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METHODS AND RESOURCES FOR CLIMATE IMPACTS RESEARCH

Achieving Synergy

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Assessing climate impacts and adaptation options requires judicious use of finite computational resources as well as appropriate degrees of integration and specialization in the climate impacts research community.

CLIMATE IMPACTS. Atmospheric concentrations of carbon dioxide, methane, and nitrous-oxide are now substantially higher than they have been for hundreds of thousands of years (Spahni et al. 2005; Siegenthaler et al. 2005) and there is every indication that they are continuing to rise at alarming rates (Anderson and Bows 2008). This will have wide-ranging global impacts, affecting food production systems, human health, energy demand, and water availability. Crops, for example, will increasingly be grown in a warmer environment with higher levels of carbon dioxide. In addition to these large-scale changes, regional changes in climate, especially extremes of temperature and rainfall, will produce localized stresses on food production. To understand the potential risks to future food production, we need assessments of both the mean large-scale impacts of climate change and the more local and regional impacts. Furthermore, regional variations in agricultural systems and the broader food production and distribution systems must be taken into account.

Climate change is increasingly seen not only as a problem for the future but also as a current or emergent problem. Adaptation efforts need to

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be based on sound understanding of impacts on a range of spatial and temporal scales (see, e.g., Adger et al. 2005; Challinor 2009). Can decisions based on short-lead-time forecasts really be a form of adaptation to climate change? After all, attribution of climate impacts to anthropogenic or natural sources is not trivial and can only be done probabilistically. Fortunately, for practical purposes—especially for adaptation—such attribution is often unnecessary. Adaptation efforts are therefore underpinned by both seasonal forecasting of climate and its impacts (e.g., WCRP 2007) and longer-term assessments of the sort reviewed by the Intergovernmental Panel on Climate Change (IPCC; Easterling et al. 2007).

Changes in the way that science is perceived and funded increasingly encourage researchers to focus on real-world problems using a combination of disciplines (see Robinson 2008). Weather and climate research naturally lend themselves to a use-inspired approach (Pielke and Carbone 2002). In addition to the influence of societal demand, research into climate and its impacts is influenced by ongoing improvements in resources. In particular, increases in computational capacity allow our models to be increasingly complex, to operate on increasingly fine spatial grids, and to quantify more fully the uncertainty in our predictions. However, computer power is still limited, so these demands compete with each other.

This paper asks how, given these ongoing developments, climate impacts research can most effectively underpin and inform adaptation. The focus is primarily on food crops, although the commonality in methodology and the disparity in spatial scale between climate models and most impacts models implies broader relevance. First, we discuss uncertainty in the simulation of climate and its impacts. Second, we examine crop modeling methods. A discussion on model complexity and spatial scale follows, first for impacts models and then for climate models. Finally, using existing projects and studies, we ask how, given the competing demands on computer power, climate impacts research can best use the methods and computational resources at its disposal.

ENSEMBLE CLIMATE IMPACTS ASSESSMENT. Climate change prediction contains many inherent uncertainties (Schellnhuber et al. 2006): uncertainties in projected emissions, and resultant concentrations, of greenhouse gases mean that the climate forcing cannot be known precisely. The response of climate to a projected forcing, as calculated by climate models, is also uncertain. Any forecast of weather (beyond a few days), climate variability, or climate change cannot be made deterministically. This is because sensitivity to uncertainty in the model initial conditions, as well as uncertainties caused by parameterized model physics, limits the predictability of the atmosphere. The response of physical and biological systems, such as crop growth or disease dynamics, to any projected climate also contains uncertainties (see, e.g., Mearns et al. 2003).

