Paper:
Challinor, AJ, Simelton, ES, Fraser, EDG, Hemming, D and Collins, M (2010) *Increased crop failure due to climate change: assessing adaptation options using models and socio-economic data for wheat in China.* Environmental Research Letters, 5 (3). 034012.

http://dx.doi.org/10.1088/1748-9326/5/3/034012

Environ. Res. Lett. **5** (2010) 034012 (8pp) doi:10.1088/1748-9326/5/3/034012

Increased crop failure due to climate change: assessing adaptation options using models and socio-economic data for wheat in China

Andrew J Challinor[1], **Elisabeth S Simelton**[2], **Evan D G Fraser**[2], **Debbie Hemming**[3] **and Mathew Collins**[3,4]

[1] Institute for Climate and Atmospheric Science, School of Earth and Environment, University of Leeds, Leeds LS2 9JT, UK
[2] Sustainability Research Institute, School of Earth and Environment, University of Leeds, Leeds LS2 9JT, UK
[3] Met Office Hadley Centre, FitzRoy Road, Exeter EX1 3PB, UK
[4] College of Engineering, Mathematics and Physical Sciences, University of Exeter, Exeter EX4 4QF, UK

E-mail: a.j.challinor@leeds.ac.uk

Received 12 July 2010
Accepted for publication 7 September 2010
Published 29 September 2010
Online at stacks.iop.org/ERL/5/034012

Abstract
Tools for projecting crop productivity under a range of conditions, and assessing adaptation options, are an important part of the endeavour to prioritize investment in adaptation. We present ensemble projections of crop productivity that account for biophysical processes, inherent uncertainty and adaptation, using spring wheat in Northeast China as a case study. A parallel 'vulnerability index' approach uses quantitative socio-economic data to account for autonomous farmer adaptation.

The simulations show crop failure rates increasing under climate change, due to increasing extremes of both heat and water stress. Crop failure rates increase with mean temperature, with increases in maximum failure rates being greater than those in median failure rates. The results suggest that significant adaptation is possible through either socio-economic measures such as greater investment, or biophysical measures such as drought or heat tolerance in crops. The results also show that adaptation becomes increasingly necessitated as mean temperature and the associated number of extremes rise. The results, and the limitations of this study, also suggest directions for research for linking climate and crop models, socio-economic analyses and crop variety trial data in order to prioritize options such as capacity building, plant breeding and biotechnology.

Keywords: climate change, crop yield, adaptation

S Online supplementary data available from stacks.iop.org/ERL/5/034012/mmedia

1. Introduction

The world faces an enormous challenge over the coming decades, as a combination of environmental change and a growing population make food security harder to achieve. A number of studies have examined aspects of this multi-facetted issue, demonstrating that there is no panacea, since inherent trade-offs exist in maintaining food security [1, 2]. However, it has proven difficult to include this qualitative increase in understanding within quantitative models of future crop production [3]. Part of such an effort involves the development of tools to project crop productivity under a range of different climate, technological and socio-economic conditions. We focus here one aspect of this issue: the constraints and opportunities associated with climate change. As mean temperature increases, the magnitude of impacts on ecosystems tends to increase [4]. Furthermore, there may be threshold values of carbon dioxide, or of mean temperature, beyond which ecosystem services undergo a step change in productivity [5, 6]. Opportunities associated with climate change include productivity gains through the expansion of land suitable for crops as climate changes.

Progress in understanding the biophysical impact of climate change on crops has been significant and has included an understanding of the importance of changes in both the mean and extremes of climate [7]. Changes in mean temperatures can shorten the time to maturity of a crop, thus reducing yield. Experimental studies have also shown that even a few days of temperature above a threshold value, if coincident with anthesis, can significantly reduce yield, through affecting subsequent reproductive processes [8]. Irrespective of whether agricultural technology is able to increase yields over the coming decades, drought and heat stress are likely to be increasingly important in determining crop productivity in many regions [4]. This issue is currently being addressed through investment in the development of drought and heat-tolerant crops, and also through examining how to empower and encourage farmer adaptation to climate change at a range of spatial scales [9]. Methods have also been developed to explore and quantify exposure to socio-economic and climatic stresses across a range of sectors at a range of scales, from household through to national [10, 11]. The complexity of these stresses, and of the interactions between them, means that projecting the likely influence of climate change on food systems requires careful selection of the aspects studied; selecting too narrow a part of the system is likely to lead incorrect conclusions. Thus explicit and careful account of uncertainty, such as is now common in climate modelling through the use of ensembles [12], is critical to projecting changes in food productivity. Ensemble and perturbed parameter approaches are becoming an increasingly common method of projecting future yields, assessing the relative contributions of crop and climate uncertainty [13], optimize parameters [14] and support the development of probabilistic assessments [15].

