the 'climate*prediction*.net' experiment (Allen (1999), Stainforth et al. (2002)). The results presented in the Stainforth et al. (2005) study show the range in climate sensitivity from an ensemble of 2,017 distinct independent simulations[3] in which just six parameters were varied. More recent experiments using the climate*prediction*.net infrastructure have included even larger PPEs (Knight et al. (2007)). A number of other studies have focussed on the potential application of PPEs in understanding and projecting climate change (Annan et al. (2005), Barnett et al. (2006), Knutti et al. (2006), Niehörster et al. (2006), Rougier et al. (2009)).

The Stainforth et al. (2005) approach does not attempt to provide an objective PDF of the climate sensitivity because of a "lack of an observational constraint combined with the sensitivity of the results to the way in which paramaters are perturbed". However, the Murphy et al. (2004) study introduced a Climate Prediction Index (CPI) to weight model runs according to their ability to represent "present-day climate variables". The effect of weighting increased the median from 2.9°C to 3.5°C and altered the 5-95% range from 1.9-5.3°C to 2.4-5.4°C. Allen et al. (2002) are critical of likelihood-weighted PPEs because observations "are almost certainly used twice, first in determining the perturbations made to the inputs and second in conditioning the ensemble". Piani et al. (2005) explain that by allowing the parameters to vary in the Murphy et al. (2004) study, the ensemble members are less well tuned to observations but the authors also note that the Murphy et al. (2004) results were sensitive to the ensemble design strategy, therefore preventing the output of objective probabilities.

Given the inability of any individual climate model to be isomorphic with the climate system, many studies have taken a multi-model approach to address structural model uncertainty (Palmer et al. (2004), Tebaldi et al. (2005), Tebaldi and Knutti (2007)). Tebaldi and Knutti (2007) state that the multi-model approach is required to fully explore model uncertainty in addition to a PPE, which explores uncertainty within a single model. The Coupled Model Intercomparison Project (CMIP) was first introduced by the World Climate Research Programme (WCRP)[4] in 1995 as a framework to allow scientists to analyse the results from atmosphere-ocean general circulation models (AOGCMs) from modelling centres across the world in a systematic fashion (PCMDI (2011). The initial phases of the project involved performing model runs for a set of consistent idealised experiments to explore current climate (CMIP-1) and simulations of climate change when subject to a 1% increase in CO_2 each year

[3]The analysis used 2,578 simulation but some were duplicates used to verify the model design.

[4]More details available at http://www.wcrp-climate.org/

(CMIP-2) (Meehl et al. (2000a)). CMIP-3 provided a more comprehensive analysis with a number of more 'realistic' scenarios developed to feed directly into the AR4 process (Meehl et al. (2007a)). In assessing the reliability of the CMIP-3 ensemble, Annan and Hargreaves (2010) state that the ensemble appears "fairly reliable when tested against recent observations" while the spread in results tends to be "over-broad". The authors advance the use of probabilistic interpretation based on the ensemble, a topic covered further in section 2.2.5. Knutti et al. (2010) analyse the use of multi-model ensembles, particularly the CMIP-3 ensemble, arguing that it is unclear how to combine model projections to provide useful output information and that multi-model comparisons often under-represent extreme behaviour. The next set of CMIP experiments[5] (CMIP-5) are now underway to provide multi-model information for the forthcoming IPCC Fifth Assessment Report (AR5).

Collins et al. (2010) compare the approaches of PPE experiments (using the HadCM3 model) with multi-model experiments in an attempt to identify their desirable characteristics to inform future modelling efforts which aim to produce improved probabilistic assessments of climate risk. The study deems the ability to control the design of the ensemble as a key strength of the PPE approach but lists a number of competing constraints which make the design process complicated. Collins et al. (2010) state that multi-model approaches suffer from not being able to represent an adequate sample of all possible models. The authors conclude that the process of model tuning (to observations) might result in an unrealistically narrow spread of future climate change responses. Allen and Ingram (2002) refer to a limited model sample as an 'ensemble of opportunity' and state that the range of uncertainty from such results are likely to underestimate the true range of uncertainty.

