Executive Summary

The climate is changing

There is overwhelming scientific consensus that the climate is changing and that greenhouse gas (GHG) emissions from human (anthropogenic) activities is largely responsible. The expected rate of warming depends on the level of GHG concentrations in the atmosphere but it also depends on the sensitivity of the climate to the changes we make.

Dangerous global average warming of 4 deg C is likely

In the absence of any international agreement on binding GHG emission targets our central assumption is "no action": that means the an average global warming estimate is for an increase of 4 deg C. Such a warming represents dangerous climate change on many different levels.

The impact of the forecast temperature rises on ecological and human systems, including food and water, are likely to be very severe. It also follows that the magnitude and frequency of extreme weather events will increase. In addition, the melting of mountain glaciers, permafrost and ice sheets will contribute to rising sea levels.

Global Climate Models inform adaptation and mitigation strategies

If they are to develop effective adaptation and mitigation strategies it is vitally important for public policymakers and business leaders to understand climate change and the wide range of impacts that could result.

Climate projections are based on sophisticated Global Climate Models (GCMs) that have been refined by scientists over many decades. These numerical models, which run on supercomputers have been used by the Intergovernmental Panel on Climate Change (IPCC) to support its five assessment reports.

Global Climate Models have a good track record at high level predictions

GCMs have accurately predicted the evolution of the climate system in response to rising GHG emissions and they have predicted the timing, magnitude and spatial pattern of certain climate events. GCMs have predicted:

- The nature and magnitude of Arctic amplification, whereby the Arctic has warmed more in relation to the rest of the earth;
- The pattern of warming between the land and oceans;
- The overall timing of global warming and the general magnitude in response to GHG forcing;
- The impact of stochastic events such as volcanic eruptions and the extent of sea level rise.

Recognising uncertainty in Global Climate Model output is important

Despite the clear success of GCMs in providing scientists and policymakers with a detailed understanding of the climate system and its behaviour, there are nevertheless aspects of the climate system that have proved hard to model. As a result, recognising the uncertainties in GCM outputs and projections is crucial if climate-dependent decisions are to be made without regret.

One key uncertainty is GHG forcing, because the future level of GHG emissions and their atmospheric concentrations is unknown. Another key uncertainty stems from model inadequacy, whereby the degree to which models capture all the physical processes which are relevant to the system under study is not known. Earth surface system response is also problematic: scientists don’t yet fully understand how ice sheets behave during periods of warming, for example.

Understanding Global Climate Model output uncertainty is an economic imperative

Because the costs of adapting to climate change are expected to be very large, understanding and living with the uncertainty in climate predictions is essential. Understanding model uncertainty is important for policymakers because it will improve planning for resilience. Understanding model uncertainty is important for risk carriers because it will lead to better regional predictions and improved accuracy across decadal timescales.

Clearly a better understanding of climate model uncertainty will contribute to making better risk management decisions. Uncertainty is not an excuse for inaction.

More historical data will help reduce model uncertainty

Despite the advances being made in reducing uncertainty, a better understanding of the magnitude and frequency relationships of climate related events is needed. Past data sets, most of which are of short duration, are of limited use when reconstructing recurrence intervals and when the climate displays non-stationarity.

The shortage of historical data in flood models, for example, can be addressed by exploiting geological data from floodplain sediments. Similarly, past tropical cyclone activity can be studied by means of geological proxies as well as historical documentary records.

The tools for obtaining useful geosurvey data are available but are not being widely deployed.
Introduction

The fifth Intergovernmental Panel on Climate Change Working Group 1 report (IPCC AR5 2013) was recently published. It shows that the highest Representative Concentration Pathway by 2100, the amount of CO2 in the atmosphere at that time associated with radiative forcing of 8.5 Wm^{-2}, (RCP 8.5), projects global warming of 4°C over pre-industrial temperatures. Current Greenhouse Gas (GHG) emissions and assessment of climate sensitivity mean that this is the present temperature trajectory. Even with strong emissions reduction (RCP 2.6) it is unlikely that a global temperature rise of 2°C can be avoided. As a result, ‘dangerous climate change’ (Smith et al. 2009) will result. Assessing the adaptation strategies which must be employed in the light of this requires modelling the future global climate and the feedbacks associated with warming. Policy-relevant information for adaptation purposes such as local infrastructure planning might also require modelling climate change impacts at small spatial and temporal scales. Understanding the uncertainties associated with climate modelling and likely future advances in this field is therefore of great importance if policymakers are to make meaningful decisions in the light of climate change.

