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Crops and climate change: progress, trends and challenges in simulating impacts and informing adaptation

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Abstract

Assessments of the relationships between crop productivity and climate change rely upon a combination of modelling and measurement. As part of this review, we discuss this relationship in the context of crop and climate simulation. Methods for linking these two types of models are reviewed, with a primary focus on large-area crop modelling techniques. Recent progress in simulating the impacts of climate change on crops is presented, and the application of these methods to the exploration of adaptation options is discussed. Specific advances include ensemble simulations and improved understanding of biophysical processes. Finally, the challenges associated with impacts and adaptation research are discussed. It is argued that the generation of knowledge for policy and adaptation should be based not only on syntheses of published studies, but also on a more synergistic and holistic research framework that includes : (i) reliable quantification of uncertainty; (ii) techniques for combining diverse modelling approaches and observations that focus on fundamental processes; (iii) judicious choice and calibration of models, including simulation at appropriate levels of complexity that accounts for the principal drivers of crop productivity, which may well include both biophysical and socioeconomic factors. It is argued that such a framework will lead to reliable methods for linking simulation to real-world adaptation options, thus making practical use of the huge global effort to understand and predict climate change.

Key index words or phrases

Climate change, crops, uncertainty, model integration, modelling frameworks, adaptation

1. Introduction

Crops exhibit known observed responses to weather and climate that can have a large impact on crop yield (e.g. Porter and Semenov, 2005). Since atmospheric concentrations of greenhouse gases continue to rise at rates that are both unprecedented (Spahni et al. 2005; Siegenthaler et al. 2005) and alarming (Anderson and Bows, 2008), efforts have been made to understand the implications for crop production. These efforts are primarily based on climate models, which use spatial grids with resolutions typically of the order of a hundred kilometres. Such simplification of the spatial heterogeneity of processes has direct implications for the assessment of the impacts of climate change. Some of these assessments are performed at the regional scale (referring here to tens to a couple of hundred kilometres – commensurate with climate model grids). In contrast, location-specific methods have also been developed, to account for the variety of climatic and non-climatic stresses on crop productivity often not observable at aggregated spatial scales. It is at this smaller field scale that crop models were originally designed to operate (see e.g. Sinclair and Seligman, 1996; van Ittersum et al, 2003 for reviews), resulting in applications in decision support (e.g. Boote and Jones, 1998) and 'discussion support' (Hansen, 2005).

This review examines the use of crop and climate models in climate change research. As with the bulk of the literature, it focuses primarily on crop yield, which has the greatest impact on food security. By their nature, regional-scale assessments lend themselves more clearly to generalisation than do local-scale assessments; hence the focus here is primarily, though not exclusively, on larger scales. Section 2 examines the methods used to link crop and climate models, including the implications of the disparity in spatial scale between these two types of model. Section 3 reviews recent progress in modelling methods and in our resultant understanding of the impacts of climate change. Section 4 asks how we can generate useful information on impacts and adaptation with the methods reviewed. Future trends and challenges are identified in section 5, resulting in concluding comments and recommendations in section 6.

2. Linking crop and climate models

2.1 Overview

Simulation models act as a surrogate laboratory. They are a particularly important tool for understanding climate change and its impacts, since only one physical realisation of climate is possible, thus limiting the amount of observed data available for comparison with model output. (This is in contrast to the forecasting of weather, which can be tested repeatedly against observations). A number of different methods can be used to link crop and climate models. Figure 1 summarises the methods discussed in this paper (a more detailed review is presented by Hansen et al., 2006). The box labelled 'climate model' represents a range of models, from short-term local-scale numerical weather prediction to longer term simulations of climate change. These models are based on the same fundamental physics, and efforts are underway to carry out and present weather and climate simulation as part of 'seamless' continuum, such that the commonality of methods across weather and climate prediction is strengthened and made more clear to users (see e.g. Challinor et al., 2009b). For this reason, all model-derived climate and weather information is represented in this simple fashion.

Climate model output can be used with crop models either directly (e.g. Mavromatis and Jones, 1999; Challinor et al., 2005a,b,c) or via some post-processing. In the latter case, a weather generator (e.g. Semenov and Barrow, 1997) may be used, and/or the change in climate simulated using a model can be applied to observed climate (Zalud and Dubrovsky, 2002 compare the two methods; Southworth et al., 2002 use both methods). Results when using processed output are sensitive to the underlying assumptions (Mearns et al., 1997; Mavromatis and Jones, 1998). Unprocessed climate model output has the advantage of being a consistent representation of climate, thus avoiding the need for such assumptions. The corresponding disadvantage is that any errors in the climate model may have implications for the simulation of crop growth. For example, climate models tend to overestimate the number of rainy days whilst underestimating rainfall amounts (i.e. ‘drizzle’), and may also fail to represent the observed month-to-month variation in rainfall; some of these biases are easier to correct than others, and this can affect crop simulation (Challinor et al., 2005a). However, model error may not be overly problematic: Challinor et al. (2005c) found predictability in crop yields using climate model output both with and without correction of bias in the simulation of mean climate.

As well as dealing with climate model error, post-processing can deal with the disparity in spatial scale between climate and crop models (see e.g. Hansen and Jones, 2000; Challinor et al., 2003, 2004). The former uses a grid that is coarse relative to the spatial scale at which field-scale crop models (see section 1) typically operate. The disparity can either be ignored (e.g. Trnka et al., 2004) or it can be dealt with by downscaling climate model output (see Wilby and Wigley, 1997; Wilby et al., 1998; Kidson and Thompson, 1998). With or without downscaling, it is clear (e.g. Moen et al., 1994; Faivre et al., 2004) that regional prediction using crop and climate models cannot rely solely on methods developed as part of the longer-standing tradition of crop simulation at the field scale. Whilst the results of field scale models can be compared directly to regional scale yields (e.g. Yun, 2003; Nain et al., 2004; Xiong et al., 2007), it can be argued that this requires design or selection of crop models that have a low input data requirement (e.g. Priya and Shibasaki, 2001; de Wit et al., 2005). An alternative is to take a field-scale crop model and make it applicable to the regional scale through one or more procedures, such as calibration (e.g. Chipanshi et al., 1999; Jagtap and Jones, 2002), aggregation of inputs (Haskett et al. 1995), and aggregation of outputs from multiple sub-grid simulations. This latter method can either use simulations sampled by varying model inputs such as planting date and crop variety (Jagtap and Jones, 2002; Irmak et al., 2005) or else simulations explicitly carried out at the sub-grid scale (Thornton et al., 1996).