A number of studies have concluded that multi-model means provide improved forecast skill on climate time scales (Krishnamurti et al. (2000)), Hagedorn et al. (2005)). In the TAR report, the IPCC used multi-model means as 'best guess' results (IPCC (2001)). However, Du et al. (2011) show that the apparent skill of a multi-model mean is potentially misleading, and the use of route-mean-square error to determine the skill score is contentious. Furthermore, averaging multi-model ensembles can reduce the information content from an individual model. There is a danger in using multi-model means as a 'best-guess' forecast for the future behaviour of the climate system as all models are imperfect and the mean result is not necessarily the most likely outcome. The danger in using multi-model means is illustrated in the Dailey et al. (2009) study that analyses the financial risks of climate change to insurers, in which the authors state, "the multi-model mean suggests a weak shift towards the warm phase of the [ENSO] cycle". In the preceding lines, the authors state, "some models project greater variability of the ENSO cycle in response to global warming, others reduced variability, and others no change at all". The multi-model mean result therefore provides no information about the large uncertainty in the range of responses of ENSO under future warming scenarios.

[5] More details available at http://cmip-pcmdi.llnl.gov/cmip5/

2.2.4 Handling initial condition uncertainty

For the time scales of interest to weather forecasters, it is well acknowledged that uncertainty in the ICs prevents successful long-term weather prediction (Palmer (1993)). In the study of climate change, ICs are sampled to account for internal variability, which is the climate variability not forced by external agents (IPCC (2001)). Yet conventional wisdom in the climate science community is that internal variability, and thus IC uncertainty, becomes less important with lead-time and on the multi-decadal time scale the uncertainty associated with the radiative forcings and model imperfections are the dominant sources of uncertainty (Cox and Stephenson (2007), Hawkins and Sutton (2009)). However, there are a number of studies which challenge this line of reasoning (Lorenz (1976), Pielke and Zeng (1994), Rial (2004)). In an early modelling study using a simple idealised model, Lorenz (1976) shows that small disturbances in ICs can influence long-term variability. The nonlinear interaction between forcing trajectories and modes of internal variability have been examined and Pielke and Zeng (1994) show that long-term variability can be influenced by short-term natural variations in climate forcings. Rial (2004) focuses on abrupt shifts in climate explaining that the shifts are likely to be the result of nonlinear responses impacted by both internal and external forcings.

The tension between the relative contributions of uncertainty arising from imprecise and uncertain boundary conditions, compared to the uncertainty in the initial state of the system, fuels the debate about the extent to which IC uncertainty is important for decadal, multi-decadal and centennial scale climate change. In recent years, considerable attention has been focused on increasing the skill of climate model forecasts on decadal time scales (Collins et al. (2006), Smith et al. (2007), Keenlyside et al. (2008)). In the design of the CMIP-5 experiments, it has been recognised that initialising the ocean component of the coupled models, using observed ocean states, is key to improving the accuracy of model forecasts on a 10-year time scale “when the initial climate state may exert some influence” (Taylor et al. (2009)).

With a longer forecast time horizon, incorporating multi-decadal time scales, Collins and Allen (2002) develop a simple framework to perform a comparison between the two sources of uncertainty. The authors suggest that skilful lead times may be ‘state dependent’ and conclude that “both initial and boundary condition information will need to be considered when designing operational climate forecasting systems in the future” although their analysis was limited to assessing predictive skill on time scales shorter than 50 years. The experimental results presented in the main chapters of this thesis build on the work of those examining the nonlinear interaction of ICs and external climate forcings to further develop hypotheses regarding the role of IC uncertainty in the medium- and long-term prediction of future climate states.

2.2.5 Probabilistic climate model information

Schneider (2001) suggested that in the absence of subjective probabilistic information for specific climate scenarios, decision makers would make implicit assumptions about the probability of a climatic event occurring. Whilst acknowledging the difficulties in providing such probabilistic information, Schneider argued that experts ought to be able to provide more trustworthy estimates than non-experts. Pittock et al. (2001) explains that probabilistic climate information allows decision makers to adopt risk-based climate change adaptation strategies. Over the past decade, methodologies to assign subjective probabilities, to quantities of interest, has driven much of the research conducted by the climate modelling community.

The UK Climate Impacts Project (UKCIP) has recently collaborated with UK Met Office to provide probabilistic projections (UKCP09) for twenty-first century climate change in the UK (Murphy et al. (2009)). The previous UKCIP02 projections simply provided four descriptions of how the climate in the UK may evolve consistent with four emissions scenarios (Hulme et al. (2002)). The lack of computing power, system understanding and availability of alternative RCM results meant that uncertainty was not comprehensively treated in the UKCIP02 projections (Jenkins and Lowe (2003)). Gawith et al. (2009) note that users responded to the projections by calling for better quantification of the likelihood of climate scenarios, including an improved assessment of the associated uncertainties. To address the lack of a formal uncertainty assessment, the UKCP09 projections provided probabilistic information in the form of conditional PDFs, at a 25km grid resolution over the UK, for three emissions scenarios. The projections are subjective probabilities "providing an estimate based on the available information and strength of evidence" (Defra (2009)).

