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6. Crop Modelling of Adaptive and Mitigating Potential of Climate Smart Practices

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Abstract:

As the world population continues to rise, food production will have to be increased to meet and sustain the demands of our rapidly growing population. Not only will food production need to increase, but yields will need to be able to withstand climate changes which include increased temperatures and decreased rainfall patterns. By understanding and being able to predict crop production outcomes under various climatic situations and management approaches, farmers will be better equipped with adaptation strategies to maximize crop growth as sustainably as possible. Crop modelling tools offer a way to evaluate potential adaptations in climate and can help form the basis of decision-support systems for farmers.

Crop models are a formal way to present quantitative knowledge about how a crop grows in interaction with its environment. Using weather data and other data about the crop environment, these models can simulate crop development, growth, yield, water, and nutrient uptake. Crop models are sets of mathematical equations that represent processes within a predefined plant system as well as the interactions between crops and the environment. Considering the complexity of agricultural systems and the existing gaps in present knowledge, it seems impossible to express entire processes of a crop system in mathematical terms provided that agricultural models are still simplified versions of reality (Wallach et al., 2014). The ultimate purpose of developing crop models is to get a precise estimation of the economic yield. However, depending on the availability of information and data at the interested scale, crop models are developed at different levels of complexity (Jones et al., 2017).

Therefore, they may range from multivariate regression, so-called empirical models based on monthly weather variables intended to predict crop yields at regional scale (Paswan and Ara Begum, 2013), to process-based ones, so-called mechanistic models of plant growth, developed for getting insight into the crop physiological interactions (Janssen et al., 2017). Since 1970, several mathematical models at different levels of sophistication have been developed for simulation of growth, development, and yield of cultivated crops. These models are extensively used for different purposes such as crop management, yield gap analysis, crop-pest interactions, and climate change impact studies (Jin et al., 2018; Jones et al., 2017; Ritchie and Alagarswamy, 2002; Van Ittersum et al., 2013). Crop models are used for an increasingly broad range of applications, with a commensurate proliferation of methods. Careful framing of research questions and development of targeted and appropriate methods are therefore increasingly important.

Keywords:

Crop Models, Adaptation, Mitigation, Stakeholders.

6.1 Introduction:

Crop modelling in agriculture uses quantitative measurements of ecophysiological processes to predict plant growth and development based on environmental conditions and crop management inputs. These models simulate a crop's response (growth or yield, for example) to the environment, management, water, weather, and soil parameters, as they interact over the course of a growing season. These tools mimic the growth and development of crops to mathematically represent the various components within the cropping system. The concept of crop modelling dates back to the 1960s when researchers modelled agricultural systems by combining both physical and biological principles. Crop models rely on measurable inputs (by sensors, machines, or hand measurement) to determine whatever output is of interest (plant growth, crop yield, soil nitrogen, crop staging, etc.).

Figure 6.1: Crop Modelling

Crop models are mathematical algorithms that capture the quantitative information of agronomy and physiology experiments in a way that can explain and predict crop growth and development. Crop models are a formal way to present quantitative knowledge about how a crop grows in interaction with its environment. Using weather data and other data about the crop environment, these models can simulate crop development, growth, yield, water, and nutrient uptake.

The data used in crop models include daily weather data, such as solar radiation, maximum and minimum temperatures, rainfall, as well as soil characteristics, initial soil conditions, cultivar characteristics, and crop management. Crop models are mathematical algorithms that capture the quantitative information of agronomy and physiology experiments in a way that can explain and predict crop growth and development.

They can simulate many seasons, locations, treatments, and scenarios in a few minutes. Crop models contribute to agriculture in many ways. They help explore the dynamics between the atmosphere, the crop, and the soil, assist in crop agronomy, pest management, breeding, and natural resource management, and assess the impact of climate change.

6.2 Modelling for Crop Improvement:

Crop models can also be used as a guide for breeding programmes or as a means to envision a crop idiotype (Boote ***et al.***, 1996). While simulation models can be used to predict appropriate trait phenotypes and selection protocols in breeding programmes to achieve ideotypes (Boote ***et al.***, 1996), for a true integration of crop models and breeding, the inheritance of model parameters is required (Yin ***et al.***, 2003). One objective that can be pursued in a breeding programme is to optimize plant carbon allocation among plant components (i.e. leaf, stem, rhizome and root), which requires at least (1) phenotypic and genotypic data, and (2) a crop model that can capture the impact of different carbon allocation schemes on growth and biomass production.

This approach can be used to study the effects of genotypes with different biomass participating schemes. However, there is clearly a balance between the support and nutrient acquisition provided by rhizomes and roots and the benefit of partitioning more biomass to above-ground organs that can be harvested. One factor that is likely to have a major impact on carbon allocation is the manipulation of flowering time (Sticklen, 2007). By reducing the energy invested in reproductive structures, the proportion of biomass available for harvest can be increased (Ragauskas ***et al.***, 2006) and optimized to develop cultivars adapted to particular regions.

