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Use of agro-climate ensembles for quantifying uncertainty and informing adaptation

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ABSTRACT

Significant progress has been made in the use of ensemble agricultural and climate modelling, and observed data, to project future productivity and to develop adaptation options. An increasing number of agricultural models are designed specifically for use with climate ensembles, and improved methods to quantify uncertainty in both climate and agriculture have been developed. Whilst crop–climate relationships are still the most common agricultural study of this sort, on-farm management, hydrology, pests, diseases and livestock are now also examined. This paper introduces all of these areas of progress, with more detail being found in the subsequent papers in the special issue. Remaining scientific challenges are discussed, and a distinction is developed between projection- and utility-based approaches to agro-climate ensemble modelling. Recommendations are made regarding the manner in which uncertainty is analysed and reported, and the way in which models and data are used to make inferences regarding the future. A key underlying principle is the use of models as tools from which information is extracted, rather than as competing attempts to represent reality.

1. Introduction

The use of climate ensembles with agricultural models, particularly crop models, is an increasingly common method for projecting the potential impacts of climate change (see e.g. reviews by Challinor et al., 2009a,b). These developments are timely, given the significant societal interest in both the implications of climate change and the uncertainty surrounding predictions. Ongoing increases in greenhouse gas emissions will continue to alter climate for some decades. Climate and impacts ensembles provide a tool for predicting the implications of these changes and for developing adaptation options.

This special issue demonstrates the maturity of this field by highlighting recent progress in methodologies for the design and use of ensembles and in the agricultural modelling that is used in such studies. The word ensemble is used here to indicate any multiple model simulations that seek to quantify uncertainty. This includes both ensembles that quantify parametric uncertainty using one model and ensembles that quantify structural uncertainty by using a number of models. Ensemble agricultural and climate modelling, or more briefly agro-climate ensemble modelling, refers here to a set of directly comparable agricultural simulations generated using one or more climate projections with one or more agricultural models in one or more configurations. The direct comparability of the simulations makes the ensemble a tool for quantifying and exploring uncertainty. An ensemble crop simulation, for example, seeks to quantify uncertainty due to some or all of: climate, crop response to climate, and other determinants of crop productivity.

The papers in the special issue reflect the growing breadth of topics that are being assessed using ensemble techniques. They also suggest a parallel with the development of ensemble methods within climate change science itself, whereby a “new era” in prediction was identified as a result of the increasing use of ensembles (Collins and Knight, 1857). The increase in the use of ensemble techniques in agriculture has been largely enabled by this development in climate science. The influence of climate science is evident from the common use of multiple climate realisations in agro-climate ensembles, compared to the far rarer use of multiple crop models.

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Thus agro-climate ensembles are often the result of the use of an agricultural model as a tool for interpreting climate ensembles in an agriculturally relevant way.

The generation of robust projections of agricultural production requires adequate account of uncertainty in future atmospheric composition and climate, the subsequent response of agricultural systems, and the range of non-climatic drivers that affect agriculture. Only in this way can appropriate adaptation and mitigation actions be determined. The question of how much account of uncertainty is adequate for any specific adaptation and mitigation action is not trivial. This important question is discussed briefly in Section 3.2, but falls largely outside the scope of this special issue. Our starting point here is the recognition that, in an effort to ensure that treatments of uncertainty are at least adequate, the climate impacts community is putting increasing efforts into improving the methods used to assess impacts and adaptation, and understanding the associated uncertainties. This includes assessing, intercomparing and improving tools and methodologies (see Rosenzweig et al., 2012) and asking: what do our models tell us about the real world?

The choices in climate impacts modelling regarding model complexity, ensemble size and spatial resolution, whether made explicitly or resulting from the inherent trade off forced by limited computer power, affect the way in which the model results need to be interpreted (Challinor et al., 2009a). Computing power limits the potential for studies to employ complex models over a large spatial domain and systematically sample uncertainty, so that modelling work tends to focus on one, or maybe two, of these three characteristics. The agricultural simulation studies in this special issue demonstrate this trade off: they vary in their sampling of uncertainty and can broadly be divided into those that have relatively high spatial resolution (Ewert et al., 2012; Gouache et al., 2012; Graux et al., 2012; Teixeira et al., 2011; Ramirez-Villegas et al., 2011; Kroschel et al., 2012) and those that use relatively complex models and/or simulate a number of different agricultural processes and practices (Ruane et al., 2011; Tao and Zhang, 2011; Hemming et al., 2011; Osborne et al., 2012; Fraser et al., 2012; Berg et al., 2012). The studies also reflect the increasing ability to simulate agricultural responses across large or multiple regions, including global assessment (Berg et al., 2012; Fraser et al., 2012; Hemming et al., 2011; Kroschel et al., 2012; Osborne et al., 2012; Ramirez-Villegas et al., 2011).

