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Ensembles and uncertainty in climate change impacts

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The increasing use of multi-member climate model ensembles for making future climate impact assessments presents both opportunities for understanding uncertainties, and challenges for interpreting the results. We outline current approaches to assessing uncertainties in climate impacts, statistical methods for assessing uncertainties, issues regarding model integration and complexity, and ways in which uncertainty frameworks can be used to inform adaptation decisions, with case studies focused on agriculture. Finally, we highlight future research needs and provide recommendations for making further progress.

Keywords: climate change, climate impacts, ensembles, uncertainty, modeling

INTRODUCTION

Robust assessments of climate change impacts are important for assessing the scale of adaptation required, and for estimating the implications of climate mitigation pathways (Collins, 2007; IPCC, 2014). A comprehensive understanding of uncertainties in projected impacts is a key element of making robust assessments (Challinor et al., 2013; Katz et al., 2013). Uncertainties arise from a range of sources in climate projections (model structural differences, initial conditions, scenarios, parameters and resolution/bias-correction), climate impact models (CIMs) and observations (e.g., Challinor et al., 2009a,b; Hawkins and Sutton, 2009; Osborne et al., 2013). Multi-member model ensembles (Collins et al., 2010, for example) and model intercomparison projects (MIPs) are used to assess uncertainties in future climate and climate impacts. These studies include the Coupled MIP (CMIP—Taylor et al., 2012), Water MIP (WaterMIP—Haddeland et al., 2011), the Agricultural MIP (AgMIP—Rosenzweig et al., 2013), and the Inter-Sectoral Impacts MIP (ISI-MIP—Warszawski et al., 2013), which contributed to the IPCC reports (IPCC, 2013, 2014).

The use of ensemble projections and the outputs of MIPs in impact assessments raises the issue of how to interpret the resulting uncertainty ranges (e.g., Smith et al., 2009; Knutti et al., 2010; Tebaldi et al., 2011), which are dependent on experimental design. For instance, "high-end" impacts (e.g., under global mean temperature changes >4 K) are less sampled (Challinor et al., 2009a, 2010). Uncertainty ranges may be interpreted differently by scientists and decision-makers, potentially resulting in poor decision making.

The appropriate treatment of uncertainty ranges will vary according to the nature of adaptation required. In agriculture for example, adaptation could mean coping (altering planting dates or crop varieties), adjusting (new crops or livestock species), or transforming (new production systems, livelihoods, migration). Bottom-up approaches (beginning by assessing the decision-making context) are important for incremental (coping) strategies while top-down approaches (beginning with climate scenarios) are important for transformative strategies (Vermeulen et al., 2013; **Figure 1**). Our aim is to highlight challenges in using ensembles to assess uncertainties in future climate impacts and identify priorities for making further progress.

STATISTICAL METHODS FOR UNDERSTANDING AND REDUCING UNCERTAINTY

Large-scale models of natural and physical systems inherently contain uncertainties. These uncertainties originate from the complex nature of the system, and from our limited knowledge of it. Uncertainty is described in a variety of ways, from qualitative statements such as "likely" and "unlikely," or "low," "medium" and "high" confidence (IPCC, 2012, 2013, 2014) to quantitative representations like a range of plausible values, a standard deviation or a full probability distribution providing confidence bounds.

MULTI-MODEL DIVERSITY

For models of large-scale complex systems, a common approach to assessing model uncertainty is the use of MIPs (see introduction). This involves taking a selection of models which often differ in their representation of system processes, and evaluating their outputs for a range of scenarios. The resulting comparisons allow uncertainty in predictions due to model diversity to be quantified. However, these estimates must be used with caution if the models compared are not independent, or contain mutual errors and omissions (e.g., regional precipitation biases), as this can lead to