For example, an improved carbon allocation scheme can result in reduced leaf area by increasing the nu ber of stems and/or their thickness. In addition, maintaining leaf area index at optimum values (Hay and Porter, 2006) also has the potential of reducing crop transpiration and thus improve water use efficiency which can be especially important for biomass production in dry environments (Richards ***et al.***, 2002). This reduction in leaf area index will be most beneficial if it does not impact on the timing of canopy closure and maximum light interception. It should also be considered that flowering is an important component in triggering senescence processes which, in perineal crops, initiate translocation of nutrients and carbohydrates to below-ground storage (Heaton ***et al.***, 2009).

If delayed flowering prevents this from happening, the nutrient use efficiency will decrease, impacting the sustainability of the cropping system, since synthetic fertilizers need to be added and the excess N in the exported biomass needs to removed or treated (Beale and Long, 1997).

A gap between the potential and practical realization of adaptation exists adaptation strategies need to be both climate-informed and locally relevant to be viable. Place-based approaches study local and contemporary dynamics of the agricultural system, whereas climate impact modelling simulates climate-crop interactions across temporal and spatial scales. Crop modelling studies have projected a 7–15% mean yield change with adaptation compared to a non-adaptation baseline. Climate change adaptation and mitigation strategies and the impacts on the global food system and socio-economic development can be simulated over long-term predictions.

While this lo ng-standing approach may remain an essential three further key components:

- Working with stakeholders to identify the timing of risks. What are the key vulnerabilities of food systems and what does crop-climate modelling tell us about when those systems are at risk?
- Use of multiple methods that critically assess the use of climate model output and avoid any presumption that analyses should begin and end with gridded output.
- Increasing transparency and inter-comparability in risk assessments.

Adaptation can be understood as the process of adjusting to the current and future effects of climate change. Mitigation means making the impacts of climate change less severe by preventing or reducing the emission of greenhouse gases (GHG) into the atmosphere. The adaptation strategies include the application of organic fertilizers, changing of planting dates and growing of short duration crop varieties. The application of organic fertilizers increases crop yields by improving soil moisture content and supply of nutrients to crops (Below et al. 2020). The mitigation actions are planning and zoning, floodplain protection, property acquisition and relocation, or public outreach projects. Examples of preparedness actions are installing disaster warning systems, purchasing radio communications equipment, or conducting emergency response training.

6.3 Crop Modelling of Adaptive and Mitigating Potential of Climate Smart Practices

6.3.1 The Role of Crop Models in Assessing Risk and Adaptation:

Crop models have a long history, during which their focus and application have altered in response to societal needs. They have contributed to decision support and risk assessment and have resulted in conceptual and practical advances in publicly-funded agricultural development work. The last decade has seen an increase in the use of crop-climate ensembles targeted at informing adaptation. Food systems risks can be defined narrowly as the potential for reduced food production (e.g. Li et al., 2009), or broadly as the risk to food security.

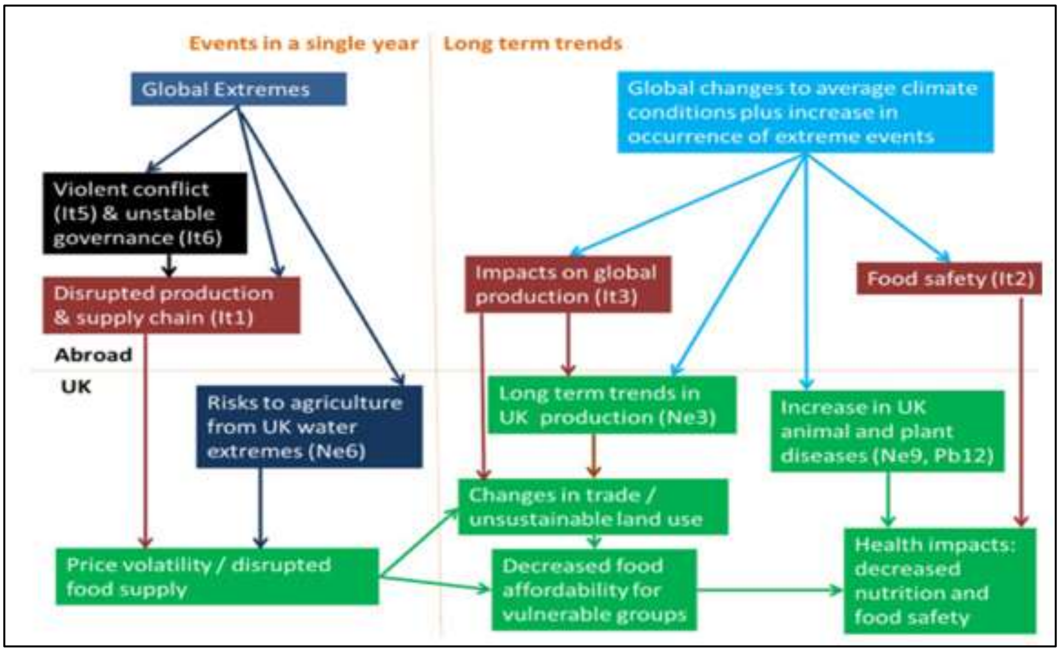

Figure 6.2: Improving The Use of Crop Models for Risk Assessment and Adaptation.

