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REVIEW

Developing higher resolution climate change scenarios for agricultural risk assessment: progress, challenges and prospects

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Abstract Climate change presents perhaps the greatest economic and environmental challenge we have ever faced. Climate change and its associated impacts, adaptation and vulnerability have become the focus of current policy, business and research. This paper provides invaluable information for those interested in climate change and its impacts. This paper comprehensively reviews the advances made in the development of regional climate change scenarios and their application in agricultural impact, adaptation and vulnerability assessment. Construction of regional climate change scenarios evolved from the application of arbitrary scenarios to the application of scenarios based on general circulation models (GCMs). GCM-based climate change scenarios progressed from equilibrium climate change scenarios to transient climate change scenarios; from the use of direct GCM outputs to the use of downscaled GCM outputs; from the use of single scenarios to the use of probabilistic climate change scenarios; and from the application of mean climate change scenarios to the application of integrated climate change scenarios considering changes in both mean climate and climate variability.

Keywords Development of climate change scenario · Agricultural risk assessment · General circulation models · Downscaling

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Introduction

Climate change attracted people's attention in the middle of the 1980s. Extensive studies on the potential impacts of climate change on agricultural production have being conducted over the past 20–30 years. A top-down approach has been adopted in agricultural impact assessment and adaptation evaluation. In this approach, climate change scenarios (CCSs) were first constructed and then applied to biophysical models to quantify the potential impacts of climate change on agricultural production. How a regional CCS is developed directly influences the results of climate change risk assessment (CCRA). According to the ways in which they are constructed, there are three types of CCS: analogue scenarios, incremental synthetic (or arbitrary) scenarios, and model-based scenarios (Mearns et al. 2001a). Changes in both mean climate and in climate variability are considered in the latter two types of CCS. Model-based scenarios are the mainstream CCSs utilized in risk assessment.

Assessment of climate change impact, adaptation and vulnerability has shifted progressively from being applications of scientific curiosity to a policy-relevant orientation (Lu 2006). To enhance the understanding of climate change and the capacity to assess climate change risks and better inform decision/policy making, this paper comprehensively reviews current methodologies in the development of regional CCSs and their application to agricultural risk assessment. Although this review focuses on the development of CCSs from an agricultural perspective, the information provided will be invaluable to other relevant sectors and disciplines, such as forestry, ecology, fisheries, water resources, public health and energy supply.

This review firstly introduces analogue scenarios and their application, followed by incremental synthetic CCSs and their application to system sensitivity studies. Last are model-based scenarios, including several subsections such as transient versus equilibrium CCSs, use of direct outputs versus downscaled outputs of GCMs, single scenarios versus probabilistic CCSs, and mean CCSs versus CCSs with changes in both mean and variability integrated. Summaries and recommendations are given at the end.

Analogue scenarios

Analogue scenarios can be either spatial or temporal—in both cases a recorded climate regime that may resemble the future climate at the location in question will be used (http://www.parc.ca/pdf/conference_proceedings/jan_01_barrow1.pdf). In the spatial analogue approach, regions with a climate similar to that projected for the study region in the future are identified. However, this approach is generally restricted since the non-climatic conditions of the two regions, e.g., soil type, day length etc., are dissimilar. Parry and Carter (1988) applied the spatial analogue approach to assessment of the impact of climate change on agriculture.

In the case of temporal analogues, past climate at a given location, which resembles the projected future climate for that location, is utilised. Both palaeoclimate information and actual observed instrumental records can be used. There are a number of caveats regarding palaeoclimate analogues: (1) changes in the past were unlikely to have been caused by increased greenhouse gas (GHG) concentrations, (2) the data and resolution are generally insufficient, (3) uncertainty about the quality of palaeoclimatic reconstructions, (4) higher resolution (and most recent) data generally lie at the low end of the range of anticipated future climatic warming. The instrumental analogue has its own advantages and disadvantages. Its advantages reside in data availability on a daily and local scale, and that scenario changes in climate are actually observed and so are internally consistent and physically plausible. Its disadvantages are that climate anomalies during the past century have been fairly minor compared to anticipated future changes, and any anomalies are probably associated with naturally occurring changes in atmospheric circulation rather than changes in GHG concentrations (http://www.parc.ca/pdf/conference_proceedings/jan_01_barrow1.pdf). Nishioka et al. (1993) applied instrumental analogue scenarios in a study examining the effects of climate change on rice production in Japan.