Estimates of yields at the regional scale can also be made by designing a crop model that operates on that scale. Such a model may be empirical, with weather variables used within a statistical regression of output from a field-scale crop model (Iglesias et al., 2000) or of observed yield data (e.g. Lobell et al., 2008). The use of regressions of field-scale crop models can introduce significant errors through the linearization of the equations for crop yield and/or an inability to account for subseasonal climate variability (Challinor et al., 2006). More generally, the validity of empirical methods under climate change is limited by the necessity of using data outside the range for which the models were fitted. Also, statistical models have no explanatory power to enable understanding as to why certain changes have occurred. This is one reason why process-based regional-scale (or large area) methods have been developed.

2.2 Large area crop modelling

Large area crop modelling resulted mainly from the need to simulate the impacts of climate variability and change on crops in a process-based fashion using directly (i.e. without any downscaling) the output from climate models. The rationale for such techniques (Challinor et al., 2004) lies in the combination of the benefits of empirical approaches (low input data requirement; validity over large spatial scales, thus avoiding site-specificity) with those of field-scale process-based models (validity under a range of environments, including climate change). The development of meta-models, based on existing simulation models, takes a similar approach, but for simulation at the field scale (e.g. Brooks et al. 2001). We focus here on larger scales, at which the modelling methodology is based upon a number of principles:

1. A basis in observed relationships. Where a response to climate variability exists in observations, the possibility of simulating that response also exists. Challinor et al. (2003) examined observed relationships between yield and climate in India at a number of spatial scales, and concluded that large-area modelling (i.e. using the same grid as climate models) of that response was possible. Such empirical studies are prone to the risk of confounding causality (Bakker et al., 2005); this is the reason that subsequent modelling should be both based on physiological processes and at an appropriate level of complexity. The limited length of historical records means that studies of observed relationships have focussed principally on year-to-year variability (e.g. Challinor et al., 2003; Kumar et al., 2004). However, climate change implies longer-term relationships, and these are beginning to be explored (see Lobell and Field, 2007).

2. Appropriate complexity. The crop modelling community has long been aware of the dangers associated with modelling at a level of complexity unwarranted by the degree of uncertainty and potential error associated with the parameterisations used (e.g. Monteith, 1996). The greater the number of processes simulated, the greater the number of potential interactions between them and the number of parameters that require calibration, thereby increasing the potential for error. Sinclair and Seligman, (2000) discuss this issue using the concept of hierarchical levels of biological organisation, from molecules to ecosystems. They argue that it is rarely justified for a crop model to simulate processes more than one hierarchical level below the level of immediate interest, because of the 'burgeoning complexity inherent in increasing the number of lower hierarchical levels.' Therefore, if yield is the variable of interest, then only the mechanisms near to the yield-determining processes should be simulated. This approach reduces the risk of over-tuning a model to one environment (i.e. confounding causality), which can result in a lack of applicability in other environments. The spatial scale and complexity of a model are related, as discussed by Challinor and Wheeler (2008b) and Tubiello and Ewert (2002).

3. High fraction of observable parameters. In order to avoid over-tuning, parameters should where possible be based on observations. This means that the parameterisations used are directly testable. Empirically-determined parameters can be based entirely on processes (Challinor et al., 2004), or else a semi-empirical approach can be used, e.g. with a process-based plant water stress index being empirically related to yield (Potgeiter 2005). Care should be taken not to use parameters observed for the current climate in situations where their value may have changed, as occurs for some processes under climate change. For current climates, discrepancies between the yield simulated by process-based models and observed regional yields can be minimised through a process-based yield gap parameter (Challinor et al., 2004) or an explicit error metric (Casellas et al., 2009). The choice of calibration method and the level of model complexity have implications for the reliability of model simulations (see section 4.1).

The principles above result in large-area crop models differing substantially from field-scale crop models. Large-area models tend to be less complex and have fewer parameter, and fewer non-observable parameters in particular. For example, the model of Challinor et al. (2004) simulates leaf area growth by using a parameter specifying the maximum rate of change of leaf area index, rather than simulating the appearance of individual leaves. The model uses transpiration efficiency, another observable parameter, to simulate the accumulation of biomass, rather than employing leaf-level assimilation equations, as most field-scale models do. Such an approach is appropriate in water-limited environments; a parallel approach in the UK might employ radiation use efficiency.

As with any model, large area crop models should be used judiciously. By design, they have the advantage of being both process-based and applicable over large areas. However, their focus on the influence of weather and climate, and their basis in observed relationships, means that large-area crop models do not currently simulate the non-climatic determinants of crop yield. These non-climatic stresses contribute to the yield gap, which is the difference between the potential yield for a current crop variety (i.e. under the given climate and for optimal agronomic practices) and the corresponding observed farm yields (see e.g. Herdt and Mandac, 1981; van Ittersum et al., 2003). These observed (farm and regional) yields include the effects of weeds, pests and diseases, and air pollutants such as tropospheric ozone. Where variability in yield is driven by these factors, rather than climate, or where there is high sub-grid spatial variability in weather (see Baron et al. 2005), the rationale for large-area modelling may be undermined. However, the significance of the climate signal tends to be greatest at regional scales (Bakker et al., 2005; Challinor et al., 2003). Thus, the proven ability to simulate current yields (e.g. Challinor et al., 2004), together with assessment of skill under likely climate change conditions (Challinor et al., 2005d), has built confidence in the use of large area models as part of efforts to simulate the response of crops to climate change.

3. Progress in modelling and understanding the impact of climate change on crops

3.1 Ensemble modelling

Under climate change, inherent uncertainties in the predictability of climate limit the precision with which impacts can be assessed. Furthermore, the response of crops to elevated carbon dioxide is not known with precision at field and larger scales (Ewert et al., 2002, Tubiello and Ewert, 2002). Quantification of uncertainty is therefore an important endeavour in climate impacts research (see e.g. Challinor et al, 2009b). Estimates of ranges of yield impacts vary across studies (see e.g. the review of Luo and Lin, 1999). The simulated responses of maize in Africa to a doubling of carbon dioxide, for example, can be as broad -98 to +16%, or as narrow as -14 to -12%. These ranges have been determined using different methods and are therefore not directly comparable (Challinor et al., 2007). Ensemble modelling is a technique that enables more objective quantification of uncertainty. It is commonly used in climate change prediction, which is based on estimates of future emissions of greenhouse gases, and on the simulation of the resultant influence on climate. Multiple climate simulations, known as ensembles, are used to sample the inherent uncertainties in this process. Uncertainty in model structure 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). These ensembles of climate simulations can be used with crop models, and sometimes weather generators, to produce an ensemble of crop yields that captures uncertainty due to climate simulation (e.g. Trnka et al., 2004).