Currently, information about how climate change will impact regional and local scales is needed to support adaptation strategies and as motivation for mitigation efforts. Much of this effort focuses on changes in the climate itself along with research into impacts; the latter is usually interpreted as the effects on Earth Surface Systems (ESS). Climate models are regularly used to inform policy and planning on climate change adaptation. However, Global Climate Models (GCMs) are known to be of limited use in predicting climate change impacts at small scales, and Regional Climate Models (RCMs) have therefore been developed to allow climate projections down to scales as small as 25-50 km (see projects like PRUDENCE (Christensen et al. 2007)) and even down to 10km (Kendon et al. 2012).

Successful climate projections at such small spatial scales which are useful for policymakers and the insurance industry, assume:

(1) that the uncertainties in climate projections are well known and knowable
(2) that the impact of climate change on ESS is predictable at those scales,
(3) that climate model uncertainty and system response uncertainty is fully appreciated by policymakers and end-users.

Here we explore these assumptions, discuss the latest science on the response of ESS to climate change and assess this in the light of adaptation policy.

Climate Models

Climate models are based on fundamental physical laws (e.g., energy, mass, and momentum conservation) and subdivide the Earth surface, oceans and atmosphere into 3D grids. The processes within each grid square are computed and discretised and these form the future integrations.

From the late 1950s attempts to model the global climate originally used General Circulation Models to examine the nature of atmospheric and oceanic circulation. By the 1980s models were relatively simplified, portraying oceans with no currents and fixed atmospheric cloudiness (NAS 2012). Over the past few decades the resolution of the models and the range of physical processes that are now included in the models has increased enormously. In more recent decades Global Climate Models (GCMs) have been developed by a number of modelling teams, and the outputs from these have been used extensively in IPCC reports since 1991. Much effort has also gone into developing the computer resources to run sophisticated climate models, especially as multiple simulations (ensembles) are now routinely run to evaluate model and initial condition uncertainty.

The size of grid squares defines the model resolution, and for the current range of models this is about 1 degree for the ocean and between 1-2 degrees for the atmosphere. The oceans are typically subdivided into 30-60 layers and the atmosphere into 30-40 layers. IPCC AR5 (2013) GCMs have increased their resolution from about 50 to 25km since IPCC AR4 (2007) with Regional Climate Models (RCMs) operating at 10km or better resolution (eg Kendon et al 2012) (FIGURE 1 AND 2).
Climate Models

The resolution of global climate models has improved

1. First IPCC assessment report (1990)
3. Third IPCC report (2001)
Model Types

There are three main types of climate models.

1. **Atmosphere-Ocean General Circulation Models (AOGCMs)**

Developed from earlier GCMs and incorporating more sophisticated modelling treatments of atmosphere and ocean processes, AOGCMs had developed sufficiently by 2007 to become the main climate model in AR4. Despite this, they lacked detailed components concerning biogeochemical cycles, and representations of ice sheet processes.

2. **Earth System Models (ESMs).**

For IPCC AR5 (2013) these now form the current cutting edge in modelling with much better representation of elements of the carbon cycle, which enables the models to better characterise the feedbacks that are expected to develop when the carbon cycle is disrupted by climate change.

3. **Earth-System Models of Intermediate Complexity (EMICs)**

In some instances more focused modelling schemes aim to answer specific scientific questions concerning long term climate change and climate sensitivity, or for developing large model ensembles, and for these projects lower resolution models called EMICs are used. For example LOVECLIM model includes representations of the atmosphere, the ocean and sea ice, the land surface (including vegetation), ice sheets, the icebergs and the carbon cycle (see Goosse et al. 2010).