Analogue scenarios are valuable in testing and validating impacts models but it is not usually recommended that they be adopted in representing future climate in quantitative impact assessment (http://unfccc.int/files/national_reports/non-annex_i_natcom/cge/application/vnd.mspowerpoint/climate_scenarios.pps).

Synthetic scenarios

Synthetic (or incremental or arbitrary) scenarios were used in early climate change impact assessment. For this type of scenario, the change in each weather variable is unrelated to changes in other variables. This approach is normally applied through system sensitivity analysis, in which the user modifies the historical climate conditions through an absolute difference (for temperature change) and/or a ratio (rainfall, radiation and other variability changes). Generally, arbitrary incremental changes in climate (for example, a temperature increase of 2°C or 4°C and/or a rainfall change of ±20%) are specified and uniformly applied to the baseline climate to explore the response of crop production systems to changed climate with the aid of crop models (McKeon et al. 1988; Wang et al. 1992; Aggarwal and Sinha 1993; Tubiello et al. 1995; Menzhulin et al. 1995; Seino 1995; Rosenzweig and Iglesias 1998). Single climatic variables (Aggarwal and Sinha 1993; Tubiello et al. 1995) or combinations of climatic variables (McKeon et al. 1988) were considered in sensitivity studies. Arbitrary scenarios accompanied GCM-based CCSs in later impact studies (Barry and Geng 1995; Baethgen and Magrin 1995; Brklacich and Stewart 1995; Menzhulin et al. 1995; Seino 1995; Rosenzweig and Iglesias 1998).

The importance of changes in climate variability drew people's attention in the 1990s. Several studies around the world tested the sensitivity of crop yield to changes in temperature and rainfall variability, which were made arbitrarily (Mearns et al. 1992 and 1996; Riha et al. 1996; Luo and Lin 1999; Trnka et al. 2004; Torriani et al. 2007; Luo et al. 2010). Due to the poor performance of GCMs in simulating the behavior of climate variability and the absence of access to daily outputs of GCMs to derive changes in climate variability at that time, impact assessment of changes in climate variability was limited to sensitivity analysis. In other words, the impact of arbitrary changes in climate variability were explored.

Synthetic CCSs maintain the statistical distribution of historical climate but do not consider the statistical links between climate variables. They are often used in sensitivity analysis rather than climate impact assessment. This type of scenario is therefore unrealistic and not related to the wider scenario framework. However, as arbitrary sensitivity tests are dissociated from the processes that influence climate, they simulate a controlled experiment and provide a better understanding of the factors affecting crop model responses. They can also be used in impact model sensitivity tests and model comparisons for the improvement of impact models or better parameterization (Addiscot et al. 1995; Riha et al. 1996; Wolf et al. 1996). Moreover, they can also help identify climatic thresholds of critical impacts. Sensitivity studies allow the consideration of the question: 'What type, magnitude, and rate of climate change would seriously perturb the system in question'?

Model-based scenarios

Model-based scenarios are derived from simple climate models (radiative forcing algorithms), full GCMs and regionalization model/downscaling techniques. Simple climate models allow multiple simulations to be conducted rapidly, enabling exploration of the climatic effects of alternative scenarios of radiative forcing, climate sensitivity and other parametrization uncertainties. Simple climate models are unable to represent the non-linearities of some processes that are captured by more complex models (http://unfccc.int/files/national_reports/non-annex_i_natcom/cge/application/vnd.mspowerpoint/climate_scenarios.pps). The model for the assessment of greenhouse-gas induced climate change [MAGICC/SCENario GENerator (SCENGEN), Wigley 2003] has been used widely in producing future CCSs. GCMs provide the most advanced tool for projecting the potential climatic consequences of increasing radiatively active trace gases in a consistent manner. GCMs are used extensively to create CCSs because they produce climate variables that are internally consistent (i.e., the climate variables within the scenario vary in a physically realistic way; Wigley 1987). Thus, they are more realistic and allow for comparisons between or among regions (Rosenzweig and Parry 1994; Rosenzweig and Iglesias 1998). Application of GCM model-based scenarios have evolved from equilibrium CCSs to time-slice CCSs or transient CCSs; from the use of direct GCMs outputs to downscaled outputs of GCMs including both spatial and temporal downscaling; from the application of single scenarios to probabilistic CCSs, and from mean CCSs to the integration of both mean and variability change scenarios.