The response of crops to any projected climate also contains uncertainties (see e.g. Mearns et al., 2003). Inputs to crop models, such as the choice of variety and planting date, can be varied in order to produce an ensemble of crop simulations (e.g. Jagtap and Jones, 2002; Irmak et al., 2005). Large area modelling studies have been carried out where both crop and climate parameters have been varied, thus permitting a better estimate of total uncertainty and of the relative contributions to that uncertainty (Challinor et al., 2005b, 2009a). Large-area crop modelling is well-suited to this approach, since it operates with direct climate model output. Studies using this technique have contributed to our understanding of the key processes that are likely to reduce crop yield, and the quantification of associated uncertainty.

3.2 Understanding biophysical processes under climate change

Direct impact of atmospheric composition

Elevated levels of carbon dioxide and ozone will have direct impacts on crops: C3 crops are likely to accumulate more biomass, and both C3 and C4 crops are likely to use less water as atmospheric carbon dioxide concentrations increase. These processes have received much attention by both experimentalists and modellers in recent decades. Significant increases in plant growth and yield due to CO_2 elevation have been reported from controlled, semi-controlled and open-field experiments for a range of crops, and to a lesser extent for crops grown in the field (e.g. Kimball et al., 1983, 2002). Many recent studies modelling the impact of climate change on crops have simulated the effects of elevated CO_2; however, the number of free air carbon dioxide experiments (FACE) available to validate these models under field conditions is still limited (Tubiello and Ewert, 2002).

It has been argued (Long et al., 2006) that crop models overestimate the effect of CO_2 on plant growth and yield, as a result of the CO_2-related model parameters being mainly derived from controlled and semi-controlled experiments, which typically show a higher

CO_2 response than observed under field conditions. However, there is growing evidence that crop models are able to reproduce the observed crop responses in the FACE experiments (Ewert et al., 2002, Asseng et al. 2004, Tubiello et al., 2007a). This evidence is contributing to an ongoing dialogue (see Ainsworth et al., 2008a). Progress in modelling CO_2 effects crops at the field scale will mainly depend on the ability to improve simulations of leaf area dynamics as compared to photosynthesis or radiation use efficiency (Ewert, 2004). For modelling CO_2 effects at larger areas the relative importance of other factors such as diversity in climate, soil and crop management including land use change for explaining yield variability (and possible interactions with the effects of elevated CO_2) need to be better understood (Ewert et al., 2007).

Crops are subject to multiple stresses, so that analysis of climate change alone provides only a partial view of likely future crop yields. In order to produce robust results of climate change impacts, a range of drivers need to be assessed. Such assessment is beyond the scope of this paper. However, we consider here one further environmental variable that affects crop yield. We choose ozone since it is a second atmospheric gas that can have serious implications for yield. Atmospheric ozone is formed in the Earth's lower atmosphere through sunlight-driven chemical reactions involving volatile organic compounds and nitrogen oxides (NOx). It is a strong oxidant that is harmful to plants and crops. Exposure of plants to elevated ozone concentrations can result in acute visible injury, which may have economic implications for food producers, as the damaged crop commands a reduced market price or cannot be sold at all (e.g. Velissariou 1999). Plants chronically exposed to enhanced ozone take up an increased flux of ozone through their leaves, resulting in reduced capacity for photosynthesis and accelerated leaf senescence (McKee et al., 1997). Protection mechanisms allow the plant to repair ozone damage and detoxify leaf tissue, meaning that plant function can remain unaffected up to a threshold value of ozone uptake. The reduced photosynthetic productivity and allocation of plant resources to these mechanisms leads to reduced carbon assimilation for plant growth, and a reduction in biomass and crop yield (Mauzerall & Wang 2001; Emberson et al. 2003). At higher ozone exposures, plant protection mechanisms may be overwhelmed completely, and ozone entering the plant can result in direct damage to plant tissue. There is also evidence that exposure to enhanced ozone reduces the nutritional value of crops. European wheat crops have demonstrated an ozone-induced reduction in protein yield per area grown (Piikki et al. 2007).

Ozone is likely to play an increasingly important role in determining crop yields as anthropogenic sources of its precursors continue to increase in developing economies, leading to increasing background concentrations, especially in the northern hemisphere. Studies suggest large enhancements in surface ozone over SE Asia, central Africa and tropical South America over the next 50 years under projected emissions and climate changes (Royal Society, 2008). Many of these regions are those where food security is already at risk from rising populations, loss of cultivated land and climate change. Reductions of 5% in current yields due to ozone enhancement have been estimated in China, and projected to rise to 30% by 2050 (Long et al., 2005). A wide range of sensitivity to ozone damage is exhibited between crop species and between strains within a species (e.g. wheat) (Ainsworth *et al.* 2008b). This may make it possible to reduce ozone impacts on crop yield and food security through the targeted planting of more ozone-resistant crop strains.

Progress to date in modelling ozone and its impacts includes global-scale estimates of future ozone impacts on crop-yield over the next 30 years, based on modelled surface ozone concentrations (on a one degree square spatial grid) and an exposure-based ozone damage relationship (Van Dingenen et al., 2008). Yield losses for wheat and rice in India and wheat in sub-Saharan Africa were found to be particularly significant. These results are subject to large uncertainties, due to application of ozone exposure-damage relationships over large scales, uncertainties in modeled ozone and choice of exposure index. Some local experimental data indicate that ozone-induced crop losses exceed those predicted by the large scale model predictions, which rely on US-based exposure-response relationships. Additional uncertainty stems from the reliability of modelled surface ozone fields. These rely on estimates of ozone precursor emissions, which are particularly poorly constrained in developing regions of the world such as Asia and Africa. The sensitivity of future ozone concentrations to climate change is also poorly understood, and depends on future land-use change, and how natural emissions from the biosphere, and the stratospheric flux of ozone to the lower atmosphere, will respond to future climate. These impacts are not well understood and are currently only rudimentarily considered by current generation atmospheric chemistry-climate models.

Indirect impact of atmospheric composition

As greenhouse gas emissions continue to rise, and climate changes, crops in the majority of regions will increasingly be grown in a warmer environment. These increases in mean temperature are already resulting in longer growing seasons (Rosenzweig et al., 2007), although there is no indication that this is having a positive effect on yield, at least up to 2002 (Lobell and Field, 2007). Projections of the future impacts of warming seem to indicate a negative response of crop growth and yield to 1-2^{o}C warming at low latitudes and small beneficial response at higher latitudes; yet large uncertainties remain (Easterling et al., 2007).