Whilst many of the uncertainties associated with the UKCP09 approach are acknowledged (Defra (2009)), many scientists have been wary of how the model probabilities will be interpreted by non-specialists and caution that highly conditional PDFs may inadvertently lead to bad practice amongst users. Clark and Pulwarty (2003) argue that probabilistic climate projections can mislead decision makers by actually obscuring the real range of futures they face and by appearing to provide a greater degree of certainty about the future than is warranted. In relation to model-based PDFs, Smith et al. (2009) state that it is irrational to base decisions on a model-based PDF when known model inadequacy dominates the PDF. Furthermore, Smith et al. (2009) show that without an assessment of the lead-time over which probabilities can be considered robust, model-based PDFs are uninformative.

Dessai and Hulme (2004) presents a review of the studies for and against probabilistic approaches to climate prediction, demonstrating the existence of a bifurcation in the literature regarding the provision of model information for climate adaptation policy. The authors differentiate between a 'top-down' approach, where the initial focus is on global scales and large-scale drivers of change as inputs to more regional and local scale models (favoured by researchers studying the biophysical effects of climate change in the mid- to long-term), and a 'bottom-up' approach, where the focus is on the coping capacity of vulnerable groups regarding existing economic resources and infrastructure (favoured by scholars concerned with social vulnerability). The alternative approaches lead to different perceptions of the need for probabilistic information to inform decisions. Proponents of the 'top-down' approach tend to favour probabilities and those adopting a 'bottom-up' approach consider the use of probabilistic information to be of limited value. More recently, Hall (2007) questioned the value of probabilistic forecasts stating that the incomplete exploration of uncertainty leads to probabilities highly conditional upon the model runs performed and the statistical method used to compute probability distributions. The author argues that without effectively communicating the limitations in probabilistic approaches, decision makers will not appreciate the ambiguous nature of the information being provided and bad adaptation decisions will be made.

In the context of adaptation decision making, Ranger et al. (2010) argue that continued research to refine probabilistic climate projections is costly and because of irreducible uncertainties the approach is unlikely to yield significant decreases in uncertainty in the short-term. The authors advocate the use of robust decision making in the face of large irreducible uncertainty; a methodological approach advanced by Dessai (2004). Wilby and Dessai (2010) assert that focussing on the adaptation options rather than climate change scenarios may yield significant benefits for the user community. Robust decision making strategies therefore aim to determine low-regret options and reversible measures which are robust to the range of climatic uncertainty. Hallegate (2009) discusses the approach advocating the consideration of 'soft' adaptation measures in addressing climate risk. The approach does not require a formal probabilistic assessment of climate risk and is therefore seen as advantageous for adaptation policy in the midst of considerable climatic uncertainties. Ranger and Garbett-Shiels (2011) outline a number of principles which are consistent with a robust approach to managing uncertainty and state that focussing on long-term adaptive capacity and avoiding inflexible decisions which 'lock in' future climate risk is a central principle in successfully managing uncertainties.

2.3 Use of Climate Information by the Insurance Industry

2.3.1 Climate change risks and insurance

The insurance industry is becoming increasingly susceptible to the risks associated with climate variability and climate change (Lloyd's (2006b)). In the IPCC AR4 report, authors highlighted the role of the insurance sector in providing means to spread losses and encourage adaptation practices, whilst stressing that the industry itself must also adapt to climate change to stay "financially healthy" (Wilbanks et al. (2007)). According to the global auditing company Ernst & Young the most pressing strategic risk facing insurers is climate change, ahead of demographic change, emerging markets and regulatory intervention (Ernst & Young (2008)). Climate change can directly impact insurance risk assessments by altering the nature of the hazards that are covered by insured policies. Hazards such as drought, flooding and windstorms can change in an altered climate by becoming more (or less) frequent or becoming more (or less) intense (Lloyd's (2006b)).

Vaughan and Vaughan (2003) define insurance as "an economic device whereby the individual substitutes a small certain cost (the premium) for a large uncertain financial loss (the contingency insured against) that would exist if it were not for the insurance contract". As stated by Bühlmann (2005), the calculation of insurance premiums is based on the assumption that "a contingent claims experience can be compensated by fixed payments; these fixed payments are known as premiums". Establishing an appropriate premium for an insurance policy requires an evaluation of the expected loss, $E[X] = \mu$ (where X is the loss of a random event), over a given coverage period. μ represents the *pure premium* and a *loading* is also added to provide for administration costs, the costs of holding capital[6] and profit margins (Bowers et al. (1986)). According to Bowers et al. (1986), a loaded premium, denoted by H, can be calculated according to equation 2.1:

$$H = (1 + a)\mu + c \qquad a > 0, c > 0 \tag{2.1}$$

where $a\mu$ represents the expenses that vary with expected losses and c is a constant for expected expenses that do not vary with losses.