Equilibrium and transient climate change scenarios

Development of equilibrium and transient CCSs is in line with the development of GCMs. Earlier generations of GCMs (UKLO, Wilson and Mitchell 1987; UKHI, Mitchell et al. 1990) were equilibrium climate models that were based on equilibrium climate experiments. The climate models are allowed to fully adjust to a change in radiative forcing in equilibrium climate experiments. Such experiments provide information on the difference between the initial and final states of the model, but not on the time-dependent response. Later and current climate models (UKTR, Murphy 1995; Murphy and Mitchell 1995; GFDL, Manabe et al. 1991, 1992) are transient climate models in which the forcing is allowed to evolve gradually according to a prescribed emission scenario. In this way, the time dependent response of a climate model can be analyzed.

Substantial progress has been made in the development of transient (time-evolving) scenarios of climate change for use in agricultural impact assessment. Many crop models contain cumulative functions that retain environmental information over consecutive years (e.g., water balance, soil nutrients). These factors could account for substantial yield response differences between transient and equilibrium CCSs. A few studies have deliberately compared simulated yields using transient and equilibrium CCSs. Using the UKHIv equilibrium scenario with increased interannual variability at Rothamsted, Semenov et al. (1996) simulated a loss of wheat yield relative to the present with two crop models, and no change with a third. With the UKTR transient scenario, all three models showed yield increases relative to the present. The US Country Studies Program (Smith et al. 1996) used the CERES-Wheat model (Tubiello et al. 1999; Jones et al. 2003) to simulate larger average increases in winter wheat across Kazakhstan with the GFDL transient climate scenario (for the tenth decade) (+21% winter wheat yield) than when using the GFDL equilibrium CCS (+17% winter wheat yield). Spring wheat yields were decreased in both scenarios, but once again the yields simulated with the transient scenario were not as adversely affected as those simulated with the equilibrium CCSs.

Menzhulin et al. (1995) studied the possible impacts of three equilibrium CCSs (GISS, GFDL, UKMO) and three levels of GISS transient CCSs for 2010, 2030 and 2050 respectively on wheat yield with CO_2 induced physiological effects taken into account. The simulated result showed that yield for winter wheat increased from 9% to 41%, with the greatest increase under the equilibrium GISS scenario and least increase under the equilibrium UKMO model. Spring wheat yield decreased under equilibrium UKMO and GFDL scenarios, but increased under other scenarios. Yield responses for winter wheat and spring wheat under equilibrium and transient CCSs were quite different. Rosenzweig and Iglesias (1998) also found wheat yields to be less adversely affected by transient CCSs than equilibrium CCSs. Similar conclusions were drawn by Delécolle et al. (1995). Lack of consistency in the application of CCSs to impact modelling (i.e., based on the outputs of different climate model type: equilibrium vs transient) between studies gives competing explanations about differences in impact estimates.

Use of direct and downscaled GCM outputs

The outputs of GCMs have been linked extensively to dynamic crop models to assess climate change risks. There are three mismatches between the outputs of GCMs and crop model requirements. First is the different spatial resolution. The outputs of GCMs have a coarse spatial resolution with grid-points spaced around 200–400 km or more apart, which is too coarse for regional agricultural impact assessment if the estimated change in climate is affected by sub-grid scale surface features such as topography, lake, coast, vegetation, soil and variations in land use (Semenov and Barrow 1997; Orlandini et al. 2008). Crop models simulate processes regulating the growth and development of crops at fine scales such as a few kilometers or even finer. For example, where two or more soil types exist in a single paddock, it may be appropriate to parameterize the soil module for the different soil types) (Barrow and Semenov 1995; Easterling et al. 1998; Luo 2003). The second mismatch lies in the different temporal resolution between outputs of GCMs and crop model requirements. Most crop models operate at a daily time step. Although nowadays GCMs can produce daily or even hourly outputs, the most common and reliable temporal resolution for the CCRA community to access and apply is monthly climate change data. It is not sensible to use hourly and/or daily GCM outputs directly for agriculture impact assessment because of the difficulty in interpreting the higher temporal resolution data over large grid boxes. The last and most important mismatch is that GCMs do not perform well on high-frequency events affecting smaller scales (Dubrovsky 1996; Semenov 2007). The fundamental lack of mesoscale parameterizations in GCMs may be improved by statistical and or dynamical downscaling approaches.