AOGCMs and ESMs are applied at the largest scales (ie for climate projections at continental, hemispheric or global resolutions). However, adaptation planners, risk managers and other end users of climate services want climate projections at small spatial (and sometimes temporal) scales, and for this various techniques have been used to downscale information from GCMs to regional scales. As a result, Regional Climate Models (RCMs) have been developed to simplify climate processes and to provide detailed information on regional-scale climate change (e.g. Marioti et al. 2011).
Climate Model Uncertainty

Climate modelling has developed enormously in the computational power and resources available, complexity, model resolution and understanding of the physical process driving the climate and associated feedbacks. Climate models can be seen as one of the success stories of modern science, giving us unrivalled insight into the workings of the climate system. Despite this, huge uncertainties in the outputs from GCMs remain and these are discussed here. There are several ways in which to assess model uncertainty, and these are highlighted in work by Stainforth and colleagues (2005, 2007a,b) and by Hawkins and Sutton (2009). Model uncertainty may be classified as: forcing uncertainty; microscopic initial condition (IC) uncertainty; macroscopic initial condition uncertainty; model uncertainty; and model inadequacy (see Stainforth et al. 2007a,b) and are defined further below. These interact with each other at certain times and places and in non-linear ways, and are therefore not independent.

General Issues:

Difference between boundary condition values and initial condition values.

There are many types of uncertainty and several of these relate conceptually to the distinction between so-called boundary value problems and initial value problems. Boundary value problems (for example atmospheric greenhouse gas concentrations) are those which set the parameters driving the evolution of the system. Uncertainties arise when the structural or architectural elements of the system are incompletely specified and the start and end-points of system evolution are difficult to constrain. Initial value problems on the other hand, occur when the evolution of the system is driven by the precise specification of the system. Uncertainty in this evolution concerns the exact disposition of the internal states of the system. The differences between boundary value problems and initial value problems are one of scale and we must recognise that the small-scale dynamics of a system (e.g. weather) may be effectively decoupled from its large-scale average behaviour (e.g. climate).

Specific Issues:

1 Uncertainty associated with model parameterisation. Processes that cannot be explicitly resolved in climate models have to be parameterised. In other words assumptions are made which approximately allow for the process. An insurance analogy might be a loading applied to allow for claims inflation for very large claims (“demand surge”); while this isn’t modelled explicitly in the catastrophe models a loading is applied. In climate modelling parameterisations include those processes that occur at spatial or temporal scales which are too small for the model to resolve, such as those associated with convection, aerosol physics and boundary layers. Other processes also have to be parameterised that occur at broader scales but which are not yet resolved in climate models and these include the operation of large-scale gravity waves (e.g. Geller et al. 2011), large-scale ocean processes (Ferrari et al., 2010), and land surface/boundary layer interactions.

2 Forcing uncertainty relates to uncertainty in current future drivers of the climate system and in the context of current forcings, relates to changes in the emissions of GHG or in their atmospheric concentrations. IPCC AR4 used a set of scenarios (from the Special Report on Emissions Scenarios) which modelled emissions pathways, depending on the ways in which the global economy developed, land use changed etc. Recent IPCC AR5 has used four RCPs which assess the radiative forcing associated with different CO2 atmospheric concentrations in 2100 and these are: RCP 3-PD2; RCP4.5; RCP6 and RCP 8.5. Clearly, significant climate uncertainty derives from not knowing how much CO2 will be emitted and the rate of drawdown (by artificial as well as natural processes). Until binding carbon targets are agreed we should assume no action as our central assumption. On this basis the best estimate temperature by 2100 is around a 4 degrees impact – this is potentially very dangerous.

3 Initial Condition (IC) Uncertainty can be subdivided into those uncertainties associated with macroscopic, and those with microscopic initial conditions. Macroscopic IC uncertainty dominates when the scale of enquiry is macroscopic and where the boundary conditions of the system are not well known. This is less of a problem with current understandings of climate change and its drivers. Some of the uncertainties associated with Microscopic IC are irreducible, associated with the practical and logical limits in measuring all the variables contributing to system behaviour and their variations over the timescales required to produce complete information on the system. This is a problem if the small-scale parts of the climate system display non-linear behaviour AND if this behaviour is magnified at large scales. The first clearly occurs, but it is not known whether the second position holds true. One way in which Microscopic IC uncertainty has been analysed in climatology is by using ensembles of models, each with slightly different initial states. The outcome from this is a Probability Distribution Function (PDF) which displays all the possible model outcomes and these are regularly used as predictive tools for future climate change (see Stainforth et al, 2005). An insurance example might be where a company has exposure data which is uncertain – so the location and construction data could contain errors – if various plausible exposure data sets were run through the model this would give an indication of the sensitivity of the loss distribution to these “initial conditions”.