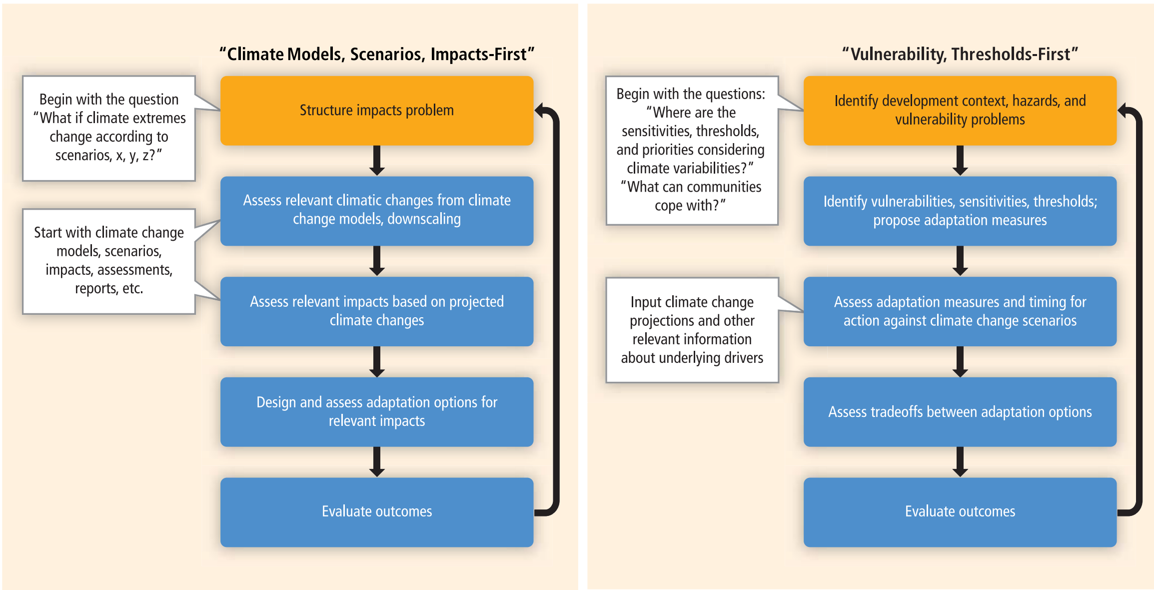

FIGURE 1 | Top-down scenario, impacts-first approach (left panel) and bottom-up vulnerability, thresholds-first approach (right panel)—comparison of stages involved in identifying and evaluating adaptation options under changing climate conditions (© IPCC, 2012; from Lal et al., 2012).

unrepresentative estimates of uncertainty. It can also be difficult to determine the causes of uncertainty since the resulting ensemble contains little information on how process representations affect the outputs (Davie et al., 2013).

By focusing on a single model, sources of uncertainty within that model may be evaluated more rigorously (Deser et al., 2012). While uncertainty is quantified for only one model, evaluation of how the uncertainty in the processes and parameters within that model affects the outputs can be very informative, leading to more focused model development.

PARAMETRIC UNCERTAINTY

There are many statistical tools for understanding model parametric uncertainty. Classical methods involve direct Monte Carlo simulation, where the entire parameter space is explored by running the simulator for a large number of input parameter combinations and evaluating the model response (e.g., the Generalized Likelihood Uncertainty Estimation: GLUE (Beven, 2007) method used in hydrology). For a complex model with a large run time this may become unfeasible, although distributed experiments such as climateprediction.net are pioneering such approaches (Stainforth et al., 2005).

Bayesian statistical framework-based approaches have been used to overcome such computational barriers. For example, Lee et al. (2013) explored the sensitivity of cloud condensation nuclei (CCN) concentration estimates to parameters in a global aerosol model following the Bayesian approach of Oakley and O'Hagan (2004). Here, Gaussian process emulation (O'Hagan, 2006) was used to reduce the computational cost and probabilistic variance-based sensitivity analysis (Saltelli et al., 2000) was applied to evaluate which inputs were driving uncertainty in the outputs. This approach is rarely used for assessing climate change impacts, in comparison to projections of climate.

Inverse modeling approaches involving Markov chain Monte Carlo simulation to evaluate a full Bayesian posterior parameter distribution have been used to assess the effects of parameter uncertainty for aerosol-cloud interactions (Partridge et al., 2012) and hydrology (Vrugt et al., 2008). The comparison of model simulations to observations (model calibration) and the use of observations to reduce an uncertain parameter space (history matching) can help to assess model uncertainty. For example, McNeall et al. (2013) show the potential of these methods to constrain a complex ice sheet model.

TREATMENT OF UNCERTAINTY IN IMPACT STUDIES: A CASE STUDY FOR WHEAT

Climate impact studies depend on the choice of climate data and the impact model used. Recent impact studies have used climate model ensembles to account for the uncertainty due to global climate models (GCMs) and their parameterizations, building on earlier approaches using small numbers of scenarios or models. Less emphasis has been placed in making progress via impact studies using raw GCM output (e.g., Falloon et al., 2011; Taylor et al., 2013; Betts et al., 2013; Mathison et al., 2013), and in understanding uncertainty introduced through downscaling methods, bias-correction methods or the use of weather generators. Bias-correction methods for GCM output may be as important as GCM uncertainty (e.g., Done et al., 2013), and potentially greater than uncertainty due to scenarios as shown for the number of summer days where maximum temperature exceeds a certain threshold across Europe (Hawkins et al., 2013).