Even more broadly, food systems have many interactions with other systems, e.g. the energy system (Homer-Dixon et al., 2015). Crop models will have a greater or lesser role in the analysis, depending on the nature of the risks being assessed. Integrated assessment of risks from climate change is a relatively recent focus for crop modelling.

6.3.2 Towards Improved Framing of Risks Posed by Climate Change to Food Production Systems:

A. Risk, Uncertainty and Livelihood:

Risk and uncertainty are concepts that apply where the range of future possibilities is largely known (Stirling, 2010). The difference between them lies in whether or not probabilities can be calculated (Wynne, 1992). This distinction is often a matter of (expert) opinion rather than provable fact, so that the same crop-climate ensemble can be presented as an assessment of risk or as an assessment of impacts expressed using uncertainty ranges. True assessment of risk implies a knowledge of the consequences of an event, since risk is the product of two factors: the probability that an adverse event will occur and the consequences of that adverse event (Jones, 2001).

B. Frameworks for Interconnected Risks:

Interactions between sectors (e.g. agriculture, forestry, water) are important in determining climate change impacts (Harrison et al., 2016, Elliott et al., 2014, Piontek et al., 2014). The interactions that lead to climate change risks go beyond those amongst ecosystem-based sectors and into governance, society, health and economics, to name but a few areas. Key issues that emerged in that assessment are the fundamental interconnectedness of both climatic and non-climatic risks and the transmission of risks across international boundaries (e.g. transnational transmission of risks to crops from ozone Hollaway et al., 2011).

Thus, the relevance of crop modelling goes well beyond an understanding of food production, or even food security, and there is a concomitant breadth required in the systems boundaries used in crop modelling studies (Campbell et al., 2016, Waha et al., 2012), especially where broad system boundaries are used.

Integrated assessment models (IAMs) may be expected to deliver frameworks for interconnected risks; however, the use of crop models within IAMs is at a relatively early stage (Ewert et al., 2015). Further, IAMs may not be the best tool to assess the range of trade-offs and synergies that are important to food systems. The complexity of the inter-related set of climate change and food security risks and responses has led to them being labelled a "wicked problem" requiring a range of approaches (Vermeulen et al., 2013). Food security targets are not solely a matter of increasing yield, but also of improving food access, quality and diversity.

There may be direct yield trade-offs involved in actions and activities that contribute towards food security (Campbell et al., 2016). The integration of local knowledge and the input of social scientists within interdisciplinary modelling research can contribute to the identification and outlining of realistic scenarios of socio-technical change, crop-climate indices, or of model output priorities (i.e. not solely yield Herrero et al., 2015, Campbell et al., 2016).

The insights gained may inform the design of models and modelling studies that go beyond conventional projections of yield and yield response and are designed to analyse trade-offs (Wessolek and Asseng, 2006), determine least regrets options, or inform multi-criteria analyses (Hallegatte, 2009, Challinor et al., 2010).

C. Joint Adaptation and Mitigation Frameworks:

Much of the current focus on assessing the risks of climate change is focused on the stringent 1.5–2 °C limit on global warming agreed at the international climate negotiations in Paris in 2015 (COP21). In order to be consistent with a 2 °C target, emissions across all sectors need to decrease by over 80% by 2050 (Edenhofer et al., 2012), with even greater reductions required for a 1.5 °C target. The agriculture, forestry and other land use sector is responsible for 24% of all human greenhouse gas (GHG) emissions (Smith et al., 2014), so is a critical sector for delivering the Paris Agreement. More than even before, it is clear that agricultural systems require changes that address both adaptation and mitigation.

Both sustainable intensification and climate-smart agriculture (Lipper et al., 2014) seek to address the challenge of joint adaptation and mitigation challenge. Climate-smart agriculture targets the simultaneous achievement of increasing agricultural production, adapting to climatic change, and mitigating this change through reduced agriculture-related emissions. Understanding and addressing the trade-offs and synergies between these objectives is therefore a research priority for the climate-crop modelling community

(Campbell et al., 2016), which is particularly well placed to contribute given its capabilities to simulate regional and global scale change. How might the crop-climate modelling community develop joint adaptation and mitigation frameworks? One approach would be to calculate, or at least estimate, the emissions associated with modelled adaptation options.

Tian et al. (this issue) exemplify this approach by quantifying the non-CO2 greenhouse gas emissions associated with different paddy rice management strategies and examining yield emissions trade-offs. Composite measures, such as yield emission efficiency, might also be used to assess how climate-smart specific adaptation options are. A set of recent studies exemplify different existing frameworks for the joint assessment of adaptation, productivity and mitigation outcomes for different types of agricultural interventions, technologies and practices (e.g. Shirsath et al., 2017; Shikuku et al. 2017; Notenbaert et al., 2017).