Much of the small-scale behaviour of a system is likely to be highly non-linear and sensitive to initial conditions, while the broad-scale system may display predictable trajectories. There is therefore a mismatch between the small-scale evolution of the system (weather) and the larger scale (climate). This explains why the weather is generally not predictable more than a few days into the future, while we can make meaningful climate projections to the end of the century and beyond.

Climate Change Risk Management (www.ccrm.co.uk)
4 Model Inadequacy and Model Uncertainty

Given the long timescales over which the future climate will evolve it is rarely possible to evaluate the accuracy of the model used to describe the system dynamics. Modellers have divided such issues into model inadequacy and model uncertainty (Stainforth et al. 2007a). They argue that model inadequacy reflects the degree to which models capture all the physical processes which are relevant to the system under study. There are at least three problems associated with this. First, we can have only partial understanding of all the processes that may be relevant for system development, especially those that occur over long timescales. Second, our understanding of small-scale processes must involve a form of parameterization, where the scale of model analysis is too coarse to capture all the relevant processes. Our understanding of how such small-scale processes affect the large-scale evolution of the system is, again, partial. Even if our model accurately described past system evolution, there is no guarantee that future change will similarly be defined. Third, because of the scale of enquiry adopted, there may be elements of the system behaviour that follow from the physical processes driving the model, but which are not represented at all. As a consequence, our model only gives us a partial account of real-world processes and system behaviour, and therefore enables only a partial account of system evolution.

For example, understanding the amount of carbon stored in soils is important if we wish to understand how the carbon cycle might respond to future warming. This is especially important in Arctic regions underlain by permafrost where melting of the ground would release large methane and CO$_2$ stores to increase global warming. Despite this, the latest evaluations using CMIP5 models vary by a factor of 10 in their assessment of Northern Hemisphere soil carbon stores. The reasons for this variation are most likely to be associated with inability of models to adequately factor in permafrost processes, the role of fire and elements of the nitrogen cycle. No CMIP5 models adequately represent carbon loss from permafrost and their ability to model present permafrost extent in the Northern Hemisphere produces estimates ranging from 2 million-30 million km$^2$ (Koven et al 2013) (Figure 3).

![Figure 3 CMIP5 model estimates for permafrost extent under RCP 8.5 (Koven et al. 2013)](image)

Projections of future permafrost behaviour will improve with better understanding of physical processes operating in permafrost regions, better parameterisation schemes and better use of land surface models such as the Joint UK Land Environment Simulator (JULES).
4 Model Inadequacy and Model Uncertainty

Model uncertainty arises because, while most models of complex systems can be expected to plausibly mirror system development at the largest scale (and we can use these to explore likely future macroscopic system trajectories) the range of possible outcomes at the small scale is, however, large. Although ensembles of models could be run and PDFs generated, this would only provide us with a sense of uncertainty within the parameter space. An insurance example here would be where a company licences AIR, RMS and Eqecat (or other models) – they would get three different answers for the same exposure data set – and this would give a sense of the uncertainty. The resultant shape of the distribution of model probabilities may not have any clear relationship with the system probabilities in the real world. As such, a model will be essentially subjective (see Stainforth et al. 2007a,b). In essence, we need to distinguish between those things that we can model and compute (e.g. biogeochemical cycles) and those that we cannot (some elements of landscape change).

More recently researchers such as Cox and Stephenson (2007) and Hawkins and Sutton (2009) take a broader view of uncertainties in climate projections. Hawkins and Sutton (2009) subdivide uncertainty into three groups. The first is uncertainty associated with internal variability of the unforced climate system (without any radiative forcing). Understanding this is important if we wish to evaluate the effects of GHG for instance on the climate, and differences between forced and unforced variability play a central role in climate change attribution. The second represent model uncertainty. Different models with different construction and parameterisation schemes will respond differently to the same radiative forcing. The third recognises the uncertainty involved in predicting which emissions scenario or concentration pathway will be followed. As this is uncertain so is the radiative forcing and temperature response.