There are a number of ways to get around these mismatches. The most straightforward way is to apply coarse-scale climate change projections (direct outputs of GCMs) to a high resolution observed climate baseline—the change factor approach (Wilby et al. 2004). This approach assumes stationarity of climate variability from the daily to interannual scale and requires longer term observed daily climate data. Changes are derived from 30-year periods between the future and the baseline period, and such changes can be monthly, seasonal or yearly depending on the application. Normally, absolute changes are applied to temperature records while ratio changes are applied to historical rainfall and solar radiation. Another simple approach is spatial interpolation, as is used in packages such as Bias Correction Spatial Disaggregation (BCSD, Maurer 2007), and Bias-Correction Constructed Analogs (BCCA), OZClim (http://www.mssanz.org.au/MODSIM01/Vol%202/Page.pdf). These tools provide publicly available scenarios on the Climate Wizard, including downscaled climate projections across the whole globe or region from multiple climate models, emission scenarios, and over different time periods. Luo et al. (2005a, b, c; 2006) applied the outputs of OZClim (a pattern-scaling approach) to wheat impact assessment in the context of climate change. Similar approaches were also applied to other agricultural impact assessment (Trnka et al. 2009; Kocmankova et al. 2011; Audsley et al. 2006). More complicated downscaling techniques emerged in the middle of the 1990s and were applied widely to develop higher spatial and temporal resolution CCSs for risk assessment.

Mainstream downscaling techniques

Statistical downscaling (SD), dynamical downscaling and weather generators are typical downscaling techniques used worldwide. Each have their own strengths and weaknesses.

Statistical downscaling The main concept of SD is to derive statistical transfer functions between large-scale variables that are resolved by GCMs and local variables of interest that are not resolved in typical GCMs (Leung et al. 2003). A number of assumptions apply to the SD approach (Timbal et al. 2003; Leung et al. 2003; Wilby et al. 2004):

1. the statistical relationship between large scale predictors and local predictands must remain valid under altered climatic conditions;
2. strong predictor variables for current climate must carry climate change signals;
3. predictors relevant to the local predictand should be reproduced adequately by the host climate model at the spatial scale used to condition the downscaled responses; and
4. the predictors used for determining future local climate should not lie outside the range of the climatology used to calibrate the SD model

Typical SD methods include weather classification (analogue and spatial rainfall occurrence classification), regression models (multiple regression, canonical correlation analysis and artificial neural networks) and weather generators (Prudhomme et al. 2002; Wilby et al. 2004). There are a couple of advantages of SD. The main advantage of SD is that they are computationally inexpensive, and can be applied to the outputs of a range of GCM experiments (Timbal et al. 2003) and therefore address uncertainty issues, especially (climate) model-to-model differences. The other advantage is that they can be used to provide site-specific climate change information, which can be critical for many impact studies (Wilby et al. 2004).

However, SD does have some limitations. For example, it cannot take account of small-scale processes with strong time-scale dependencies (e.g., land-cover change; Carter et al. 2007). The first and the last of the assumptions mentioned above seem to be controversial in dealing with climate change, indicating the limitations of this approach. Most SD techniques so far (e.g., Schmidli et al. 2006; Timbal et al. 2008) focus on temperature and rainfall, while the downscaling of other climate variables relevant to agro- and bio-meteorology (e.g., solar radiation, air humidity) and of extreme climate events has received far less attention. Nevertheless, there have been a few attempts to address these aspects (Huth 2005; Kyselý 2002; Busuioc et al. 2008; Hundecha and Bárdossy 2008).

To date, most of the SD approaches mentioned here are practised by climatologists, rather than by impact analysts undertaking fully fledged, policy oriented impact assessment. This is because the scenarios have been regarded largely as unreliable, too difficult to interpret, or do not embrace the range of uncertainties in GCM projections in the same way that simpler interpolation methods do (Wilby et al. 2004).

