Chapter 7

Discussion

7.1 Introduction

> **"We perceive the world, both as theoreticians and as citizens of the universe, according to our experiences and expectations, not always, perhaps even never, according to how the world actually is."**
>
> *Daniel Everett: Don't Sleep, There are Snakes (2008)*

Our expectations of weather and climate in the future are conditioned on what we perceive to be both plausible and likely given our experiences of weather and climate in the past. Daniel Everett's supposition of human perception in the discipline of linguistics is therefore applicable to the field of climate modelling. In using models to predict future climate change, scientists are attempting to predict the future evolution of the climate system, based on limited knowledge of how the climate has responded in the past and information on how the system evolves in computer simulations under current and future forcing conditions.

Given the societal relevance of climate science, it is vital that climate model experiments are designed appropriately to provide credible, robust and relevant information for the decision-making community. The work presented in this thesis has been focused on addressing the needs of the user community and particularly the insurance industry by exploring what climate model information is relevant and useful given the chaotic, nonlinear and highly complex nature of the climate system. In this final chapter, the themes of the research are discussed with reference to the analysis presented in the core chapters of this thesis. In section 7.2, the definition of climate under climate change is re-examined in light of the experiments conducted with the L63, L84 and LS84 models. Section 7.3 highlights the value of these experiments for gaining insight into the predictability of the climate system. The relevance of exploring transitivity in simple models to inform understanding of the behaviour of the climate system is discussed in section 7.4. The design of IC ensemble experiments, advocated throughout the thesis, is outlined in section 7.5. Section 7.6 discusses the links between the core thesis chapters, outlining the implications of the research for the insurance industry. The limitations and difficulties experienced while conducting research are discussed in section 7.7. Section 7.8 details possible future research areas. Finally, section 7.9 reconsiders the thesis aims and presents final conclusions based on the experimental evidence and the analysis of the results.

7.2 Defining Climate Under Climate Change

7.2.1 The concept of climate

The climate system is deterministic (von Storch and Zwiers (1999)) so given a perfect model and perfect initial observations of the system, one would be able to produce an entirely accurate prediction of the system's evolution. Of course we are not fortunate enough to know the exact state of the system and we do not (and never will) possess a perfect model. Numerical models of the climate system are therefore inherently limited in their predictive capabilities. Over time scales longer than a few weeks, knowledge of *typical* atmospheric and oceanic conditions are therefore relevant to society and the notion of *climate* becomes a useful concept.

7.2.2 Competing definitions for climate

One of the recurring themes that has shaped the experiments presented in the preceding chapters, is the notion of climate under climate change. Defining climate is necessary to form an understanding of climate change, yet the definition of climate remains contested and has led to confusion in both the public and scientific discourse surrounding global warming and climate change. As discussed in section 2.1.1, there are broadly two classes of definition for the term climate. Firstly, *temporal* definitions have been widely adopted where climate is defined as a set of statistical quantities that can be derived from the evolution of the atmosphere (as well as other sub-systems) over a period of time (e.g Dymnikov and Gritsoun (2001), Burroughs (2003)). Secondly, *nonlinear dynamical* definitions exist where climate is expressed as a distribution of physical states consistent with the underlying boundary and forcing conditions, as dictated by the composition of the atmosphere and ocean as well as the radiative properties acting on the atmosphere-ocean system (e.g. Fraedrich (1986), Smith (2002)).

When using a temporal definition of climate, it is challenging to disentangle internally produced climate variability from externally driven climatic changes. Modes of short-term internal variability (such as ENSO) and longer-term variability (such as the AMO) have to be taken into account when deciding the length of time over which to define climate. Whilst all modes of variability are intrinsically related to the dynamic motions in the atmosphere-ocean system, we may wish to define some of the longer term modes, such as the glacial-interglacial cycle, as climatic changes. The statistics of climate will inevitably be influenced by sampling length; even in the absence of changes in the external forcings on the climate, climate change between two periods is inevitable.

It is argued here that the nonlinear dynamical definition of climate as a distribution of system states is more appropriate for climate change adaptation purposes. The definition utilises the concept of a climate attractor, or pseudo-attractor, which is useful in generating a thorough conceptual understanding of what climate is for a nonlinear dynamic system. Furthermore, investigating how changes in the system forcings affect the geometry of the attractor (pseudo-attractor) can provide a basis for understanding what constitutes climate change.

7.2.3 Climate as a distribution

To clarify what is meant by climate defined as a distribution, it is important to note that the word *distribution* has (at least) three different uses within climate science discourse. Firstly, climate is spatially distributed as different regions on Earth experience different climatic conditions. The Köppen, or Köppen-Geiger, climate classification map (and variations thereof) illustrates the spatial distribution of classified climate-types across the world (Wilcock (1968))[1]. The spatial distribution of climate model output, and observational data, is commonly communicated using colour-coded maps. For example, figure 7.1 shows the spatial distribution of mean air temperature over Europe in winter and summer, using data from the Climatic Research Unit (CRU) CL 2.0 data bank (New et al. (2002)) at a horizontal resolution of 10' lat/long (approximately 18 km × 18 km at the equator). The graphics are compiled using observed temperature data for the period 1961 to 1990.

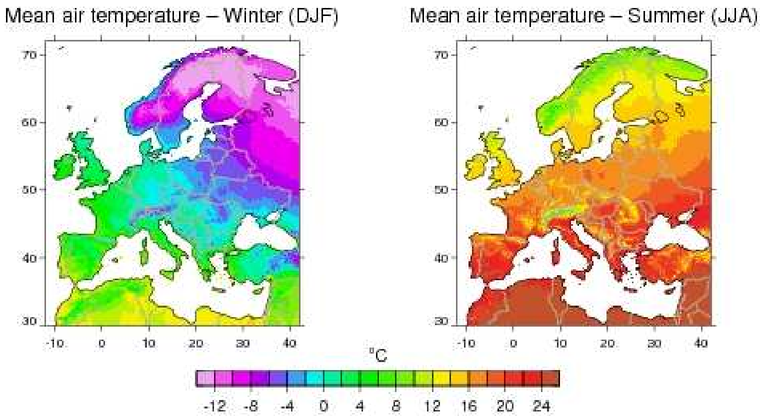

Figure 7.1: CRU CL 2.0 mean observed climate for Europe and N. Africa (1961 - 1990). Reproduced from CRU Ecochange climate data website: available at http://www.cru.uea.ac.uk/projects /ecochange/climatedata/desc.

The word *distribution* is also commonly used within the climate science community to refer to a multi-model or perturbed parameter ensemble (PPE) distribution. A PPE is simply a special case of the multi-model ensemble where each PPE member can be thought of as a different model version with the same underlying model structure. The use of multi-model ensembles and PPEs was discussed in more detail in section 2.2.3. Figure 7.2 shows the distribution of climate sensitivity from the PPE used in the climate*prediction*.net experiment (Stainforth et al. (2005)). The frequency distribution illustrates a range of model results and provides a quantified uncertainty assessment of the climate sensitivity within a single GCM (HadCM3), subject to substantial assumptions, particularly regarding parameter space sampling. The

[1]A recent version of the map by Kottek et al. (2006) presents an updated spatial distribution of climate-types to account for climatic conditions in the latter half of the twentieth century.

spatial distribution of climate will be different in each model version so for each PPE member, it would be possible to determine alternative versions of the plots shown in figure 7.1.

