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Issues in the interpretation of climate model ensembles to inform decisions

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There is a scientific consensus regarding the reality of anthropogenic climate change. This has led to substantial efforts to reduce atmospheric greenhouse gas emissions and thereby mitigate the impacts of climate change on a global scale. Despite these efforts, we are committed to substantial further changes over at least the next few decades. Societies will therefore have to adapt to changes in climate. Both adaptation and mitigation require action on scales ranging from local to global, but adaptation could directly benefit from climate predictions on regional scales while mitigation could be driven solely by awareness of the global problem; regional projections being principally of motivational value. We discuss how recent developments of large ensembles of climate model simulations can be interpreted to provide information on these scales and to inform societal decisions. Adaptation is most relevant as an influence on decisions which exist irrespective of climate change, but which have consequences on decadal time-scales. Even in such situations, climate change is often only a minor influence; perhaps helping to restrict the choice of 'no regrets' strategies. Nevertheless, if climate models are to provide inputs to societal decisions, it is important to interpret them appropriately. We take climate ensembles exploring model uncertainty as potentially providing a lower bound on the maximum range of uncertainty and thus a non-discountable climate change envelope. An analysis pathway is presented, describing how this information may provide an input to decisions, sometimes via a number of other analysis procedures and thus a cascade of uncertainty. An initial screening is seen as a valuable component of this process, potentially avoiding unnecessary effort while guiding decision makers through issues of confidence and robustness in climate modelling information. Our focus is the usage of decadal to centennial time-scale climate change simulations as inputs to decision

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making, but we acknowledge that robust adaptation to the variability of present day climate encourages the development of less vulnerable systems as well as building critical experience in how to respond to climatic uncertainty.

Keywords: climate change; probability; decision making; vulnerability

1. Introduction

Anthropogenic climate change represents a challenge at many levels of society. The global challenge is to minimize the risk of 'dangerous' climate change; reducing greenhouse gas (GHG) emissions being the most obvious method. But climate change is already being observed (Solomon *et al.* 2007) and further changes cannot be avoided. Past GHG emissions provide a commitment to further increases in global mean temperature and related changes in the climate system over the next century and beyond (Meehl *et al.* 2005; Wigley 2005), while socio-economic inertia (Ha-Duong *et al.* 1997) limits our ability to constrain the levels of future atmospheric GHG concentrations. A range of 0.3–1.3° increase in global mean temperature has been suggested for the 2020s over the 1990s (Stott & Kettleborough 2002), almost independent of the GHG emission scenario assumed. Society will therefore have to adapt to further changes in climate on time-scales of 20–100 years at least.

Efficient and effective adaptation presents a completely different set of challenges compared to those of mitigation. Governments, individuals, industry and other organizations need to build climate change-related risks into their existing decision-making processes, with the aim of maximizing the long-term value of today's decisions. The approach of integrating climate information alongside other decision drivers is referred to as climate risk management (Connell *et al.* 2005; Bouwer & Aerts 2006; Hellmuth *et al.* 2007). Climate science has a role here in terms of the availability of observational records, the assessment of climatic vulnerabilities and the better utilization of weather and climate prediction services. The approach may be combined with attempts to maximize flexibility to future changes, keeping options open for adjustments in response to changes which are greater than or different from those initially considered most likely. For instance, flood protection measures could be designed with foundations which simplify expansion, should it become necessary. This approach makes no attempt to maximize the value of today's decisions under a probability distribution for future climate and no such probabilities are required.

Nevertheless, if we are to go beyond minimization of vulnerability to today's climate, we desire information on how climate will change in the coming decades on regional or smaller scales (Bharwani *et al.* 2005)—preferably in the form of a seamless prediction across time-scales (Washington *et al.* 2006). To the extent that model-based information is relevant to our decision, it can be used in a climate risk management framework, i.e. not as a primary decision driver but as extra information to guide the choice of the best, 'no regrets', option. Frameworks for incorporating such information are the subject of ongoing research (Jones 2001; UKCIP08 2006), but we should not underestimate the fundamental difficulties in extracting decision-relevant information on the time-scales of climate change (Stainforth *et al.* 2007). Care is required to separate interpretations of value in understanding climatic processes or climate models from those which may usefully inform real-world decisions. This presents challenges for scientists and their funders. For climate science, the challenge is to provide information which is relevant in societal decision-making processes (Stainforth *et al.* 2007). For research funding bodies, the challenge is to ensure that the necessary inter- and multi-disciplinary activities are in place to make connections between societal needs and climate research, and thus guide the direction and interpretation of the science.