D. Risk Frameworks Need to Incorporate Multiple Perspectives:

In addition to being a technically challenging issue, understanding risk and uncertainty requires cognisance of the multiple perspectives and interpretations that exist (Wesselink et al., 2014). The frameworks used to conceptualise uncertainty determine the potential for crop-climate modelling to distinguish risks. A range of interpretations on these related topics exists not just between different groups (scientists, politicians, public), but also within them. Even experts within the same project can disagree on the meaning and adequacy of reported uncertainty ranges, based on their assessment of whether or not all risks are known and whether or not the known risks are adequately quantified (Wesselink et al., 2014).

Systematic assessment might seem to be a way to ensure objectivity. However, herein lies the thorny issue at the heart of uncertainty analysis: attempts to be systematic, for example by quantifying parametric uncertainty by using ranges of values, can result in ranges that are not informative, and even unrealistic (Challinor et al., 2007). The range of all simulated events is an attempt to capture all possible events, yet the overlap is not only partial; models and model ensembles are collections of methodological choices and assumptions that may not explore the full range of possibilities (Whitfield, 2013). Equally, the range of model results may extend beyond the realms of possibility (Spiegel halter and Riesch, 2011).

Hence risk assessment with models should not be reduced to the process of equating multiple model outputs with a probability distribution.

6.3.3 Developing and Running Crop Models:

A. Good Practice in Crop Modelling Underpins Accurate Risk Quantification:

The results of using a risk framework will only be as good as the models and methods used within that framework. A model needs to be skilful if its assessment of risk is to be correct. We turn now to the technical challenges of running crop models. For a long time, it has been recognised that studies using crop models need to satisfy certain criteria in order to contribute to the literature in a valuable way (e.g. Sinclair and Seligman, 2000). A more recent review found significant issues with the way that crop models are described and used for assessing climate change impacts (White et al., 2011).

The supplementary information also presents the full list of our criteria for application of crop modelling to impacts, adaptation and risk assessment. The crop model used, and the processes simulated, should be of appropriate complexity given the evidence from available data and the spatial scale of the simulations. This helps to avoid over tuning during the calibration process, especially if a broad array of observed data is used (e.g. yield, LAI) across a broad range of observed values. Different models were developed to address different questions. High complexity is warranted where yield-determining processes are demonstrably complex. Field scale models are often used at spatial scales greater than those at which they were developed for, implying challenges to aggregation and parameterization. The model(s) used should be evaluated using historical observed data. A broad range of data (not just yields) over a broad range of environments should be sought and used in evaluating crop models, and error checking of the data is important. Attention to interannual variability is particularly important (see e.g. Hoffmann et al., this issue, and Müller et al. (2017)). The simulations carried out should be documented in sufficient detail to demonstrate the extent of good practice, and to ensure reproducibility of the work carried out.

B. Crop Model Improvement Supports Accurate Risk Quantification:

With improved measurements and availability of reference data, crop models are continually being improved by more faithfully representing the processes they simulate and by identifying new processes and interactions. As long as this process does not result in unwarranted complexity (Section 3.1), this often improves skill (Maiorano et al., 2017). Several researchers have made a case for seeking consensus amongst models and for the inclusion of N dynamics responses to elevated CO2 (Bannayan et al., 2005, Boote et al., 2013, Yin, 2013, Li et al., 2014). Few models (e.g. Reyenga et al., 1999, Børgesen and Olesen, 2011, Asseng et al., 2014) capture this response, yet it remains key for realistic simulation of source-sink relationships, yield quality (through protein content), sink-strength related photosynthetic acclimation to elevated CO2, fertilizer use, and greenhouse gas emissions from agricultural practices (Muller et al., 2014, Vanuytrecht et al., 2011).

Particularly sensitive and/or high frequency processes are another area needing improvement, since they can be especially difficult to simulate. Sensitivity studies from the AgMIP-wheat and AgMIP-rice pilot showed that uncertainty in simulated yield increased with increasing temperatures (Li et al., 2015, Asseng et al., 2013, Asseng et al., 2014). For both crops the large spread between models could be partly attributed to how phenology was simulated, i.e. the choice of cardinal temperatures, the choice of thermal time accumulation function and, for wheat, the inclusion of accelerated leaf senescence with high temperatures (Asseng et al., 2011). Similar results have been shown for potato (Fleisher et al., 2016) and for maize (Wang et al., 2015), even though this was not a general finding of the AgMIP-maize model intercomparison (Bassu et al., 2014). Furthermore, the increased uncertainty between models was due to how models dealt with an increased frequency of high-temperature events around and after anthesis and its simulated impact on crop growth.

A third area for crop model improvement is the potential need to account for microclimate, which requires simulations of canopy temperature. Recent studies have demonstrated the importance of microclimate when predicting heat sterility in rice (Julia and Dingkuhn, 2013). For wheat, canopy microclimate studies indicate that temperatures can be several degrees warmer or cooler depending on whether evaporative cooling is present (Kumar and Tripathi, 1991; Asseng et al., 2011).