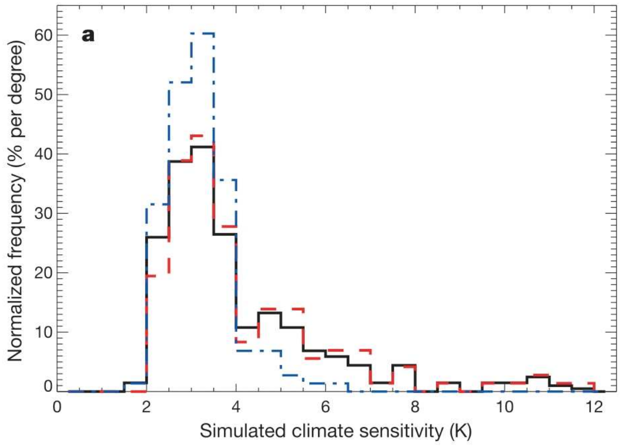

Figure 7.2: Frequency distribution of simulated climate sensitivity using all model versions (black), all model versions except those with perturbations to the cloud-to-rain conversion threshold (red), and all model versions except those with perturbations to the entrainment coefficient (blue). Reproduced from Stainforth et al. (2005).

The final use of the word *distribution* is that used in the nonlinear dynamical definition of climate. This form of the word is central to the proposed definition of climate suitable for climate change adaptation applications (highlighted in the conclusions in section 7.9.1) and is utilised in previous chapters in relation to the simple model experiments. In this context, climate is the distribution of states consistent with the system's forcings, conditioned on the uncertainty in the initial state of the climate system. The conditioning on the initial state of the system is crucial as not all states consistent with the system's attractor(s) or pseudo-attractor(s) will be possible given long-term variability and IC memory. The distribution of states is therefore intrinsically related to internal climate variability. An example IC ensemble distribution, shown in figure 7.3, is a reproduction of figure 3.5(a) and shows the distribution of states, as projected onto the X variable, for the L63 attractor with conventional parameters. In climate modelling, an IC ensemble is necessary to generate a frequency distribution of the form shown in figure 7.3, for some variable of interest under transient changes in the climate forcings; if the forcing isn't changing and the system is not intransitive, then a sufficiently long control run will suffice (see discussion in section 7.4). It follows that each PPE member used to generate the plot in figure 7.2 can be run with an associated IC ensemble to reveal the frequency distributions of climate variables at a given spatial resolution.

7.2.4 Determining climate variable distributions

In analysing historical climates and projecting future climates, scientists often use time series data to estimate the climate distributions for variables of interest. In order to illustrate the spatial inhomogeneity of mean temperatures across Europe and north Africa, shown in figure 7.1,

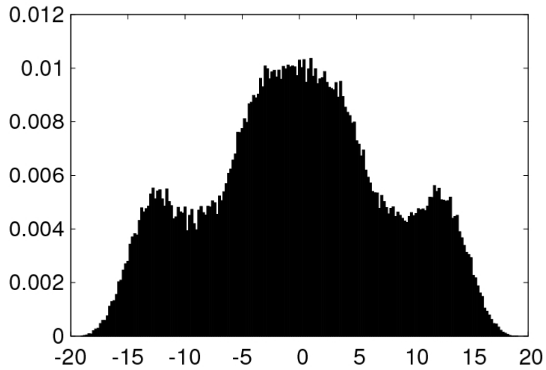

Figure 7.3: Normalised frequency distribution for the X variables in the L63 model, from a 100,000 member IC ensemble with ICs spread evenly along a transect from $(X_l, Y_l, Z_l) = (-20, -25, 1)$ to $(X_h, Y_h, Z_h) = (20, 25, 40)$ after a simulation period of 1,000 LTUs. The y-axis corresponds to the frequency of ensemble members per occupied bin; bin width = 0.2. (Reproduced from figure 3.5(a))

the mean of observed temperatures over the 1961 to 1990 interval were extracted and plotted. One could also use the thirty years of data to plot the distribution of observed temperatures for each grid-box as a set of frequency distribution plots. Crucially, the forcings on the climate system in 1990 were different to the forcings in 1961. In the PMS, an IC ensemble forced with 1961 conditions is therefore likely to yield different model PDFs compared to an IC ensemble forced with 1990 conditions. Furthermore, one would not expect the temperature in the year 1975 (the mid-point of the time series) to have a 50% probability of exceeding the median value from the 1961 to 1990 period, unless one assumes that the climate changed linearly between 1961 and 1990; a highly questionable assumption given known nonlinearities in the climate system. In a non-stationary climate the use of temporally averaged data can therefore be misleading.

In reality there is no perfect model with which to estimate the actual climate variable distributions for past years using large IC ensemble simulations. It is therefore inevitable that scientists and analysts use observational time series data to determine the statistics of climate in the past. In predicting future climate distributions however, it is important to find ways to extract useful information from imperfect models. Consequently, estimating and understanding the reliability of imperfect model projections is crucial.

In order to assess the reliability of climate models, modellers have traditionally opted to compare model realisations against observations (Annan and Hargreaves (2010)). Knutti (2008) states, "If the model and data do not agree, the scientist should be worried (assuming the model was designed to reproduce the data), because it implies that the model (or the data) is in error". However, this notion is potentially misleading. Owing to the complexity of the climate system, the presence of various modes of internal variability, and the possibility of almost intransitive behaviour, the observed trajectory of climate may exhibit long-term dependence on the initial state of the system. In order to have confidence in a particular model (over a specified time scale) it is only necessary that one IC ensemble member, from a sufficiently large model ensemble simulation, tracks or "shadows" the observations (Gilmour (1998), Judd et al. (2004)). Disqualifying or down-weighting a climate model based on the ability of a limited sample of single model trajectories to reproduce observed data is flawed. Whilst observations are crucial for model development and process understanding, successfully reproducing an observed time series from a limited IC ensemble size is not a necessary condition in determining model reliability.

In the context of climate change adaptation, climate is best defined as a distribution and comparing distributions from different climate models is a way to establish confidence in model projections. The use of climate distribution statistics to evaluate model reliability is common in climate science but evaluations are typically reliant on the problematic, and often implicit, ergodic assumption (e.g. Perkins et al. (2007)). Boer (2000) and later Räisänen (2007) comment that model evaluation ought to be based on comparisons with real world data, presenting three broad categories for comparison. Räisänen (2007) states, "the first is morphology of climate as given by the spatial distribution and structure of means, variances, covariances and possibly other statistics of basic climate parameters." In practice this means assuming ergodicity and determining statistical measures from time series data. Moreover, comparisons are limited to specific properties of the distributions such as means and variances rather than the full distribution. The distributions of the L63, L84 and LS84 models show that nonlinear chaotic systems are often associated with irregular variable distributions so statistical properties which assume Gaussian distributions are limited. In the next section, further insights from the exploration of these models are identified.

7.3 Insights from Simple Models

The experiments conducted on the L63, L84 and LS84 models have been central to the development of the thesis conclusions. In this section, the specific insights gained from using each model are presented.

7.3.1 L63 model

The much studied L63 model has been a valuable tool in developing hypotheses relating to the predictability of the atmosphere. It is therefore a natural starting point to address the research theme of climate predictability under climate change. In section 3.3.1, the climate of the autonomous L63 model is defined as the distribution of states across all model variables consistent with the model attractor for fixed parameter values. A change in climate is therefore observed when the geometric properties of the model attractor change in response to a perturbation in one (or more) of the model parameters. The climate distributions of the L63 model (estimated using a 100,000 member IC ensemble in section 3.5) are governed by the values of the parameters, ρ, β and σ. For conventional parameter values, IC ensemble distributions are shown to converge to the model climate distributions over a time scale of approximately 50 LTUs, irrespective of the original location of the ensemble in model state space. This is illustrated in figure 3.10 using the KS test. The relatively short-lived memory of ICs in the L63 model is related to the transitive nature of the model.