Mean temperature, together with photoperiod (e.g. Nigam et al., 1994), determines plant development rate. The fundamental thermal time response functions that determine the rate of crop development (e.g. Challinor et al., 2004) suggest that warming will decrease both duration and yield, at least up to the optimum temperature for development. However, since a given response function of development rate to temperature may not fit observations (e.g. Zhang et al., 2008), care should be exercised in their use. Challinor and Wheeler (2008b) showed that differences in the form of these response functions, particularly at temperatures beyond the optimum temperature for development, means that different models can respond very differently to increases in mean temperature.

In addition to large-scale changes in mean temperature, regional changes in climate will likely affect crops. These regional changes, particularly where they involve rainfall and/or variability in weather (as opposed to changes in mean quantities, such as season-mean temperature), are particularly difficult for a climate model to predict. Examples of potentially important regional changes include atmospheric humidity, which affects assimilation and alters transpiration efficiency (e.g. Kemanian et al., 2005). This process may be very important in determining future yields in India (Challinor and Wheeler 2008b) and other regions. There is also evidence that anthropogenic aerosol and other air pollutants have changed the optical properties of clouds, with resultant implications for solar radiation and hence agricultural productivity (Stanhill and Cohen, 2001).

The short-term events that are most likely to affect crops are extremes of temperature (Wheeler et al., 2000) and drought, particularly during anthesis. Challinor et al. (2005d) reported reductions of up to 20% in both observed and simulated crop yield when a six-day heat stress event was imposed on groundnut. The importance of sub-seasonal variability in rainfall is illustrated in figures 2 and 3. Figure 2 shows that whilst rainfall during the development of the crop has a clear influence on observed yield (44% of the variance explained), the crop model simulations (55% of observed variance explained) suggest the importance of other processes. One such process is likely to be the sub-seasonal variability of rainfall. This can be illustrated by noting that two years with different yields (44% lower in 1981 than in 1975), but with very similar total rainfall (see figure 2), have different sub-seasonal rainfall distributions (figure 3): the timing of rainfall in the 1975 season is such that water availability during pod filling (from approximately 50 days after planting) is likely to be higher than that of 1981. This indicates the beneficial value of considering important processes in large-area models.

The predictability of the above indirect influences of increased atmospheric greenhouse gases varies across environmental variable and across space. Temperature is generally more predictable than rainfall, for example, and consensus across climate models in tropical seasonal total rainfall tends to be weaker than consensus at mid- and high-latitudes. The lead time of a forecast also affects the predictability: any prediction of weather beyond a few days contains inherent uncertainties, which can amplify as the predictions are made further into the future. At multi-decadal timescales, it is uncertainties in the concentrations of greenhouse gases that limit predictability. Further discussion on this topic can be found in Challinor et al. (2009b).

Interactions between biophysical processes

Crop yield is the result of many non-linear interactions between a range of processes, including those outlined above. Experimental field studies and crop models are two complementary tools that can be used to examine these interactions. The importance under field conditions of interactions between elevated CO_2 and other factors such as ozone exposure and temperature, water and nitrogen stress is not fully understood. Evidence from field experiments is limited and also points in different directions.

Consider as an example the interaction between water stress and CO_2. From a physiological perspective, water-stressed crops are expected to show greater CO_2 stimulation than well-watered crops. This expectation has been cited in literature as a reason for believing that rainfed cropping systems will benefit more from elevated CO_2 than irrigated systems (IPCC, 2001; Easterling et al., 2007). Tubiello and Ewert (2002) showed that for a range of models and observations, water-stressed crops did indeed show a greater percentage increase in yield under elevated CO_2. However, when Challinor and Wheeler (2008a) reviewed Free-Air CO_2 Enrichment (FACE) meta-analyses and presented results from a range of crop models, this response was not seen consistently in either the models or the observations. Detailed analysis led to the preliminary conclusion that the relationship between water stress and assimilation may vary with spatial scale. The associated level of model complexity was also shown to be a factor. Despite the lack of a consistency across studies, model comparison studies with the few experiments available have shown that, at the field scale, crop responses to elevated CO_2 can be satisfactorily reproduced for a range of models under a range of conditions of water availability (Ewert et al., 2002; Asseng et al., 2004), nitrogen supply (Jamieson et al., 2000) and ozone exposure (Ewert et al., 1999; van Oijen and Ewert, 1999).

Ozone also interacts with the environment in a way that alters its effect on plants. Since these interactions are non-linear, assessing the response of crops to future ozone concentrations requires consideration of future changes in atmospheric CO_2 and other environmental variables affecting plant function and stomatal conductance (Fuhrer, 2003; Ashmore, 2005; Harmens et al., 2007). The interaction between ozone and CO_2 is mediated by stomata, which, in addition to admitting ozone, allow CO_2, water vapour and oxygen to pass in and out of the plant during photosynthesis and respiration. Increased atmospheric CO_2 reduces stomatal conductance, and the flux of ozone into the plant, and can provide additional carbon for repair and detoxification against ozone damage (Royal Society, 2008).

The interactions between ozone and carbon dioxide have implications for the way in which ozone damage is modelled. Dose-response relationships based on ozone flux are preferable to atmospheric ozone exposure (e.g. Accumulated dose Over a Threshold of 40 parts per billion, AOT40; see Fuhrer et al. 1997), since they are able to account for the varying influences of temperature, water vapour, radiation, soil water, phenology and atmospheric ozone on ozone uptake. With exposure-related indices, different meteorological and environmental conditions may result in a given atmospheric ozone exposure producing different crop impacts. In addition, several studies have shown that plant response is more closely related to stomatal ozone flux than to a time-integrated atmospheric ozone exposure (e.g. Pleijel et al, 2000). This puts a high priority on the development of coupled process-based models that explicitly calculate the stomatal flux of ozone into the crop, and its dependence on a range of environmental drivers. Limited efforts have so far been made to model ozone effects at the explanatory process level, accounting for interactions with other factors such as CO_2 and climate (Ewert et al., 1999, van Oijen and Ewert, 1999, Ewert and Porter, 2000; van Oijen et al., 2004). The validity of these approaches for large scale applications awaits further testing against reliable experimental data. Such data are still scarce (van Oijen and Ewert, 1999, see also Long et al., 2006) and are urgently required for a range of important crop species under a range of climatic conditions.

Abiotic stresses are also likely to interact with biotic stresses. For example, the effects of ozone on plant function (allocation of resources to ozone resistance) and structure (e.g. leaf damage) may leave plants more susceptible to damage from pests, disease and extreme weather, which are themselves likely to be affected by global climate change. Detailed discussion on biotic stresses is beyond the scope of this review.