It is useful to consider these challenges in two timeframes. First, how to use and interpret information from models/ensembles available now or in the near future. Second, how to structure climate research to facilitate the provision of useful information for decision support in the long term. A theoretical assessment of the climatic processes and resolutions that we require to have significantly improved confidence in model-based projections would usefully guide the model development process. In the meantime, interpretation of current models requires exploration of uncertainty, which demands new computing facilities and novel computational strategies (e.g. Stainforth *et al.* 2004). Much further effort is required in experimental design but recent work (e.g. Murphy *et al.* 2004; Stainforth *et al.* 2005) provides ensembles of simulations which can be used to explore methods and define a research path for meeting societal needs.

The theoretical opportunity for climate science to add value in many sectors of society can only be addressed with a multi-disciplinary approach. Understanding the possibilities and limitations of climate science is important. Understanding the decisions and vulnerabilities of each different sector is of equal importance, not just in making decisions but also in the analysis of model output. Where one decision might be most vulnerable to changes in mean seasonal precipitation, another may be influenced only by changes in extreme precipitation or by details of the daily time-series through the season (Wilby *et al.* 2000). In climate forecasting one size will not fit all. This is not simply a matter of presentation, although the multifarious demands and semantics of user communities certainly provide a communication challenge, but also influences the interpretation of climate projections, where to focus climate research, and how to design ensemble experiments. For instance, grand ensembles exploring model uncertainty could be optimized to explore the range of behaviour in any, but not all, of the above variables. A two-way communication between climate scientists and users of climate science is therefore of fundamental importance. Only by understanding the needs of different sectors can the science be usefully directed and communicated. Only by understanding the conditions, assumptions and uncertainties of model-based statements about future climate can decision makers evaluate the relevance of the information and make informed, if subjective, assessments of risk.

In the following sections, we discuss how we can use current strategies for the exploration of uncertainty in climate predictions. We illustrate how we can interpret large climate ensembles using results from the climate*prediction*.net experiment. The output of complex climate models is often used as an input to impact models (e.g. Hayhoe *et al.* 2006), sometimes via a dynamic or statistical downscaling step. The output of these models may then be taken as an input to the decision-making process. We consider the same problem of connecting climate models with decision making but explore how this can be structured in the context of large climate ensembles, the cascade of uncertainty between the different components of the climate/impacts system, and some of the assumptions and judgements necessary to connect the different stages. We describe an analysis pathway to evaluate the potential implications of the simulations for some particular decision. This is potentially useful for both the decision maker and the researcher in terms of judging the level of complexity worth investing in a particular question. We illustrate the process using two simplistic and idealized examples; one involving flood protection in Europe, the other agricultural development goals in Africa.

2. Interpretation of climate ensembles

In this section, we discuss the types of information available to decision-making processes from recent developments in the field of climate prediction. Section 3 examines the process of applying that information to a specific decision.

Detailed statements about future climate are usually based on the output of complex climate models, three-dimensional atmosphere/ocean global circulation models (GCMs), which are designed with the aim of encapsulating our understanding of the physical climate system. A handful of these have been developed by modelling centres worldwide (McAvaney *et al.* 2001; Meehl *et al.* submitted). When driven by scenarios of future atmospheric GHG concentrations, their output is sometimes taken as indicative of a possibility for the future and considered informative in decision making (e.g. UKCIP02 2002; Hayhoe *et al.* 2006).

Much effort is currently focused on exploring the uncertainties in model-based climate predictions (Palmer & Raisanen 2002; Stott & Kettleborough 2002; Murphy *et al.* 2004; Frame *et al.* 2005; Piani *et al.* 2005; Stainforth *et al.* 2005; Knutti *et al.* 2006; Lopez *et al.* 2006) with some focusing on regional scales (Tebaldi *et al.* 2005; Stainforth *et al.* 2006; Stott *et al.* 2006) which are arguably more relevant for decision making. The consequences of uncertainty in how to build a climate model are receiving particular attention. Many comparisons are made between the order 10 different models which exist worldwide (Covey *et al.* 2000; McAvaney *et al.* 2001; Meehl *et al.* submitted). In addition, two projects are carrying out systematic uncertainty analyses based on a single GCM. These are the quantifying uncertainty in model predictions project (Murphy *et al.* 2004) with a few hundred simulations and the climate*prediction*.net project (Stainforth *et al.* 2004) with a few hundred thousand simulations. Both create 'model versions' by varying uncertain parameters in the base model (Allen & Stainforth 2002).