The projection of future impacts of climate is particularly difficult in the case of extreme weather and climate events. Integrating our quantitative understanding of the future likelihood of extremes with efforts to understand how farmers may adapt requires weather and climate data at high temporal resolution and process-based crop models that can quantify the importance of high-frequency variability, as well as grounded socio-economic insights into farm management options. Thus studies tend to be either focused relatively narrowly, using process-based models to determine the response of crops to weather and climate (see e.g. [7]), or else they do not consider biophysical processes at all. For example, empirically based studies (e.g. [16]) tend to analyse the impacts of climate on mean yields at large scales, and implicitly include autonomous adaptation, but do not analyse extreme climate events; though there are notable exceptions [17].

Process-based modelling can be used to analyse extremes of weather and climate using known causal mechanisms. Integrated assessments (e.g. [18]) tend to focus less on fundamental processes, but have the advantage of combining biophysical and broader socio-economic drivers of change, such world trade or access to land or labour. Accounting for both the biophysical and socio-economic implications of climate change within a single process-based model has proven difficult. A first step in this direction is the development of methods to explore the socio-economic reasons why crop losses can be high during relatively minor meteorological droughts, whilst in other cases, crop losses can be minimal during relatively large meteorological droughts [19]. Through this work, and subsequent modelling [20], a framework is emerging whereby socio-economic factors can be included in crop-climate models, thus permitting an estimate of how current and future socio-economic conditions may affect adaptation [7].

Projecting future crop productivity requires that three elements are captured: first, the fundamental biophysical processes that determine productivity; second, the uncertainty associated with those processes; and third, the influence of adaptation. This study aims to quantify these influences using two parallel and linked approaches: process-based crop modelling and an analysis of adaptive capacity in the region based on the calculation of an index that quantifies the vulnerability of crop yields to drought. Subject to data and simulation constraints, the methodology is applicable to any crop in any region of the globe. We choose spring wheat in northeast China, a critical grain producing region where climate change has the potential to increase vulnerability if farmers are unable to adapt under the rapidly changing socio-economic conditions.

2. Materials and methods

2.1. Crop and climate simulation

Crop yield data and socio-economic data were obtained from the Chinese Natural Resources Database, Institute of Geographical Sciences and Natural Resources Research, Chinese Academy of Sciences (www.naturalresources.csdb.cn/index.asp). Climate model output was taken from the coupled atmosphere–ocean simulations of the Hadley centre quantifying uncertainty in model prediction (QUMP) project in which climate-modelling uncertainties are sampled by varying uncertain model parameters [21]. The data used were taken from the unperturbed baseline climate (1950–1989) and the seventeen-member projection ensemble forced by the SRES A1B emissions scenario for 1990–2099. We used daily solar radiation, rainfall and maximum and minimum temperature output from the model. The study region comprises 18 climate model grid cells across four provinces (presented in figure 1). The baseline simulation period was the maximum possible given the data—i.e. the period for which both historical climate

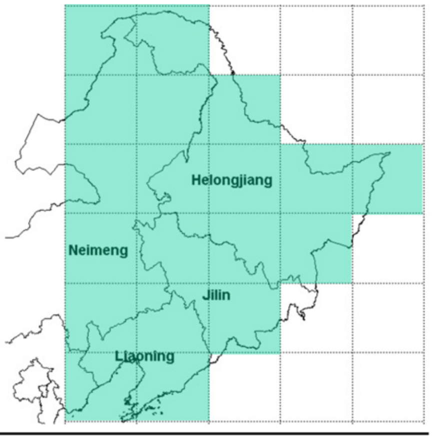

Figure 1. The study region, showing the four provinces and the model grid with simulation cells shaded.

simulation and observed crop yield data exist, namely 1980–1989. The projection period was the full 1990–2099 period simulated by the perturbed parameter ensemble (PPE) study. More details of the climate ensemble are provided in the supplementary data, section S1 (available at stacks.iop.org/ERL/5/034012/mmedia).

Crop yields were simulated using the general large area model for annual crops (GLAM; [22]). This model, which is freely available for non-commercial use via a licence agreement[5], has been used to simulate the mean and variability of yields in current and future climates across the tropics [22–31]. The model was calibrated and run according to standard parameter perturbation procedures that account for uncertainty in the simulation of both baseline and projected yields. As with the vast majority of crop modelling studies, the model does not attempt to simulate trends in yield due to changes in technology; rather it quantifies the impact of climate variability and of the trend due to rising CO_2 concentrations. In order to account for the uncertainty due to the technology trend, the model was calibrated and run using values of mean yield for the four year periods at the beginning and end of the baseline period. The baseline simulations also accounted for uncertainty in the planting date, by using two plausible values of the first day of the planting window, resulting in four baseline simulations. The projection simulations, in addition to these four parameter perturbations, quantified uncertainty due to the magnitude of the CO_2 fertilization effect, by co-varying the parameters responsible for transpiration efficiency and water use, resulting in eight parameter sets. These eight parameter sets were used with all 17 of the realizations of future climate, resulting in 136 projections. Each of these projections was carried out for four adaptation cases: none, temperature, water, and temperature plus water. Temperature adaptation refers here to complete tolerance to threshold temperature exceedance during anthesis—a process discussed briefly in section 1. Water adaptation removes any limitations on growth due to water stress. Thus the three adaptation simulations represent an upper limit on the extent of biophysical adaptation possible. Progress towards this limit may be achieved through using or developing appropriate stress-tolerant varieties or, in the case of water, through ample irrigation. More details of crop model, its calibration and the simulations performed are presented in the supplementary data, section S2 (available at stacks.iop.org/ERL/5/034012/mmedia).