4. Generating useful information

4.1 Ensuring reliability

How can the progress highlighted above be used to generate useful information? At least two conditions apply (see Patt and Gwata, 2002): useful information should be both reliable and relevant to the user of the information. The existence of complex interactions such as those described above presents a challenge to the reliability of process-based crop models. As shown in section 2, mechanistic modelling necessarily involves a reduction of real-world processes to a set of fallible rules. A model that is too simple will fail to represent some of the interactions that strongly influence output variables. A model that is too complex will have more parameters than can be constrained by observations, increasing the risk of reproducing observations without correctly representing the processes involved. Some parameters are not directly observable, and must be inferred as part of the calibration procedure. The risk of over-tuning – where the right answer is obtained for the wrong reason, due to an excess of tuneable parameters that cannot be related directly to observations – is compounded by the existence of non-linear interactions in biological systems. A range of observations under a range of conditions is therefore needed to ensure that each of these interactions is correctly represented. When an over-tuned model is run in a new environment (such as under climate change), the errors may be large. This implies that, despite the progress highlighted in section 3, we should be wary of being over-confident in our assessments of the impacts of climate change, especially where it is based on the 'validation' of a model followed by subsequent 'black box' use of that model (see Monteith, 1996). Judicious model choice and calibration are therefore crucial, as is the evaluation of historical performance (e.g. Easterling et al., 1996), if our simulations are to be consistently accurate (i.e. reliable).

Calibration parameters may be process based, acting on, for example, leaf area index (Challinor et al., 2004) or soil fertility (Boote and Jones, 1998). Calibration may also be applied to model output as a yield correction factor (Jagtap and Jones, 2002; Casellas et al., 2009). A range of more detailed approaches have also been tried and compared (Irmak et al., 2005). The potential for over-tuning means that calibration should be performed by using observations of as many growth variables as possible. For example, leaf area index can be used in addition to yield (e.g. Guerif and Duke, 2000; Jones and Barnes, 2001). Internal consistency checks are also very important in spotting unrealistic simulations. Possible checks include radiation use efficiency and specific leaf area (where these are not input parameters; see e.g. Challinor et al., 2004). Checks such as these can be combined with the methods outlined in section 3.1: observations can be used to constrain ensembles of crop simulations (Challinor and Wheeler, 2008a). This approach can result in a reduction in the associated uncertainty from the estimates with unconstrained ensembles, as shown by Challinor et al. (2008a). That study, which accounted for both crop and climate uncertainty, also showed that, for the region and crop studied, doubled-CO_2 without adaptation was highly likely to result in a reduction in yield. Thus quantifying uncertainty does not preclude relatively certain statements. Ensemble methods can ensure that we avoid unwarranted precision in our simulations, and observations can ensure that we avoid unnecessarily large uncertainty ranges.

4.2 Informing adaptation

Once we are confident that our estimates of climate change impacts are reliable, they can be used to create information relevant to the adaptation actions taken by stakeholders. Challinor (2009) discusses this topic at length, and assesses the potential for adaptation to climate for a crop in India. In that study, a number of existing model results were used to assess the extent to which genotypic variation might be used to adapt to climate change. The requisite crop genetic properties determined from the simulations were compared to those of existing germplasm. Interestingly, a separate study showed that under doubled-CO_2 in India, the uncertainty in the simulation of adapted crops may be greater than that of non-adapted crops (Challinor et al., 2008a).

When considering adaptation, it is important to consider how weather and crop yield forecasts will be used, and what spatial and temporal scales will be the most appropriate for the users. Useful weather/climate forecasts can range from a few days ahead for some crop management decisions, to decades in the future for infrastructure and strategic planning. For example, ensemble climate modelling can be used with crop models in order to predict crop yield a season ahead of the harvest (Challinor et al., 2005c).

Information should also be provided in relevant formats (Stone and Meinke, 2005). Whether the information best-suited to users is based on computer-intensive systems, or on less high-tech systems such as observational networks and capacity building, depends to a large extent on the particular users considered (see e.g. Patt et al., 2005). In Africa, for example, a prudent way to address the threat of climate change may be to focus on strategies for coping with climate variability, rather than longer-term climate change (Washington et al., 2006). This may mean a greater focus on in situ and remotely sensed observations as well as consideration of the multiple stresses that act on food security (Verdin et al., 2005; Haile, 2005; Gregory et al., 2005).

In the seasonally arid regions of the developing world, people are particularly vulnerable to interannual and intraseasonal rainfall variability, through dependence on rainfed agriculture. The skill of forecasts is also often higher in these mid-latitude regions than it is further north (e.g. DTI, 2001). Hence the potential benefits of climate forecasting may be particularly high in tropical regions, where there may be strong relationships between climate and impacts variables such as crop yield (see also WCRP, 2007).

5. Future trends and challenges: Holistic impacts and adaptation research

Having reviewed progress in modelling the impact of climate change on crops, and examined how reliable and useful information may come from this endeavour, what can be said of the progress needed in the near future? Part of generating relevant and reliable information is synthesising knowledge effectively and applying it appropriately. One of the tools that enables this endeavour is the hardware on which models are run. Ongoing increases in computer power create the potential for increasingly sophisticated modelling techniques. For climate and impacts modellers, this presents a choice (see Challinor et al, 2009b): increase the complexity of the model, increase the number of simulations, or increase the spatial resolution. Increases in complexity are subject to the constraints identified in section 4.1. Increases in the number of simulations create larger ensembles and hence more objective quantification of uncertainty (see section 3.1). Increases in spatial resolution will permit analyses across a broader range of spatial scales. This in turn may create one of the ingredients in a synergistic modelling approach that aims to increase the accuracy and reliability with which yield is simulated.

5.1 Synergistic approaches to yield prediction

Efforts to synthesise knowledge on the response of crops to climate change have increased in recent years (see Easterling et al., 2007; Tubiello et al., 2007b). These studies, which review existing modelling efforts and try to form a consensus, are an important part of the process of increasing our understanding. They are faced with a difficult task, since each of the individual studies tend to use only one method for one region, and for a limited number of crops (see section 3.1 and Challinor et al., 2007). In order to address this, some crop model inter-comparison studies have been performed (e.g. Jamieson, 1998; van Oijen and Ewert, 1999; Jamieson et al., 2000; Ewert et al., 2002). These have shown that simulations differ across models, due to significant differences in the structure of the models. For example, some models are based on the concept of radiation use efficiency whilst others are based on water- or nitrogen use efficiency; some models emphasise sink development, whilst others focus mainly on sources. Clearly, the structure of a model and the processes considered, including their relative importance, are determined by the aims for which the models are developed. These aims are in part determined by the region for which the model was developed, since there are considerable regional differences in the factors determining crop responses (Reidsma et al, 2009).