Multiple climate simulations, known as ensembles, are used to sample the inherent uncertainties outlined above. Scenarios of future greenhouse gas emissions are used to sample the possible ranges of climate forcings. Uncertainty in the model initial conditions can be assessed by running a model many times with different initial conditions. Uncertainty in model structure (e.g., representation of atmospheric physics) can be assessed by using more than one model (e.g., Randall et al. 2007) or by varying model parameters (e.g., Murphy et al. 2004; Stainforth et al. 2005). On seasonal time scales, ensembles that use more than one model can give more skilful results on average than any single model ensemble (Hagedorn et al. 2005). Such multimodel ensembles are an efficient way of providing information for climate impacts because a range of existing models are used, thus making good use of globally available computer resources (see, e.g., Palmer et al. 2004, 2005). Because the models used for both seasonal and multidecadal time scales are based on simulation of the same fundamental processes, skill at the shorter time scale in part supports our confidence in longer-term projections. However, skill at one time scale does not imply skill at the other, since the principal source of uncertainty varies with lead time: initial conditions are important at seasonal time scales but less so at multidecadal time scales, whereas model structure is important in both cases.

There are currently efforts to consider holistically the broad range of time scales in climate prediction and to move toward seamless weekly-to-decadal ensemble prediction of the complete climate system (see, e.g., WCRP 2007). In particular, decadal time scales may prove to have both quality (i.e., skill) and value (Troccoli and Palmer 2007). Such systems may be able to capture the emergent climate change signal. It has been suggested, by using a simple model (Cox and Stephenson 2007), that total uncertainty in climate prediction may be at a minimum at 30–50-yr lead time, when the uncertainty in initial conditions will have fallen significantly but the uncertainty in greenhouse gas emissions is not yet prohibitively large.

In agricultural impacts, the methods used to bridge the gap in spatial scale on which crop and climate models operate compound the inaccuracy and imprecision in the climate model (Hansen and Jones 2000). Furthermore, current and future adaptive crop management practices are not known with precision. Despite these uncertainties, a consensus on some impacts is emerging. However, such conclusions need to be continually updated as knowledge advances. For example, even though a consensus is emerging on the response of crop yield to mean temperature changes (Easterling et al. 2007), the response functions are not universally applicable (Challinor et al. 2009). Furthermore, the response of crops to pests, weeds, diseases, and climate extremes is still not well understood.

Recent years have seen a move toward the use of ensemble methods with impact modeling (e.g., Collins and Knight 2007; Lejenäs 2005; Challinor et al. 2005a) so that at least some of the uncertainties in prediction are quantified. Although the quantification of uncertainty is being increasingly recognized as important in the broader scientific literature, it is only relatively recently that its importance is being recognized in regional impacts assessments (e.g., Cruz et al. 2007). Because the impacts model itself can be a significant source of uncertainty (Challinor et al. 2005c, 2008), we now look in some detail at the methods available for crop yield modeling.

CROP MODELING FOR CLIMATE IMPACTS RESEARCH. There are three broad (and to some extent overlapping and complementary) approaches to crop yield modeling. The first uses simple empirical (e.g., Lobell et al. 2008) or semiempirical (e.g., Iglesias et al. 2000) parameterizations of crop yield. This method has the advantage of being applicable on large spatial scales, thus facilitating the quantification of impacts in human terms such as levels of risk of hunger (e.g., Parry et al. 2004, 2005). One disadvantage of this method is the potential to introduce significant errors through the linearization of the equations for crop yield (Challinor et al. 2006) and/or the use of monthly data (e.g., Fischer et al. 2005), which may not be able to account sufficiently for subseasonal variability in weather. Interestingly, at least one study of this first kind reports that the skill of the parameterization of crop yield was lowest in the tropics (Parry et al. 2004). The validity of empirical methods may be compromised when used with data outside the range for which they were fitted (e.g., climate change).

The second method takes model-derived climate projections, sometimes scaled down in space (Busuioc et al. 2001), to provide inputs to detailed process-based crop models (Carbone et al. 2003). This method, which has been used by many authors (e.g., Izaurralde et al. 2003; Southworth et al. 2002; Luo and Lin 1999; Mavromatis and Jones 1999), can capture the complex biophysical processes associated with climate change that are usually overlooked by studies of the first kind. However, these models may sometimes be overparameterized (Cox et al. 2006). The use of many parameters produces results that are location specific because the yields depend on the specific crop variety, soils, and management practices used. Although this can be useful for decision support, it presents a problem when estimates over large areas are required. While this problem can be overcome through the identification of representative farms, this choice can itself be problematic (Antle 1996; Luo and Lin 1999). Furthermore, unless any downscaling methods used are dynamic, there is a risk of nonstationarity in the downscaling relationships (Jenkins and Lowe 2003), thus putting into question their use in future climates (Challinor et al. 2005b).