At the core of a private insurer's business model is the calculation of the financial risk associated with a given peril. Actuaries assess the risk associated with insured perils to inform specific business lines, helping to design and price insurance products. The pricing process often utilises techniques developed in multiple disciplines, from finance and economics to computer science and statistics. Ultimately, it is insurance underwriters who determine the premium, level of coverage and specify the precise terms and conditions for insurance policies. It is also the responsibility of an underwriter to evaluate the level of risk in the context of other business pressures and issue policies accordingly. Of particular relevance to underwriting activity is the

[6] Insurers must hold a sufficient level of capital to cover payments in the event of a loss and this capital can be held in the form of cash, bonds, investments and other financial instruments.

dynamic state of the insurance market (Winter (1994)); in a "soft market" premiums are low, capital is high and competition is high whilst in a "hard market" (or "tight market") premiums are higher and the capital base is lower, usually as a result of a significant catastrophe affecting the market. While underwriters aim to derive premiums that are appropriate for the level of underlying risk, premiums also reflect business realities such as rules imposed within the regulatory environment. According to Lester (2009), "most classes of insurance are usually delivered through private markets and insurance regulation tends to reflect solvency concerns and information asymmetry between suppliers and policyholders".

Insurance can be divided into life (including pensions) and non-life (or general) insurance. In 2009, global insurance premiums were approximately $4.1 trillion with life insurance accounting for 57% of premiums and non-life insurance accounting for the remaining 43% (TheCityUK (2010)). Climate change undoubtedly has implications for the life insurance sector. Peara and Mills (1999) describe the potential effects on mortality from an increasing frequency and magnitude of natural disasters, heat waves and improved conditions for the spread of vector-borne diseases. The IPCC AR4 Working Group II chapter on health outlines the projected impacts of climate change on mortality, the spread of infectious diseases and other key health related issues such as malnutrition (Confalonieri et al. (2007)). The authors conclude that climate change will "bring some benefits to health, including fewer deaths from cold, although it is expected that these will be outweighed by the negative effects of rising temperatures worldwide, especially in developing countries". Nevertheless, the chapter highlights the complex interaction of other important health determinants (e.g HIV/AIDS) noting that areas in which there is a heavy burden of disease and disability are more likely to be severely impacted by the effects of climate change. Nissan and Williams (2009) state that quantitative assessments of climate risk for the life sector are complex and the associated costs are highly uncertain but the authors urge life insurers to conduct further research to understand the implications of climate change for their sector. However, the available literature and the apparent concern of insurers over the past decade has been predominantly focussed on the impacts of climate change on the non-life sector. With respect to non-life insurance, Maynard (2007) argues that insurers will be hit by a "quadruple whammy" of increased liability, falling asset values, increased capital requirements and potential risks to reputation.

For the purposes of this thesis, the use of the term *vulnerability* refers to the set of socio-economic conditions which determine the ability of people (or an institution) to cope with a stress or change (Allen (2003)). With respect to the insurance industry, insurers can be considered vulnerable to climate change if their business practices are unable to absorb or cope with the altered nature of loss events or return periods of hazards and catastrophes. For climate-related perils Füssel and Klein (2006) define *exposure* as "the nature and degree to which a system is exposed to significant climatic variations". An insurer is therefore exposed to climate change if insured policies are located in regions in which the hazard is expected to be affected by altered climatic conditions. Consequently, the risks faced by insurers are a combination of hazard, vulnerability and exposure. Whilst climate change acts to increase or decrease the hazard component, an increase in either the exposure or vulnerability to climate-related perils will ultimately affect an insurer's profitability.