[5] See www.see.leeds.ac.uk/research/icas/climate_change/glam/glam.html.

2.2. Vulnerability index

The crop modelling described above accounts only for the biophysical processes determining yield. A parallel approach was used to assess the vulnerability of crop yield to drought indicated by socio-economic metrics. This method uses modelling based on the province-scale socio-economic data to account for cases when crop losses were high during relatively minor meteorological droughts versus cases when crop losses were minimal during relatively large meteorological droughts. Mechanisms leading to this observation include, for example, the use of farm labour to minimize the impact of poor irrigation systems [32]. Following [20], a vulnerability index (VI) was defined as the ratio of a crop failure index to a drought index. The crop failure index is the detrended yield for that year, which represents an 'expected harvest' based on a long-term trend, divided by the actual harvest for the year (H). The drought index is the mean growing season rainfall, averaged over the full time period, divided by the actual rainfall in a season. This is equivalent to an anomaly approach, with high indices indicating below-average values. Thus a high vulnerability index identifies years and/or regions where the yield loss was large relative to the size of the drought. A low value of VI indicates that the efficacy of the socio-economic adaptation to drought is high, for example due to good water management, increasing fertilizer, per capita investments in agriculture, and falling numbers of rural households (see section 3.1). The analyses used here differs in only three ways from that of [20]: (i) March to August rainfall was used instead of annual, since this matches the core crop cultivation period; (ii) yield was used, instead of production, in order to enable combination with crop model results; (iii) the time period used was 1980–2001, so that the analysis is representative of the baseline period. The period chosen for the VI analysis extends beyond the baseline period, in order to gain a greater sample of values. The sensitivity of VI to this choice is not large, except for when an earlier starting year—1968—is chosen, and the maximum VI rises from 1.51 to 2.06. However, this results in very little difference in projected crop failures from the GLAM no-adaptation simulations, since any at value of VI above 1.51 is associated with sufficiently high vulnerability that no significant adaptation takes place.

The above analysis resulted in a time series of historical vulnerability index (VI) for each of the four provinces. These time series were reduced to three scenarios of VI (low, medium and high), each consisting of a single value for the entire spatio-temporal domain. These values were the minimum, mean and maximum values of historical VI across the four provinces and across the full time series (0.54, 0.97, and 1.51, respectively). It is unlikely that any of these values is a truly

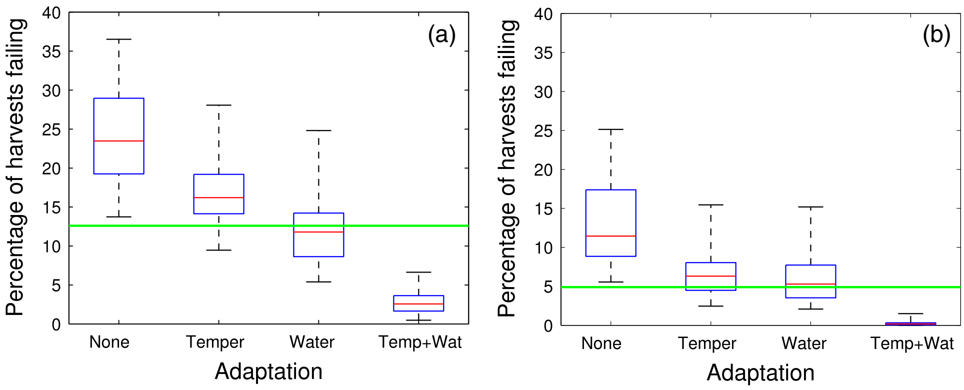

Figure 2. The percentage of harvests failing under no adaptation ('none') and the three biophysical adaptation options for crop failure, which is defined as yields less than (a) one and (b) two standard deviations below the corresponding baseline mean. Each box and whiskers shows the median, inter-quartile range and maximum and minimum values, calculated from the 136 projected 110-year time series of crop yield. The horizontal line shows the baseline failure rate, which is the average of the failure rates in the four baseline simulations.

representative time series of VI, since VI is itself a function of yield and fluctuates from year to year. However, constructing a time series of VI with the proper covariances is likely taking the analysis beyond its domain of applicability, since it would be overly prescriptive and insufficiently explanatory.