As a result of this spatial heterogeneity in the determinants of yield, several studies show that crop models have difficulties in reproducing yields at multiple sites (Ewert et al., 1999; van Oijen and Ewert, 1999), farms (Ewert et al., 2002) and regions (Reidsma et al., in review). Unsatisfactory model performance at the regional scale can be due to the inappropriate consideration of factors and processes determining yield variability (Reidsma et al. in review) and/or the aggregation of input data which may inconsistently reproduce the spatial variability of growing conditions (e.g. climate and soils) within a region (e.g. Hansen and Jones, 2000). Also, factors explaining spatial yield variability across regions can be different from those explaining temporal variability within regions (Reidsma et al., 2007, 2009).Thus, there is no single modelling approach that performs evenly well across regions.

Similar reasoning can be applied to simulation across a range of spatial scales, since this is another determinant of the structure of a model. For some scales and regions, climate may be the dominant determinant of crop yield. Where biotic stresses (see e.g. Tubiello et al., 2007b) or other non-climatic processes dominate, there may be no observed relationship between climate and crops; here, more detailed site-specific modelling may succeed in demonstrating predictability (e.g. Carbone et al., 2003; Gadgil et al., 2002), by explicitly including determinants of yield variability other than climate. Bakker et al (2005) showed that the significance of the climate signal increases with spatial scale, suggesting that non-climatic factors such as management or soils may become more important at smaller scales.

Given the importance of scale and geography in determining crop productivity, perhaps the greatest challenge for future syntheses of knowledge on the response of crops to climate change is the balance between generality and specificity in region and scale. Reducing complexity to the most important yield-determining factors and processes may result in different region- and/or scale- specific models. This in itself may reduce the generality of the results. Efforts to improve synergy between crop modelling approaches must therefore choose whether to emphasise generality or specificity. Increasing generality has been proposed by Yin and van Laar (2005), who developed improvements to the underlying physiological relationships in the GECROS model, resulting in wider applicability across a range of conditions. Adam et al., (in review) propose a generic modelling framework that assembles regional-scale models depending on the regions and the relative importance of the determinants of yield in those regions.

The ensemble techniques reviewed in section 3.1 are an attempt to avoid unwarranted precision (i.e. specificity). The techniques have been used to examine the form of the response of crop yield to mean temperature (Challinor et al., 2008a). The results showed that the response derived from an ensemble systematically varying both climate and crop responses to elevated CO_2 can have a different form to that derived from a study synthesising a range of disparate results (that of Easterling et al., 2007). The results also showed variation in response of crop development and yield to mean temperature across a range of crop models. Similar techniques were used by Challinor and Wheeler (2008a,b), who used a crop simulation ensembles combined with sensitivity analyses on two other crop models. Coupled with observational studies, approaches such as these can be used to understand the fundamental biophysical processes determining crop yield across scales and across regions.

5.2 Combining bio-physical and socio-economic drivers

Biophysical processes are not the only determinants of crop yield and productivity. The role of socio-economic drivers is increasingly being realised by the climate and impacts modelling community. Efforts to increase the reliability, and also relevance, of predictions are therefore beginning to draw on a parallel body of work that has explored the influence of human action (e.g. adaptation) on crop productivity. Unsurprisingly, these studies show that productivity relies on capital and labour inputs and a range of other factors (Mendelsohn, 2007). Such factors may trigger a range of inseparable responses in yield, including step-changes (e.g policy, infrastructure, pest), smooth trends (e.g. technical innovation) or cyclical changes (e.g crop rotation, rainfall). Drawing on development studies, and household/village scale livelihoods work in poorer parts of the world (see e.g. Adger, 1999), a range of more qualitative data suggest that the way farmers adapt to climatic problems results from the complex and unpredictable interactions between society and the environment (O'Brien and Leichenko, 2000).

Much of this work has involved asking key informants about how weather related problems were overcome in the past. As such, these studies tend to use participatory methods (Dougill et al., 1999) and find their intellectual foundations in the work of Amartya Sen who studied the causes of 20th century famines and presented his "food entitlement theory". Sen concluded that those socio-economic factors that constrain an individual's ability to switch entitlements are more important in creating a famine than simple meteorological anomalies (Sen, 1981). Food Entitlement Theory has been expanded on by researchers doing field work where key interviews, focus groups, and questionnaires are used to conduct studies on how households and villages adapt to overcome weather-related problems (Bebbington, 1999). Researchers have explored how household members switch between different livelihood strategies (Scoones, 1995), and found that by diversifying their income sources householders can become less vulnerable to climate variability (Hageback et al., 2005) . Thus far, however, it has proven difficult to "up-scale" results from these field studies and current attempts have only generated quite general and qualitative conceptual frameworks (Turner et al., 2003, Ericksen, 2008).

Recent studies have analysed relationships between farm characteristics and yield variability (Reidsma et al., 2007, 2009) across regions in Europe. As evident from these studies farm intensity, farm size and land use have been identified as important characteristics for explaining a significant part of the spatial and temporal yield variability. It was also shown that farm diversity in a region can strongly affect (and cancel out) the climate signal (Reidsma and Ewert, 2008). Considering these farm characteristics in a model evaluation study revealed that some of the deviation of the simulated regional yields from observations could be explained by these characteristics. Yet, the integration of this information into biophysical models remains difficult (Vincent, 2008).

In order to bring socio-economic and biophysical approaches together and develop formal mathematical models of climate impacts on food security, those socio-economic factors that limit or enhance production and adaptation can be identified and quantified using the same spatial scale as climate models and large-area crop models. Work supporting this has been undertaken by characterizing those socio-economic factors that, in the past, seem to have buffered harvest from drought (e.g. Fraser et al., 2008) and the development of indicators of socio-climatic exposure (Diffenbaugh et al., 2007). Simelton et al. (2008) have shown that regions may be vulnerable to drought due to land, labour or capital constraints and that, as regions develop economically, the source of vulnerability may shift from economic constraints to a lack of land or labour. However, these results are preliminary; more work is needed to fully understand how socio-economic processes influence climate-crop relationships, and trends in production, at the regional scale. Once this has been done, the socio-economic and biophysical aspects of crop productivity can be examined together using state-of-the-art methods and at common spatial scales, resulting in more holistic assessments of climate change impacts and adaptation. Methodologies are therefore required that can integrate the main food system processes (e.g. Schmidhuber and Tubiello, 2007; Tubiello et al., 2007b) and suggesting adaptation options that take account of the full range of stresses on agriculture (see Morton, 2007; Howden et al., 2007). Integrative work such as this needs to be based on an understanding of fundamental processes and their associated uncertainties (see section 4.1).