The industry initially became concerned about increasing losses from weather and climate-related perils following a series of costly loss events in the 1980s and 1990s (Munich Re (2003)). The most costly insured loss event of the last century was Hurricane Andrew in 1992, totaling $15.5 Billion USD in private insurance claims[7]. Following the hurricane, 11 insurance companies with insufficient reserves and/or reinsurance cover went bankrupt (Jametti and von Ungern-Sternberg (2009)). As a consequence, the remaining insurers dramatically increased premiums and there was a surge in interest in the use of catastrophe models to estimate the risk of large losses (mostly from Atlantic land-falling hurricanes). However, in assessing the contribution of climate change to the increase in weather-related losses, studies have suggested that the increased losses were caused primarily by enhanced exposure to hazards from the movement of populations to high-risk coastal and low-lying areas (Changnon et al. (2000)). Berz (1999) states, "there is absolutely no doubt that this increase in losses is due to a large, if not overwhelming, extent to mounting economic values and insured liabilities in heavily exposed metropolitan areas". A recent analysis by Barthel and Neumayer (2012) builds on a previous study (Neumayer and Barthel (2011)) to examine normalised trends of extreme weather and climate related perils, taking into account the increase in wealth accumulation over time. The authors conclude that there is no statistically significant increase in normalised insured losses globally, though they do find positive trends in the US and western Germany. Based on their findings, Barthel and Neumayer (2012) make the bold statement that "climate change neither is nor should be the main concern for the insurance industry". In addition, commentators such as Tol (1998) have argued that the impacts of climate change on hazards is unlikely to greatly affect the profitability of insurers and is more of an issue for policyholders. In any case, insurers are becoming increasingly aware of the possibility for climate change to impact their business lines and at the end of the twentieth century, insurers began to question the use of past data alone to guide the management of climate related risks (White and Etkin (1997)).

Over the course of the first decade of the twenty-first century, the science of global warming has become increasingly well understood (Solomon et al. (2007)) and as a consequence the insurance industry has become evermore engaged with climate scientists and the climate modelling community. Furthermore, the record losses of the 2004/2005 hurricane seasons (Swiss Re (2005), Swiss Re (2006)) prompted insurers to re-assess the contribution of climate change to the underlying risks to which insurers are exposed (Munich Re (2005), Lloyd's (2006a)). Mills (2005) provides an overview of the impacts of climate change on the insurance industry, stating, "virtually all segments of the industry have a degree of vulnerability to the likely impacts of climate change". The author explains how climate change might affect the availability and affordability of insurance and argues that if insurers manage the changing risks appropriately, the adverse impacts of climate change on society will be diminished.

[7]According to data compiled by the Insurance Information Institute from the ISO's Property Claim Services (PCS) unit. Available at http://www.iii.org/media/facts/statsbyissue/catastrophes/#households

Valverde and Andrews (2006) examine the role of uncertainty in the management of climate risk stating that the level of ambiguity and uncertainty associated with climate change "generates considerable anxiety for industry stakeholders". The study adopts an econometric approach to assess the impact of "worst-case" scenario extreme weather events on the insurance industry, concluding that the industry displays a high-level of macro-resilience to severe shocks that may be a more common occurrence under altered climate conditions. Yet the authors acknowledge the significant challenge faced by individual insurers in responding to the possibility of both gradual and abrupt changes in risk as a result of climate change. Ranger and Ward (2010) assert that the largest threat to insurers will likely be in the form of unanticipated changes in weather-related hazards and risks. The authors use the example of increased exposure to hurricane risk in the late twentieth century leading to largely unforeseen losses in the 1990s and 2000s. In reacting to future climate change Ranger and Ward (2010) advocate the incorporation of flexibility in long-term strategies to allow for rising ambiguity in hazards and risks on decadal time scales. Section 2.3.2 examines the ways in which the industry has responded to climate change highlighting the different initiatives and approaches to manage future climate risk.

2.3.2 Insurer responses

Mills (2007) provides a comprehensive list of the ways in which insurers can and are reacting to the threat of climate change. The review outlines a large number of examples where insurers are actively engaged in addressing the risks posed by climate change, including the promotion of risk management strategies, the development of new insurance products and sustainable, climate-sensitive investments (e.g. Dlugolecki and Lafeld (2005), AXA (2006), CEA (2007)). The majority of insurance initiatives highlighted focus on GHG emissions reductions but Mills (2007) does mention the role of insurance regulation in maintaining solvency and comments on recent efforts to include climate change in catastrophe modelling, discussed further in section 2.3.3.

The ABI (Association of British Insurers) produced a report in 2004 which stated that the part of an insurers' business which will be most directly affected by climate change is underwriting (ABI (2004)). Herweijer et al. (2009) examines the impacts of climate change on underwriting and investment performance highlighting the need for a forward-looking view of risk in assessing underwriting practices. The study also stresses the need for a long-term perspective to address the continued insurability of business lines and the potential dwindling returns on investments which are sensitive to climate change. Ward et al. (2008) suggest financial measures that individual insurers can use to incentivise policyholders to mitigate against climate risks, thereby rewarding the policyholder with lower premiums and decreasing the vulnerability of insurers covering the risk.