However, recognition of importance does not necessarily transfer into increased model skill. A study comparing nine wheat models that use three different approaches to simulate canopy temperature found only minor improvements when simulated canopy temperature was used for heat stress effects and no improvements when canopy temperature was additionally used for various other processes (Webber et al., 2017).

6.3.4 Crop-Climate Resembles:

A. Forming A Crop-Climate Ensemble:

a. Model and Bias Correction Choices:

The first task in implementing a risk assessment framework is to choose crop and climate models to work with. Climate model ensembles are usually chosen by the impacts community based on availability and so are to a large extent ensemble of opportunity. Similarly, crop modelling groups may have in-house crop models that they favour, often for good reasons such as confidence in their sound use of the model. However, explicit justification of model choice is often missing: White et al. (2011) found that only 18% of 221 studies reviewed thoroughly justified their choice of crop model. Justification for use of a particular crop model in an ensemble can come entirely from a-priori reasoning – i.e. demonstration that the model is fit for purpose.

However, in the context of an ensemble a second criterion presents itself: to what extent will that model contribute to the correct capturing of the underlying distribution of probabilities.

b. Use of Ensemble Mean and Spread:

Ensemble mean or medians can serve as a best-estimate for the impact of climate change. Recent MIPs in crop modelling also find that the median compares better to reference data than most or even any individual model (Asseng et al., 2013, Fleischer et al., 2016, Martre et al., 2015, Bassu et al., 2014, Li et al., 2014). This result is in line with what the climate modelling community found in their model intercomparison work, which showed that the superior performance of model ensembles is a result not only of error compensation, but also greater consistency (Hagedorn et al., 2005) and robustness (Knutti and Sedlacek, 2013).

B. Skill-Based and Spread-Based Selection of Resemble Members:

Two categories of selection criteria for ensemble members can be identified: i. skill-based approaches, whereby appropriate model (s) are chosen for a targeted study, and ii: spread-based approaches, which focus on capturing the underlying distribution of possible futures using ensembles. McSweeney and Jones (2016) offer the fraction of the full range of future projections captured by a subset as a useful spread based climate model selection metric.

Skill-based approaches use model evaluation statistics, whilst spread-based approaches focus on the assessment and use of ensemble ranges. Purely skill-based approaches, on the other hand, may tend to underestimate the full range of future realisations. Although looking at cryosphere rather than agricultural climate impacts, Wiltshire (2014) offer an interesting combination of the skill and spread- based approaches by choosing models which are shown to best represent key features of the Indian Summer Monsoon and sample either end of the spread of precipitation projections. A more complex combination of the two approaches is commended in Lutz et al. (2016): model selection follows a three step protocol: first, splitting the envelope of projections into four portions based upon a combination of temperature and rainfall and selecting one model from each portion (for example one model from the cold and dry portion); second, sampling of extremes; and finally filtering the remaining models based on skill in representing the annual cycle of temperature and precipitation. Work across crop and climate modelling community can lead to improved treatments of uncertainty (Wesselink et al., 2014, EQUIP, 2014, Challinor et al., 2013). Despite the progress made with existing methods, new methods are needed for objectively determining the criteria for inclusion of models within a given multi-model study.

Wallach et al. (2016) provide a valuable discussion of model selection approaches and identify a broad range of lessons for crop modellers based on methods in ensemble climate modelling. Objective criteria for model selection and weighting of ensemble members are amongst the suggestions made in that paper for improving ensemble crop modelling.

C. Scale-Dependency of Model Choice and Ensemble Member Selection:

Choice of parameterisations (and by extension, models) that are appropriate for the spatial scale of a study is critical, since measured and modelled responses to the atmosphere can differ across scale (Challinor and Wheeler, 2008).

However, in more than half of studies, models are applied at scales other than those for which they were originally designed (Ramirez-Villegas et al., 2015) – specifically, field-scale models are used above field scale in roughly 50% of the cases. Hoffmann et al. (2015), Hoffmann et al. (2016) and Zhao et al. (2015) studied the effect of using aggregated, low-resolution climate or soil input in field-scale models applied at regional scales. The extent to which model output is biased by aggregation depends upon the crop model, environmental conditions and spatial variability of weather and soil (Hoffmann et al., 2016).

Skill-based crop model selection is likely to be particularly important and possibly much easier at smaller spatial scales, where the specifics of the agro ecological system being studied become increasingly important (Challinor et al., 2014a). Models often perform better in some regions than in others. This may be simply because of variation in the strength of relationships between yield and climate (see e.g. Watson et al., 2014, Watson and Challinor, 2013). However, model structure and complexity, and data and calibration issues, are also likely to play a role. The precise cause of variation in skill is difficult, if not impossible, to determine. At larger spatial scales, it is often more difficult to assess model skill, owing to scarce and uncertain reference data and aggregation issues (Porwollik et al., 2017, Müller et al., 2017). Here, spread-based crop model selection is likely to be more common.