Stainforth *et al.* (2007) rule out 'the possibility of producing meaningful probability density functions for future climate based simply on combining the results from such ensembles; or emulators thereof'. These ensembles produce a wide range of possibilities but exploration of uncertainty has so far been limited, in terms of base models and parameter space explored, so we should expect these ranges to increase if we carry out further experiments exploring model uncertainty. Therefore, they argue that the ensembles may provide a lower bound on the maximum range of uncertainty; 'Lower bound' because further uncertainty exploration is likely to increase it; 'Maximum range of uncertainty' because methods to assess a model's ability to inform us about real-world variables, e.g. shadowing techniques (Judd *et al.* 2004), could potentially constrain the ensemble and reduce the range. This description highlights some of the conditions applying to the uncertainty estimate. Such information can nevertheless be valuable as a guide to decision makers.

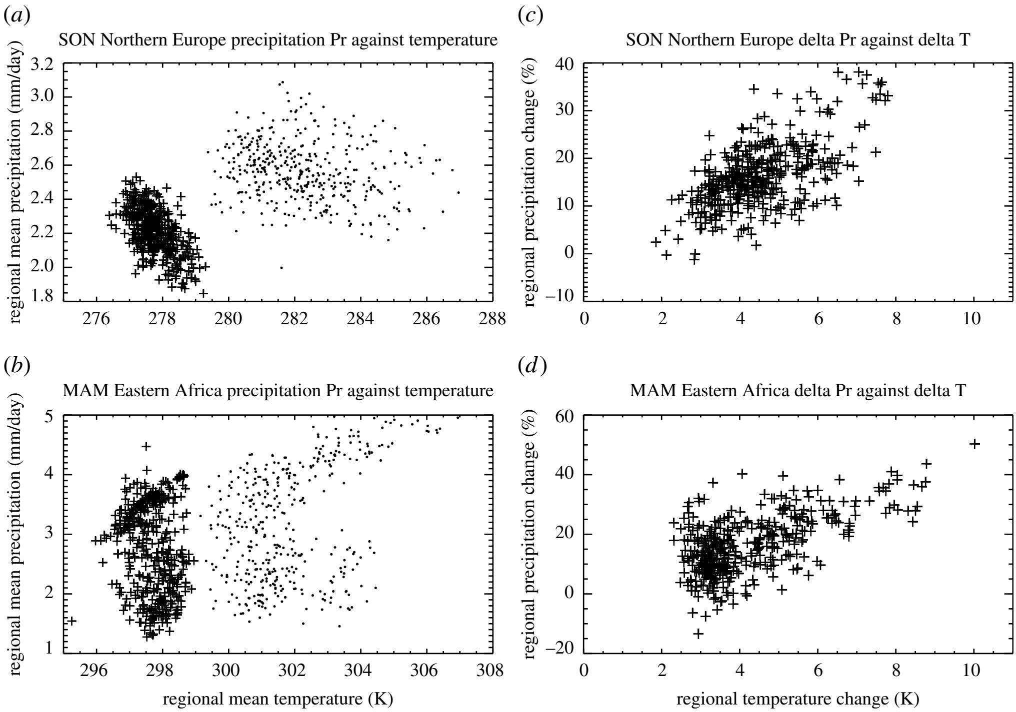

Figure 1. Distribution of modelled precipitation and temperature for Northern Europe (September/October/November) and East Africa (March/April/May) from the climate*prediction*.net first ensemble (Stainforth *et al.* 2005). (*a*,*b*) Crosses represent a control climate roughly equivalent to the second half of the twentieth century with pre-industrial levels of atmospheric carbon dioxide and atmosphere/ocean heat fluxes derived to maintain sea surface temperatures at approximately 1960–1990 mean values. The dots show the mean response in years 8–15 after doubling atmospheric CO_2 concentrations. (*c*,*d*) Response to doubling CO_2 concentrations, averaged over years 7–15 after an instantaneous change in atmospheric CO_2 levels.