Hawkins and Sutton (2009) show that which type of uncertainty dominates depends on the time and space scale of interest. They say that “for time horizons of many decades or longer, the dominant sources of uncertainty at regional or larger spatial scales are model uncertainty and scenario uncertainty. However, for time horizons of a decade or two, the dominant sources of uncertainty on regional scales are model uncertainty and internal variability” (p. 1096). As a result, internal variability in the climate system (associated with the non-linear ways in which the climate operates) increases as spatial and time scales decrease (see Figure 4).

**Figure 4 Fractional uncertainty in decadal mean and global mean climate projections, defined as the uncertainty divided by the expected mean change for precipitation and surface air temperature (Hawkins and Sutton) 2009**
This is similar to the insurance situation where county losses for example are more uncertain than state losses and this is represented by “secondary uncertainty” in the current catastrophe models.

However, recent work by Daron and Stainforth (2013) caution against the idea that IC uncertainty is relatively unimportant at decadal and multidecadal timescales. They argue that if the IC uncertainty is not well specified and analysed then probabilistic scenarios using multi-model ensembles will simply reflect the uncertainties in the distributions produced by each model. They use the example of trying to model floods from probabilistic predictions of rainfall and argue that failure to consider IC uncertainty “could lead to overconfidence resulting in either over-adaptation, with significant additional costs, or under-adaptation leaving residual and unexpected risk”. However some of this uncertainty may be irreducible – in which case multiple adaptations may have to be carried out – even though some may prove unnecessary. These are an example of the additional costs of climate change that can be avoided or reduced through earlier mitigation as described in the Stern review. It also suggests the need for flexible resilience measures that can be moved or re-deployed.

Examples of Model Uncertainty

Model uncertainty impacts our understanding of how Earth Surface Systems behave. This can be shown by using four systems as examples.

1. Uncertainty in modelling precipitation

Understanding future precipitation change, especially at regional and local scales, would help end-users such as adaptation planners, water management engineers and risk managers understand the likely magnitude and frequency of future floods and periods of drought. However, models are more successful at reconstructing and predicting changes in temperature than other variables, notably precipitation because modelling precipitation at short timescales and small regional scales requires parameterisation of cloud processes, and IC uncertainty is likely to play a significant role.

An example from recent climate change illustrates this. Uncertainty in future precipitation is a characteristic of many attempts to model the climate evolution in low-latitude regions (e.g. Lin 2007; Allan and Soden 2007). For instance in the Sahel region of Africa researchers (Held et al. 2005; Giannini et al 2008) argue that there has been a shift in focus with regard to the causes of recent drought in African rainfall from those that stress land-use change, over-grazing and deforestation to those recognizing the role of global climate change, driven by anthropogenic greenhouse gas emissions.

In trying to model such changes, scientists have used GCMs to simulate 20th century climate change in the region in an attempt to demonstrate their usefulness for future predictions. In one study, Lau et al (2006) used 19 coupled GCMs to examine the 1970s to 1990s Sahel drought (which caused considerable loss of life, migration and conflict). Of these models only eight produced a reasonable simulation of the drought, while seven produced excessive rainfall over these time periods. Clearly, if many of the models have failed to simulate this long-lasting regional drought, then their usefulness in predicting future water shortages in other regions may be questioned. It is not immediately clear what are the reasons for this model failure as a number of climate trajectories are possible. Continued drought could result from enhanced oceanic convection producing rainfall over ocean areas and drying of continental interiors. Alternatively, ocean current variability in the North Atlantic may be driving Sahelian drying; these conditions could reverse leading to increased future rainfall. Other hypotheses suggest changes in monsoonal patterns but resolution of these issues is complicated by inadequacies in how models predict critical oceanic and atmospheric processes (see Giannini et al. 2008).

However we can be sure that droughts and floods will occur somewhere and this means adaptation will be required. Uncertainty doesn’t remove the need to act but, unfortunately, it makes it more difficult to know where to act and exactly how. These are the additional costs that uncertainty brings and
Examples of Model Uncertainty

gives another illustration to why early mitigation is so important because this can tame some of the largest uncertainties.