For fixed parameters it is shown that the L63 model is ergodic; the single trajectory distributions converge to the IC ensemble distributions illustrated in figure 3.5. The time scale for convergence for the single model realisation selected is approximately 150 LTUs. The ergodic assumption is therefore valid in estimating the climate of the L63 model and computationally more efficient than the IC ensemble method (for fixed parameters). Ergodicity is observed because the model is transitive and a single trajectory is able to visit all regions of the attractor. In the absence of parameter changes, and assuming the climate system is a transitive system, the results support the conceptual model of viewing trajectories which orbit the attractor as "weather" (noise), whilst viewing the climate as the statistical properties of the fixed attractor determined from a single trajectory or an IC ensemble distribution.

Understanding the L63 climate under climate change requires an exploration of the model under altered parameter conditions. Sections 3.5 to 3.8 focus on the impact of varying the model parameter ρ. Considered as an analogy to the GHG forcing, periodic and nonperiodic fluctuations in ρ are introduced into the L63 model. Figure 3.12 shows how periodic fluctuations in ρ, varying on a time scale comparable to the time scale for regime orbits, influence the IC ensemble distributions. The altered distributions occur as a result of the changing geometry of the model attractor. The dependence on the frequency of the periodicity in ρ suggests evidence of resonant model behaviour. Yet even in the presence of resonance the model continues to be ergodic as described in section 3.6.1.

Experiments with nonperiodic fluctuations in ρ reveal evidence of hysteresis in the L63 model as the IC ensemble distributions are dependent on the pathway of the parameter ρ. The ergodic assumption fails when the model is subject to fluctuating frequencies in ρ which induce model resonance because the ensemble distributions are path-dependent as well as time-dependent. IC ensembles are therefore required to determine the model PDFs at particular time instants. Interestingly, figure 3.22 shows that the IC ensembles from different locations on the pseudo-attractor[2] converge to the climate distributions of the model when subject to nonperiodic fluctuations in ρ. This result is useful as it tells us that even if the ergodic assumption is no longer valid, transitive behaviour of the model ensures that the memory of IC uncertainty is finite. Furthermore, the convergence of ensembles to the model climate distributions is more rapid under nonperiodic parameter changes, as shown in section 3.7.5.

If the climate system were subject to resonance induced by a nonperiodic fluctuating forcing, then the results shown in this chapter would have far-reaching implications for the way climate model experiments are designed to explore uncertainty. When predicting future climate changes with a unique set of forcings that has not existed throughout Earths history (Dessai and Hulme (2004)), it would be unwise to rule out the potential impact of fluctuating radiative forcing frequencies on the global climate system simply because the relevant results presented in chapter three are confined to a low-dimensional model. Further experiments on more complex climate models would yield additional insights to inform the possibility of observing this phenomena in the real climate system.

Perhaps of more immediate interest to climate modellers is the path dependence, or hysteresis, exhibited in the model ensemble distributions for nonperiodic fluctuations in ρ. The implication for the climate system is that climate variable distributions might be dependent on the pathway of a particular forcing scenario. In the context of twenty-first century anthropogenic climate change, the resulting hypothesis is that the response of the climate system is not only dependent on the cumulative build-up of GHG concentrations (Allen et al. (2009)) but also on the *pathway* of the build-up in GHG concentrations. The hypothesis is consistent with the Epstein and McCarthy (2004) study which postulates that the stability of the climate system is a function of the system's forcings. In relating the impact of GHG concentrations to the variability and stability of the climate system, Epstein and McCarthy (2004) state:

> "Stabilization of CO_2 at 450 or 550 ppm may possibly avoid some critical adverse thresholds; but, there is no assurance that the rate of change of greenhouse gas build-up in the interim will not force the system to oscillate erratically and yield significant and punishing surprises, or even force the system to jump into another equilibrium state."

Running large IC ensembles with multiple forcing scenarios in a number of climate models would help address both the hypothesis regarding climate system hysteresis and the stability of

[2]The term pseudo-attractor is introduced in chapter four.

climate for different rates of GHG build-up.

The definition of an attractor as a region in state space to which trajectories evolve loses its precise meaning when the properties of the attractor become time-dependent. The introduction of the term pseudo-attractor in chapter four is an attempt to be consistent with nonlinear dynamics theory in developing an understanding of the climate for non-autonomous systems. In any case, the notion of an attractor and the associated geometric properties that denote the climate of the system has value in creating a conceptual model of the nonlinear chaotic climate system under climate change.

The main message that emerges from the work conducted on the L63 model is that large IC ensemble experiments are likely to be a vital ingredient in aiding understanding of the dynamic behaviour associated the climate system under climate change. Using the L84 and LS84 models, further experiments were conducted to refine this message and gain additional insight into potential future areas of focus.

7.3.2 L84 model

Employing a definition of climate as a distribution consistent with the system's attractor has its limitations; not least because of the potential coexistence of multiple attractors. The main advantage of analysing the behaviour of the L84 model in addition to the L63 model, is that large regions of parameter space have more than one coexisting attractor (Lorenz (1984), Freire et al. (2008)). Given the complex interactions in the climate system, and the fact that the system is constantly adjusting to time-dependent forcings, it is difficult to assess the existence of multiple coexisting attractors. However, as described in section 4.6.1, Budyko (1969) explains that the present configuration of continents and oceans could support two climatic regimes. In addition, observed abrupt shifts in climate over the past millennia suggest that the climate system consists of multiple equilibria (Schneider (2004)), which suggests the possibility of coexisting attractors.

Utilising the definitions of summer and winter, adapted in the Lorenz (1990) study, the model climate distributions are determined in section 4.3.2. For experiments in the permanent summer configuration, in which more than one attractor coexist, the ergodic assumption is shown to be invalid (see section 4.3.3). The two periodic attractors identified for the summer configuration of the L84 model are associated with intransitive behaviour. Figure 4.6 displays the basins of attraction for the X-Y plane illustrating the foliated nature of the basins dictating the evolution of model trajectories from different ICs. For an initial state with uncertainty that spans the basins of attraction, the attractor to which the model trajectory evolves is also uncertain.

The climate of the L84 model is investigated with a seasonal cycle in which F (equator-to-pole temperature difference) varies as a sinusoid with a wavelength equal to one model year. The ergodic assumption is tested for mid-winter and mid-summer where F returns to $F = 8$ and $F = 6$ respectively. Figure 4.22 shows the time scale at which single trajectory distributions converge towards the ensemble climate distributions. The ergodic assumption is shown to be valid over a simulation period of many thousands of model years. The long simulation period is necessary because only one data point is selected each year at mid-winter and mid-summer. Including more data points, from the months of January and July, in the single trajectory distributions to speed up the convergence time is shown to be problematic (see section 4.4.4). In this case, the single trajectory distributions do not entirely converge towards the ensemble distributions. Including data points from the model under different parameter conditions distorts the single trajectory distributions. In the analogy to the climate system, the result suggests that in estimating a climate distribution at a specific time instant, inclusion of data points that are associated with alternative forcing and/or boundary conditions could potentially lead to the creation of misrepresentative PDFs.

The L84 model is also used to explore transient climate change (see section 4.5). The value of F is decreased over time in a transition to more summer-like conditions as an analogy to a possible future climate and the ergodic assumption is again investigated. Despite a linear change in F_m, the changes in the geometric properties of the climate distributions are not smooth over time and the ergodic assumption is shown to be invalid. Additionally, the memory of ICs is investigated in the transient phase between two fixed climates. The results presented in section 4.5.3 show multi-decadal memory exists as model trajectories propagate according to the unstable pseudo-attractor (PA2) before transitioning to the stable pseudo-attractor (PA1). The rate at which trajectories transition to PA1 reveals an exponential-like decay function, illustrated in figure 4.33. The results suggest that under transient climatic conditions, the memory of the system can be affected.

7.3.3 LS84 model

In the L84 model, the climate change analogy considers a transition from a transitive region of parameter space to an intransitive region of parameter space. To extend the analogy, the LS84 model is investigated, in which the L84 model is coupled to the S61 ocean-box model creating almost intransitive dynamic behaviour for certain parameter values.