Dynamic downscaling In parallel with the development of SD, there have been developments in dynamic downscaling techniques with the advent of regional climate models (RCMs) and high resolution limited area models (HRLAMs). RCMs take boundary conditions from coarser resolution GCM simulations and provide a higher spatial resolution of the local topography and more realistic simulation of fine-scale weather features (Semenov 2007). Theoretical limitations of the RCM approach include the effects of systematic errors in the driving large-scale fields provided by the global model, the lack of two-way interactions between regional and global climate, and the internal variability due to non-linear internal dynamics not associated with boundary forcing. The high demand for computing resources presents a practical limitation (Mearns et al. 2003a). HRLAMs such as DARLAM (Zhang et al. 2001) can enhance the spatial resolution of GCMs as LAMs can represent surface characteristics more effectively than GCMs. The LAM approach consists of a HRLAM, one-way nested at its lateral boundaries with low-resolution GCM. One advantage of a LAM is that it can also be driven by (accurate) atmospheric reanalyses rather than by GCMs (with their inherent biases); this feature is very convenient for development and validation purposes (Laprise 2008). As limited-area models, RCMs cover only a portion of the planet, typically a continental domain or smaller. There has been limited two-way coupling between RCM and GCM (Laprise 2008).

Stretched grid (variable resolution) and time-slice experiments are new dynamic downscaling methods used in modelling regional climate (Timbal and McAvaney 2001; Leung et al. 2003). The stretched grid method is often used in global models with the highest resolution over the area of interest. In time-slice experiments, high-resolution atmospheric models are forced by coarse oceanic anomalies derived from coupled atmospheric–ocean general circulation models (CAOGCMs). A practical weakness of high resolution model is that they generally use the same formulations as at the coarse resolution at which they have been optimized, so that some model formulations may need to be “re-tuned” for use at higher resolution. Another issue concerning the use of variable resolution models is that feedback effects from fine scale to large scale are represented only as generated by the region of interest, while in the real atmosphere, feedbacks derive from different regions and interact with each other (Mearns et al. 2003a).

While there have been, particularly during the last decade, significant advances such as the development of variable resolution climate models, scenarios resulting from dynamic downscaling by RCM do still not provide the resolution necessary to match the spatial scales considered in most agro- and bio-meteorological studies. For instance, in the context of the EU Project ENSEMBLES (http://ensembles-eu.metoffice.com), the highest resolution achieved with RCM was only 25 km × 25 km. Therefore, a combination of dynamic and statistical downscaling or stochastic weather generation could be necessary in some cases.

Dynamic downscaling has one advantage over empirical downscaling techniques that have been used frequently to increase the resolution of climate model results in that the resulting higher- resolution climate is physically based, and therefore the assumption of constancy of derived empirical relationships between large-scale and local climate conditions under perturbed climate conditions need not be made (Mearns et al. 1997; Semenov 2007), Dynamic downscaling has been applied substantially to agricultural impacts assessments since 1998 (Mearns et al. 1998, 1999, 2000, 2001b; Brown et al. 2000; Thomson et al. 2002; Semenov 2007; Luo et al. 2009 and 2010). Prior to this time point, these techniques were used mainly in pilot studies investigating the effects of changes in climate variability on wheat yields (e.g., Mearns et al. 1997). Agricultural impact assessment based on dynamically downscaled climate change information was limited in addressing uncertainty issues due to the high demand for computing resources. Most RCMs and variable resolution climate models rely on only one driving AOGCM, and scenarios are usually available from only one or two RCMs (Carter et al. 2007). More elaborate and extensive modelling designs have facilitated the exploration of multiple uncertainties (across different RCMs, AOGCMs, and emissions scenarios) and how those uncertainties affect impacts. Giorgi and Francisco (2000) examined the uncertainty in regional climate change simulations for the twenty-first century across five coupled AOGCMs and different anthropogenic forcing scenarios over 23 regions in the world. The PRUDENCE project in Europe produced multiple RCM simulations based on the ECHAM/OPYC AOGCM and HadAM3H AGCM simulations for two different emissions scenarios (Christensen et al. 2007a). Uncertainties due to the spatial scale of the scenarios, stemming from the application of different RCMs versus different GCMs (including models not used for regionalization), have been elaborated on in a range of impact studies. For example, Olesen et al. (2007) found that the variation in simulated agricultural impacts was smaller across scenarios from RCMs nested in a single GCM than it was across different GCMs or across different emissions scenarios.