If the available number of model versions is large then we can hope to extract such ranges, or domains, for combined behaviour in multiple variables. We refer to such a domain as a ‘non-discountable’ climate change envelope. Non-discountable highlights that we should not disregard the possibility that the response could be anywhere within the envelope. No claim is made about the possibility of a response outside the envelope; it is not ‘discountable’, it is simply a region for which we have no data. The envelope provides the prospect of evaluating ranges for real-world vulnerabilities which usually have dependencies on a number of climatic variables (Hulme & Brown 1998). Figure 1 shows the range of combined behaviour in mean regional precipitation and mean regional temperature for Northern European autumn and East African spring, from the climate*prediction*.net ensemble analysed in Stainforth *et al.* (2005). This ensemble consists of 408 versions of a complex climate model with a slab ocean; data is available as means over years 7–15 after the start of simulations with both pre-industrial (control) and double pre-industrial ($2\times CO_2$) atmospheric CO_2 concentrations. In most cases, the value for each model version is the mean over an initial condition ensemble (Stainforth *et al.* 2005). The same quality control procedures as in the earlier work were applied. Despite the idealized nature of the experiment, it illustrates how from a suitable experiment we might extract a domain of response space representing the two dimensional 'lower bound on the maximum range of uncertainty'. The currently ongoing climate*prediction*.net experiment is based on scenarios of twentieth and twenty-first century GHG concentrations and will thus provide additional information. The design and implementation of such experiments to extract and explore these ranges nevertheless remains a significant challenge for the climate modelling community.

In figure 1*a*,*b*, there is a clear separation of temperatures between control and $2\times CO_2$ simulations. At these large regional scales, the global scale warming effect of doubled atmospheric CO_2 almost takes us beyond the limits of model uncertainty in the control temperature. In precipitation there is some overlap in Northern Europe and almost complete overlap in East Africa; the effect of increased CO_2 is mostly within the minimum bounds of uncertainty in the model itself. However, when we look at the anomalies between $2\times CO_2$ and control (figure 1*c*,*d*) we see a fairly consistent message on precipitation change in both regions—almost all model versions show an increase. Interpreting this as meaningful for the real world involves the assumption that the regional precipitation response to increased CO_2 is independent of the absolute value in the region since the changes are relative to very different control values. Selecting ensemble members which are consistent with observations would remove this assumption but leads to the unuseful exclusion of all model versions (Stainforth *et al.* 2007; a consequence of model inadequacy) and assumes that the model variables have a direct correspondence with their real-world namesakes; other assumptions for this relationship are possible and may be useful. Therefore, we are left with the domain of anomalies as the lower bound on the maximum range of uncertainty; our climate change envelope. For many variables, this may be the best information climate modelling can currently provide as a potential input to a societal decision.

Figure 1 presents regional, seasonal, long-term means. Climate is however a distribution of possible behaviour (Stainforth *et al.* 2007) and decisions are rarely dependent simply on the mean. The climate*prediction*.net ensemble presented here includes small initial condition ensembles (between 2 and 7 members) for most model versions (Stainforth *et al.* 2004, 2005). The points in figure 1 are means over these distributions. A grand ensemble is the combination of perturbed physics and initial condition sub-ensembles. If such ensembles can be implemented with large initial condition sub-ensembles it will be possible to go beyond the means of the distribution; perhaps looking at the lower bound on the maximum range of uncertainty for the 5 or 95% values for a variable. Such information is likely to provide valuable additional information for risk assessments.

Although we cannot confirm the relevance of any climate forecast (Oreskes *et al.* 1994; Stainforth *et al.* 2007), we may be able to judge some to be irrelevant for decision support. For instance, complex climate models qualitatively misrepresent the diurnal cycle of tropical precipitation (Trenberth *et al.* 2003); so model predictions of changes in that cycle may be judged irrelevant. Scientific judgement on whether the model structure can simulate the processes we believe to be important for our chosen variables is therefore an important complement to the model results in terms of providing decision support.