The third method used to quantify the impacts of climate change on food production is process-based crop modeling at the scale of the climate model. This may be carried out using field-scale models, either directly (e.g., de Wit et al. 2005; Xiong et al. 2007) or in a manner that accounts for subgrid heterogeneity (e.g., Irmak et al. 2005; Jagtap and Jones 2002; Haskett et al. 1995). Alternatively, a "large area" process-based model—with a focus on the influence of weather and climate on crop growth and development—can be designed to capitalize on known large-scale relationships between climate and crop yield (e.g., Challinor

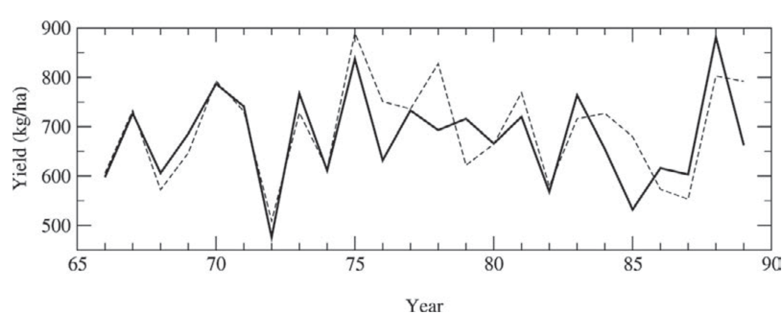

Fig. 1. Observed (solid line) and simulated (dashed line) groundnut yields for all India, using the General Large-Area Model for annual crops (GLAM) driven by observed weather data on a 2.5° grid (Challinor et al. 2004). Observed yields have been linearly detrended to 1966 levels.

et al. 2003, 2004). Figure 1 shows that a large-area crop model can simulate interannual variability in crop yield well when forced with observed weather data. The skill seen at the country level masks regional variations in skill. However, the importance of low skill in regions that are not major producers of the crop is small, since the country-level results are area weighted according to cropped area. Simulation using climate model output leaves crop simulations prone to the propagation of errors from the climate model or other input data, which can be significant. Despite this, the method has shown promising results in current climates in India (Challinor et al. 2005a,b) and in other tropical regions (Osborne 2004; Chee-Kiat 2006).

These assessments build confidence in the use of this method with climate change scenarios and permit the quantification of uncertainty in a manner that is substantially different from the common approach of random sampling of uncertainty using a range of crops, locations, models, or scenarios (see, e.g., Challinor and Wheeler 2008a,b). While large-area crop modeling can omit important finescale information (Baron et al. 2005), the spatial scale of the large-area approach becomes increasingly relevant to the scale of crop production as computer power increases, allowing finer resolution of climate and improved climate simulation skill. Further discussion on the large-area approach can be found in Wheeler et al. (2007) and Challinor (2008). A broader look at a range of approaches is presented by Hansen et al. (2006).

COMPLEXITY, SPATIAL SCALE, AND CALIBRATION OF IMPACTS MODELS. The variety of methods used to assess impacts on crop yields can lead to large variation in results (see, e.g., Challinor et al. 2007b). The range of processes involved in determining yield and the range of associated spatial scales make it impossible to simulate the crop–climate system entirely realistically. Some sort of aggregation of environmental variables is therefore needed to assess practically all climate impacts. This process, together with the associated process of reductionism, masks complexity in the system. The larger the spatial scale of the model, the greater the level of aggregation needed [whether at the input or output stage; see Hansen and Jones (2000)]. Therefore, the spatial scale of an environmental model is related to its complexity. A model should be sufficiently complex to capture the response of the system to the environment while minimizing the number of parameters that cannot be estimated directly from data (Sinclair and Seligman 2000). The appropriate level of complexity can be assessed prior to modeling by testing observed data for relationships between weather/climate and the impact variable (e.g., Challinor et al. 2003).