There is considerable diversity in present crop models (Rivington and Koo, 2010): e.g., statistical models based on observed relationships, dynamic process-based models for particular crop types, and generalized large and field scale process-based models. Crop models vary in their complexity, how they simulate dynamic processes (e.g., crop development), and which processes they simulate (e.g., high temperature stress around anthesis and/or microclimate). Crop models based on observed relationships have set parameters for a given cultivar ("genetic coefficients"), determined through field experiments; thus not accounting for parametric uncertainty. Regional scale crop models may be optimized to observed yield data and a parameter ensemble may be used (Challinor et al., 2009a). Impact model studies are limited by the number of observable output variables that can be used for parameterization, regardless of the approach taken and the application.

Several studies have assessed the importance of different sources of uncertainties in crop models. An ensemble of wheat models performed well compared to experimental data from four contrasting growing environments but only when provided with sufficient calibration data (Asseng et al., 2013). With increasing temperatures, crop development may make a large contribution to uncertainties in simulated impact, both between models (Asseng et al., 2013) and in one model exploring a range of common functions and cardinal temperature settings (Koehler et al., 2013). Changes in growing season precipitation affected simulated yield but showed little change in the variation between models in simulated yield change (Asseng et al., 2013). Warming may expose crops to more high temperature stress around anthesis (the onset of flowering). However, not all models include a direct temperature effect during anthesis, and accounting for anthesis may not result in correctly simulating the effect (Asseng et al., 2013), illustrating the importance of understanding model behavior for predictive uses. For processes where threshold values are important (e.g., heat stress), ignoring microclimate may lead to large systematic errors, since in irrigated systems panicle (loose branching flower cluster) temperatures may vary strongly from air temperature depending on vapor pressure deficit (Julia and Dingkuhn, 2013).

Lessons learnt from the AgMIP-wheat pilot study (Asseng et al., 2013) were taken forward into the next set of simulations, which cover a wide temperature range during different growth stages with non-limited conditions for nutrients and water (Ottman et al., 2012). Crop models are often developed for a specific region and/or purpose and may depend on regional characteristics. With the strong focus on global studies, the same crop model may be applied outside its "design region," so key processes for crop growth need to be identified, and contrasting regions (e.g., hot humid versus hot dry) should be prioritized in MIPs.

DOES UNCERTAINTY INCREASE WITH GREATER INTEGRATION OF IMPACTS?

A more comprehensive integration of sectors and processes in Earth System Models (ESMs) and CIMs should provide a more complete picture of system behavior since impacts and the earth system are interlinked in reality. There are also numerous feedbacks between impacts and weather and climate (Falloon and Betts, 2010). Critical thresholds and non-linear responses also exist between impacts and climate drivers, such as the effect of extreme temperature on crop flowering (Wheeler et al., 2000).

To illustrate the interactions between climate impacts, we describe how water systems may be affected by climate change with implications for agriculture (Falloon and Betts, 2010). Direct climate effects on water include changing location, amounts and timing of precipitation, snowmelt, runoff, evaporation and groundwater recharge. Indirect effects include altered water management practices, responding to the changing climate and direct effects. For example, higher summer temperatures may increase industrial and domestic water demand, increase abstraction and reduce river flows. This may increase inter-user competition for water, affecting agricultural water availability. Higher summer temperatures may increase agricultural water demands, further increasing inter-sectoral pressures.

Feedbacks between climate and impacts include both changes in local and remote weather and climate, and biophysical and biogeochemical effects. For example, Falloon et al. (2012) used an ESM to investigate the effect of future vegetation change on the climate itself, finding warming of $\sim$1 K in high latitudes where forest expansion reduced albedo, and over the Amazon where reduced tree cover reduced evaporative cooling. Carbon storage increased in the high latitudes but was reduced over Amazonia. McCarthy et al. (2010) showed that the inclusion of cities in a climate model led to increased frequency of extreme hot nights, due to both the urban land surface and due to increased anthropogenic heat sources.