The crop modelling and VI analyses were combined by applying these scenarios of VI to drought-induced crop failure events identified by the crop model (i.e. those years where the none and water simulations described above resulted in crop failure and no crop failure, respectively). For each grid cell and each ensemble member, model crop failures were identified as those years when simulated yields were less than either one or two standard deviations (of the baseline simulation time series with the corresponding planting window and calibration parameter) below the projected time series mean. For each of these identified failures, a 'socio-economic' yield anomaly was calculated, by using the PPE rainfall anomaly and the vulnerability index. This yield anomaly was used to determine the number of 'socio-economic' crop failures, defined using the same yield threshold as for the model crop failures. By quantifying the number of model crop failures that are deemed avoidable for a given value of VI, this method resulted in an assessment of the potential for socio-economic adaptation to water stress.

The methods used have the advantage of quantitatively integrating biophysical and socio-economic approaches to the prediction of crop failure. Weaknesses include the uncertainties outside of the four quantified (i.e. climate, planting date, response to CO_2 and crop model calibration) and the omission of non-climatic drivers in the crop model. Thus field-based modelling studies and inter-comparisons would complement the modelling results presented here (see [7]). In addition, the crop model takes no account of flood damage. We note also that the uncertainties analysed have only been partly quantified—the uncertainty in climate, for example, is for one climate model under an A1B scenario only. No attempt has been made to project changes in farming practice out to the end of the century. Nonetheless, the VI analysis does provide a tentative indication of the influence of farming methods on the incidence of crop failure. Also, the fundamental processes simulated by the crop model (extremes of water and heat stress in particular) are likely to continue to be key drivers of crop yield despite spatial and temporal variation in the crop cultivation methods used; particularly since ongoing increases in extreme events are expected under climate change [33]. We also note that the vulnerability index analysis is predicated on the relationship between yield anomaly and VI—and hence implicitly seasonal total rainfall—being due to short-term farmer adaptation. In reality, errors in observed yield and rainfall, as well as other processes such as the impact of sub-seasonal rainfall variability, weaken this relationship.

3. Results and discussion

3.1. Options for adaptation

3.1.1. Biophysical adaptation. The performance of the crop model was assessed before proceeding with the projections to the end of the century (supplementary data section S3 available at stacks.iop.org/ERL/5/034012/mmedia). Figure 2 shows the percentage of harvests failing across the full scenario period and across all seventeen model grid cells. Without adaptation, the percentage of harvests failing is in all cases higher than the baseline value, confirming the importance of heat and water stress quantified elsewhere (e.g. [33]). Comparing the biophysical adaptation scenarios across figures 2(a) and (b) shows that water stress plays a more important role than temperature stress for yields between one and two standard deviations below the baseline mean. For crop failures defined as two standard deviations below the mean, adaptation to water and temperature stress each have similar potential to maintain crop failure at approximately the baseline rate. Temperature and water adaptation together reduce crop failure to below the baseline value. Whilst the analysis presented here stops short of identifying specific varieties for drought and/or heat tolerance, methods do exist to more closely link modelling work with field studies in order to assess the potential for adaptation contained within existing germplasm (e.g. [28, 34]).

The above analysis examines the potential for adaptation across the whole projected time series, with no assessment

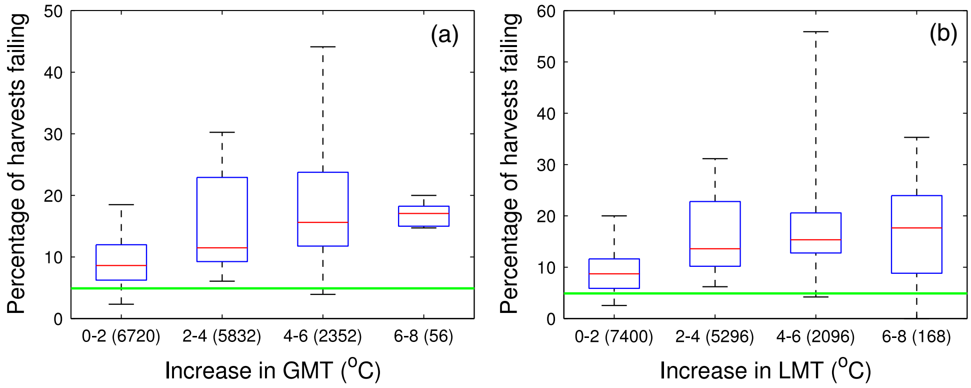

Figure 3. The percentage of harvests failing under no adaptation as a function of increase in (a) global mean temperature (GMT) and (b) local mean temperature (LMT), for the full 136-member ensemble of crop yield. The numbers in brackets indicate the number of data points (note that the 6°–8° bin has a low population compared to the other three bins). GMT increase is defined using Jan–Dec data referenced to the average GMT over the full baseline period. LMT increase is defined using the crop growth cycle period and is referenced to the average LMT over the full baseline period. Crop failure is defined as yields less than two standard deviations below the corresponding baseline mean. Each box and whiskers shows the median, inter-quartile range and maximum and minimum values. The horizontal line shows the baseline failure rate, which is the average of the failure rates in the four baseline simulations.