Despite a growing interest in food quality (Porter and Semenov 2005), yield is often the only output variable of interest in studies of the impacts of climate change on crops. Apart from remotely sensed data on leaf area index (LAI), which can be incorporated into crop modeling studies (Guerif and Duke 2000; Jones and Barnes 2001), yield and cropped area are also often the only observed crop variable available over large areas. Hence, modeling over large areas (the first and third methods described above) tends to simulate only yield and biomass (e.g., Fischer et al. 2005), or else a more mechanistic approach is taken, with yield as the only variable used to calibrate the crop model (e.g., Challinor et al. 2005a). Alternatively, the crop model can be calibrated at a site, using more detailed data (the second method described above), producing more location-specific information.

Where there is a shortage of observed data for calibration, a model with many parameters is likely to have a relatively large number of unconstrained parameters, thus increasing the risk of reproducing observed yields without correctly representing the processes involved. Such overtuning decreases the credibility of the model when it is run with climate model output. Through an appropriate choice of model complexity, the risk of overtuning can be minimized. Provided this is done, it is likely that a range of impacts models can profitably be used, rather than having faith in one or two "validated" models. For example, in hydrological modeling, there is evidence that many models can give a good fit to observations, leading some authors to conclude that there may be more than one acceptable model (Beven 2006). Thus, no single method of determining climate impacts can claim to be a panacea. This view is consistent with a more generalized analysis of computer simulations of real-world processes (Goldstein and Rougier 2004).

Unfortunately, relatively few crop yield studies use more than one crop model. Exceptions include the study of Ewert et al. (2002), who used three field-scale crop simulation models and found that they were all able to adequately reproduce observations. However, they concluded that the relationships that determine yield variation at larger spatial scales were still uncertain. This was subsequently confirmed by Challinor and Wheeler (2008a,b), who combined a large-area crop model ensemble with simulations of field-scale models, which were carried out to assess the robustness of the ensemble results. Such disagreement between impacts models (as with climate models) should be seen as an opportunity to increase understanding and ultimately improve model skill. Because different models may perform well in different environments (e.g., water- or nutrient-limited crop growth), this process of learning is likely to create natural opportunities for synergy.

Many of the challenges posed by the integration of crop and climate models are similar for other biological systems, such as the dynamical systems that represent the transmission of infectious diseases by vectors. The most important of these diseases is malaria. It is estimated that annually over 350–500 million clinical episodes occur worldwide (WHO 2005) and epidemics cause up to 310,000 deaths per year in Africa (Worrall et al. 2004). Malaria incidence has been simulated using output from seasonal ensemble prediction systems with both a statistical malaria model (Thomson et al. 2006) and a dynamical malaria model (Morse et al. 2005). Forthcoming work will link climate model output to models of bubonic plague (Begon et al. 2006), blue tongue (Purse et al. 2005), and Rift Valley fever (Lacaux et al. 2007).

A key issue in modeling crop yields and diseases is that biological systems have critical thresholds and nonlinear responses to the climatic drivers. One example is the impact of extreme temperatures during the flowering of crop (see, e.g., Wheeler et al. 2000). As a result of this nonlinearity, skill in the forecasting of weather or climate does not necessarily imply skill when that forecast is used to drive an impacts model (see Morse et al. 2005).

COMPLEXITY AND SPATIAL RESOLUTION IN CLIMATE MODELING. As with impacts modeling, there is range of possible levels of complexity and spatial scales in climate models. The spatial resolution of the model determines the spatial scale of the processes that can be represented and is therefore an important factor in determining model skill (we will return to this issue later on). Complexity is also an important determinant of skill. Recent decades have seen an increasing number of processes represented in climate models. The importance of coupling between the ocean and atmosphere—seen, for example, in El Niño–Southern Oscillation—led to the inclusion of ocean models. Similarly, the importance of land surface processes for representing weather and climate has been increasingly recognized (e.g., Pielke et al. 1998). Simulated climate is sensitive to historical (Chase et al. 2000; Reale and Dirmeyer 2000; Reale and Shukla 2000) and projected (Feddema et al. 2005) changes to the land surface. Land surface processes have been shown to impact the representation of climate and its variability at the regional scale in Europe (Heck et al. 2001; Vidale et al. 2003, 2007). The importance of representing the water and carbon cycles concurrently has also been recognized (Arora 2002; Bonan 2008). Thus, the next generation of climate models will in fact be earth system models. The skill of dynamical forecast systems has been shown to improve following the implementation of more realistic land surface parameterizations (Beljaars et al. 1996).

