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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.

Keywords: Climate models, Crop models, Ensembles, Climate change, Adaptation, Food security, Climate variability, Uncertainty, Crop yield

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, 2007). 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. 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, Robertson et al. 2012, Teixeira et al. 2012, Ramirez et al. 2012, 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. 2012, Tao et al. 2012, Hemming et al. 2012, 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. 2012, Kroschel et al. 2012, Osborne et al. 2012, Ramirez et al. 2012).

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 et al. 2012, 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

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

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. 2012) to empirical models (Lobell 2012) and diverse models of intermediate complexity (e.g. Ramirez et al 2012, Osborne et al 2012, Watson et al 2012). Model complexity is inherently linked to the spatial scales at which crop responses are being simulated (for a full discussion, see e.g. Challinor et al., 2009a,b). Ramirez et al (2012) integrate the FAO-EcoCrop database with a basic mechanistic model that uses environmental ranges as inputs to determine the main niche of a crop and then produces a suitability index as output. Ruane et al. (2012) investigate the ability of empirical models of crop yield to reproduce the results from more complex process-based crop model simulations and infer pros and cons of each approach. The range of models now available is increasingly enabling spatially explicit global assessments of the actual (Osborne et al. 2012) and potential (Berg et al. 2012) productivity of crops and the impact of specific processes such as heat stress (Teixera et al.2012).

The studies collected here also demonstrate the relatively recent increase in the use of non-crop simulation models for climate impacts studies. The simulations of Hoglind et al. (2012) indicate increased grass yields into the future, mainly due to increased temperatures; Graux et al. (2012) find new opportunities for herbage production in spring and winter, although future conditions show increased interannual variability in production. Section 2.2.2 highlights progress in other non-crop simulations, for example socio-economic processes and pests and diseases.

2.2 Improvements in the design of agro-climate ensembles

2.2.1 Improved quantification of uncertainty

The papers in this special issue present advances in both the methods used to assess uncertainty and the knowledge resulting from agro-climate ensembles. Methodological improvements address the inability to associate occurrence of events across an ensemble with the probability of those events occurring. More broadly, methodologies are required that enable the calibration and evaluation of ensemble prediction systems in order to better constrain ensemble outputs. Tao et al. (2012) applied Bayesian probability inversion and a Markov chain Monte Carlo (MCMC) technique to a large-scale crop model in order to attempt to make probabilistic predictions. This study, which focuses on the use of statistical tools to constrain ensembles, contrast with approaches that focus on specific processes such as heat and/or water stress (e.g. Teixida et al. 2012, Challinor et al. 2010), sometimes constraining ensembles using relatively simple techniques (e.g. Challinor and Wheeler, 2008a).

New knowledge on sources of uncertainty contained in this special issue can be divided into two categories:

(i) Uncertainty in specific processes such as CO2 fertilisation and pest occurrence. Gouache et al. (2012) simulate the occurrence of *Septoria tritici* blotch on winter wheat and find that the contribution of the disease model to total uncertainty was greater than that of the climate model. Ruane et al. (2012) used the positive and monotonic relationship between CERES-Maize yield and carbon dioxide concentrations as a metric for the uncertainty associated with CO2 fertilisation and found this uncertainty to be significant (10 to 20%). This issue may be addressed by constraining the response of crops to increased CO2 using observations (Challinor et al., 2009c). However, interactions between water stress and CO2 can add significantly to the uncertainty in the response of crops to changes in CO2 (Challinor and Wheeler, 2008a).

Model simulations with fully coupled vegetation and climate also provide evidence of the magnitude of the CO2 fertilisation effect. Hemming et al. (2012) examine both direct and indirect plant physiological responses to CO2 using such a model. The direct effects of elevated CO2 account for a 75% increase in net primary productivity (NPP), whilst indirect effects (i.e. the sum of effects mediated through the associated change in climate) account for a 21% decrease in the ensemble average. The extent to which results for NPP can be directly compared to results from calibrated and/or constrained crop model simulations is not yet clear.