Due to the focus on the use of climate ensembles, either to achieve large geographical coverage, or to capture uncertainty through the use of many ensemble members, relatively few studies here employ downscaling techniques (Gouache et al., 2012; Graux et al., 2012; Hoglind et al., 2012; Ramirez-Villegas et al., 2011; Kroschel et al., 2012). Efforts to produce coordinated ensembles of regional climate model simulations (e.g. ENSEMBLES, COREDEX) are likely to lead to an increasing potential to sample uncertainty at higher spatial resolution. Downscaling is not covered explicitly in this introductory paper, except to note that two studies in this special issue (Hawkins et al., 2012; Hoglind et al., 2012) are relevant to weather generation.

Every approach to climate impacts assessment has its pros and cons. In the development of each approach, a number of questions are addressed, either implicitly or explicitly. The following list is drawn in part from a workshop on climate impacts held in April 2010[1]:

1. What is the appropriate degree of complexity for simulation? This is relevant both to the biophysical model (Section 2.1) and in considering the influence of, and interactions between, the range of other drivers of agricultural productivity, such as pests and diseases and management practices (Section 2.2.2).
2. What are appropriate methodologies for quantifying and representing uncertainty (Section 2.2.1)? There are an increasing number of sets of climate ensembles produced from a range of research programmes. How are impacts modellers and, more broadly, users of climate information to choose between these? Which uncertainties in climate and its impacts dominate under which circumstances? Given that complete sampling of uncertainty using ensembles is not possible, can objective probabilities be determined? How should uncertainty in agricultural models be represented and evaluated?
3. How should uncertainty be presented and communicated? How do these choices affect the methods used to quantify uncertainty? These questions have implications for the design and use of ensembles (Section 3.2).

In addition to introducing and framing the special issue, this opening paper seeks to identify methodologies for making effective use of agro-climate ensembles. Thus, the summary of progress in Section 2 is used as a basis for a discussion of knowledge gaps (Section 3.1) and some brief reflections on the utility of agro-climate ensembles (Section 3.2). Conclusions are presented in Section 4. Throughout the manuscript, the word uncertainty, where used without further qualification, is used to denote a lack of predictive precision due to either inherent limitations to predictability (e.g. due to unknown future greenhouse gas emissions) or to a lack of predictive skill (e.g. errors in the design of a model).

2. Progress in agro-climate modelling

Here we highlight progress in the models used for agricultural impacts assessment (Section 2.1) and improvements in the methodological design of studies that use those models, both in terms of the quantification of uncertainty (Section 2.2.1) and the use of modelling studies to inform adaptation, which necessarily implies simulating crop yield but also a range of other quantities and processes (Section 2.2.2).

2.1. Agricultural models designed for use with climate ensembles

Judicious choices of both agricultural model and the technique used for calibration are crucial for the development of robust conclusions regarding the impacts of climate change. Implicit in this choice is a judgement on the appropriate degree of complexity for simulating biophysical and agricultural processes. Insufficient complexity, by definition, renders a model incapable of simulating the processes that result in observed quantities. Excess complexity in a model results in sufficient degrees of freedom to reproduce observations, but this will often require parameter values that cannot be adequately constrained – thus increasing the chances of getting the right answer for the wrong reason (Challinor et al., 2009b). In practice, use of a range of approaches, with associated recognition of the pros and cons implicit in the assumptions made, is a way of assessing the robustness of results. This observation has been developed and labelled in a number of research fields and in a number of ways, e.g. equifinality (Beven, 2006) and consilience (Wilson, 1998).

The use of a range of approaches within agricultural modelling is perhaps most evident with crops, as is indicated by the papers in this special issue, which range from detailed process based models (e.g. Ruane et al., 2011) to empirical models (Lobell, 2012) and diverse models of intermediate complexity (e.g. Ramirez-Villegas et al., 2011; Osborne et al., 2012; Watson and Challinor, 2012). Model complexity is inherently linked to the spatial scales at which

[1] See the report on the EQUIP user meeting at http://www.equip.leeds.ac.uk/user-workshop-3-269.html.