Coupled crop–climate models. Continuing with our primary theme of crops, we now consider the simulation of cropped land surface within climate/earth system models. Because cropped land is managed, we must consider not just biological and physical interactions in earth system models, but also human, and therefore ultimately socioeconomic, processes. Such is the level of complexity that is required if we are to simulate real-world processes.

As population, and hence demand for food, continues to grow, croplands will expand into land previously occupied by natural ecosystems. Increasing demand for biofuels compounds this pressure on land use. The associated changes at the land surface may have significant impacts on the climate via alterations to the surface energy balance and hydrological cycle, such as those that have been observed and modeled for past land cover changes. For example, the replacement of forests in the eastern United States by crops led to a significant summertime cooling (Bonan 1997).

Observations suggest that including crop–climate feedbacks may improve the skill of seasonal forecasts over cropped regions. McPherson et al. (2004) observed different weather patterns over the winter wheat growing area of Oklahoma compared to the adjacent grasslands and attributed this to the different seasonal development of vegetated canopy for the crop compared to the grasslands. Regional climate modeling has shown that including a better representation of croplands and their dynamical response to seasonal weather can improve the simulation of near-surface climate (Tsvetsinskaya et al. 2001). Therefore, including prognostic croplands in seasonal forecast models may improve the ability to simulate surface climate over croplands, potentially improving crop simulation. Osborne et al. (2007) incorporated crop growth parameterizations of a large-area crop model into the land surface scheme of a climate model, thereby developing a tool to examine the importance of land–atmosphere feedbacks for crop impact projec-

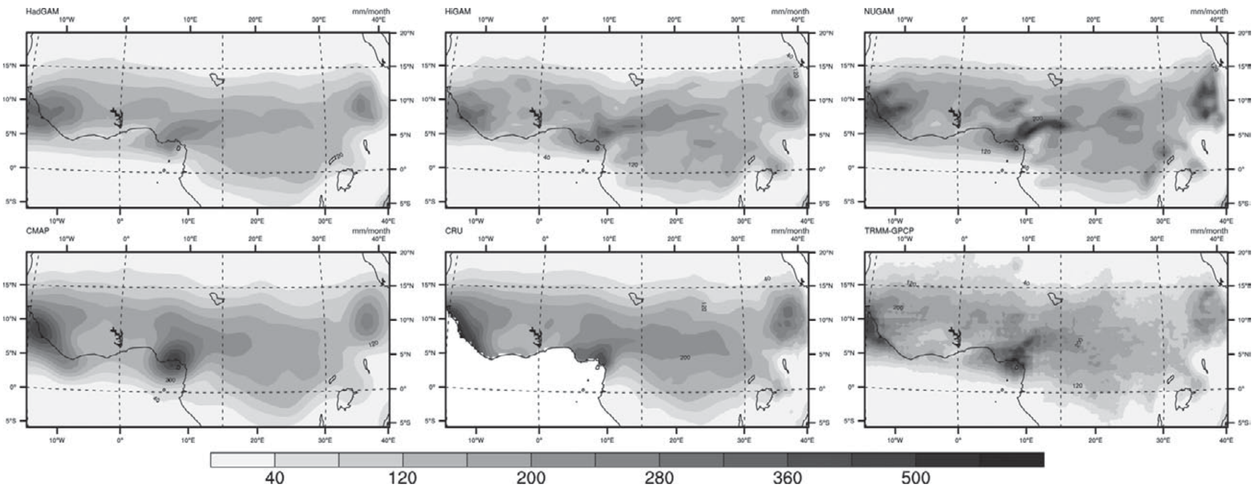

Fig. 2. (top) June–August precipitation climatology (1 Jan 1979–31 Mar 1996—the AMIP2 period) for a chain of atmospheric climate models with increasing resolution from left to right: HadGAM (N96 = 135 km), HiGAM (N144 = 90 km), and NUGAM (N216 = 60 km). (bottom) Also shown are three observational datasets, from left to right: CMAP (1° = 100 km, approximately), CRU (0.5° = 50 km, approximately) and TRMM+GPCP (0.25°–1°, depending on the region).

tions. However, direct comparison of coupled crop–climate simulations with offline crop simulations is challenging (Wheeler et al. 2007).