The extent to which long-term climate change is dependent on the current state of the climate system is an area which divides opinion. Whilst is has become widely acknowledged that initialising the ocean is important for improving the accuracy of decadal forecasts, the impact of IC uncertainty on multi-decadal and longer time scales is largely ignored in the climate modelling community. Experiments with the LS84 model are therefore driven by an interest in system IC memory. With the addition of an ocean component the interaction of two sub-systems evolving with different time scales is investigated. The goal is to generate further insight into the interactions between nonlinear chaotic behaviour and long-term internal variability.

The coupling of the L84 model and the S61 model is based on the study by Van Veen et al. (2001). Two sets of coupling parameters, referred to as "active" and "passive", are explored and figure 5.2 illustrates the behaviour of the ocean variables T and S, associated with the different coupling parameters. The terms *active* and *passive*, coined by Van Veen et al. (2001), lose their literal meanings when subject to a seasonal cycle in F_0 but for continuity with the Van Veen et al. (2001) study, the terms continue to be used in the analysis presented in chapter five. Under passive coupling parameters, the model exhibits two distinct regimes referred to as the LT and HT regimes. Figure 5.4(b) shows the centennial scale variability in the T and S variables. In T the transitions are abrupt and the residence time in each regime lasts from tens to hundreds of years. The long residence times in each regime convey almost intransitive behaviour which is of particular interest in the analogy to climate under climate change. The figure also shows the resemblance between T and f, denoting the strength of the THC, highlighting that the model is temperature driven under the parameter conditions chosen.

Section 5.2.5 explains the logic for focussing analysis on the ocean variables. In the LS84 model, the phase of the ocean is a major controlling factor in the annual variability in the atmosphere. By analogy to the climate system, large-scale oscillations in the oceans, such as the South Pacific and the North Atlantic, can dominate the atmospheric circulation in many regions across the world. The analysis of model memory and ergodicity is therefore presented for the ocean variables but the results extend to the long-term predictability of the atmosphere.

The ensemble climate distributions and ergodicity of the seasonally driven LS84 model are determined in section 5.3. The results show that a model simulation of thousands of years is required to demonstrate the convergence of single trajectory distributions. The convergence is slower under passive coupling because of the long residence periods spent in each regime. Figure 5.11 illustrates the convergence of single trajectory distributions to the model "climate" distributions (estimated from a 100,000 member ensemble) showing that the model is in fact ergodic under both forms of coupling but very long simulations (thousands of years) are needed before the single trajectory distributions converge to the ensemble climate distributions. Furthermore, the convergence is not smooth and over some periods, particularly under passive coupling, increasing the simulation length for a single trajectory might not improve the estimates of the underlying climate distributions. The results suggest that almost intransitivity limits the use of the ergodic assumption. Even under fixed parameter conditions (albeit with a seasonal cycle in F_0) a large IC ensemble is more appropriate in estimating the climate distributions.

The size of IC ensembles required to accurately estimate model PDFs is investigated in section 5.4. A simple experiment is devised to determine the proportion of ensemble members in each regime as a function of ensemble size. The results indicate that an ensemble size of 2,000 to 4,000 members is necessary to provide robust probability estimates regarding the probability of a transition between the two specified regimes. To improve tail estimates, more ensemble members may be required but the result highlights a minimum IC ensemble size requirement to provide robust estimates of some climate variable distribution properties. It would be interesting to pursue this result further by extending the experiment to higher-order climate models.

The experiment is also inverted to provide a measure of the IC memory in the LS84 model under passive coupling. The IC ensemble distributions are found to be dependent on ICs for a period of up to 200 model years. In section 5.5, the memory of the ensemble distributions is further investigated for ensembles originating in different regimes. The results show that the initial values of T are more important than those of S in determining the convergence rates between ensembles. Crucially, the findings suggest that IC uncertainty limits predictability more significantly when the variables have an important role in the dynamic evolution of the system.

Finally, the LS84 model under passive coupling is used to investigate climate change in the LS84 model by introducing a linear trend in F_0. The model is forced from a region of parameter space associated with transitive behaviour, where $F_m = 8$, to the previously identified almost intransitive region of parameter space, where $F_m = 7$. Three single model realisations with slightly different ICs are shown which expose differences in the evolution of the T variable over the 2,000 year simulation period. In the original parameter configuration, the internal variability exhibited by the model trajectories is similar. After a linear decrease in F_0, two of the trajectories, labelled *IC 1* and *IC 2*, show relatively frequent transitions between the LT and HT regimes whilst the trajectory labelled *IC 3* spends more time in the LT regime (see figure 5.20). The KS test is used to quantify the differences between single trajectory distributions under the initial transitive climate and in the altered climate associated with almost intransitive behaviour. The results imply that skill in the ability of a single model realisation to capture the statistics of climate should not necessarily lead to confidence in the ability of a single trajectory to provide reliable estimates of the climate variable distributions under altered parameter conditions. In the next section, the issue of the transitivity of the climate system and the implications for climate prediction are discussed in greater detail.

7.4 The Transitivity Debate

The extent to which the climate system can be considered transitive under current and altered forcing conditions underlies much of the research presented in this thesis. Lorenz (1990) reasons that the “atmosphere-ocean-earth system” is unlikely to be intransitive. The conclusion was based on experiments with the seasonally driven L84 model (explored in chapter four) in which the winter evolution is chaotic and a single attractor exists whilst in the summer the model behaviour is periodic and multiple attractors coexist. The presence of chaos in the winter ultimately yields transitive model behaviour as the attractor to which a trajectory propagates in the succeeding summer is a “virtually randomly chosen circulation pattern”. However, the L84 model was only investigated in a stationary mode and with periodic changes to F. The real climate system is non-stationary and includes modes of variability on all time scales. The research presented in chapter five shows that when the L84 model (representing the rapidly evolving atmosphere) is coupled to the S61 model (representing the slowly evolving ocean component) the evolution of the atmosphere in the summer parameter configuration is no longer “randomly” chosen as the probability of an *active* or *inactive* summer is affected by the underlying state of the ocean (see section 5.2.5). This dependence on the slowly evolving ocean means that statistics of the atmosphere taken over *long* finite periods, in which the ocean is displaying one type of behaviour, will be different from the infinite-term statistics; a property referred to as almost intransitivity (Lorenz (1968)). The conclusion of Lorenz (1990) that the climate system is unlikely to be intransitive does not rule out the possibility of almost intransitive behaviour and the model results shown in chapter five reveal the presence of this behaviour in an idealised coupled atmosphere-ocean model.

Considering the possibility of almost intransitivity in the climate system raises important questions for how climate is defined and how GCMs are run to explore climate under climate change. In section 2.1.4, the work of Schneider and Dickinson (2000) is discussed. Schneider and Dickinson (2000) state that because the climate system may not be transitive, a time-averaged definition of climate is more appropriate than a definition which includes all states consistent with the forcing and boundary conditions. The implied logic behind this assertion is that in studying past climates, it is more useful to analyse the observed behaviour of the system rather than speculate about theoretically possible states that haven’t been experienced. Whilst this reasoning may be appropriate for specific analyses of the past *observed* behaviour of the climate system, applying the same reasoning to advocate a temporal definition of climate when considering future climate change adaptation is flawed.

Under transient climate change, even if the climate system is transitive not all possible system states will be realised as the climate distributions change in time with the underlying modulations to the system attractor/pseudo-attractor(s), in response to the altered forcings. In the PMS, a sufficiently large IC ensemble will elucidate the range of possible states for a particular forcing scenario. The additional possibility of almost intransitive system behaviour means that conditioning the IC ensemble on the current uncertainty in the initial state is crucial.