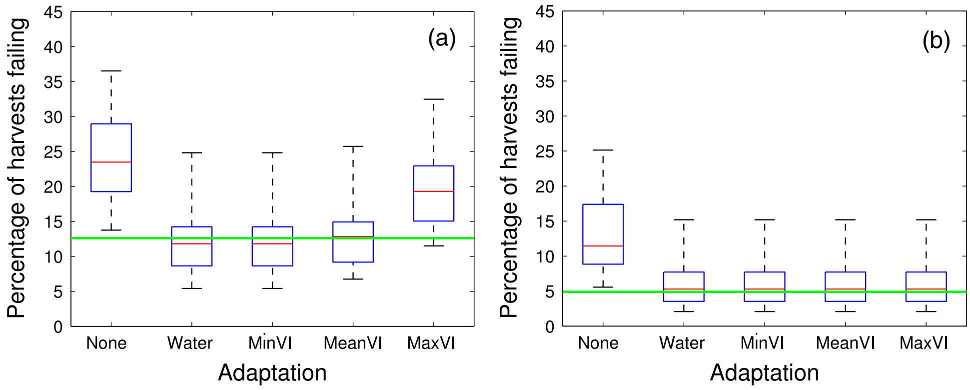

Figure 4. The percentage of harvests failing under no adaptation ('none'), with full adaptation to water stress ('water') and for three scenarios of vulnerability index (min, mean and max—0.54, 0.97 and 1.51) for crop failure defined as yields less than (a) one and (b) two standard deviations below the corresponding baseline mean. Each box and whiskers shows the median, inter-quartile range and maximum and minimum values, calculated from the 136 projected 110-year time series of crop yield. The horizontal line shows the baseline failure rate, which is the average of the failure rates in the four baseline simulations.

of the manner in which this may change over time as the magnitude of climate change increases. In studies of the impacts of climate change, and in key syntheses such as that of the Intergovernmental Panel on Climate Change [35], mean temperature can provide a convenient metric for the magnitude of climate change, since it measures one of the causal factors contributing to crop yield change. Figure 3 presents the projected yields subsampled according to both global and local mean temperature increase. In both of these cases, crop failure becomes increasingly likely as mean temperatures rise. Both the median and maximum crop failure rates increase with temperature, with increases in the maximum failure rate being greatest. This increase is due to heat stress during anthesis, as can be seen by comparing figure 3 with supplementary figure S1 (available at stacks.iop.org/ERL/5/034012/mmedia). Thus, adaptation to heat stress becomes increasingly important as mean temperature, and the associated number of extremes, rise. Whilst there is no full consensus in the literature on the response of crops to local mean temperature [13], this result is consistent with the results of controlled environment and field-scale studies [8, 36], as well as analyses of larger-scale yields [17].

3.1.2. Socio-economic adaptation. The performance of the VI analysis was assessed before proceeding with the generation of scenarios from the vulnerability index model (supplementary data section S3 available at stacks.iop.org/ERL/5/034012/mmedia). The three scenarios from the VI model are compared to the crop model results in figure 4. For crop failures defined as one standard deviation below the baseline mean, it is clear that some socio-economic adaptation is possible, but that there is insufficient precision in the value of VI to determine the extent—all that can be said is that the degree of adaptation lies between very near the maximum and near the minimum adaptation possible, as indicated by the crop model. For two standard deviation crop failures, however, there is strong potential for adaptation to extremes of water stress, with very nearly all the biophysical potential identified by the crop model simulations being realized in all three of the VI scenarios. Since the time series of historical

VI showed no temporal trends (supplementary data section S3 available at stacks.iop.org/ERL/5/034012/mmedia), it is clear that significant adaptation to future climates may be possible with current socio-economic conditions.

The values of vulnerability index in this study are based on the recent past (1980–2001). They therefore represent a likely lower limit on socio-economic adaptation, since the vulnerability of crop yields to drought may be expected to decrease due to agricultural modernization [19]. Previous studies in northeast China have shown that the vulnerability of wheat yields to drought is correlated with data representing access to capital and land: increasing fertilizer, per capita investments in agriculture, and falling numbers of rural households are all associated with reduced vulnerability [20, 37]. GDP, and the share of GDP generated by agriculture, are both important proxy variables for these changes [38]. For the current study, no significant correlations were found between vulnerability index and GDP. This may in part be due to a short time period, a lack of discrimination in the data between winter and spring wheat, a lag between investment and the impact of investment on vulnerability. Hence whilst, GDP may continue to be one quantitative proxy for adaptive capacity and vulnerability, specific macro- and micro-level political and socio-economic contexts are important in assessing future vulnerability (see [37, 39, 40]). For example, countries in economic and political transition might be expected to be highly vulnerable to drought, since traditional drought coping strategies may be in declines, whilst more modern strategies may not yet be in place.