Several approaches may be taken to integrate climate impacts. Bio-physical impacts may be linked in "online" approaches where impacts are included within weather/climate models. "Offline" approaches may link different impacts in stand alone models driven by climate model outputs (e.g., Krysanova et al., 2007; Mahmood et al., 2007; Davie et al., 2013). Integrating biophysical impacts with socioeconomic factors is complex but approaches include integrated assessment models (e.g., Warren et al., 2008), global economic models (e.g., linking crops, trade, irrigation and river flows—Calzadilla et al., 2013), and loose linkages (e.g., Barthel et al., 2008).

There are a range of potential issues to consider when integrating climate impacts. In some cases, meaningful comparisons between models and observations may be challenging. For instance, ESMs provide a wide range of estimates of contemporary soil C stocks (510–3040 Pg C), and observational estimates vary widely (500–1260 Pg C). There are also differences in what is represented by models (Todd-Brown et al., 2013). It may be difficult to find data to parameterize impact models for all the processes needed to realistically reproduce observed behavior (Challinor et al., 2013). Finite computing resources mean that tradeoffs will need to be made between complexity/breadth, detail, and risk assessment—the ability to represent multiple sectors, processes and sample uncertainties using large ensembles. The ISI-MIP study suggested that ensembles of both impact and climate models are needed for making robust future assessments, although the bias-correction applied to the climate model output may alter the impacts (e.g., Ehret et al., 2012; Hawkins et al., 2013). Finally, interactions between biophysical impacts and socioeconomic drivers are important, including decisions made on small space/time scales.

Several approaches may be taken to assessing the appropriate level of model integration and complexity for a particular purpose. Testing for relationships between observed impact (e.g., crop yield) and weather would provide a top-level justification for combining models of impact and climate (e.g., Challinor et al., 2003), as would the existence of significant feedbacks between impact and climate (e.g., river flow impact on ocean circulation; carbon cycle; or albedo). Several authors have selectively removed model components or fixed parameters, and then retested model performance (e.g., Crout et al., 2009; Tarsitano et al., 2011). This may be challenging with large, complex models. The appropriate level of model integration will also depend on the time and space scale in question, the location, climate and needs of stakeholders (Challinor et al., 2009a).

HOW SHOULD UNCERTAINTY BE TREATED FOR ADAPTATION?

Adapting to a changing climate is a complex societal process of activities, actions, decisions and attitudes that reflect existing social norms and processes (Adger et al., 2005). Systems and actors do not adapt to climate change in isolation—adaptation happens in a world of multiple stresses and drivers of which climate is one. The significance of the climate driver depends on the adaptation context.

There are two approaches for evaluating climate adaptation options (IPCC, 2012; **Figure 1**): "top-down" and "bottom-up." The top-down climate models, scenario, impacts-first approach starts with the question: "how will future climate change?" (Dessai and van der Sluijs, 2011), and the assessment of uncertainty at each stage led Schneider (2001) to coin the phrase: "cascade and explosion of uncertainty" (**Figure 2**). Once relevant impacts have been assessed, adaptation options can be designed and assessed. Given the uncertainties involved in climate impact assessments, a more fruitful approach may be to begin with the decision-making context (Dessai et al., 2009a,b; Wilby and Dessai, 2010). Such bottom-up, vulnerability, threshold-first approaches first identify vulnerabilities, sensitivities, and thresholds to proposed adaptation measures. These measures and their timing are assessed against present and future uncertain drivers of which climate is but one. The characterization of climate uncertainty should be commensurate with that of other uncertain drivers in adaptation assessments. Rigorous sensitivity analysis of models that inform adaptation decisions (e.g., Saltelli et al., 2000) can produce a more robust assessment of relevant uncertainties, which is more fit-for-purpose for decision making. However, individual responses to climate change and adaptation may themselves be a significant source of uncertainty.

The top-down approach has been dominated by climate model projections. A bottom-up approach can use climate model information to characterize climate uncertainty. However, other approaches (that are potentially more appropriate alongside other uncertain drivers) include climate change narratives (e.g., a description of how circulation changes will affect climate in a location), expert judgment and theory based principles. The bottom-up approach enables the assessment of trade-offs between different adaptation options due to different uncertainties (e.g., climate, socio-economic, land use changes) and multiple criteria (e.g., maximizing expected utility, saving lives, protecting the environment).

While the top-down approach is still very common, there is an emerging body of work which applies the bottom up approach, particularly in water resources (Risbey, 1998; Lempert and Groves, 2010; Prudhomme et al., 2010; Korteling et al., 2013). The bottom-up approach requires information providers to work and communicate closely with decision makers (Dilling and Lemos, 2011) to understand their plans and goals, before tailoring the uncertainty description to focus on key factors. This can be very effective, but often needs to be individually customized for each decision context (Lempert and Kalra, 2011; Lempert et al., 2012).