3. From climate model ensembles to decision inputs

Section 2 illustrates how, with suitably designed ensembles of climate model simulations, we can extract a domain representing a non-discountable climate change envelope for some aspects of future climate. In this section, we present an analysis pathway, which highlights some of the stages required in extracting the relevant climate change envelope and linking model results with specific societal decisions. Although discussed in general terms, we illustrate the process using two hypothetical and highly idealized decisions; our focus here is on the required climate analysis and research, not the overall risk-assessment or decision-making framework.

The first is a decision on what level to invest in a major flood protection measure for some inland town in Northern Europe. Given the substantial floods experienced in recent years, this is a question which is facing planners in a number of countries in the region. Two design options are examined: option one represents a lower cost response sufficient to protect against what is thought to be a one in a 130 year extreme river flow today; option two costs 50% more but protects against what is thought to be a one in 200 year event today. If protection against a one in a 100 year event is judged, e.g. by local planning organizations, to be an acceptable risk then option one is sufficient today. The question is whether it will still be sufficient in the future; will either option limit inundation of the town to at least a one in a hundred year event in the 2050s? The second example is a decision of whether or not to invest in a substantial storage and transport infrastructure to enable export of an agricultural product (e.g. coffee or sorghum millet) from a region in East Africa. This is a question which may be faced by national and local governments in the countries of the region and by international aid agencies. For simplicity of illustration, both are presented as binary decisions; of course real decisions would involve many alternative options.

(*a*) *Initial steps*

The analysis pathway consists of a number of steps, illustrated in figure 2*a*. The first two steps may be obvious but are nevertheless worth highlighting. The first is a review of whether climate change is likely to influence the decision (Hulme & Brown 1998). If changes in regulations or guidelines led to protection against the one in 150 year event becoming the acceptable standard then option two would become the default flood protection option regardless of climate change factors. Local regulations such as protection of areas or buildings may rule out one option or the other. In Africa, other developments may be leading to soil degradation or population migration, making the investment unwise. Or the benefit to the local region may be so great—based on recent production statistics, local interest and anticipated costs—that facilities which have a lifetime of only 10 years would nevertheless be worthwhile to the community and judged to be a good investment. This step is simply a reminder to reflect that even though the system under study may be affected by climate change, related decisions may not. In reality, few long-term investment decisions in Africa have taken climate into account (Washington *et al.* 2006).

Step 2 involves an assessment of the aspects of the decision which may be sensitive to climate change; the climate change sensitive factors (CCSFs). In our examples, these might be the return period for an event which overcomes flood