5.3 Linking simulation with adaptation

The challenges identified above have focused principally on increasing the reliability of simulations. How can we go about increasing the relevance of the information produced by crop and climate models? Closer links with efforts to develop adaptation options would seem to be an effective way to do this. For example, plant breeding operates on a 7-10 year timescale, producing the varieties that are best adapted to the environment (e.g. Austin, 1999). This timescale is unlikely to be sufficient to prepare for the increase in extreme events expected under climate change (see Randall et al., 2007). Also, plant breeding cannot take place at all the locations where adaptation to climate change will be needed. Just as judicious use of crop models can complement field studies, there is the potential to link simulation studies more closely to plant breeding and other adaptation measures. Such methods could be used to identify the regions where newly-bred varieties may perform well, thus broadening their domain of applicability. They also provide a tool for making the simulation studies relevant to a specific adaptation endeavour. A sequence of links is likely to be needed in order to connect simulation and plant breeding; existing concepts (e.g. ideotypes: Donald, 1968; Sylvester-Bradley and Riffkin, 2008) may prove to be a useful part of this.

Efforts such as these can only be carried out with the will and ability of a range of scientists. Our understanding and modelling of climate impacts is based on fundamental physics, biology and chemistry, and the interactions between them. Our ability to predict is therefore dependent on the quality of our single- and cross- disciplinary research. Similarly, our ability to inform adaptation will depend upon the extent to which we can combine all relevant scientific analyses into holistic assessments. Just as there are many successful studies linking crop and climate science (e.g. Huntingford et al., 2005; see also Slingo et al, 2005), it should be possible to link more closely simulation studies with a range of adaptation endeavours.

6. Conclusions

There are many complex processes and interactions that determine crop yield under climate change (section 3.2). These include the response of crops to mean temperature, the interaction between water stress and CO_2, and the interaction between ozone and a range of environmental variables. As a result of this, and of the importance of scale and geography in determining crop productivity, perhaps the greatest challenge for future syntheses of knowledge on the response of crops to climate change is the balance between generality and specificity in region and scale. It is clear that climate impacts research requires appropriate degrees of integration and specialisation (Challinor et al., 2009b). To date, efforts to generate knowledge for policy and adaptation have been largely based on syntheses of published studies. Synergistic approaches are now needed that include:

(i) Reliable quantification of impacts uncertainty. This should be carried out as objectively as possible and is likely to include the use of crop simulation ensembles and/or sensitivity analyses (section 3). Since the quantification of uncertainty does not preclude a high degree of certainty regarding some statements (section 4.1), there is every reason to believe that this approach will prove to be productive.

(ii) Techniques for combining diverse modelling approaches and observations. A focus on processes, employing a range of models and observations in order to increase our understanding of non-linear interactions, is likely to be an effective strategy for reducing uncertainty (sections 3.2, 4.1 and 5.1). Coupled modelling approaches are likely to form a part of this strategy, since non-linear interactions between yield-determining processes may result in complex coupling between, for example, atmospheric composition and climatic drivers. Observations are also important: whilst ensemble methods can ensure that we avoid unwarranted precision in our simulations, observations can ensure that we avoid unnecessarily large uncertainty ranges.

(iii) Judicious choice and calibration of models, including simulation at appropriate levels of complexity that accounts for the principal drivers of crop productivity (section 2). Even when a range of models is combined in some way, judicious choice and use of models is required. Since no one model can claim to represent reality entirely accurately (section 5.1), models should not be calibrated or run as ‘black boxes.’ Thus different models may be used for different regions, depending on the relative importance of driving variables in these regions. Also, modelling methods are needed that can account for both the biophysical and socio-economic determinants of crop productivity (section 5.2).

In addition to providing a new paradigm for the generation of knowledge, such an approach will lead to reliable methods for linking simulation with adaptation (sections 4.2 and 5.3). Thus we can move beyond synthesising knowledge and begin to make the best use of the huge global effort to understand and predict climate change.

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Figures

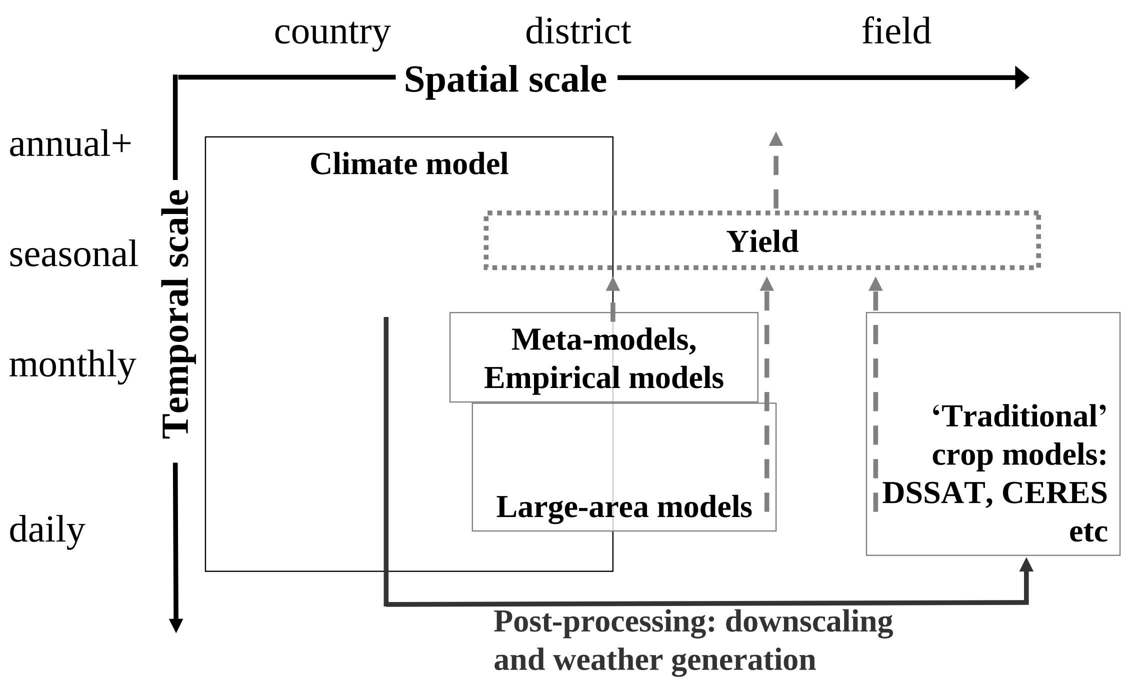

Figure 1. Schematic representation of methods used to combine crop and climate models. Solid arrows show climate information, dashed arrows and lightly-shaded boxes show crop growth simulation. Solid boxes show numerical models, boxes with dotted outlines show model output. Areas where boxes overlap indicate models that operate on commensurate spatial and temporal scales.