Weather generators As mentioned above, one of the mismatches between the outputs of GCMs and crop models is temporal scale. To bridge the gap between the outputs of GCMs at monthly scale and the crop model requirement of daily time steps, stochastic weather generators are often used. Commonly used weather generators include LARS-WG (Semenov and Barrow 1997), PRECIS (Jones et al. 2004), WGEN (Richardson 1985), AAFC-WG (Qian et al. 2004) and Met & Roll (Dubrovsky 1996). These weather generators were developed and applied as computationally inexpensive tools to generate long time series of CCSs randomly with high temporal resolution by using the variability, means and other characteristics of historical daily climate records. Weather generators have been improved to produce weather series from single site to multiple sites and/or at regional scale (Wilks 1999a, 1999b; Apipattanavis et al. 2007; Semenov and Brooks 1999; Khalili et al. 2009). They also have been improved to better simulate extreme weather events (Semenov 2008). These afore-mentioned weather generators have been evaluated rigorously around the world with diverse climates and demonstrate good performance in reproducing various weather statistics including extreme weather events (Semenov et al. 1998; Qian et al. 2004, 2005; Kyselý and Dubrovský 2005; Semenov 2008) and interannual variability, although there is not much understanding at a statistical level of the modes characterizing variability at the interannual to decadal scale for many regions of the world. There are many applications of these weather generators to CCRA. Qian et al. (2005) quantified a number of climate indices for three locations in Canada by using the AAFC-WG. Semenov (2007) quantified a drought-stress index of wheat and the probability of the occurrence of hot days during flowering time at Rothamsted, UK, using LARS-WG. Luo et al. (2003, 2009, 2010) assessed the impacts of changes in mean climate and/or climate variability on wheat production and evaluated the effectiveness of a range of adaptation options using the LARS-WG. It should be noted that these five weather generators handle only common climate variables such as temperature, rainfall and solar radiation. In addition to these three types of climate variables, ClimGen (http://www.bsyse.wsu.edu/CS_Suite/Climgen/index.html), which is part of the CropSyst suite, has the capacity to analyze humidity and wind speed.

Inter-comparison of impact assessment with and without downscaling application

Substantial comparison studies have been conducted in crop yields modelled by applying direct outputs of GCMs and dynamically downscaled outputs of GCMs. Significant differences in simulated crop yields were found between the use of high resolution scenarios produced from a regional model, and the use of coarser resolution GCM scenarios (Mearns et al. 1998; 1999, 2001b). For simulated corn in Iowa, for example, the large scale (GCM) scenario resulted in a statistically significant decrease in yield, but the high resolution scenario produced a non-significant increase. Significant differences in simulated crop (corn, cotton, rice, soybeans, sorghum, and wheat) yields were also found by Mearns (2003, and references therein) and Mearns et al. (2003b) except for wheat. In general, fine-scale scenarios produced larger decreases in yield, which is contrary to the finding of Mearns et al. (1998; 1999; 2001b). These controversial conclusions are associated with the particular crop considered, the scale of aggregation of the cropping results, and whether crop management options considered or not. A study by Guereña et al. (2001) found by applying the direct outputs of GCM and outputs of RCM (dynamically downscaled) that there was no significant difference in irrigated crop yields for the Iberian peninsula. Most likely the management practice (i.e., irrigation) masked the effects of downscaled rainfall on crop production. Downscaling is required when the land surface is highly heterogeneous, or the research aims to investigate the effects of changes in climate variability, and extreme climate events or impact indicators (e.g., crop yield) are sensitive to climate variables.

Single scenarios and probabilistic climate change scenarios

Because of the large uncertainties surrounding the projection of climate change, it is common to employ climate scenarios to estimate the impacts of climate change on a specific system (Wigley 1987; Lamb 1987). Single scenarios or a range of scenarios derived from different GCMs have been applied to impact assessment. Assessment results derived from single scenarios appear precise, but are conditional to those particular scenarios. Such results are unlikely to represent other possible futures as the results are not based on the full spectrum of future CCSs and thus are highly speculative (Hulme and Carter 1999). Outcomes based on single scenarios, or even on a range of scenarios, are plausible, but contain no information as to their likelihood. While appropriate for testing sensitivity and vulnerability of a particular system, the use of plausible CCSs without investigating likelihood is poorly suited to planning or policy purposes (Jones 2000a; Ahmad et al. 2001).