2. Uncertainty in modelling ice sheet dynamics

Predicting the amount and rapidity of future sea level rise is a major issue for planners and risk managers. New infrastructure is being built near sea level (e.g. new build nuclear power sites) and risk managers are being increasingly asked to assess H++ events, those with very high magnitude and very low frequencies (ie 1:10000 events). Increasingly valuable resources are also at risk if rising sea levels change the magnitude and frequency of storm surges and hurricane landfalls.

Therefore, in view of the potential social and economic impacts of future sea level rise, a huge amount of modelling resources are being devoted to improving the accuracy of sea level rise models. Most of the present rise in global sea levels is due to the thermosteric rise, caused by expansion of the oceans as they have warmed. However, by the middle of the 21st century it is estimated that the dominant contribution will be from melting of the major ice sheets in Greenland and Antarctica (Rignot et al. 2011). IPCC AR5 WG1 has estimated that mass loss from the Antarctic ice sheet between 2002-2011 was 147 Gt/yr, and that from the Greenland Ice Sheet (GIS) has increased to 25 Gt/yr over the same period. Evaluating whether these rates are part of an accelerating trend is of crucial importance and there are major challenges in modelling how ice sheet dynamics will evolve and how rapidly.

It is likely that IPCC AR4 (2007) underestimated future sea level rise because modelling of the dynamic behaviour of the ice sheets was incomplete. Since then there have been advances in understanding ice sheet dynamics and better parameterisation of ice sheet models (e.g. Pattyn et al. 2012); although these still fail to capture crucial physical processes (Drouet et al. 2013; Pattyn and Durand 2013).

Physical modelling takes into account the melting of mountain glaciers and ice caps, thermal expansion of the oceans and the melting of the GIS and West Antarctic Ice Sheet (WAIS). Estimates of the sea level rise attributed to melting of mountain glaciers and ice caps by 2100 range from 5-37cm (Raper and Braithwaite 2006; Bahr et al. 2009) with the contribution of thermal expansion following moderate warming under an A1B emissions scenario in the order of 20cm. As a result, most of the sea level rise projected under high end (RCP 8.5) scenarios (which ranges from 52-98 cm) comes from rapid ice sheet melting and collapse of marine-terminating margins. However, future assessment of the dynamic evolution of the major ice sheets is hampered by a lack of understanding of the physical processes driving ice sheet melting and collapse. These physical processes include: the role of algae and aerosols in changing ice sheet albedo; the stability of grounding lines; the ways in which ice shelf and ice tongues calve and break up, the implications of this on the discharge of inland ice streams as debuttressing effects increase with ice shelf removal, and the role of meltwater in the subglacial zone of ice sheets.

Recent research suggests that risk managers should be planning for up to 2m of sea level rise by 2100, although considerable regional variation is likely.

3. Uncertainty in how the land surface will respond to climate change.

River (formally ‘fluvial’) systems respond to changes in climate at a range of scales; some change quickly and reach a new equilibrium rapidly; others respond much more slowly and are always in disequilibrium with the prevailing climate. Understanding how fluvial systems develop and the timescales over which this occurs is crucial if risk managers and adaptation planners are to better estimate flood risk. The ways in which fluvial systems respond to climate change may also differ considerably in adjacent catchments; in other words there may be no consistent or uniform response to climate forcing. For example, it can be shown that adjacent mountain catchments with similar topography and geological history have responded differentially in the past to the same climate forcing (Harrison et al. submitted). Similarly, work by Wells and Harvey (1987) describe the landscape response to an intense rainstorm in upland northwest England in 1984. The rain storm was intense with 55-80mm of rain falling within 2.5 hours and with a return period of between 100-500 years. Following this, flooding from the upland rivers deposited thirteen fan shaped alluvial deposits (alluvial fans) at the valley mouths, but the type and nature of these varied considerably between the valleys. In large, shallow bedrock-floored catchments, streamflow deposits predominated. Conversely, in smaller and steeper catchments containing extensive glacial sediments, the response to the storm was the deposition of boulder debris cones and debris flows. The amount of sediment deposited in the catchments also varied, ranging over an order of magnitude from 50 m3 to 2380 m3. Here is a clear example of the non-linear response of a system to the same forcing event, and the requirement for better quantification of such non-linearity if decision-relevant information for adaptation planning is to be available. As a result, location specific information will be needed to properly inform planners and infrastructure managers.