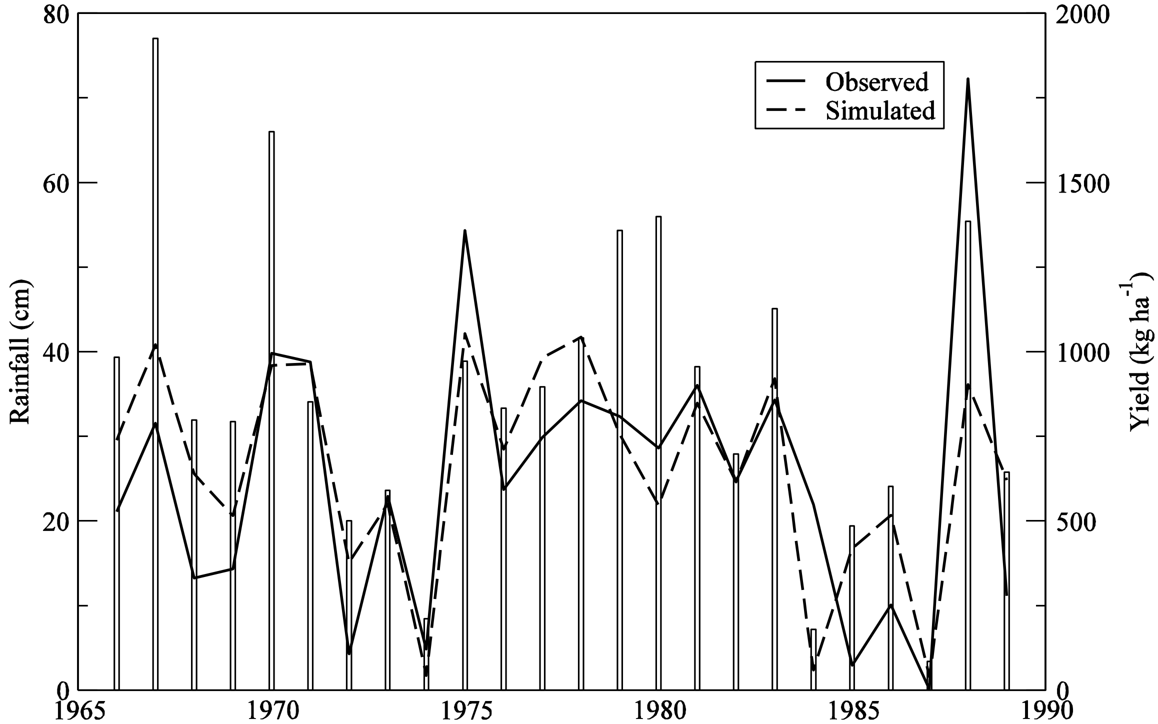

Figure 2. Observed and simulated crop yield (lines) for a grid cell in western India taken from the study of Challinor et al. (2004). Bars indicate total rainfall during the simulated development period of the crop (planting to physiological maturity).

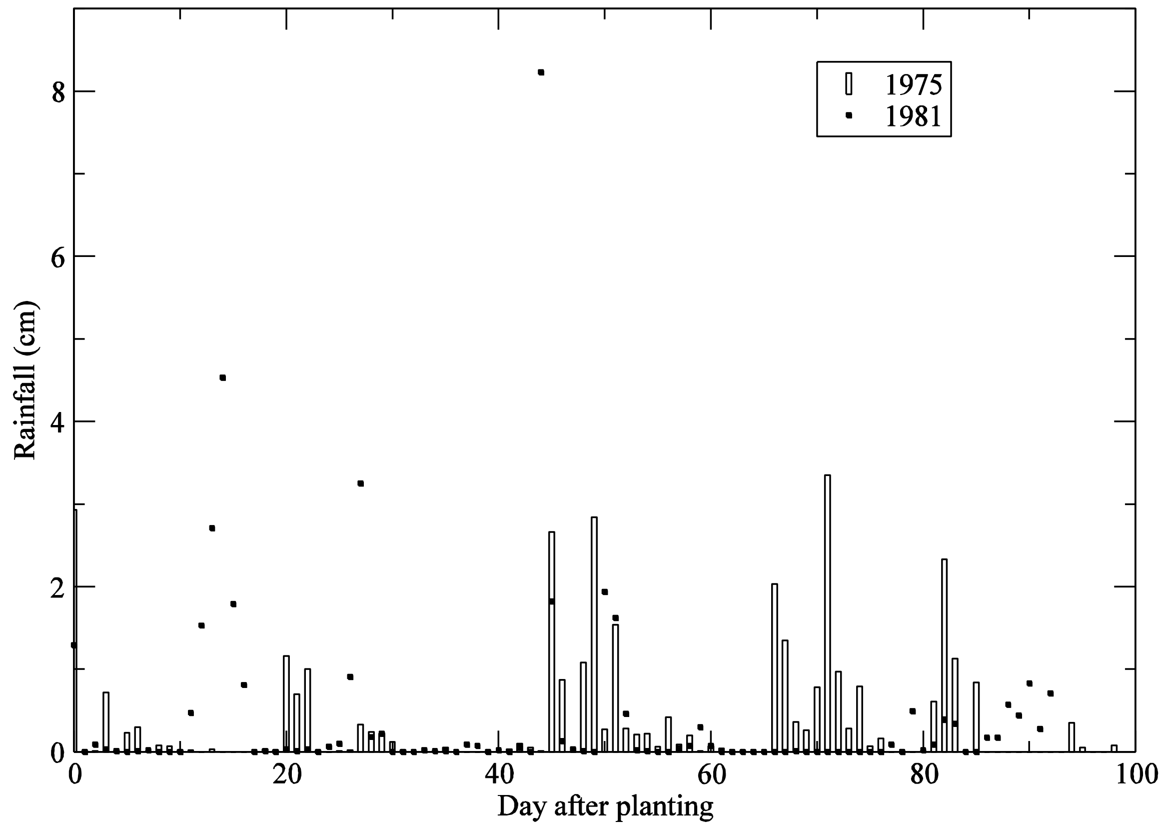

Figure 3. Timeseries of rainfall, starting with the simulated planting date, from two of the years shown in figure 2. Redrawn from Challinor et al. (2004).