It is not only seasonal time scales at which crop–climate feedbacks may be important. Croplands play an important role in the biogeochemical cycling of numerous elements, in particular carbon and nitrogen. In the past four decades world grain harvests have doubled because of an increase in world cropland area (~12%) and productivity gains from technology, such as high-yielding cultivars, chemical fertilizers, and extensive use of irrigation. This increase in cropping system intensity has had considerable environmental consequences (Foley et al. 2005). Assessments of environmental change will require representation of croplands and their interaction with the biogeochemical cycles (Bondeau et al. 2007; Kucharik and Brye 2003).

The benefits of increased resolution. As more computer power becomes available for environmental modeling, the feasible resolution applied in global climate modeling starts to be comparable to that used in current operational weather forecasting. For example, the Japanese Earth Simulator supercomputer (Habata et al. 2004; Yokakawa et al. 1998), with a theoretical peak performance of 41 Tflops (26.6 Tflops sustained) was, at its introduction in 2002, about one order of magnitude more powerful than any computer available to individual weather or climate centers and three times more powerful than its nearest rival. Moreover, it could be dedicated to single, very large computational tasks that are impossible to execute on any other computer and could sustain a large concurrent number of operational simulations of the more conventional type, being the equivalent of several joined research centers in one single facility. This machine has been used by the U.K.–Japan Climate Collaboration and U.K. High-Resolution Global Environmental Model (HiGEM; Shaffrey et al. 2009) project to perform coupled climate model simulations with an atmospheric resolution of up to 60 km and an ocean resolution of 30 km. At present the 90-km HiGEM model has been integrated for several centuries and a higher-resolution version (NUGEM) with a 60-km atmospheric model has been run for several decades. The speed of such modeling systems permits the completion of very high-resolution climate integrations within weeks to months.

These developments allow weather phenomena (e.g., fronts, blocking, cyclones, and potentially mesoscale convective complexes) to be realistically represented in climate simulations. The resolved weather (e.g., intense precipitation, winds associated with cyclones, and storm and river surges) can be used with impacts models, providing forcing variables at the proper spatial and temporal scales. Scientific issues such as the regional distribution and frequency of floods and droughts can therefore be treated in "two-way" coupling mode, in which both the impact of localized phenomena associated with weather and their feedbacks to the atmosphere can be treated jointly. This localized skill was previously the exclusive domain of regional climate models, which are normally run as stand-alone downscaling tools, prior to running the impacts models themselves. Phenomena such as tropical cyclones are, however, hardly tractable with regional models, given the wide oceanic areas over which they develop and track and the high level of variability of their coupling with the mean state climate.

Figure 2 illustrates the level of regional detail in the simulation of precipitation that can be achieved by 60- and 90-km global atmospheric models over a 135-km model. For models with higher resolutions, the rainfall interacts with the orography and coastlines in a manner more similar to the high-resolution observational dataset. The increase in resolution is driven by the desire to improve the simulation of climate. Both the increase in accuracy and the increase in resolution *per se* are beneficial to impacts assessments also.