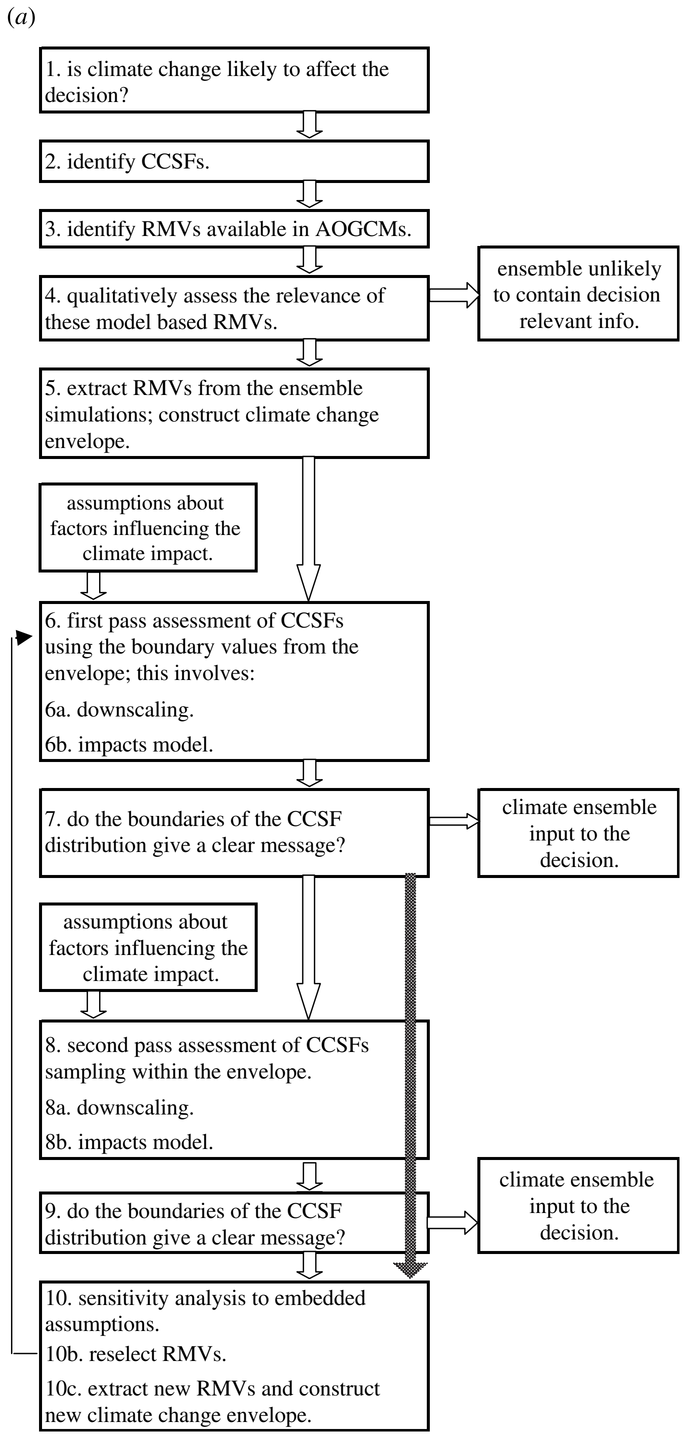

Figure 2. (*a*) Analysis pathway for the interpretation of large climate ensembles as information in decision-making processes. (*b*) Illustration of how a climate change envelope can be translated into a distribution of behaviour in the CCSF of a decision.

(*b*)

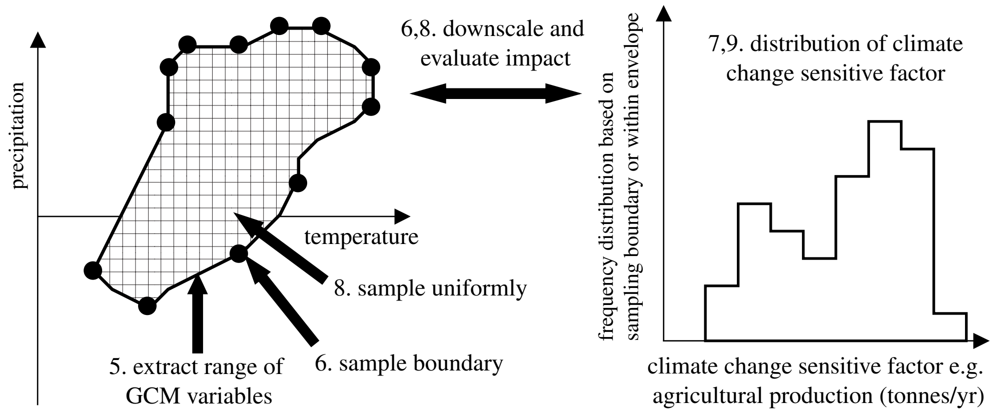

Figure 2. (*Continued.*)

defences and inundates the town or tonnes of crop produced per hectare. Climate may not be the only, or even the major, influence on these factors. For instance, flood risk may be influenced by constructions up or down stream; agricultural production by changing farming practices. But to the extent that climate change influences our decision it does so via these factors.

(*b*) *Selecting model variables*

In *step 3*, we jump to the climate model side of the problem and identify the variables (including time and spatial scales) in our model simulations, which we can use to derive information about our CCSFs. We call these relevant model variables (RMVs). A plethora of choices will exist at this stage, but the experimental design of the ensemble and data storage structures will provide many restrictions. Precipitation and temperature will be the most significant variables for Northern European flood risk but wind speed, evaporation and humidity may also be included. Extreme precipitation on a daily basis may be useful, better still daily time-series of our chosen variables, since river flows are not governed simply by individual extremes but also by integrating factors of the local hydrology (Wilby & Harris 2006). Since we are interested in risk (e.g. the 99% extreme river flow in the 2050s), aspects of the distribution of these variables over large initial condition sub-ensembles is likely to be relevant if available. In our Africa example, the same variables are likely to be important but here changes to the seasonality of rainfall may also be critical as this may strongly influence agricultural production.

Some variables, and particularly some temporal scales, may not be available either due to limits on the amount of data which can be extracted and stored from each simulation or operational decisions to make available only means or distributions rather than the whole dataset. Greater involvement of decision makers and risk assessment specialists in the design of climate model experiments therefore has the potential to increase the usefulness of resulting datasets.