For an almost intransitive system, the range of possible future states will be constrained as certain states, which may be consistent with the underlying boundary and forcing conditions, may not necessarily be possible given constrained IC uncertainty. Moreover, the time-mean climate for each IC ensemble member trajectory is likely to be different over a finite interval given almost intransitive behaviour yet the distribution of future states (for a specific forcing scenario) will represent the full range of uncertainty conditioned on uncertainty in the initial state. It is this distribution of states which is relevant to climate change adaptation. The most suitable definition of climate under climate change is therefore the distribution of states consistent with the system's forcings, *conditioned* on the uncertainty in the initial state of the system.

For altered system behaviour under climate change, not only might we expect a shift in variable distributions (changes in the mean statistics) but also significant changes in the shape of the distributions such as altered modal properties. Observing these changes in climate model simulations using single model trajectories is problematic. In the *climate change* experiments conducted with the LS84 model the results show that a shift from transitive to almost intransitive conditions can have significant impacts on the model dynamics. Single model realisations are unable to fully represent the model climate distributions associated with the different dynamic regimes.

In relation to climate change adaptation decisions, particularly within the insurance industry, establishing reliable probability estimates for possible future climate states is the ultimate objective. In order to meet this challenge, the evidence provided in the model results shows that incorporating IC uncertainty into the design of climate model experiments is a critical ingredient. Given the possibility for almost intransitive behaviour, resulting from the interaction of subsystems operating on different dynamic time scales, it is also vitally important to condition IC ensembles on the current uncertainty in the initial state of the climate system.

7.5 IC Ensembles in Climate Model Experiments

Climate model output is used to estimate changes in climate variable statistics at a number of prediction lead times. Using past observations (e.g. 1961 to 1990), time series data is often multiplied by a change factor derived from the mean statistics of individual model projections. This transformation is being done, albeit with crude adjustments for changes in variability, to provide guidance to certain sectors that are interested in climate change adaptation (e.g. the construction sector, Belcher et al. (2005), CIBSE (2006)). However, if the future variability of climate is subject to nonlinear changes, such that the shape and range of the distribution of climate variables are altered, then a transformation reliant solely on past observations is inappropriate. Utilising large IC model ensembles would be preferable to avoid crude assumptions in guiding climate change adaptation.

The experimental results from the study of the L63, L84 and LS84 models suggest that large IC ensemble simulations will benefit climate prediction, and remove reliance on the ergodic assumption. Adopting this approach will ultimately have value for decision makers wishing to be robust to climate uncertainties, for at least four reasons. Firstly, even in the absence of changes in external forcings conditions (such as the GHG forcing and solar forcing) the climate system is subject to a number of modes of internal variability on spatial and temporal scales of interest for climate change adaptation. As a consequence, even armed with a perfect model, single model trajectory frequency distributions could fail to converge to the system climate distributions over a relevant time scale. Secondly, if the climate system contains multiple coexisting attractors or pseudo-attractors, then a single trajectory will not capture the range of possible futures consistent with the ICs, if indeed the IC uncertainty spans more than one basin of attraction. Thirdly, because all climate models are imperfect, IC ensemble distributions from different models subjected to the same boundary and forcing conditions could reveal discrepancies between the model climates. Finally, abrupt changes in the model climate, in response to altered/transient forcing conditions, will be more easily observed in IC ensemble results as the climate change signal can be distinguished from internal variability exhibited by an individual model realisation.

Listed below are a number of steps, guided by the results obtained using simple models, which need to be considered in designing IC ensemble experiments to produce climate variable distributions relevant for climate change adaptation applications:

- Establish the extent of observational uncertainty in the initial state of the atmosphere, ocean and other subsystems included in the climate model.
- Determine the necessary IC ensemble size required to generate robust quantitative information for the variables of interest.
- Select models, model versions (from a PPE) and forcing scenarios to be explored.

- Choose an appropriate sampling methodology for each variable in the IC ensemble[3] (e.g. Monte Carlo techniques).
- Test the sensitivity of model climate distributions to IC selection/sampling method for a sub-sample of the model versions being investigated by examining the rate of convergence between the distributions.

An inevitable criticism of advocating large IC ensemble experiments with AOGCMs is that IC ensemble simulations will increase computational costs and be time-consuming. For each step listed, the modelling resource required is indeed potentially very significant. Scientifically, this argument is irrelevant but on a practical level such a consideration needs to be addressed. There are methods that can cope with increasing ensemble size requirements. The use of distributed computing, utilised by Stainforth et al. (2005), is a vast resource that has the capacity to run large numbers of individual model realisations. In addition, the emergence of cloud computing offers a potentially valuable avenue for running large ensembles with coupled AOGCMs (Evangelinos and Hill (2008), Vecchiola et al. (2009)). Ultimately, compromises will need to be made between achieving an appropriate level of model complexity and spatial resolution whilst preserving the ability to sample uncertainty. However, in providing quantitative information to decision makers, under-sampling of (IC) uncertainty risks undermining the value and trust placed in the provision of climate model information. The choices and compromises climate scientists make in designing climate model experiments will benefit from knowledge of how users understand and interpret the model output.

In order for quantitative information from climate model output to be considered robust across models, the information should be insensitive to model choice. Comparing IC ensembles for multiple *imperfect* models may show that information regarding certain variables of interest is highly dependent on the model used and the parameters chosen. Therefore, the value of model information for influencing decisions may come from the range of possible behaviour across multiple models and PPEs. Model output can be useful in bounding uncertainty and providing a range of future climate states, at a number of spatial and temporal scales, within which adaptation decisions can be assessed. In the absence of robust information from climate models, confident statements about future climate will be more qualitative than quantitative (Stainforth et al. (2007a).

[3] A detailed discussion of sampling methods for ensemble forecasting in relation to numerical weather prediction is given by Leutbecher and Palmer (2008).

7.6 Implications for Insurance

7.6.1 Informing insurance strategy

In a strategic analysis of insurance activity, Ernst & Young (2008) identified an "over-reliance on model-based risk management" as a major threat to the insurance industry, given the inability of various modelling approaches to deal with extreme volatility. In relation to climate change, the lack of formal uptake of climate model information within the industry means that the threat of an over-reliance on climate model output is small at present. However, in the future as insurers work more closely with climate scientists and climate modellers, it is important to avoid the situation where insurers become reliant on climate model projections which are not fit for purpose. Ignoring the issues of model inadequacy and directly using highly conditional climate model output in pricing and strategic decision making could exacerbate the risks faced by insurers.

In section 6.2, ten strategic insurance issues are identified which are likely to be affected by climate variability and climate change. Figure 6.1 illustrates the time scales over which climate model information may be useful in guiding general (non-life) insurance decisions. Whilst the majority of business practices within the insurance and reinsurance sectors are typically dictated by short time scale considerations (with a lead time of up to one year), section 6.2.3 explains how climate information can be relevant for strategic planning on time scales of greater than five years. The impacts of climate change on issues such as *risks to reputation* and *liability* may be viewed as largely negative for the insurance industry but the impact of climate change on other strategic considerations such as *emerging markets* and *investments* present significant opportunities for insurers. If insurers are proactive in utilising climate model information and can form strategies which are robust to climatic uncertainties, the industry can become resilient and aid society in adapting to the impacts of climate change.

7.6.2 What climate model information is relevant?

Stainforth et al. (2007a) state that climate change adaptation decisions are sensitive to more than just the mean of the distribution. This assertion is particularly relevant to the insurance industry which exists primarily to mitigate extreme risk associated with tail events. Risk-based pricing requires knowledge of return periods and recurrence probabilities that are typically estimated using available meteorological observations and loss datasets. In a non-stationary climate, insurers cannot rely on probability estimates derived purely from past observations. In addition, nonlinearities in the climate system and abrupt transitions between climatic regimes mean that assuming ergodicity to estimate climate variable distributions from single model realisations in the future is inappropriate.