ClimateWise has been created as an initiative through which individual insurers and reinsurers can compare and disclose efforts to address climate change within their organisations

(ClimateWise (2011)). The initiative has 40 members[8] globally and each member signs up to a set of six principles committing insurers to action on climate change. The ABI has produced a report to underpin the ClimateWise initiative to address key areas such as changing customer requirements, barriers to implementing new policies and potential opportunities arising in relation to climate change (ABI (2007)).

In enabling policyholders to deal with the emerging threat of climate change, some authors have suggested that multi-year insurance policies ought to be made available. Kunreuther (2008) argues that long-term insurance (LTI) contracts (in the order of 10 to 20 years) will be attractive to policyholders who wish to protect their properties and assets against climate-related risks. Kunreuther (2008) states that LTI contracts "provide [policyholders] with stability and an assurance that their property is protected for as long as they own it". The argument in favour of LTI contracts was later developed by Jaffee et al. (2011) which addressed the interests of insurers. Using an example of a modification to the US National Flood Insurance Program (NFIP) for property cover, the authors state that the reduced administration costs of yearly renewals will offset the additional risk covered by the insurer; in this example, the federal government. Another related option for encouraging long-term protection from catastrophic risk is to link home insurance to mortgages; an option advocated in the study by Kunreuther et al. (2007).

However, Lloyd's (2008) address the possibility of multi-year contracts for properties liable to flooding in coastal locations, stating that the vast uncertainties associated with future climate change mean that offering multiple-year insurance policies would be inappropriate. A study by ABI (2010) highlight a number of potential practical problems with LTI. They comment that pricing would have to be guaranteed for the duration of the contract to be attractive to the consumer. In addition, the availability of reinsurance, the ambiguity in the administration costs, and the uncertainty in future conditions may lead to higher than expected premiums. Nonetheless, they do state that LTI may benefit the insurer in being able to manage larger investments and assert that LTI would incentivise the insurer to invest in adaptation measures to reduce the impact or probability of future loss events. Maynard and Ranger (2010) demonstrate that the high level of capital required to ensure solvency for LTI products would render the approach inappropriate for the non-life insurance market. The authors use a simple example to explore the claims, expenses and investment processes of a multi-year policy versus a single year policy and conclude that due to stakeholder expectations for increasing return on capital over the duration of the policy, premiums are likely to be unaffordable. Given that knowledge of the risk is likely to change over the duration of a policy and coupled with changing regulatory and environmental conditions, the premium estimates presented by Maynard and Ranger (2010) were also deemed to be an underestimate.

In recent years, insurers have become focussed on their role in aiding climate change adaptation in developing countries. IIASA (2008) suggests that "pro-poor" insurance should form part

[8]As of August 2010 - see http://www.climatewise.org.uk/member-signatories/

of the UN post-Kyoto international negotiations. Mills (2004) explains that insurance can act as an adaptation strategy augmenting international aid and improving the capacity of affected communities to cope with the impacts of natural disasters. The author also highlights the role of micro-insurance in developing markets. A form of micro-insurance that has received a considerable amount of attention in the past few years is index-based weather insurance, where a meteorological threshold is used to trigger payouts. Skees et al. (1999) examines the role of index-base insurance for agricultural applications in developing countries asserting that the lower administration costs of index-insurance make the insurance more affordable to farmers. The use of index insurance has been advocated as a potential soft form of climate change adaptation (UNDESA (2007)). Carriquiry and Osgood (2008) explore the potential of utilising seasonal climate forecasts in pricing. However, the use of climate model information to assess medium- to long-term insurance viability has not been thoroughly examined. The use of climate information in the emerging index insurance sector is explored in detail in Part B of chapter six.

Throughout the industry, there has been limited formal consideration of climate model output in the day-to-day decisions made by insurers regarding climate-related risks. Mills (2005) attributes this to disjointed modelling traditions, with insurance models being past-focused and climate models being future-focussed. However, one sector within the insurance industry, catastrophe modelling, is becoming increasingly involved in the direct use of climate models and this activity is described further in section in section 2.3.3.

2.3.3 Catastrophe modelling

An area of insurance activity which has recently forged strong links with the climate modelling community is catastrophe modelling. Insurers, and more notably reinsurers, rely on the output of catastrophe modelling companies to assess exposure in regions of the world which have a relatively high-risk of experiencing large losses from major natural and human-caused disasters (Grossi et al. (2005)). The current use of climate model output in the insurance industry is largely confined to the catastrophe modelling sector, where analysis is focussed on extreme hazards, such as land-falling Atlantic Hurricanes, in developed regions of the world.