3.1.3. Prioritizing adaptation efforts. The importance of socio-economic context in assessing future vulnerability of crop yields to drought suggests that there is a need to focus on targeted measures to increase the resilience of cropping systems, rather than rely on autonomous adaptation. These measures may include institutional policies to support adaptation; schemes to ensure that the requisite crop varieties are available to farmers; crop insurance schemes or weather derivatives to aid management of climate variability; plant breeding; and building capacity for agricultural extension services to effectively prepare farmers for extreme events [41, 42]. Simulation results, such as those presented here, can form part of the body of evidence used to prioritize these methods. For example, arguments can be made for a focus on addressing either water scarcity (e.g. [43, 33]) or temperature stress (e.g. [40]). The analysis above (figure 2) suggests that where high stability in yield is required (i.e. crop failure threshold one standard deviation from the mean), reducing water stress may more beneficial than reducing temperature stress. However, in addition to the potential benefits, the costs of—and fundamental physiological limits to—achieving reductions in abiotic stresses must be considered.

Through focusing on crop failure, this study has highlighted the importance of future climate variability, on seasonal to sub-seasonal timescales, in determining crop yield. The effect of mean temperature, mediated through changes in crop development rate and subsequent duration, is also important in this regard. Whilst not the case for the current study, this process can be the dominant influence on yield in the absence of a change in crop variety [24, 25]. However, longer duration varieties can be developed to compensate for increases in mean temperature (e.g. [13]), thus mitigating this effect. Whether the dominant process is due to means or extremes, detailed process-based modelling of crops, combined carefully with observations of physiological traits, can contribute to this effort by informing plant breeding (e.g. [44]).

Biophysical and socio-economic approaches to adaptation are inherently linked. The development of stress-tolerant crop does not naturally lead to its availability to the farmers who need it, for example. Thus, it is difficult to accurately quantify the relative costs and benefits of the available adaptation options. Nonetheless, the relationship between mean temperature increase and crop failure (figure 3) demonstrates the importance of this endeavour. The work presented here shows the potential for both biophysical and socio-economic measures to provide adaptation to climate change.

3.2. Limitations and future work

Some of the limitations of this study (see section 2.2) indicate possible topics for future progress in research. The crop model simulations focus on the response of crops to climate, ignoring other important drivers of crop yield. For example, increases occurrence of pests and diseases may result in additional stresses that cannot easily be adapted to. The simulations also ignore socio-economic drivers of crop productivity. Conversely, the vulnerability analysis assumes that in all instances when rainfall and crop yield are not correlated, this is due to socio-economic adaptation; it does not account for, for example, sub-seasonal rainfall variability, as the crop model does. These limitations are the reason for presenting these analyses together, rather than only one of them. They also point the way towards improved methods in the future. In particular, the work presented here suggests the following areas of research.

(1) If we are to understand the potential for biophysical adaptation of crop productivity to climate change, existing crop germplasm needs to be linked with crop models in a way that is relevant to regional-scale production. Such work has begun (e.g. [44, 13, 45]). Further progress is likely to result from closer integration of models with detailed field trial data, for example through the use of 'virtual crops' that can be compared to both existing germplasm and the potential for new varieties through breeding (see e.g. [46]) and biotechnology. Closer integration of this kind is starting to take place, for example within the Climate Change, Agriculture and Food Security programme (www.ccafs.cgiar.org).

(2) The dependence of crop failure rates on future climate, and the inherent uncertainty in prediction of future climates, implies a need for end-to-end analyses of the cascade of uncertainty from climate to crop production. Through understanding this causal chain of uncertainty, key observations needed to constrain ensemble simulations

may be found. If such analyses can be conducted from a decision-making perspective—rather than being motivated purely for the sake of understanding, they may permit the development of risk-based, targeted adaptation plans. Efforts to take a decision-based approached have increased in recent years (see e.g. [47], www.equip.leeds.ac.uk).

(3) Food security research involves many perspectives. A key challenge is integrating these perspectives holistically using appropriate quantitative and qualitative methods. This study, amongst others (e.g. [48]), can be seen as a first step in one aspect of this integration. It may be that biophysical and socio-economic perspectives can be integrated more closely, for example by using socio-economic variables to constrain crop model parameters, or by seeking to explain discrepancies between observed and simulated yields using socio-economic variables [49]. However such integration is achieved, it should lead to a more complete understanding of the response to climate change of the human and biophysical elements of crop production. This in itself should improve our understanding of how national and regional policy can be used to support adaptation, for example through improved access to suitable crop varieties.

4. Conclusions

The results from this study suggest that climate change will result in increasing spring wheat crop failure in northeast China due to increasing extremes of both heat and water stress. The simulations show significant potential for adaptation through both socio-economic and biophysical measures. The methods used could form part of a methodology to link climate and crop models, socio-economic analyses and crop variety trial data. By examining at the regional scale the range of abiotic stresses likely to be experienced by crop production systems in the future, the relative importance of these stresses could be determined using a risk-based or probabilistic framework. This work could in turn be used with analyses of current and potential future germplasm, and socio-economic conditions, in order to prioritize efforts to adapt regional-scale crop production to climate change, using a range of measures such as policy, plant breeding and biotechnology.