Insurance decisions are typically made at regional and local scales so high resolution information from climate models appears desirable. In addition, climate models currently operate with parameterisation schemes at subgrid-scales and moving to higher resolution models might enable some subgrid-scale processes to be better resolved. It would therefore appear that developing higher resolution models would be beneficial to both scientists wishing to understand the behaviour of the climate system and in providing valuable information to insurers. The arguments articulated in relation to experimental design do not refute the value of high resolution models in climate science. Used in a research mode, high resolution models have the potential to generate useful insights to increase scientific understanding of key climate processes. However, high resolution models require additional computational capacity and the number of possible model runs is decreased. The ability to run large IC ensembles would be diminished and the problems associated with relying on single model realisations to project future climate change would remain. Therefore, extending the use of high resolution model information into the public domain could be hazardous. Precise information in the absence of an adequate uncertainty analysis is both scientifically naive and potentially misleading for the user community.

It is valuable to make a distinction between need and desire. The needs of insurers represents the minimum information required from climate projections to justify any changes to policy structures, strategies and/or premium prices. The desires of insurers relate to information that would enable insurers to make robust, accurate and timely adjustments to climate-related policies and business lines. The desire for ever higher resolution information is likely to remain because insurers are often interested in assessing risk at high resolutions, particularly in areas with major concentrations of exposure as noted by Ranger et al. (2009). However, the needs of insurers are diverse and it is likely that climate model output cannot satisfy the needs of all insurers interested in adapting policy and strategy in the face of climate change. This does not mean that coarse scale climate model information is irrelevant but it suggests that quantitative output from climate models cannot be directly used in all areas of the insurance industry.

Qualitative information from climate model projections can be valuable in the absence of robust quantitative information. Inherently, climate prediction under climate change is conditional on assumptions about GHG emissions and changes to other system forcings (such as solar and volcanic influences). Quantitative output from climate models is therefore scenario dependent. For strategic insurance decisions, knowledge about the possible and plausible impacts of climate change is potentially of more value than highly conditional "best" estimates. Ultimately, for insurers to remain solvent and ensure resilience to climate change, awareness of the capacity of climate model projections to explore uncertainty is beneficial. If climate model experiments are to be useful in providing information to guide strategic, and perhaps operational insurance decisions, it is important that all sources of uncertainty, including IC uncertainty, are appropriately acknowledged in the design of ensemble based experiments.

7.6.3 Insights from case study

One sub-sector of insurance that could directly benefit from the appropriate use and interpretation of climate model output is the burgeoning index insurance sector. The case study presented in chapter six, sections 6.3 to 6.6, demonstrates the use of climate model information in determining the pricing and viability of index insurance for crop cover in India, under climate change. The focus on index weather insurance allows the socio-economic considerations affecting insurance losses to be side-stepped as payouts are triggered according to meteorological proxy measurements. The case study highlights the interest of insurers in thresholds and threshold exceedance probabilities. In the design of index insurance products, estimates of exceedance probabilities are currently based on the observational record assuming both stationarity and ergodicity in the climate system. The dangers of assuming stationarity are well acknowledged by insurers and scientists alike (Wunsch (1999), Dlugolecki (2008)). However, as discussed throughout this thesis, under climate variability and climate change the ergodic assumption can be misleading; this assumption is however rarely stated in the use of climate information to inform policy.

In designing index insurance products, insurers need to account for imperfect and incomplete climate information whilst dealing with significant uncertainty and ambiguity. The climate model information from the regional HadRM3 model runs are only available in the form of single model realisations. Inevitably, the user community if forced to assume ergodicity in using the information to estimate exceedance probabilities. The case study also shows how reliance on only one source of information (i.e. one model) can create false confidence and potentially lead to maladaptation. The output of the HadRM3 model is strongly dependent on the driving data. The figures presented in section 6.6 illustrate the differences in the model output when driven by the HadCM3 model, the ECHAM5 model and the ERA-interim reanalysis data. When the data is ingested into the BN, the viability of the index insurance design is shown to be highly sensitive to model choice, as described in section 6.6.2. Introducing bias corrections, as described in section 6.6.3, is problematic and requires careful consideration regarding the physical interpretation of bias corrected model data. Diagnosing the reasons for the differences in the model output is of course a challenging task and not something that the user community is likely to be able to accomplish alone. Therefore insurers and the adaptation community more generally are likely to benefit from making decisions that are insensitive to model choice. Robust decisions are therefore likely to be associated with low-regret options, such as diversifying portfolios, but the risk appetite of different insurers is variable and certain companies may accept less robust policy options.

The strength of BNs to support climate change decision problems is also discussed in relation to the case study. In section 6.6.5, it is noted that the BN tool is useful not only to provide quantitative decision support but also to reveal node and state dependencies which have a large impact on the decision outcome. The tool aims to be transparent and enables users to see the effects of node choices on the probabilities throughout the network. However, the BN approach is limited and despite aiming to be exhaustive, the decision tool requires quantitative input for all variables, either in the form of continuous data or subjective probabilistic choices, which may not always be possible and/or appropriate. A more detailed discussion of the value of BNs and the success and limitation of the case study is provided in section 6.7. In communicating climate model information to users, BNs provide a useful framework enabling diverse information sources to be combined while tailoring information to a specific decision problem. Nonetheless, a variety of tools and approaches are likely to be needed to address the different types of decisions being made by insurers wishing to utilise climate model output.

7.6.4 The balance of quantitative versus qualitative information

Climate models are not only used in an operational setting to provide climate information to policy-makers but can also be valuable tools with which to test hypotheses and develop understanding of the complex interactions of particular physical processes in the climate system. The distinction between a model which is being used to advance research and a model which is being used to inform societal decision-making is crucial. Currently, climate modelling centres appear to be creating ever more complex climate models in an attempt to become user-relevant. A recent study by Pope et al. (2007) begins with the statement:

> "Useful climate predictions depend on having the most comprehensive and accurate available models of the climate system."

However, as noted by Pope et al. (2007), in order to create a comprehensive climate model compromises must be struck between model complexity, model resolution and the ability of the model to deal with uncertainty. A climate model prediction for adaptation decisions in general, and insurance decisions in particular, requires a comprehensive assessment of uncertainty if it is to be deemed "useful". Ultimately, it is the uncertainty rather than the best estimate, that really drives decisions related to climate variability and climate change. This is especially true in the insurance industry where uncertainty is intrinsically related to risk.

It is crucial to be able to communicate the uncertainty arising from climate model experiments and develop a modelling framework to allow for further exploration of key uncertainties. The notion that relatively low resolution model output is irrelevant for policy making is misinformed as the scales at which many insurance decisions are made can often deal with coarse resolutions. Insurance and reinsurance decisions are applied at a variety of spatial scales, and examining the uncertainty more thoroughly at coarser scales can be of use to the industry. In focussing model experiments on the exploration of uncertainty, it is of course possible to increase the uncertainty associated with climate projections. Pidgeon and Fischhoff (2011) argue that climate modellers need to confront such an apparent contradiction and find ways to carefully explain the results of more rigorous experiments to decision makers and the public. Given the existence of known unknowns in climate model experiments, finding the appropriate balance between quantified results and qualitative guidance to decision makers is therefore of utmost importance.

7.7 Limitations and Difficulties Experienced

7.7.1 Modelling by analogy

The models used in this thesis are highly idealised representations of physical systems. All models used to inform us about the evolution of the climate system are imperfect but only high-dimensional GCMs and AOGCMs can claim to be sufficiently complex to replicate the dynamic behaviour of the climate system. That said, the increased complexity and computational capacity required to run operational climate models prevents comprehensive exploration of model dependencies and makes the interpretation of model results conceptually challenging. There is enormous value in running experiments with simple models where model dependencies and sensitivities can more easily be explored and understood. The results of the model experiments are useful in providing a theoretical grounding to guide the design of GCM and AOGCM experiments to better explore uncertainty. However, the results cannot be expected to scale directly to the climate system and inform projections of future climate change. As noted by Smith (2002), identifying issues in simpler models is a first step in developing testable hypotheses. Yet to test a hypothesis in an operational model, a collaborative effort and an understanding of the intricacies of individual models is required.