Research like this suggests that IC uncertainty may exist for certain landscapes and even small scale modelling (using
Examples of Model Uncertainty

RCMs for instance) may not accurately predict future changes in landscape dynamics. The challenge for policy makers and risk managers is to embed such uncertainty into their risk models, possibly by retaining a stochastic element to key variables.

4. Uncertainty in modelling hurricane intensity and frequency.

Predicting hurricane frequency, magnitude and landfall in global ocean basins is a focus for much current research and of great interest to insurance markets, catastrophe modellers and regional policymakers. Landfalling hurricanes and Tropical Cyclones often kill large numbers of people and cause huge economic damage and loss of infrastructure. For instance, Hurricane Sandy in 2012 which made landfall on Cuba and affected much of the Caribbean and the northeast coast of the US, was the largest Atlantic storm on record, the second costliest hurricane in US history in terms of economic damage and killed nearly 300 people. Late in 2013 Typhoon Haiyan became the strongest recorded storm at landfall when it hit the Philippines, killing over 6,000 people.

As a result, being able to predict seasonal and sub-decadal hurricane activity would increase the resilience of vulnerable communities to these events. However, predicting hurricane and Tropical Cyclone activity is difficult as a number of related climate and ocean processes need to be modelled (Jin et al. 2008), such as the cyclic nature of Atlantic Ocean temperatures (the Atlantic Meridional Mode) and the state of the Atlantic Warm Pool. Prediction of hurricanes over seasonal timescales is also difficult, partly because of the important role that the Pacific El Niño Southern Oscillation (ENSO) plays in hurricane formation and the difficulties in modelling El Niño events. Hurricanes require low vertical wind shear to form (below around 8 ms-1). During El Niño events westerly winds become stronger at high altitudes and easterly winds increase at low altitudes, and this increases vertical wind shear in the Tropical Atlantic Ocean which is the Main Development Region for Atlantic hurricanes. As a result, Atlantic hurricanes are less likely to form during El Niño events, and more likely during La Niña. The converse is true for hurricanes in the eastern Pacific. Prediction skill also changes throughout the year; better prediction is possible for the rest of the hurricane season after July or August, but prediction earlier in the year is much less reliable.

Modelling ENSO has proved difficult, partly because relatively little progress has been made in creating an accurate initialised ocean state between the eastern and western Pacific (suggesting that this element of ENSO prediction corresponds to an initial value-type problem). Ocean temperature, salinity and wind data from important regions are sparse, and crucial linkages between the upper ocean, low-level wind regimes and variability in ocean salinity are not fully understood. The details of the ocean thermocline are also not well known and modelled and future improvements in modelling ENSO will come through better representing these processes (e.g. Capotondi et al. 2013).

However, the insurance industry does not necessarily seek predictions or forecasts. If there are good physical reasons that hurricanes are expected to be strengthening due to warmer seas then there is evidence enough to reflect this in risk pricing and capital calculations.
Reducing Uncertainty and increasing Resilience

Clearly reducing model uncertainty where possible is an important goal and there are several ways in which this is being attempted. These include: more focused attempts to reduce model uncertainty; bottom-up approaches to better parameterise physical processes in climate models; new attempts to produce decadal forecasts and better interrogation of geomorphic and sedimentary systems to better understand natural variability.

Hawkins and Rowan (2009) argue that uncertainties associated with internal variability and model uncertainty dominates the total uncertainty. Internal variability might not be reducible by any meaningful amount, but reducing model uncertainty would pay dividends for planners and would be possible given better observational data and improvements in model structure. Reducing this uncertainty would also lead to better regional predictions and this is certainly the case for decadal timescales and regional space scales. They end by arguing that, "Because the costs of adaptation are expected to be very large, the clear implication (of their work) is that reducing uncertainty in climate predictions is potentially of enormous economic value" (Hawkins and Sutton 2009, p. 1102).