Acknowledgments

The support of the Natural Environment Research Council (NERC) and the Economic and Social Research Council (ESRC) is gratefully acknowledged. The work was part of the NERC EQUIP programme and the ESRC Centre for Climate Change Economics and Policy. DH and MC were supported by the Joint DECC and Defra Integrated Climate Programme—DECC/Defra (GA01101).

References

[1] Gregory P J, Ingram J S I and Brklacich M 2005 Climate change and food security *Phil. Trans. R. Soc.* B **360** 2139–48

[2] McIntyre B D, Herren H R, Wakhungu J and Watson R T (ed) 2009 *International Assessment of Agricultural Knowledge, Science and Technology for Development (IAASTD) Global Report (2009)*

[3] Godfray C H J, John R B, Ian R C, Lawrence H, David L, James F M, Jules P, Sherman R, Sandy M T and Camilla T 2010 Food security: the challenge of feeding 9 billion people *Science* **327** 812

[4] IPCC 2007 *Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the 4th Assessment Report of the Intergovernmental Panel on Climate Change* ed M L Parry, O F Canziani, J P Palutikof, P J van der Linden and C E Hanson (Cambridge: Cambridge University Press) p 976

[5] Rockström J *et al* 2009 A safe operating space for humanity *Nature* **461** 472–5

[6] Van Vliet A and Leemans R 2006 *Rapid Species' Responses to Changes in Climate Require Stringent Climate Protection Targets* (*Avoiding Dangerous Climate Change*) ed H J Schellnhuber, W Cramer, N Nakicenovic, T Wigley and G Yohe (Cambridge: Cambridge University Press) chapter 12

[7] Challinor A J, Ewert F, Arnold S, Simelton E and Fraser E 2009 Crops and climate change: progress, trends, and challenges in simulating impacts and informing adaptation *J. Exp. Bot.* **60** 2775–89

[8] Wheeler T R, Craufurd P Q, Ellis R H, Porter J R and Vara Prasad P V 2000 Temperature variability and the annual yield of crops *Agric. Ecosyst. Environ.* **82** 159–67

[9] Morton J F 2007 The impact of climate change on smallholder and subsistence agriculture *Proc. Natl Acad. Sci. USA* **104** 19680–5

[10] Diffenbaugh N, Giorgi F, Raymond L and Bi X 2007 Indicators of 21st century socioclimatic exposure *Proc. Natl Acad. Sci.* **104** 20195–8

[11] O'Brien K and Leichenko R 2000 Double exposure: assessing the impacts of climate change with the context of economic globalization *Glob. Environ. Change* **10** 221–32

[12] Collins M and Knight S (ed) 2007 Ensembles and probabilities: a new era in the prediction of climate change. Papers of theme issue *Phil. Trans. R. Soc.* A **365** 1955–2191

[13] Challinor A J, Wheeler T R, Hemming D and Upadhyaya H D 2009 Crop yield simulations using a perturbed crop and climate parameter ensemble: sensitivity to temperature and potential for genotypic adaptation to climate change *Climate Res.* **38** 117–27

[14] Iizumi T, Yokozawaa M and Nishimoria M 2009 Parameter estimation and uncertainty analysis of a large-scale crop model for paddy rice: application of a Bayesian approach *Agric. Forest Meteorol.* **149** 333–48

[15] Tao F, Hayashi Y, Zhang Z, Sakamoto T and Yokozawa M 2008 Global warming, rice production, and water use in China: developing a probabilistic assessment *Agric. Forest Meteorol.* **148** 94–110

[16] Lobell D B, Burke M B, Tebaldi C, Mastrandrea M D, Falcon W P and Naylor R L 2008 Prioritizing climate change adaptation needs for food security in 2030 *Science* **319** 607–10

[17] Schlenker W and Roberts M J 2009 Nonlinear temperature effects indicate severe damages to US crop yields under climate change *Proc. Natl Acad. Sci. USA* **106** 15594–8

[18] Parry M L, Rosenzweig C, Iglesias A, Livermore M and Fischer G 2004 Effects of climate change on global food production under SRES emissions and socio-economic scenarios *Glob. Environ. Change* A **14** 53–67

[19] Fraser E D G *et al* 2008 Quantifying socioeconomic characteristics of drought-sensitive regions: evidence from Chinese provincial agricultural data *C. R. Geosci.* **340** 679–88

[20] Simelton E, Fraser E D G, Termansen M, Forster P M and Dougill A J 2009 Typologies of crop-drought vulnerability: an empirical analysis of the socio-economic factors that influence the sensitivity and resilience to drought of three major food crops in China (1961–2001) *Environ. Sci. Policy* **12** 438–52

[21] Collins M, Booth B B B, Bhaskaran B, Harris G, Murphy J M, Sexton D M H and Webb M J 2010 Climate model errors, feedbacks and forcings: a comparison of perturbed physics and multi-model ensembles *Clim. Dyn.* doi:10.1007/s00382-010-0808-0