7.7.2 The challenge of interdisciplinary research

In any field of applied science, trade-offs must inevitably be made between achieving a depth of research and enabling the findings to be translated into meaningful results for users. In relation to applied climate change research, it has long been acknowledged that studies confined to single disciplines cannot appropriately address the needs of those who have to consider a multitude of factors in the decision making process (Schneider (1977)). By examining both the role of nonlinear dynamics in climate prediction and the adaptation decisions needs of insurers, the research presented attempts to bridge climate science with the policy considerations of the insurance industry. However, as evident in the limitations of using climate model output to inform index insurance decisions, the results show that there is a significant disconnect between the information desired by insurers and the capabilities of modelling groups.

The added complexity of a policy dimension to the research places the work in the realm of post-normal science (PNS). Funtowicz and Ravetz (1993) describes PNS as "inquiries that occur at the interfaces of science and policy where uncertainties and value-loadings are critical". Clearly, this description is befitting to the work presented in this thesis and it is hoped that the implications of the research have relevance to both a scientific readership and those involved in making policy decisions sensitive to climate change.

7.7.3 Engaging with insurers

As stated in section 1.6, a key aim of the research is to determine the extent to which climate model output can be utilised by insurers. Within the industry, decisions are taken at a variety of organisational levels and risk calculations are often aggregated across entire portfolios. It is therefore challenging to illuminate the channels by which climate model information can directly influence decisions, with the possible exception of catastrophe modelling. Climate change, as a *problem* to be managed, is embedded within many other issues faced by insurers. The decision process is therefore dilute and the potential use of climate model information in guiding insurance decisions is unlikely to be similar for different insurers and different insurance sub-sectors.

In designing climate model experiments to be more relevant to insurers and reinsurers, one of the key obstacles facing the both scientists and the insurance industry is finding ways to improve communication channels. The relatively recent initiatives such as ClimateWise[4], the Willis Research Network[5] and the Munich Re Climate Change Initiative[6] are likely to play a central role in steering the future of applied climate research and the provision of climate information, at least within Europe. For the global insurance industry, the creation of climate services at different national modelling centres is likely to provide opportunities for further collaboration between insurers and scientists.

[4]http://www.climatewise.org.uk
[5]http://www.willisresearchnetwork.com
[6]http://www.climate-insurance.org

7.8 Further Research

7.8.1 Abrupt climate change and feedbacks

In the climate system, changes in the system's forcings are rarely, if ever, linear. Pulse emissions from volcanoes or feedback mechanisms, such as methane release in permafrost regions and ocean sediments, can and have disrupted the climate system over relatively short time scales (e.g. MacDonald (1990)). With respect to anthropogenic emissions of GHGs, in a palaeoclimate context at least, the increase in concentrations over the past one hundred years can be likened to an abrupt shift in the system's forcing. In developing the analogy to the climate system, it would be useful to extend analysis to consider rapid and nonlinear trends in the forcing parameters of the L84 and LS84 models. Experiments in the uncoupled L84 model could be performed to establish whether or not the increased memory of the IC location, evident in section 4.5.3 under a smooth linear change in the L84 model forcing, is increased further when subject to abrupt changes in the forcing. Additionally, introducing abrupt shifts in the parameter F in the LS84 model would be useful to investigate the effects of hysteresis in an almost intransitive system.

Further experiments could be conducted to incorporate feedback mechanisms, which are prevalent in the climate system. In the LS84 model, a positive feedback between T and F could be introduced so that as F decreases, the rate of change in T increases disproportionately. In section 5.5.2, it is shown that the convergence of IC ensembles is strongly controlled by the initial value of T under passive coupling; ensembles with similar initial values of T converge more quickly. If under a particular climate change scenario with a positive feedback, IC ensemble distributions from different locations on the original pseudo-attractor converge less rapidly, then the results would strengthen the case for running large IC ensembles conditioned on present IC uncertainty as the memory of the initial ensemble location becomes more important.

7.8.2 The imperfect model scenario

Understanding the role that model inadequacy has in capturing the statistics of climate is an essential component of the climate change prediction problem. The experiments presented have been conducted in the PMS but the issues considered could be further addressed in the imperfect model scenario (IMS). In section 3.9.3, discussion was directed towards the possible extension of the L63 model experiments to consider the IMS. Understanding how the climate distributions are affected under fixed, periodic and nonperiodic variations in ρ for various imperfect L63 models (using approximations to model variables/parameters) would reveal the extent to which model inadequacy limits the ability to capture the climate of the L63 system. As the L63 model demonstrates convergence in transitive regions of parameter space, it would be relatively straight-forward to compare the rate and extent of convergence for different imperfect L63 model climate distributions to the actual L63 climate distributions estimated in figure 3.5. Determining the time scales over which imperfect models continue to contain useful information about the climate of the L63 model would provide an interesting analogy to the inadequate modelling of the climate system.

Similarly, the IMS could also be investigated in the L84 and LS84 models. Exploring the impact of model error on the climate distributions of the model variables could provide additional insight regarding the value of IC ensemble experiments in addition to single model realisations.

7.8.3 Extension to EMICs

Consideration could also be given to the role of IC uncertainty in the dynamic behaviour of Earth System Models of Intermediate Complexity (EMICs, Claussen et al. (2002)). The decreased level of complexity when compared to GCMs affords users the ability to run EMICs numerous times under different scenarios and model assumptions. In a comparison of eight EMICs, Petoukhov et al. (2005) conclude that "EMICs could be successfully employed as a useful and highly efficient, in terms of the running time, tool for the assessment of the long-term surface air temperature, precipitation and sea level changes, under a variety of future and past climate scenarios". For particular model variables of interest, the ergodic assumption could therefore be investigated with EMICs under a number of climate forcing scenarios utilising a large IC ensemble experimental design. In demonstrating the sensitivity of decisions to IC ensemble distributions as opposed to single model trajectory distributions, EMICs could provide a valuable platform to bridge the results from simple models explored here to inform the design of experiments in GCMs.

EMICs are not only used to explore scientific hypotheses but have also been adopted in studies to address societal decision-making. For example, the MAGICC climate model (Wigley and Raper (1992), Hulme et al. (1995)) has been used to study the impact of GHG emissions scenarios on the increase in global temperatures in relation to a number of policy-related questions (Calvin and Thomson (2010), Pielke (2009)). Working with the user community, EMIC IC ensemble experiments could be run to further understand how model uncertainty can best be communicated to guide adaptation policy.

7.8.4 Further engagement with index insurers

The index insurance case study developed in chapter six would benefit from direct collaboration with practitioners in the index insurance sector. There are two research aspects which could be further explored in collaboration with a specific index insurer. Firstly, the value of imperfect climate model output in guiding index insurance pricing decisions and strategic concerns could be investigated with direct input from practitioners using model output within existing decision frameworks. A pilot project in which climate model information was utilised to inform pricing strategy could be established to analyse the impact of such additional information on decisions and to learn how model output might be interpreted in an operational setting. Secondly, the value of the BN tool as a decision aid could be further analysed by working with a specific insurer on a one or more focussed decision problems to highlight the practical benefits and limitations of the tool.

7.9 Conclusions

7.9.1 Addressing the thesis aims

In section 1.6, five key aims are listed in the form of research questions. In this section, the extent to which the thesis has been successful in answering each question is discussed in sequence.

What are the climate model information needs for strategic decision-making within the insurance industry and are the current generation of climate model experiments capable of providing such information?