Beyond practical restrictions, there is still a matter of judgement in the selection of RMVs. This comes from an assessment of the relative confidence we can place in the ability of the global models to potentially simulate the climate change response in the variables in question (Smith 2002; Stainforth *et al.* 2007). We include this assessment as a separate step, *step 4*, since it may lead to the conclusion that the ensemble contains no decision-relevant information and that there is no value in pursuing the study further. Or it may lead to a different choice of RMVs, perhaps less than ideal for statistical downscaling or use in the impact model but excluding those model variables in which we have the least confidence.

Directly relevant spatial scales are not currently available from AOGCMs for most decisions, so we might need to include a downscaling step (*steps 6a and 8a*). Consideration of how this downscaling may be done influences the choice of RMVs, so we discuss it here although difficulties in treating downscaling within the framework of grand ensembles are discussed in §3*c*. Two fundamentally different approaches are available: dynamical downscaling using a regional model (Rummukainen *et al.* 2004; Kay *et al.* 2006*a*,*b*) or statistical downscaling (Wilby *et al.* 2000; Hewitson & Crane 2006; Schmidli *et al.* 2007) in one of many forms. Using currently available techniques, the former would require integration with the global model experiment. Unfortunately comprehensive exploration of model uncertainty including that involved in dynamical downscaling is not yet available. The latter includes many different approaches requiring different inputs. It raises the prospect of sensitivity analyses using different RMVs; we may choose to deduce river flow extremes from monthly means, monthly extremes or daily time-series. Such sensitivity analyses may be of value not just in the decision-making process but also in the assessment and improvement of the climate and impact (in this case, hydrological or agricultural production) models.

So far we have considered RMVs to be variables which affect our CCSFs directly. An alternative approach is to use proposed teleconnections and take the RMVs in these distant, usually larger scale variables. This may be particularly valuable if we have greater confidence in the models' abilities to simulate these variables, and their response to increased concentrations of atmospheric GHGs. For instance, central equatorial African rainfall has been linked with large-scale circulation patterns over the North Atlantic and a possible further link to sea surface temperatures in the tropical North Atlantic (Todd & Washington 2004). Rainfall in Europe has been linked with the arctic oscillation (Thompson & Wallace 2000). These connections provide an alternative route for selecting RMVs and thus examining the ensemble implications for the decision in question.

(*c*) *Assessment of implications*

Having made a choice of RMVs, *step 5* simply involves extracting them from the ensemble and constructing their climate change envelope. Examples of this process for regional, seasonal mean temperature and precipitation were described earlier and shown in figure 1.

Step 6 is to make a first pass assessment of the implications of this envelope on the CCSFs of our decision. For any values of our RMVs, we can deduce the corresponding CCSFs; probably using a downscaling procedure and an impact model. These stages bring in their own uncertainties which should be quantified. Uncertainties in the formulation of impact models and regional climate models could be studied using a perturbed-parameter approach (Wilby & Harris 2006) similar to that being used in the global models (Stainforth *et al.* 2004). Beyond these, there may be uncertainties in the assumptions used to build the impact model. For instance, the hydrological model used to obtain the river flows and therefore flood risks will include details of the local hydrology which would be affected by developments up- and downstream. Similarly, potential crop yields in our African example will be dependent on many aspects of farming practices including availability of fertilizers and equipment. There is therefore a cascade of uncertainty from the global climate model predictions to the decision input. Where possible, it is useful to keep uncertainty in societal aspects separate from those relating to how we understand and model the process. The decision maker may have an educated view of the scale of the former while it may not be possible to have an educated quantitative view of the latter without exploring it systematically.