[22] Challinor A J, Wheeler T R, Slingo J M, Craufurd P Q and Grimes D I F 2004 Design and optimisation of a large-area process-based model for annual crops *Agric. Forest Meteorol.* **124** 99–120

[23] Osborne T M, Lawrence D M, Challinor A J, Slingo J M and Wheeler T R 2007 Development and assessment of a coupled crop-climate model *Glob. Change Biol.* **13** 169–83

[24] Chee-Kiat T 2006 Application of satellite-based rainfall estimates to crop yield forecasting in Africa *PhD Thesis* University of Reading, p 233

[25] Challinor A J and Wheeler T R 2008 Use of a crop model ensemble to quantify CO_2 stimulation of water-stressed and well-watered crops *Agric. Forest. Meteorol.* **148** 1062–77

[26] Challinor A J and Wheeler T R 2008 Crop yield reduction in the tropics under climate change: processes and uncertainties *Agric. Forest. Meteorol.* **148** 343–56

[27] Challinor A J, Wheeler T R, Craufurd P Q, Ferro C A T and Stephenson D B 2007 Adaptation of crops to climate change through genotypic responses to mean and extreme temperatures *Agric. Ecosyst. Environ.* **119** 190–204

[28] Challinor A J, Wheeler T R, Craufurd P Q and Slingo J M 2005 Simulation of the impact of high temperature stress on annual crop yields *Agric. Forest. Meteorol.* **135** 180–9

[29] Challinor A J, Slingo J M, Wheeler T R and Doblas-Reyes F J 2005 Probabilistic hindcasts of crop yield over western India *Tellus* A **57** 498–512

[30] Li S, Challinor A J and Wheeler T R 2007 Development of a large area wheat crop model for studying climate change impacts in China *J. Agric. Sci.* **145** 635–50

[31] Li S 2006 Investigating the impacts of climate change on wheat in China *PhD Thesis* University of Reading p 227

[32] Deng X, Luo Y, Dong S and Yang X 2005 Impact of resources and technology on farm production in northwestern China *Agric. Syst.* **84** 155–69

[33] Jin Z-Q and Zhu D-W 2008 Impacts of changes in climate and its variability on food production in Northeast China *Acta Agronom. Sin.* **34** 1588–97

[34] Wang F *et al* 2009 Wheat cropping systems and technologies in China *Field Crops Res.* **111** 181–8

[35] Easterling W E *et al* 2007 Food, fibre and forest products *Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the 4th Assessment Report of the Intergovernmental Panel on Climate Change* ed M L Parry, O F Canziani, J P Palutikof, P J van der Linden and C E Hanson (Cambridge: Cambridge University Press) pp 273–313

[36] Porter J R and Semenov M A 2005 Crop responses to climatic variation *Phil. Trans. R. Soc.* B **360** 2021–38

[37] Yang H 1998 Trends in China's regional grain production and their implications *Agric. Econom.* **19** 309–25

[38] Huang J, Hu R and Rozelle S 2004 China's agricultural research system and reforms: challenges and implications for developing countries *Asian J. Agric. Dev.* **1** 98–112

[39] Huang Y 2002 State grain marketing policy and farmer behaviour Asia Pacific Press http://ncdsnet.anu.edu.au

[40] Yang X *et al* 2007 Adaptation of agriculture to warming in Northeast China *Clim. Change* **84** 45–58

[41] Challinor A J, Wheeler T R, Garforth C, Craufurd P and Kassam A 2007 Assessing the vulnerability of food crop systems in Africa to climate change *Clim. Change* **83** 381–99

[42] Challinor A J 2009 Developing adaptation options using climate and crop yield forecasting at seasonal to multi-decadal timescales *Environ. Sci. Policy* **12** 453–65

[43] Heilig G K, Fischer G and van Velthuizen H 2000 Can China feed itself? An analysis of China's food prospects with special reference to water resources *Int. J. Sustainable Dev. World Ecol.* **7** 153–72

[44] Semenov M A and Halford N G 2009 Identifying target traits and molecular mechanisms for wheat breeding under a changing climate *J. Exp. Bot.* **60** 2791–804

[45] Burke M B, Lobell D B and Guarino L 2009 Shifts in African crop climates by 2050, and the implications for crop improvement and genetic resources conservation *Glob. Environ. Change* **19** 317–25

[46] Tester M and Langridge P 2010 Breeding technologies to increase crop production in a changing world *Science* **327** 818–22

[47] Lobell D B and Burke M B 2008 Why are agricultural impacts of climate change so uncertain? The importance of temperature relative to precipitation *Environ. Res. Lett.* **3** 034007

[48] Xiong W, Conway D, Jiang J, Li Y, Lin E, Xu Y and Hui J 2009 Future cereal production in China: the interaction of climate change, water availability and socio-economic scenarios *Glob. Environ. Change* **19** 34–44

[49] Iizumi T, Ishida K, Yokozawa M and Nishimori M 2010 Potential predictability of local paddy rice variation using a crop model with local areal information *Agric. Inform. Res.* **19** 36–42