6.3.5 Modelling Adaptation:

A. Limitations of Current Methods:

Risk assessments will not be accurate unless they account for the autonomous adaptation that occurs in changing climates. A significant portion of the crop modelling literature has focused on assessing adaptation options: out of 91 published studies on climate change impacts used for the IPCC AR5 (Challinor et al., 2014b, Porter et al., 2014) about a third (33) also quantified adaptation.

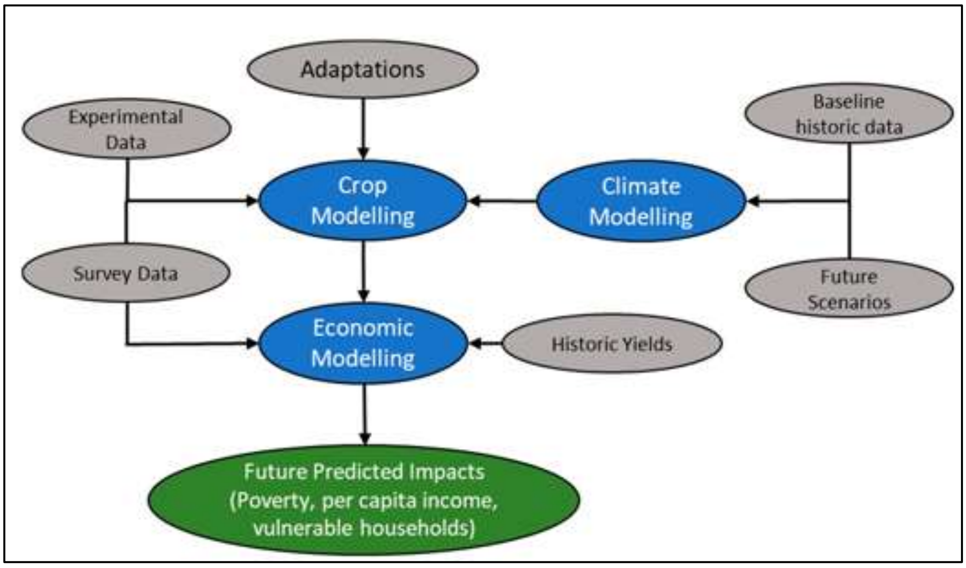

Figure 6.3: Modelling Adaptation

However, only four adaptation strategies were used in those studies, namely, changes in planting date, irrigation, crop cultivar and fertilizer. Adaptation studies therefore fail to represent the broad scope that adaptation has in the real world. Notably, little attention has been paid to changes in farm composition, including crop diversification and intercropping, which are typical of smallholding systems across the tropics (Claessens et al., 2012), as well as to long-term transformations (Rippke et al., 2016, Weindl et al., 2015). Modelled adaptations also ignore interactions within the system, e.g. changes in soil organic matter contents in mixed crop-livestock systems (Thornton and Herrero, 2015). Modelling studies also fail to represent farmers as agents who are continuously making decisions about the objectives or management of the system in the context of interacting biophysical and socio-economic drivers (Quinn et al., 2011, Below et al., 2012). As a result, framing of adaptation has skewed evidence towards a few practices and systems that can be simulated with confidence, rather than covering what is relevant in specific socioeconomic or environmental contexts. Even if the full range of adaptation options could be modelled, significant problems in quantifying adaptation benefits remain. It has been hypothesised that relative yield changes provide essentially unbiased estimates of future climate impacts that can then be applied to any technological pathway (Nelson et al., 2014, Valin et al., 2014, Springmann et al., 2016).

However, any changes to agronomic management that neglect the evolution of a system under a given socioeconomic pathway are unlikely to reflect the true response of the system, since they will neglect the interactions between adaptation and technological change. Similarly, crop production systems that will evolve due to technological progress and altered resource access will likely respond differently to climate change than the current systems that are typically represented in the models (Glotter and Elliott 2016). Improvement is therefore needed in the way adaptation is calculated and in the assumptions on future technologies, e.g. by employing scenarios. Modelling studies tend to compare a future with adaptation against a historical baseline, instead of comparing a climate change development pathway with its corresponding non-climate change counterfactual (Lobell, 2014). This leads to a systematic under-estimation of future crop yields.

Thus, crop modelling studies typically, but not always (e.g. Ewert et al., 2005), fail to account for the technological development (often agricultural intensification) that occurs regardless of adaptation (Liu et al., 2013, Garnett et al., 2013, Tittonell and Giller, 2013). A second point for improvement regarding how adaptation benefits are quantified relates to the comparative advantage of an adaptation option under a future climate with respect to the implementation of the same option under the current climate conditions.

Figure Diagram showing how crop-climate modelling studies should calculate both impacts and adaptation. A1 and A2 represent a farming system under current climate with and without adaptation (respectively), whereas B1, B2, and B3 represent the farming system of A1 but under future climate with neither adaptation nor technological progress accounted for (B1), only technological progress accounted for (B2), and with both adaptation and technological progress accounted for (B3). Based on Lobell (2014).