There are currently three major commercial catastrophe modelling companies: Applied Insurance Research (AIR) Worldwide, EQECAT and Risk Management Solutions (RMS). In 2006, following the damaging hurricane season of 2005, each company updated their models to account for increased hurricane intensity in response to increased SSTs (Seo and Mahul (2009)). As discussed by Strachan (2007a), there are two aspects of climate-related catastrophes that insurers are concerned about; changes in exposure and changes in extremes. Whilst climate model results cannot inform insurers regarding the changes to exposure, they are being used to inform on the future frequency and magnitude of extremes. Strachan (2007a) notes that the modelling of catastrophe risk under altered climatic conditions often relies on the use of stochastic models, based on historical records of losses and meteorological variables. In developing dynamical approaches, Strachan et al. (2010) used the HiGEM, high resolution, coupled AOGCM to output a 200 year time-series of dynamically created tropical cyclones in the Atlantic. The data was used to create an event-set as an input for the analysis of hurricane risk in catastrophe models. The 200 year period was chosen to account for the influence of internal climate variability on the strength and frequency of Atlantic hurricanes. Vitolo et al. (2010) extended the study to generate a stochastic event-set for tropical cyclone risk in the West Pacific.

The use of dynamic climate model data as input to the catastrophe models has only recently gained momentum. A recent report by the ABI, in collaboration with AIR and the UK Met Office, examined the implications of 2°C, 4°C and 6°C change in global mean temperature for inland flooding in Great Britain (Dailey et al. (2009)). The research assessed the insured losses associated with the 1 in 100 and 1 in 200 year return periods for flood events across regions of the UK, in addition to UK windstorm risk and Chinese Typhoon risk. The approach used scenario-based model information from a 17 member PPE of the HadCM3 model (Murphy et al. (2004)) and an 11 member PPE from the Hadley Centre regional model, HadRM3. The report provides a number of quantified projections for the changes to losses and premiums for the scenarios investigated.

Despite recent progress in aligning climate modelling and catastrophe modelling techniques, there is considerable uncertainty in the future impacts of climate change on extreme perils. Studies estimating the economic consequences of climate change for catastrophic risks are therefore largely reliant on scenario-based analyses which are highly conditional on model assumptions.

2.4 Experimenting with Simple Models

In attempting to use complex climate models to guide insurance decisions, it is important to understand their ability to represent the nonlinear dynamic nature of the climate system. Gaining a conceptual understanding of multi-million dimensional numerical models is challenging so simple analogous models are used in this thesis to develop hypotheses and explore the dynamics of chaotic nonlinear systems. As stated in chapter 1, the aim is to inform the design of climate model experiments to explore the full range of climate change uncertainties and provide relevant information for adaptation decisions.

Chapters three, four and five utilise two relatively simple models developed by Edward Lorenz (Lorenz (1963) and Lorenz (1984)) and a simplified ocean model developed by Henry Stommel (Stommel (1961)) to draw analogies to the climate system. Simple models such as those developed by Lorenz have been used extensively in the nonlinear dynamics community, partly due to their low computational demands, but also as the relative simplicity of low-dimensional models allows for a rigorous exploration of the system dynamics. Simple models also enable users to gain an appreciation for model intricacies and dependencies which can be difficult to ascertain in more complex models. The results presented in this thesis provide new insights based on original experiments investigating the behaviour of the model *climates* for time-varying (non-autonomous) parameters.

2.4.1 Lorenz-63 model

The Lorenz-63 model (hereafter L63) has been used extensively over the past half-century to draw analogies to complex systems which display nonlinear chaotic behaviour. Despite it's low dimensionality, the model contains non-trivial dynamics (Lorenz (1963)). In relation to the existence of "intermittency", Manneville and Pomeau (1979) suggested that, sixteen years after its introduction, the model had yet to be well understood. Many scientists have studied the system because certain regions of parameter space lead to interesting and insightful behaviour. Yorke and Yorke (1979) explore the existence of *metastable* chaos and note that below a certain threshold value in a particular model parameter, ρ, trajectories evolve towards stable states (fixed-points) but they exhibit chaotic behaviour for a period of time before "decaying" towards a fixed point. For values of ρ close to the threshold value, the authors show that the chaotic behaviour persists for longer. The transient chaotic behaviour was also observed to be dependent on the ICs.