(ii) Assessments of the impact of uncertainty in agricultural model inputs, including climate model data. It is clear from the analysis above, and from a broader reading of the studies presented here, that the uncertainty resulting from simulation of a climate impact (such as crop yield or disease occurrence), and the fraction that this contributes to total uncertainty, varies across studies. Studies using crop and climate models have suggested that uncertainty in climate is a significant, if not dominant, contribution to total projected uncertainty (e.g. Challinor et al., 2009c). The broader issue of error in the inputs to climate impact models is therefore an important one. Lobell (2012) finds, using an empirical crop model, that studies that ignore measurement errors are unlikely to be biased for estimating the temperature sensitivity of yields, but can easily underestimate sensitivity to rainfall by a factor of two or more. Watson et al. (2012) examine the impact of error in rainfall, temperature and yield data (used for calibration) on process-based crop model, by randomising and perturbing observed data. For their study case, errors generated by randomising the temporal sequence of seasonal total precipitation produced an error in simulated yield of approximately three times that of temperature or yield. However, perturbing input data to values beyond those found in the current climate increased all yield errors significantly and to comparable values.

The above studies all focus on the importance of input data from the perspective of agricultural models themselves. An important exception is the study of Craufurd et al. (2012), which highlights the role of crop science experiments in providing high quality data to inform crop modelling. In particular, the authors note that the diversity of genotypic responses is not well represented by existing crop science experiments, since responses have only been quantified for a limited number of genotypes.

The importance of weather and climate inputs in determining the predictive skill of agricultural models implies that appropriate effort should be made to ensure that these inputs are as accurate as possible (without introducing false confidence through unwarranted precision). After reviewing the methods available for post-processing climate model output, Hawkins et al. (2012) employ these methods using a 'perfect sibling' framework, which is similar to the perfect model approach, and find significant variation in results. Whilst that study does not employ a weather generator, the results are relevant for the on-going development of weather generators.

2.2.2. Going beyond biophysical crop yield impacts

Much of the progress in agricultural modelling using ensembles has occurred with crop models. However, in order to inform adaptation, information is needed not just on likely future crop yields as influenced by biophysical processes, but also on the influence of a broader range of processes. Many of the studies discussed in section 2.1, and those presented elsewhere in this special issue, address adaptation in some way. These studies aim for a more complete description of the system through accounting for socio-economic drivers of productivity (Fraser et al. 2012), on-farm management such as choice of crop variety or planting date (Osborne et al. 2012; Ruane et al. 2012), or the impact of pests and diseases (Garrett et al. 2012; Kroshel et al. 2012; Gouache et al. 2012). For example, Fraser et al. (2012) use socio-economic data to model adaptive capacity and hydrological data to model exposure to drought, without the use of a crop model (though such work has been combined with biophysical models: Challinor et al., 2010). Garrett et al. (2012) provide a framework for integrating models of livestock, crops, pests and disease, whilst Kroschel et al. (2012) present a specific tool for adaptation planning in the integrated management of potato tuber moth.

As the use of ensembles is extended to increasingly complete descriptions of agro-climatic processes (including biotic stresses and human actions), the complexity of the associated models and/or model chains will increase. Since the number of interactions between physical, agricultural and biological systems increases as the number of processes simulated increases, the uncertainty in the interactions will likely result in greater total uncertainty. Thus additional complexity brings with it demands for increased ensemble size in order to adequately sample uncertainty. If such models and model chains are carefully calibrated and have appropriate complexity then we may expect to see increasingly accurate representations of agro-climatic processes that in turn can be used to inform adaptation.

3. Discussion

3.1 Remaining science questions and challenges

If projections based on agro-climate ensembles are to be robust, then a number of questions remain to be answered. Crop modelling relies on measurements for development, calibration and evaluation. How can field experiments, such as those that assess crop phenotypes, be best targeted towards modelling? Without addressing this question and others like it, agricultural models will at best make sub-optimal use of environmental data, and at worst they will be relied upon in lieu of that data, thus likely misleading adaptation efforts.