Since the Third Assessment Report (TAR) of Intergovernmental Panel on Climatic Change (IPCC), probabilistic CCSs have been constructed aimed at addressing uncertainty issues in impact assessment. There is a substantial literature reporting probability density functions (pdfs) of climate sensitivity that provides significant methodological advances over the long-held estimated range. Challinor et al. (2009) addressed uncertainty issues from the perspectives of both crop and climate by considering a large number of parameters. Christensen et al. (2007b) described methods of applying different weighting schemes to multi-model ensemble projections of climate. Dessai et al. (2005) tested the sensitivity of probabilistic regional CCSs to major uncertainty sources such as GHG emissions, climate sensitivity and model-to-model difference. Buser et al. (2009) applied Bayesian methods to quantify mean changes and interannual variability of temperature from the perspective of model biases.

Two principal methods have been used to attach probabilities to impacts: (1) application of a large number of scenarios to an impact assessment, and creation of a probability distribution from the outcomes; and (2) creation of an underlying probability distribution for each successive stage of analysis, explicitly managing the underlying uncertainty at each stage. In producing a wheat yield change distribution, Luo et al (2006) used the first method to manage uncertainties from the projection of GHG emission, projection of climate sensitivity and projection of regional climate change (climate model-to-model difference). Semenov and Stratonovitch (2010) considered 15 climate models in producing the distribution of heat stress index associated with wheat crop at flowering time under climate change conditions. The second method is described by Hulme and Carter (1999) and Jones (2000b) and applied in Howden et al. (1999) and Luo et al. (2005a, b, c). Howden and Jones (2001) undertook a probabilistic analysis of the costs and benefits of climate change on Australia's national wheat crop. The ENSEMBLES research project mentioned earlier modelled various sources of uncertainty to produce regional probabilities of climate change and its impacts for Europe (Hewitt and Griggs 2004).

Major dynamical downscaling inter-comparisons such as CORDEX (Giorgi et al. 2009), NARCCAP (http://www.narccap.ucar.edu/index.html), PRUDENCE and ENSEMBLES and statistical downscaling inter-comparisons of STARDEX (http://www.cru.uea.ac.uk/projects/stardex/) can be used as sources for constructing probabilistic CCSs. Recently, a systematic approach to explore the uncertainty of a single climate model parameterization was proposed, the so-called perturbed physics ensembles (PPE) (Murphy et al. 2004; Stainforth et al. 2005). In each experiment, model parameters were set to a range of values derived from multiple prior distribution estimated by experts based on their knowledge of the relevant physical systems (Semenov and Stratonovitch 2010). The size of a PPE is particularly big due to the large number of parameters, their possible values and combinations involved for a specific model. Semenov and Stratonovitch (2010) described a sampling technique to explore uncertainty in climate prediction from very large PPEs. Murphy et al. (2007) described a Bayesian method, developed at the Hadley Center, appropriate for the estimation of a joint probability distribution function of key climate variables at a spatial scale of 25 km, for the use of regional climate impact assessment. Development and application of multiple climate models with large PPEs will be one of the key research directions in future CCRA.

Mean climate change scenarios versus mean and climate variability change scenarios

A feature of previous agricultural impact assessment is that changes in mean climate such as rainfall, maximum temperature and minimum temperature were used in crop models to quantify their effects on crop production. The possible impacts of changes in climatic variability (e.g., in the length of wet and dry spells, and in temperature variability) on crop production have been ignored in most previous studies. The focus on mean climatic change has provided useful but limited information on how future changes in climatic variability (through extreme events such as drought and extreme high temperatures) might affect agriculture (Mearns et al. 1997; Luo et al. 2010). It has long been recognised that changes in climatic variability can have serious effects on agricultural yield (Parry and Carter 1985). One of the main means by which crops are affected is through changes in the frequency of extreme climatic events (e.g., heat waves, droughts) (Mearns et al. 1984; Semenov and Barrow 1997). Changes in climatic variability have a greater effect on the frequency of extremes than changes in mean climate (Katz and Brown 1992).