In relation to weather and climate prediction, there have been attempts to relate the chaotic behaviour of the L63 model to numerical weather prediction and climate models. According to Palmer (1993):

> "While the Lorenz equations do not correspond directly to large-scale atmospheric equations of motion, there are striking qualitative similarities with the behaviour of

> the large-scale atmosphere, notably the existence of regime structure, distinct time scales and variations in local predictability estimates around the Lorenz attractor."

Using the results of the experiments with the L63 model (and adapted versions of the model), Palmer (1993) was able to gain insight into the best ways to perturb ICs to create informative ensemble prediction methods for use in extended-range weather forecasts. The author also comments on the relevance of studying such systems for guiding the experimental design of climate time scale predictions; a topic that is central to the work presented in this thesis. However the L63 model has not just been used to explore error growth related to uncertain ICs and Chu (1999) uses the model to show that the impact of uncertain boundary conditions (uncertainty of the second kind) is of a comparable magnitude to that of ICs. The study advocates increased attention in preparing accurate boundary conditions for numerical weather prediction.

The rich dynamics of the L63 model is still being explored and Chekroun et al. (2010b) reveals the "amazing complexity" of the Lorenz-63 model when being driven with stochastic perturbations to the forcing parameters. Focusing on the topology of the system Chekroun et al. (2010b) attempt to combine stochasticity with the ergodic theory of dynamical systems to outline the relevance of 'random attractors' in the study of climate variability. Whilst there is clearly a tension in improving models of a physical deterministic system by including stochastic processes, a paradox noted by Palmer and Williams (2009), many climate scientists are supporting such a move because of the desire to provide improved predictions of climate change with limited computing capabilities (Lin and Neelin (2003), Teixeira and Carolyn (2008) and Yano et al. (2008)). In relation to the discussion on ergodicity provided in section 2.1.4, Ito (1984) demonstrates analytically that the L63 model is ergodic for any value of ρ. This result will be explored numerically in chapter three of this thesis and the relevance of the ergodicity of the L63 will be examined in the context of the climate system under climate change.

2.4.2 Lorenz-84 model

Similarly, the Lorenz-84 model (hereafter L84) has been used extensively to draw analogies to the climate system. Lorenz claims that the model "may serve principally in examining existing hypotheses and formulating new ones" (Lorenz (1984)). Roebber (1995) comment that quantitative information from studies using the Lorenz-84 model should be viewed in a fairly general way but such investigations have an important role to play in understanding the dynamics of the ocean-atmosphere system. Under certain parameter combinations, the model demonstrates the presence of intransitive behaviour; the existence of more than one long-term climate. A study by Freire et al. (2008) reveals the foliated structure of the model's basins of attraction and suggests that "the final climate scenario (attractor) crucially depends on subtle and minute tuning of parameters".

In using the L84 model to investigate climate predictability, some authors have introduced a seasonal cycle in the model parameters; a seasonal cycle is also explored in this thesis and the initial model results are displayed in section 4.4. Lorenz (1990) analyses the model when subject to a seasonal cycle in the model parameter F (the equator-to-pole temperature difference) to show how chaotic behaviour in one of the seasons can lead to interannual variability in the model variables. Pielke and Zeng (1994) also used the model to investigate the hypothesis that short periodic variations can lead to long-term variability. The authors use the results to support a hypothesis that the combined effect of periodic variations (such as seasonal forcing variations) and the complex nonlinear interactions that occur in the climate system can lead to long-term variability. Investigations into the dynamics of the seasonally driven L84 model were also carried out by Broer et al. (2002) and Broer et al. (2003) to outline the routes to chaos for different parameter combinations and illustrate the associated attractors.

2.4.3 Stommel ocean-box model

The Stommel ocean-box model (hereafter S61) was first introduced by Henry Stommel in his 1961 paper examining the dynamics of the thermohaline circulation (THC) (Stommel (1961)). The dynamics of this highly simplified ocean model have been explored in great detail since its inception. Lohmann and Scheider (1998) provide a comprehensive analysis of the model dynamics, illustrating the phase diagrams associated with the model parameter space and linking the model to long-term climate variability. Like the Lorenz models, the S61 model is still actively being utilised in research projects to understand the dynamics of the climate system. A study by Prange et al. (2002) has analysed the S61 model response in relation to more complex AOGCMs to help develop hypotheses and test underlying theory.

In this thesis, the S61 model is not studied in isolation but is coupled to the L84 model to create a (highly idealised) atmosphere-ocean climate model. The method of coupling is provided in the analysis by Van Veen et al. (2001). The combination of two models allows for a closer analogy to the complex climate system which is subject to internal variability acting on multiple time scales.