A second challenge is to better understand the relationship between model complexity, measured uncertainty and actual uncertainty, and the manner in which this varies across spatial scales. Repeated projections for the near future, such as seasonal forecasts of crop yield, produce uncertainty ranges that are verifiable using standard techniques (e.g. Challinor et al., 2005). No such techniques can exist for projections of changes in the mean and variability of agricultural productivity on longer timescales, since there will be only one evolution of climate. Where climate change predictions are repeated many times, e.g. for multiple locations, ranges can be verified; but the extent to which these ranges can be compared to assessments of structural and parametric uncertainty is not clear.

The move from emissions scenarios to Representative Concentration Pathways (van Vuuren et al., 2011) facilitates improved understanding of the consequences of uncertainty for prediction: by separating the uncertainty in future greenhouse gas emissions from uncertainty in the subsequent response of the climate system, the new framework has the potential to identify the component of future climate change that we can control. However, it is not yet clear whether or not this change will lead to more robust projections. Bayesian theory demonstrates that prior assumptions, whether made implicitly or explicitly, affect uncertainty estimates. Whilst some authors (e.g. Berger 2006) maintain that this does not preclude objective quantification of uncertainty, other authors question the potential for objective uncertainty assessment, both within (O'Hagan, 2006) and beyond (Yohe and Oppenheimer, 2011) the Bayesian framework. Given this conceptual difficulty, and given that attempts to quantify uncertainty in agro-climate modelling can lead to very large ranges, and that ranges that can rarely be inter-compared (Challinor et al., 2007), it may be that new frameworks for quantifying and managing uncertainty are needed (sections 3.2 and 4). Studies that aim to compare and improve agricultural models, notably AgMIP (Rosenzweig et al., 2012), should do so in a manner that permits direct inter-comparison.

Uncertainty in projections can be reduced by detailed examination of processes (see section 3.2) and/or by using observations to constrain simulations (e.g. Watson et al. 2012). Observational data for calibration and evaluation are critical to both of these methods of reducing uncertainty. For example, the yield simulations of Ewert et al. (2012) where the crop model is calibrated for individual regions using phenology and growth parameters are more skilful than those without this calibration, leading the authors to argue for region-specific calibration of crop models when conducting pan-European assessments. Similarly, the bivariate yield emulator tested by Ruane et al. (2012) for maize in Panama underestimated the potential yield impacts of extreme seasons and revealed errors due to the omission of additional crucial metrics including the number of rainy days and the standard deviation of temperatures. Thus, at least in some cases bivariate yield emulators are not sufficient for the prediction of yield in current or future climates. This work demonstrates the need for sufficient complexity in the development and calibration of agricultural models. Similarly, Watson et al. (2012) demonstrate the importance of yield data for the calibration of regional-scale models. Crop experiments relevant to future climates are also important (Craufurd et al. 2012), for example in evaluating the performance of crop varieties under climate change and in assessing crop response to elevated CO2.

3.2 Effective use of agro-climate ensembles

The issues outlined in section 3.1 regarding data, model complexity, and simulated and actual uncertainty, make it clear that validated, definitive probabilistic ensembles of impacts are difficult, if not impossible, to produce. This implies the need for significant thought in the way that uncertainty and prediction are framed. It also implies a need to recognise that different models may be needed for different parts of the decision cycle. Depending on the aims of any given study, one of two approaches is usually taken to developing agro-climate ensembles. Projection-based approaches use models and data to increase understanding and view decision-makers as end users. Utility-based approaches focus on the decisions that need to be made, rather than projections of impacts. For a broader discussion of these two approaches to managing uncertainty in climate and its impacts, see Mearns et al. (2010) or Dessai et al. (2007).

Projection-based approaches map out the cascade of uncertainty from climate through to impact. Their success may be contingent on a degree of consilience (see section 2.2.1), which is something that the research process is apt at achieving, albeit at a speed limited by the publication cycle. Model inter-comparisons and combinations (Rosenzweig et al. 2012) – including the synthesis of information from process-based and statistical approaches – are likely to be particularly useful techniques for achieving consilience. Since attempts to combine both climatic and socio-economic drivers of agriculture (e.g. Challinor et al., 2010) are relatively few in number, it is not yet clear whether or not consilience can be achieved across the biophysical and socio-economic domains.