Increasing resolution globally, then, is one way to improve the skill of our climate impacts assessments. Resolution can also be increased locally. The use of variable-resolution models for the atmosphere is an area of active research (e.g., Läuter et al. 2007; Bonaventura and Ringler 2005; Fournier et al. 2004; Bacon et al. 2000; Jablonowski et al. 2006; Randall et al. 2002; Weller and Weller 2008). This allows high resolution in an area of interest, or where errors are large, without the prohibitive expense of high resolution globally. These techniques may also prove more efficient on massively parallel computers because calculations on latitude–longitude grids are done on latitude bands, a system that does not parallelize well. Variable resolution is an attractive alternative to using a regional model (Fox-Rabinovitz et al. 2006) both because regional models have large errors near the boundaries (e.g., Jones et al. 1997, 2004) and because there is no possibility for the small scales resolved by the regional model to influence global scales. Adaptive grids may have an immense benefit for resolving areas of severe weather or mountains—areas that degrade the accuracy of current models because they are underresolved—more accurately.

MAKING BEST USE OF OUR COMPUTATIONAL RESOURCES. Despite the above ongoing increases in computer power and improvements in techniques, resources are still finite. It is therefore likely that the impacts modeler will continue to be faced with a choice between adequate ensemble size and adequate spatial resolution. It is also clear that complexity is important for the impacts modeler because complexity can be associated with increases in the skill of the climate simulations. The impacts model can also be part of that complexity, as it is in coupled crop–climate modeling. Thus, resources are divided among the simulation of processes (complexity), the length of simulations, the sampling of uncertainty (ensemble size), and spatial resolution (grid cell size), as shown in Fig. 3.

Broadly speaking, short-range (< 1 week) weather forecasting has tended to date to use increases in computer power to increase resolution, whereas climate modeling has tended to focus primarily on simulating an increasing number of processes (e.g., chemical and biological process in the ocean and the land), with some additional sampling of uncertainty using ensembles. However, because the number of interactions among physical, chemical, and biological systems increases as the number of resolved processes

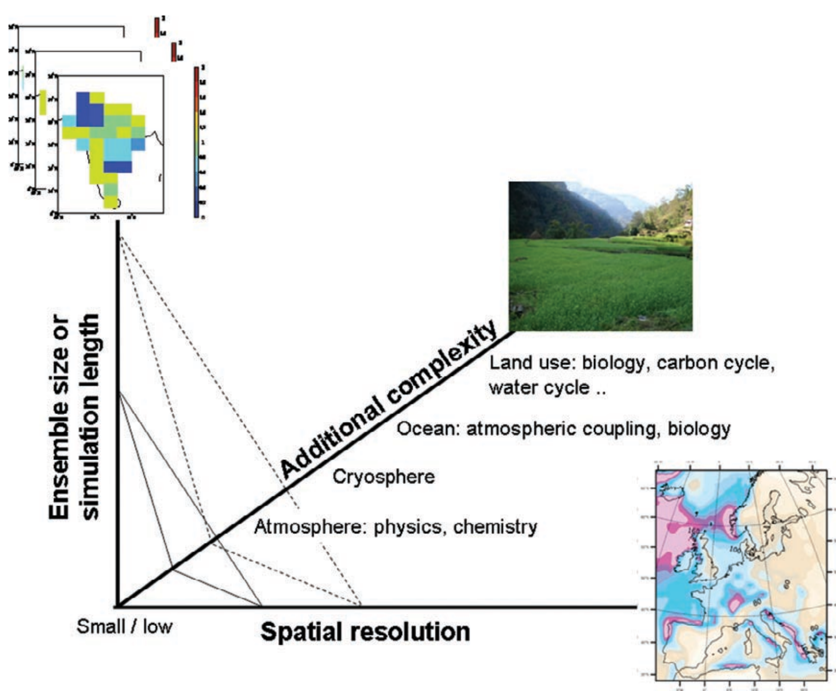

Fig. 3. Schematic representation of the trade-offs in climate modeling. Additional computer power is required whenever the spatial resolution or simulation length is increased or when additional ensemble members or processes are added. Triangles represent surfaces of approximately constant computer power.

increases, it is likely that the additional complexity brings with it demands for increased resolution and increased sampling of uncertainty. Climate change simulations are particularly expensive computationally because they must extend many decades into the future, and often the past, using a short time step (significantly less than 1 hour).