B. Recommendations for Simulating Adaptation:

Current good practice in adaptation studies involves inclusion of autonomous adaptation, since this avoids over-estimation of impacts. Less common, but equally important, is comparison of the effect of any future adaptations to their historical counterparts. As outlined above, adaptation tends to be over-estimated when comparing a non-adapted historical period with an adapted future period. Future directions for modelling adaptation include:

- New methods are needed in order to permit a broader range of adaptations options to be assessed. Model limitations currently preclude a comprehensive assessment of adaptation, skewing evidence towards a few practices that can be simulated with confidence, rather than covering what is really relevant in specific socio-economic or environmental contexts. Generally, the absence of explicitly representing management as a response to variable conditions (e.g. Hutchings et al. 2012, Waha et al., 2012, van Bussel et al. 2015) in future projections make simulations of adaptation difficlt. In addition, Beveridge et al. (submitted) present some promising ways of making crop modelling adaptation studies both more locally relevant and climate-informed.
- New methods are also needed to compute adaptation benefits, since crop modelling studies typically do not usually account for technological development (but see Glotter and Elliott, 2016), thereby underestimating the effectiveness of adaptation.

- Improved simulation of adaptation through better representation of processes. Ongoing crop model improvement is important. Many areas need attention, for example sensitivity of climate impacts to nitrogen treatments and inclusion of the response of nitrogen dynamics to elevated CO2 (Vanuytrecht and Thorburn, 2017). More generally, research needs to address the lack of consensus on the nature and magnitude of essential processes to be captured in crop models and assess the variation in essential processes with environmental conditions (Fronzek et al., this issue, provide a good example).

6.3.6 Towards Targeted Use of Models:

Ongoing work to improve crop models their use in ensembles is clearly important. However, we argue that innovative approaches to impact and risk assessments will also be needed to address the challenges faced by crop-climate modelling. The Paris Agreement has brought into sharp focus the need to address adaptation and mitigation jointly.

It has reignited scientific interest in sub-two-degree global mean temperature targets and prompted a need for risk assessments that can differentiate between 1.5 and 2.0 degrees of global warming. Detecting systematic differences in crop yields at 1.5 vs 2.0 degrees of warming is currently difficult because the range of model results stemming from methodological choices and spatial variability is large (Schleussner et al., 2016; and Fig. 3 below).

However, this approach is of little use unless the various perspectives can be addressed satisfactorily within a single framework or methodology in order to robustly address a key question and/or decision. We now present three areas of progress and potential in this kind of targeted use of models.

A. Working with Stakeholders to Identify the Timing of Risks:

The current decade has seen an increasing focus in climate science on identifying the timing of changes in climate (Joshi et al., 2011). This contrasts with the more traditional framing that asks “what will happen at a given time in the future?” Given the large uncertainties that exist, the result of these traditional assessments can often lack utility (Challinor et al., 2007).

The more recent focus on timing of risks means that uncertainty is expressed using time intervals, rather than ranges of temperature or crop yield. As a result, these new methods can answer the question “for a given important change in climate, or subsequent impact, when are changes likely to be seen?” By comparing the pace of climate change with the pace of autonomous adaptation, these new methods are generating information on the timing of risks to food production systems (Vermeulen et al., 2013, Rippke et al., 2016).

With the shift in methods towards timing, the focus of adaptation studies can now be ‘by when do key adaptations need to be in place?’ This approach helps in moving from analysis to action (Campbell et al., 2016). In some cases, the indications are that food systems are not keeping pace with climate change, as is the case for maize breeding systems in Africa, where the warming that occurs between breeding and final seed usage will result in an unintentionally shorter crop duration (Challinor et al., 2016).

Others indicate that more long-term transformations of agricultural systems are needed as land becomes unsuitable for current crops (Rippke et al., 2016). These are exactly the kind of issues that risk assessments need to address. With the focus on timing of adaptation comes increasing stakeholder relevance. Furthermore, stakeholders are often needed for robust research results, particularly where understanding of decision-making processes and priorities is required (Lorenz et al., 2015). The MACSUR project has identified agreements on goals with a wide range of stakeholders as a main challenge for European risk assessment (Köchy et al., 2017).

Participatory stakeholder approaches to modelling have taken a variety of innovative forms (Whitfield and Reed, 2012). Vandewindekens et al. (this issue) describe a method of stakeholder input informing a semi-quantitative modelling approach.

These participatory approaches have been shown to bring about benefits of improved contextual calibration and decision-making relevance as well as subsequent trust in, and action on, the emergent evidence bases produced by the research (Chaudhury et al., 2013, Reed, 2008, Prell et al., 2013). In summary, engagement with stakeholders is critical if the research is to have a practical risk management or adaptation outcome.