In figure 1, we have over 400 model versions but climate ensembles are now achieving hundreds of thousands of simulations (www.climateprediction.net). Applying a downscaling and impact assessment for each of these is a formidable task; doubly so considering the need to explore uncertainty in the downscaling and impact model. The climate change envelope provides a means of simplifying this task. As an initial screening, we can focus on the boundaries of the envelope; the solid line in figure 2*b*. Examining the impact on our CCSFs of points on this boundary (the solid circles) gives an indication of the range of values for our CCSFs, assuming no significant nonlinearities or complex behaviour in the relationship between RMVs and CCSFs. The result is illustrated by the histogram in figure 2*b*. The problem is therefore reduced back to the analysis of maybe a few tens of points in RMV space. As with the climate ensemble, the shape of the histogram provides no information about the likelihood of real-world response. But the range may represent a lower bound on the maximum range of uncertainty, now also conditional on the downscaling method and the impact model. Including uncertainty analysis in the downscaling and impact assessment produces a distribution which can be interpreted in the same way but allows for the prospect of more complex assessment because these processes may be susceptible to confirmation (Oreskes *et al.* 1994) in a way climate change models are not (Stainforth *et al.* 2007).

We can then ask whether we have a clear message for our decision (*step 7*). For instance, is the minimum (maximum) impact on crop yield so great (small) that the investment is likely to face difficulties (no difficulties) under all the climate change possibilities identified? Is the maximum impact on flood risk so small that option 1 still provides protection against at least a 100 year event at some point in the future, i.e. we have no clear information suggesting that greater protection is needed, or is it so large that option 1 may only protect against a 50 year event while option 2 still protects against at least a 120 year event, i.e. we have information suggesting that option 1 may be insufficient but have no information suggesting that option 2 may be insufficient? If so, then to the extent that we trust the models' simulations of the chosen variables, the relationship between RMVs and CCSFs, and the lack of significant nonlinearities, we have a clear input to the decision.

If we do not have a clear message then we must simply accept that this is the case and use the information gained to improve our understanding and ability to model the systems. The range of responses may include the possibility that there is no increase in flood risk and also that the increase is so high that neither option provides the desired level of protection. The range of responses may include the possibilities that the chosen crops will not be viable in the region and also the production could be substantially higher than in today's climate. Even this information can be useful to the decision maker in terms of focusing attention not on a particular response but on options which allow flexibility for adjustments in the future.

If we do have a clear message we may choose to explore the envelope more thoroughly (*step 8*). This is a matter of judgement based on an understanding of the particular decision in question. In most cases, the relationship between RMVs and CCSFs is complex. But the dominant effects over the domain of interest may be believed to be monotonic in each RMV; the envelope boundary therefore providing a good indication of the possible range of response. We might choose to question this assumption, particularly if the envelope spans regions of discontinuities such as the maximum growing temperature for our crop. Exploring the region of the climate change envelope uniformly—as illustrated in figure 2*b*—has the advantage of filling in gaps where there may be few models while still limiting overall numbers to maybe some tens or hundreds rather than hundreds of thousands. However, if there is some physical reason to believe that some part of RMV space may lead to a significantly different response in the CCSFs then it is sensible to focus on this region. Since we are only interested in the extremes of the resulting distribution (*step 9*), we are simply looking for the best way to find complex behaviour which takes the CCSFs beyond the range found by exploring the envelope boundary. More refined sampling strategies such as latin hypercubes may be useful, particularly if the dimensionality of the RMV space is greater than the two dimensions illustrated.

Finally, we highlight that the above analysis pathway included some judgements on the choice of RMVs. For some decisions, and to better understand the implications of different methodological choices, it may be valuable to carry out sensitivity analyses of these assumptions. *Step 10* represents this process in terms of reselecting alternative RMVs and repeating the procedure.

4. Conclusions

Recent developments in experimental techniques are providing large ensembles exploring a number of different sources of uncertainty in climate models. Such experiments are increasing our understanding of the range of possible model behaviour in response to scenarios of increasing levels of atmospheric GHGs. For some predictive variables, they may be interpreted as providing a lower bound on the maximum range of uncertainty. We have described an analysis pathway by which such information may provide a contribution to present day decisions. An important aspect of the approach is the concept of a non-discountable climate change envelope, a multi-variable form of a lower bound on the maximum range of uncertainty, which provides the relevant information from the global climate ensemble but helpfully limits the degree of further analysis necessary to extract information which may be relevant to some given decision.

The relevance of the resulting information is primarily governed by the confidence we have in our climate models being able to simulate the climate system sufficiently well to provide information on the variables and regions of interest under future levels for atmospheric GHGs. Further work is required to define how we may evaluate that confidence and to work towards models which meet our requirements. Part of that process involves study of the linkages between climate change and real-world decisions and the evaluation of uncertainties in each component.

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