Ten strategic issues that are likely to be impacted directly or indirectly by climate change are identified in section 6.2.3. The climate model information needs of insurers vary considerably across different business sectors. Decisions usually require estimates of return periods for damaging meteorological events such as tropical and convective storms. Probability exceedance curves are required for the appropriate pricing of insurance policies and in developing strategies to address changing degrees of exposure. Insurers typically rely on observational data despite acknowledging the limitations in the stationarity assumption. It is perceived that climate modellers ought to strive to provide information which can directly substitute for observational data to estimate current and future risk. Many insurers therefore support the efforts of climate modelling centres towards the provision of high spatial resolution climate model information. However, the findings presented in this thesis highlight some problems associated with generating high resolution model data in the absence of a thorough exploration of epistemic and aleatoric uncertainty. Furthermore, insurers have a genuine interest in incorporating the uncertainties in the estimates of exceedance probabilities and return periods into the decision-making process. The insurance industry exists to help individuals and businesses manage financial risk so insurers have both a responsibility and a vested interest in pricing contracts to accurately reflect the underlying uncertainties. This research suggests that large IC ensemble model experiments could improve both the quantification and reliability of climate model uncertainty estimates and remove reliance on the ergodic assumption.

It is clear from analysis of the literature and engagement with insurers that the relationship between climate modellers and the insurance industry is still in its infancy. Developing reliable climate model projections at the multiple temporal and spatial scales of interest for insurers places enormous demands on climate modelling centres to tailor model output and provide information which is both useful and usable by insurers. The increased level of formal engagement between insurers and climate modelling centres (at least in Europe) provides an opportunity to improve the accessibility and communication of model output. However, there is a real danger that in focussing on the provision of model output, climate modelling centres will over-simplify what is a hugely complex and uncertain prediction problem. Climate change projections will, for the foreseeable future, be subject to large uncertainties and communicating the uncertainty is as important, if not more important, than providing model output at a spatial and temporal scale of immediate use to insurers.

How should climate be defined to best address the needs of the climate change adaptation community?

There is no single definition of climate which is universal and can be considered useful for all applications. Both temporal and dynamical systems-based definitions have value in different contexts. However, in providing climate model information to decision makers concerned with robust adaptation to plausible future climate scenarios, the following definition is considered to be the most appropriate:

> Climate is the distribution of states consistent with the system's forcings, conditioned on the uncertainty in the initial state[7] of the system.

There are a number of reasons why this definition is appropriate for climate change adaptation. Firstly, the definition focusses on the possible states consistent with the climate system's forcings. In adapting to climate change it is important to know the range and distribution of states in order to enact robust solutions. By using a temporal definition, the assumption is that the forcing conditions are fixed, or linearly changing, over time which is an incorrect assumption given the known occurrence of nonlinear changes in climate forcings. Secondly, the definition is conditioned on IC uncertainty. Uncertainty in the initial state of the system is inevitable given observational uncertainties and the sparsity of observing networks in certain regions of the world. It is important to try and reduce IC uncertainty but in making adaptation decisions, decision makers need to ensure that policy responses consider the range of future model states consistent with the current level of uncertainty. Finally, the definition is compatible with nonlinear dynamical systems theory. Conceptually, climate variable probability distributions provide a measure of the system's climate for each individual system variable. These distributions can be thought of in relation to the attractor or pseudo-attractor of the climate system. This can aid the interpretation of climate under climate change as it is no longer necessary to consider time series data spanning two sets of forcing conditions.

Is the ergodic assumption valid for a climate system subject to altered forcings?

The use of the ergodic assumption in climate modelling has been challenged using numerical simulations of simple models analogous to the climate system. Three conditions under which the ergodic assumption has been shown to fail are listed below:

1. Hysteresis induced by nonlinear interactions in the presence of nonperiodic fluctuations in system forcings.
2. Coexistence of attractors (or pseudo-attractors) in which the evolution of a system trajectory is dependent on the initial state of the system.
3. Transient climate change where the attractor (or pseudo-attractor) changes nonlinearly in the presence of a trend in the forcings.

[7] where the initial state refers to the values of the system variables at time $t = 0$ in the model forecast simulation

Is the climate dependent on the pathway of the forcing?

The model results shown in chapters three to five come with the inevitable caveat that the models are highly idealised and cannot be directly related to the behaviour of the climate system. Nonetheless, each model exhibits nonlinear chaotic behaviour and displays many of the properties associated with the climate system. Experiments using the L63 model with nonperiodic fluctuations in ρ demonstrate the existence of hysteresis in the climate distributions. In response to time-varying parameters, trajectories evolve according to the changes in the underlying attractor. The IC ensemble distributions reveal the dependence of the model's climate to the pathway of the parameter. In addition, the L84 model distributions show evidence of hysteresis when subject to a seasonal cycle in F. In section 4.4.2, the model climate distributions when F returns to $F = 8$ at the maximum of the sinusoidal variation, are shown to be different to the model climate distributions when F is fixed at $F = 8$. The memory of previous model states affects the climate of the model.

The implication is that for a system as complex as the climate system, the response of the climate attractor/pseudo-attractor is unlikely to be decoupled to the pathway of the system forcings. Evidence of hysteresis in the climate is difficult to observe given only one trajectory of past climate so exploring hysteresis effects with climate models requires large IC ensembles experiments.

How should climate model experiments be designed to explore the full range of climate change uncertainties?

Predicting the range of climate states under transient climate change relies on the intelligent design of modelling experiments. It is argued here that large IC ensembles are required to provide such information from climate models. Whilst the use of large IC ensembles will not guarantee the capacity to provide decision relevant information to the user community, it is a necessary and important step in attempting to bridge the gap between climate model output and user needs.

In section 7.5, a number of steps are presented to guide the development of IC ensemble experiments using complex climate models. It is important to note that accounting for the memory of the initial state in the climate system using IC ensembles is only part of the climate change prediction problem and the uncertainties associated with physical parameterisations, model structural inadequacies and forcing scenario assumptions also require considerable attention. In order to advocate the use of climate models to inform robust decision making and to provide useful quantitative support to the insurance industry, a significant component of computational effort should be devoted to running ensembles with multiple models, multiple model versions (PPEs), many ICs and a number of forcing scenarios. Moreover, it is important that experiments explore uncertainty at the time scales of interest to decision makers. Given the value of uncertainty information to insurance decisions, the spatial scale with which models are run should be largely driven by the ability to explore uncertainty. Without an adequate exploration of uncertainty, high resolution model information is unfit for guiding decisions within the insurance industry and the adaptation community.

7.9.2 Final remarks

In the climate modelling community and the insurance industry, the use of the ergodic assumption is not justified in a changing climate. Relying on single model simulations to assess climate under climate change is therefore misguided and IC ensembles are required to detail the evolution of climate variable distributions over time. Without varying ICs it is not possible to reliably estimate the entire distribution of climate at times of interest within a model simulation. In developing model experiments to inform the user community, it is therefore vital to provide an honest appraisal of how uncertainty has been incorporated in the experimental design.

Uncertainty is the real driver of decisions regarding climate change adaptation, particularly within the insurance industry, and it is important to acknowledge this reality. Given the desire of the insurance sector for increasingly detailed knowledge of climate change impacts to guide decisions, climate modellers need to be wary of providing projections which are highly conditional on implicit assumptions. Addressing all sources of climate uncertainty thoroughly is vital if model projections are to be used wisely in quantitative climate impacts assessments. Acknowledging potential nonlinear interactions between the different sources of uncertainty is critical in improving the relevance of climate model experiments for guiding adaptation decisions. In order for the adaptation community to make sensible decisions in the face of climate change, the climate modelling community needs to provide ensemble-based model projections which are consistent with the definition of climate as a distribution of states conditioned on IC uncertainty. Useful climate predictions do not depend simply on having the most comprehensive and accurate available models of the climate system. Rather, useful climate predictions will incorporate an ensemble design that accounts for the diverse range of climate change uncertainties.