There are also clear advantages to increasing current understanding of the physical processes that need to be parameterised in climate models. For instance recent advances have been made in understanding the migration of grounding lines (the junction in a marine-terminating ice sheet between the grounded ice and the floating ice shelf) as this is a crucial factor in explaining how ice sheets will respond to warming and sea level rise. Ice sheet models with resolutions of 10-20km generally fail to reproduce grounding line migration (Pattyn et al. 2012) and much smaller resolutions may be required. Solving this requires either larger computational resources, or new modelling techniques but challenges in accurately using these to predict future sea level rise still remain (Drouet et al. 2013).

For many climate impacts such as assessing hurricane impacts and ENSO, policymakers require medium timescale climate forecasts rather than projections out to the end of the century similar to those evaluated by IPCC. Such decadal forecasts are difficult to achieve because the forced climate signal (driven by GHG) is not much larger than the internal variability (Meehl et al. 2009) and this is especially true for sub-continental scales and for precipitation change. Important questions remain before such decadal forecasts are achievable. One of the most crucial is whether enough is known about ocean variability (e.g. Pacific Decadal Oscillation, Atlantic Meridional Overturning) to produce an accurate enough initial state to the climate model to predict its evolution, suggesting that IC uncertainty plays an important role at near-term climate prediction in the same ways as it does in weather forecasting.

Finally, there have been a number of initiatives to produce the observational and historical data with which to test climate models against known unforced variation, and to better assess the nature of natural variability. For instance, more information is required on the magnitude-frequency relationships of major floods than is obtained by relatively short instrumental records (CCRM 2011). In the UK river gauges only provide around 45 years of data. It is therefore difficult for insurance risk managers to specify that a structure must be able to withstand, say, a 1:300 year flood event if the magnitude of such an event is unknown (and this is even more difficult given the usual assumption of statistical stationarity, which is arguably no longer true, in climate data). As a result, there is increasing research to extend flood records using documentary records (Longfield and Macklin 1999), the geomorphology of floodplain sediments (Macklin and Rumsby 2007) and detailed sedimentary records from floodplain sediments (Jones et al. 2010). Clearly, risk managers should use these new scientific opportunities to obtain a better idea of future risks.
Conclusions

Despite the focus on climate model uncertainty given here, it is important to state that climate models have been remarkably successful in providing credible large-scale climate projections for many years. For instance, they predicted Arctic amplification; the cooling of the stratosphere associated with GHG forcing; the differential response of land and oceans to warming and the effects of stochastic events such as the cooling associated with volcanic eruptions such as Pinatubo (e.g. Robock 2003). However, the issue of climate model uncertainty needs to be grasped by all users of climate model projections and these include adaptation planners, catastrophe modellers, infrastructure and asset managers.

With better assessment of past changes in climate, the drivers that forced these and the impacts that followed, we should be able to refine climate models so that future projections are made more robust. Understanding how climate models work, are developed, and projection uncertainty should also improve climate change resilience for society. What should be avoided are business decisions being made on the basis of incomplete understanding of climate model projections. For instance, several scientists have in the past made simplistic assertions about the likely nature of future climate in the UK, and climate sensitive sectors such as viticulture and agriculture should be wary of such pronouncements. Clearly a better understanding of climate model uncertainty would help make better risk management decisions and these will need to be robust in the face of these uncertainties. Inevitably this will increase costs. Such costs can be controlled through earlier and deeper reductions of greenhouse gases (mitigation) – it is likely they will be considerably higher if they are delayed further.

Finally, we need improved understanding of the magnitude and frequency relationships of climate related events (such as floods). Past data sets, most of which are of short duration, are of little use when reconstructing recurrence intervals and when the climate displays non-stationarity. Neither are simple extrapolations from recent data or downscaled climate projections. As a result, extension of the observational record using geological data, for instance, is needed.

Definitions

* Radiative forcing. This is the change in the net, downward minus upward, irradiance (expressed in W m–2) at the tropopause or top of atmosphere due to a change in an external driver of climate change

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References


Figure Captions

**Figure 1**
How climate models are constructed (modified from Hadley Centre, UKMO)

**Figure 2**
Differences in GCM resolution over time (IPCC AR4 2007)

**Figure 3**
CMIP5 model estimates for permafrost extent under RCP 8.5 (Koven et al. 2013)

**Figure 4**
Fractional uncertainty in decadal mean and global mean climate projections, defined as the uncertainty divided by the expected mean change for precipitation and surface air temperature (Hawkins and Sutton 2009).