Several studies worldwide have attempted to quantify the potential impacts of mean and variability changes (derived from GCM outputs) on crop production. For instance, Semenov and Barrow (1997) examined the importance of changes in climatic variability on wheat yields in Spain based on outputs of a transient GCM (UKTR) and found that there were significant differences in the distribution of wheat yield once changes in climatic variability were taken into account. Mearns et al. (1997) investigated the impacts of changes in climatic variability on wheat yields in the USA by using the outputs of a RCM. Torriani et al. (2007) quantified the effects of changes in mean and variability on the yield of winter and spring crops in Switzerland. Luo et al. (2010) investigated the effects of changed mean climate and climate variability on the mean and coefficients of variation of wheat and canola yield and harvest index in southeast Australia. There has been recent progress in this field, with expanded computer resource volume, daily outputs of GCMs/RCMs ever more widely available, and longer term simulation of GCMs/RCMs at daily time steps, enabling stable signals of climatic change to be obtained. There has also been progress in GCM performance in simulating the behavior of climatic variability, in downscaling techniques, and in the coupling techniques between the outputs of GCMs/RCMs and crop models. For example, an earlier version (v2.1) of the weather generator: LARS-WG (the coupling technique between the outputs of GCMs and crop models) could produce only mean CCSs. A later version (v3.5) of this weather generator had the capacity to incorporate changes in both mean climate and climate variability. Recently, this generator has been improved (v5.0) to more accurately represent changes in climate variability. All these advances have made it possible to study the combined effects of changes in both mean and variability on crop production. Nevertheless, advances in this direction have been/are hampered by a lack of understanding of the mechanisms leading e.g., to decadal variability. Also even in the case of the El Niño Southern Oscillation (ENSO), the ability of the current generation of AOGCM to reproduce the relevant mechanisms of change must be considered as limited (Latif and Keenlyside 2009). Changes in variability often have to come from outside of GCM projections (i.e., with the aid of weather generators).

Conclusions

Over the last 30 years, significant progress has been made in developing CCSs for agricultural impact assessment at appropriate temporal and spatial scales. This is reflected in the development of transient CCSs; construction of probabilistic CCSs with management of the uncertainty from GHG emissions, climate sensitivity and regional climate change; and construction of scenarios with changes in both mean and variability integrated; as well as the emergence of a range of downscaling techniques. All the advances made so far have been oriented to reduce/deal with uncertainties to improve the robustness of CCRA.

It should be noted that neither dynamically nor statistically downscaled daily outputs of GCMs can be used directly in agricultural impact assessment. It is first necessary to obtain climate change information between the future period and the baseline period. The length of each period must be at least 30 years to capture climate change signals over high-frequency and low-skill noise. Obtained climate change information can then be applied to weather generators to produce long time series (e.g., 100 years) CCSs for the use of crop models. Although weather generators have their own limitations, CCSs constructed in this way are more robust than the direct use of the 30-year downscaled daily outputs of GCMs, as the latter may encompasses bias from the climate model itself without integrating with historical climate data. Another advantage of this approach is that longer time series CCSs can be generated that can capture the tails of climate distribution and therefore facilitate examination of the impact of ENSO variation.

It is widely recognised that GHG, climate sensitivity, and inter-model differences at the regional scale are the major uncertainties to be represented in pdfs of regional climate change (Carter et al. 2007). Other important factors include downscaling techniques, multi-model ensembles (due to different initial condition or parameterization of a specific climate model) and regional forcings such as aerosols and land-cover change (e.g., Dessai 2005). As illustrated in the section on Single scenarios and probabilistic climate change scenarios, these major uncertainties have been incorporated into regional CCSs and applied to agricultural impact assessments. Substantial work has been done in evaluating the performance of GCMs. For example, Giorgi and Mearns (2002) introduced the reliability ensemble approach, which provides weights for climate model prediction. Application of weighted GCMs will lead to reduced uncertainties in developing regional CCSs and will become normal practice in the assessment of climate change impact and adaptation. Uncertainties due to downscaling techniques and multi-model ensembles have not been addressed rigorously in agricultural impact assessment. Intercomparison of the impact difference due to various downscaling techniques (statistical downscaling and dynamical downscaling and interpolation) is an interesting research topic in CCRA in the agricultural sector. As mentioned in the section on Mainstream downscaling techniques, there are some initiatives in Europe that have addressed uncertainty issues in relation to RCMs, but similar work has not been done in the rest of the world. Development and application of multiple RCMs forced by multiple GCMs and under multiple emission scenarios is needed in other regions. The approaches reported in Semenov and Stratonovitch (2010) and detailed in the section on Single Scenarios and Probabilistic Climate Change Scenarios represent important pathways in quantifying and managing uncertainties from the outputs of GCMs and should be encouraged in future CCRA.

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