One size does not fit all. How should the choice of modeling approach be made? Methods vary according to the particular research objectives identified. Some projects focus on a limited set of processes only. For example, to improve representation of land surface processes, a project has been set up to enable offline running (i.e., with prescribed meteorology and thus no feedbacks to the atmosphere) of the land surface model of the Unified Model of the Met Office. The resulting model, the Joint U.K. Land Environment Simulator (JULES; www.jchmr.org/jules/), is under ongoing development that is independent of that of the parent climate model. Because of its focus on earth system processes and feedbacks, the U.K. project Quantifying and Understanding the Earth System (QUEST; http://quest.bris.ac.uk/) takes a more integrative approach to coupled modeling. The focus in both of these projects is on processes rather than on ensembles or on high-resolution modeling. In contrast, the U.K. HiGEM and U.K.–Japan Climate Collaboration projects are focusing on the benefits of increased spatial resolution, as outlined above.

The diversity of modeling approaches creates opportunities for synergy. Consider, for example, two European Union Framework 6 projects: ENSEMBLES (www.ensembles-eu.org/) is a program working on the prediction of climate variability and climate change at lead times from seasons, through decades, to centuries. Research is centered on the estimation of uncertainty and the investigation of feedbacks in the earth system. African Monsoon Multidisciplinary Analyses (AMMA; www.amma-international.org) is an observational and modeling program that is investigating the West African monsoon. It is made up of a series of pan-national and national projects and has developed from a French initiative. It aims to improve our understanding of the rainfall variability in the region and to provide the underpinning science to allow this knowledge to be applied to the rain-fed agricultural systems, water resource development, and human health in the region.

ENSEMBLES, then, has a focus on long-range prediction with a global remit, whereas AMMA is a program driven by regional observation and backed up by modeling. What both programs have in common is the need to connect to users of the modeling and observational products. This commonality between the two programs has lead to a formalized agreement for the ENSEMBLES work to make a secondary focus on West Africa. Both programs have cutting-edge themes: in ENSEMBLES this is based on large computer resources being made available to run relatively low-resolution ensembles of global models over a range of forecast lead times. AMMA, in contrast, focuses on higher-resolution modeling. In AMMA, state-of-the-art observations from aircraft and ground-based instruments were performed to help diagnose errors in current forecast model performance and to allow the next generation of models to be improved. While both programs integrate across a spectrum of applied theoretical activities, ENSEMBLES sits further from the immediacy of application of AMMA.

This analysis highlights the importance of complementarity across studies, which increases the efficiency with which resources are used. The choice of focus depends on the problem being posed: the time scale of interest, the size and location of the region of interest, its meteorology (especially the predictability of climate), and the perceived needs of stakeholders. Synthesizing the broad range of knowledge that results from this work is a challenging task. Synthesis reports, such as those of the IPCC (Easterling et al. 2007), and projects, such as those described above, facilitate creative dialogue. They also create synergy by combining resources effectively to produce large datasets that can be used by impacts modelers.

Achieving synergy. How is synergy best achieved? Pielke and Carbone (2002) conclude that in the quest to meet society's needs, strong leadership in weather and weather impacts research is required. Is this the case for climate impacts research? The funding process involves creative thinking by researchers, who must identify novel approaches if their ideas are to be funded. Some degree of synergy is implicit in this process. Of course, leadership is required in the setting of the funding agenda. Perhaps the greatest challenge here is to encourage the most productive mix of blue skies and applied research. In reality, there is a spectrum of approaches between these two, including fundamental issue-driven (e.g., Robinson 2008) and use-inspired (e.g., Pielke and Carbone 2002) research. In the field of climate impacts, these approaches can provide some of the tools needed to assess vulnerability (e.g., O'Brien et al. 2004; Challinor et al. 2007b; Cox and Stephenson 2007; Lobell et al. 2008) and adaptive capacity (e.g., Kates 2000; Fraser 2007; Challinor et al. 2007a, 2008).

Development of these tools is facilitated by dialogue and cooperation between academics in relevant disciplines. This can be encouraged through specific studies (e.g., Huntingford et al. 2005), larger projects such as those outlined above, and issue-focused discussion meetings (e.g., Slingo et al. 2005). Underpinning this, awareness of the need for communication, synergy, and issue-based approaches should be promoted from school to the doctoral level and beyond.

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