RECOMMENDATIONS AND FUTURE RESEARCH NEEDS

While the design and implementation of MIPs tends to focus on comparing model responses (outputs), there is a need to consider how they can be better used to improve and develop models, and to synthesize knowledge more effectively (Challinor et al., 2014). For instance, multiple variables (e.g., nitrogen availability, water use, crop quality, yield) could be assessed within single (e.g., crop model) impact studies.

The interlinked nature of climate and impacts requires comprehensive treatments of uncertainty including relationships/feedbacks between climate and its impacts. A more consistent approach should be taken to assessing the effect of model integration, particularly considering "offline" and "online" approaches. Key issues include the ability to model the individual components at the right level of complexity, whether the components need to be modeled individually or together, impacts on model performance, and whether integration provides more insight into system behavior. There is a need to assess the benefits and tradeoffs between model complexity, resolution and ensemble size for making impact assessments.

The use of statistical methods to assess uncertainty should be promoted. The growing use of statistical methods to evaluate, understand and reduce model uncertainty means that more robust conclusions can be obtained from model applications, including an assessment of uncertainties. This can also lead to an improved understanding of model behavior, indicating where a model can be most improved and where greatest confidence can be placed in results. Impact modeling approaches may benefit from experiences gained in the climate modeling community (and potentially vice-versa).

The usability of impact assessments for decision making could be improved through:

- Greater clarity in the methods and assumptions used (e.g., use of GCMs, scenarios, timescales, ensembles, bias correction, downscaling, and impact models), and assessment of their impact on results (e.g., Watson and Challinor, 2013).
- Appropriate selection of assessment approaches—for instance a top-down framing when uncertainties are shallow (and for broad scoping assessments), or a bottom-up framing when uncertainties are deep (Dessai et al., 2009a).

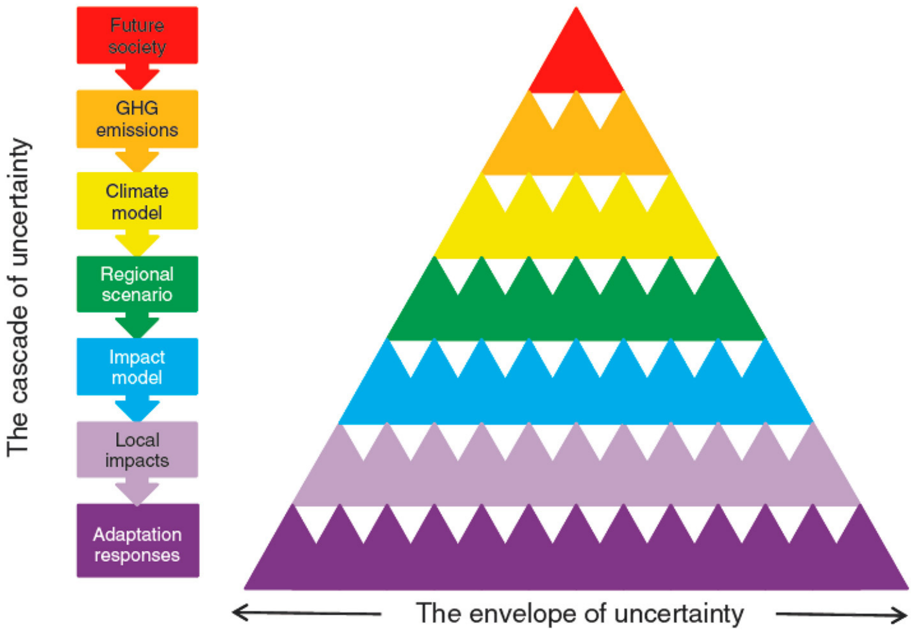

FIGURE 2 | The cascade of uncertainty from illustrating the growth of the envelope of uncertainty from various sources going from future society to adaptation response. Used with permission from Wilby and Dessai, 2010, (© Royal Meteorological Society, 2010).

- Common, clear ways of reporting and describing uncertainties (e.g., Challinor and Visman, 2014).
- The use of models as tools from which information is extracted, rather than as competing attempts to represent reality (Challinor et al., 2003).
- Assessment of methods which go directly from climate model to decision parameter, removing intermediate steps and potentially reducing embedded uncertainty (e.g., Holland et al., 2010).

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