Projection-based approaches are particularly well-suited to research and this is perhaps the approach most commonly found in the literature. Over time, new knowledge about agro-climatic systems is generated and this knowledge can then be used wherever and however the opportunity arises. Projections with well-bounded and uncertainty ranges are more likely to be useful in this context than those with wide ranges. Robust outcomes may emerge by focussing on underlying processes. For example, Ruane et al. found that avoided water stress from rapid maturity offsets the effect of temperature increases. Thornton et al. (2009) found that maize and bean yields in the drylands of East Africa responded in a similar fashion to climate change under both increased or decreased rainfall, due to the relationship between temperature and rainfall.

Utility-based approaches hypothesise that taking into account how information is used can improve its utility. Thus research design is informed by the decision-making process, for example the chain of decisions around investment in new crop varieties. Since decisions naturally involve social and economic systems, utility-based approaches usually involve the social sciences (Raymond et al., 2010; Twyman et al., 2011). The specific nature of the decisions examined in a utility-based approach may make it difficult to generalise the results from different studies. However, the embedding of information and learning within decision-making processes can provide an alternative framework within which to seek consilience: synthesising sources of information in to a decision may, in spite of some individually weak elements, enable a decision that is more robust, due to other elements being stronger in the full decision context. For example, Ash et al. (2007) and McIntosh et al. (2005) found that an integrated plant growth index was both more predictable and more relevant to farm decision-making than the rainfall and temperature data on which that index depends.

Whether a projection or utility based approach is used in any given study will depend on a range of factors. The nature of the specific agro-climatic system studied, and the ability (skill) of the tools developed to reproduce the properties of this system, may in part determine the likely success of a utility-based approach. Model skill in turn is underpinned by the development of models for understanding and for prediction. As agro-climatic ensembles are developed and applied to a range of systems, the skill and utility of these tools needs to be carefully assessed. Promising areas for future work include the use of household models of agricultural activity as part of ensemble systems, in order to assess the impact of human responses to climate change at the local scale; and ensembles of integrated assessment tools and economic models (Rosenzweig et al., 2012).

4. Conclusions

In addition to providing an introduction to this special issue, some recommendations for research may be drawn from the analysis above.

1. Analysis of processes as a tool for navigating uncertainty. The use of models as black boxes, with the associated focus on model outputs, places a significant burden on the model to correctly reproduce the interactions between processes. The examination of processes across a series of models can identify research gaps in both modelling and field data

(Challinor and Wheeler, 2008b). Such analyses are not routinely applied; indeed, it is often unclear which processes have been simulated within a given study (White et al., 2011). Model intercomparison projects – notably AgMIP (Rosenzweig et al. 2012) – provide opportunities to clearly document which processes are simulated and synthesise the results of numerous models.

2. Explicit reporting on sources of uncertainty. When seeking either to improve understanding or to produce decision-relevant information, it is important to distinguish the sources of uncertainty. For example, climate change can be affected by policies to alter greenhouse gas emissions, but there is no political control over the response of the climate system to any given greenhouse gas forcing. Thus uncertainty in these two contributions to climate change has different implications for decision making.

3. Strategies for combining diverse models and datasets. Agro-climate ensemble modelling rarely uses ensembles of agricultural models. Techniques for using multiple agricultural models could be targeted at projection- or utility- based approaches. In the latter case, different models may be needed for different parts of the decision cycle. In either case, there is likely to be a role for the development of field experiments that are targeted towards modelling, such as those that assess crop phenotypes.

Underpinning all three of these recomendations is a methodology that treats models (and also data) as tools from which information is extracted, rather than as competing attempts to represent reality. This methodology could be used to improve understanding of the role of complexity, utility, spatial scale and uncertainty in agricultural prediction and adaptation. For example: how can net primary productivity from climate models (as analysed by Hemming et al. 2012) be used as part of crop yield assessments?; what are the relationships between model complexity, measured uncertainty and actual uncertainty, and how do these vary across spatial scale?; and can utility-based and projection-based approaches to agricultural prediction be combined by explicitly simulating the decision making process in projection-based agro-climate modelling (e.g. Garrett at al. 2012)? One approach to this final question is to develop methods for combining analysis of uncertainty from projections with an assessment of the accuracy needed for a specific decision.

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