B. Thinking Outside the Grid Box:

Long-standing approaches to crop-climate modelling ask "what is the change in yield due to climate change in this location and how might cropping systems adapt?" We argue here that it is important to ask different and more useful questions of our modelling studies, using a wide range of methods and information sources. This includes recognising the potential value of interpreting climate model data both with and without using a crop model. Downscaling is often cited as a method for making crop-climate model output more relevant to stakeholders. However, climate model outputs are not primarily maps, since they do not contain geographic features in the way in which we are accustomed to reading them. Rather, they are information with applicability at spatial scales that depend upon the climate itself, which are usually greater than the domain of that grid cell (Hewitson and Crane, 1996).

Crop modelling studies either use the grid on which the input climate simulations were generated, or they downscale those data to a more relevant spatial scale. A range of downscaling methods exist, each with its pros and cons (Wilby and Wigley, 1997). Downscaling is often combined with bias correction, whereby the output of climate models is corrected towards observations.

Use of native (i.e. non-downscaled) or downscaled climate model grids is a reasonable way of determining impacts and conducting risk analysis. However, it may not be the best way in some situations. As climate models increase their resolution we might expect increases in skill (Challinor et al., 2009), but even this is not a simple or guaranteed process (Garcia-Carreras et al., 2015). Additionally, impact models have their own spatial scale issues that make comprehensive global assessments difficult, and regional-scale information important (Challinor et al., 2014). Whilst downscaling techniques are regularly applied when field-scale models are used (Vanuytrecht et al., 2016, Vanuytrecht et al., 2014), they nonetheless potentially add bias and are a source of uncertainty.

"Thinking outside the grid box" is a broad term that tries to capture the need to critically assess the use of climate model output and avoid the presumption that analyses should begin and end with gridded output. This is not a matter of further processing or aggregating grid box data, but rather of recognising the inherent limitations of it and extracting the maximum information content from the data.

Approaches used include non-spatial representations of impacts, as is common in many studies (e.g. quantification of incidence of crop failure rates, Parkes et al., 2015); analysis of collected gridcell data (e.g. Challinor et al., 2010), as opposed to being overly explicit geographically; and use of crop-climate indices (Trnka et al., 2011). In particular, the term conveys targeted analyses that employ a range of linked methods and have relatively broad systems boundaries. Challinor et al. (2016) present an example of this approach, by using data on the breeding and dissemination of new crop varieties; crop-climate indices, with uncertainty analysis to identify the time at which a climate change signal emerges from current observed variability; and 'traditional' crop modelling. These methods were used to target crop breeding applications by calculating the spatial and temporal scale of robust crop-climate signals.

C. Increasing Transparency and Inter-Comparability in Risk Assessments:

The various choices (calibrating, running and evaluating models; designing ensembles) faced by a crop modeller when contributing to a risk assessment always result in some limitations. Different choices have different limitations. The purpose of a framework is not only to minimise the limitations, but also to highlight the limitations. However, frameworks are often implicit and justification of modelling choices is often missing from crop-climate studies (White et al., 2011), which makes it difficult to compare different studies directly.

The identification of consensus views can be supported by clear critical evaluation of methodologies and model projections. Ruiz-Ramos et al. use an ex post plausibility check in ensemble wheat modelling, which usefully goes some way towards increasing robustness. However, comparability across risk assessment is only possible when some common methods or protocols are used (see e.g. Liu et al., 2016). Systematic assessments of the response of models to carbon dioxide, temperature, water and nitrogen have been suggested as a way to clearly understand and document model performance (Ruane et al., 2014, Rosenzweig et al., 2013b). The response of the model to changes in key input variables should match what is seen in observations, and a systematic comparison method would aid this assessment.

6.4 Conclusion:

Crop modelling in agriculture has the potential to provide valuable insights and solutions for agricultural professionals. With improved Agronomic data collection, predictive modelling using multiple datasets will allow researchers and farmers to better understand the parameters and management practices that are most influential on crop growth. Being able to explore potential outcomes over time, given changes in climate or other inputs, opens up a whole new perspective as we work to improve efficiency and reduce environmental footprints.

The challenge of producing locally relevant and climate-informed adaptation strategies for agriculture is complex. Adaptive decisions transcend spatial and temporal scales and interact with social, economic and environmental systems. Cross-disciplinary approaches can build our capacity to identify and understand critical factors that drive and limit agricultural adaptation at the local scale. They can also be used to assess the potential impact of an identified adaptive strategy across spatial and temporal scales, including under future climate change scenarios, which is of particular relevance to policy decisions. There are practical steps needed for successful iterative working between crop-climate modelling and place-based communities. Crop-climate modelling research needs to better address adaptation in climate change studies.

A collective action towards building consistent and accessible datasets on management and adaptation is also a pre-requisite to incorporating more adaptation processes into crop-climate modelling studies. Building trust between researcher and stakeholder will be essential for successful iterative research and assessment of locally relevant adaptation. Participatory and iterative modelling, as commonly used in place-based approaches, is a potential tool to do this, by aiding communication, developing a shared understanding and set of definitions between researchers from different backgrounds and stakeholders and improving impact and uptake of adaptation science.

6.5 References:

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