Agricultural and Forest Meteorology 170 (2013) 195–205

Contents lists available at SciVerse ScienceDirect

Agricultural and Forest Meteorology

journal homepage: www.elsevier.com/locate/agrformet

"Vulnerability hotspots": Integrating socio-economic and hydrological models to identify where cereal production may decline in the future due to climate change induced drought

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ARTICLE INFO

Article history:
Received 28 February 2011
Received in revised form 21 February 2012
Accepted 13 April 2012

Keywords:
Adaptive capacity index
Drought index
Climate change vulnerability
Food security
Food
Agriculture
Soil moisture

ABSTRACT

The purpose of this paper is to identify which of the world's cereal producing regions are likely to become vulnerable to climate change over the 21st century by identifying those regions that will be (1) exposed to climatic stress and (2) have a limited capacity to adapt. First, we use a global hydrological model to identify regions likely to be exposed to drought, defined here as a location where the available soil moisture is projected to decline by the 2050s and 2080s relative to the mean soil moisture observed between 1990 and 2005. Second, we use agricultural, meteorological and socio-economic data to develop models of adaptive capacity and run these models to show where adaptive capacity is likely to decline by the 2050s and 2080s relative to the baseline period of 1990–2005. Third, we contrast the hydrological and adaptive capacity model outputs to identify "vulnerability hotspots" for wheat and maize. Here, a vulnerability hotspot is defined as a region that the models project as likely to experience both a decline in adaptive capacity and in available soil moisture. Results from the hydrological model project significant drying in many parts of the world overt the 21st century. Results from the adaptive capacity models show that regions with the lowest overall adaptive capacity for wheat include much of western Russia, northern India, southeastern South America, and southeastern Africa. In terms of maize, regions with the lowest adaptive capacity include the northeastern USA, southeastern South America, southeastern Africa, and central/northern India. When taken together, this study identifies five wheat and three maize growing regions likely to be both exposed to worse droughts and a reduced capacity to adapt. For wheat, these are: southeastern USA, southeastern South America, the northeastern Mediterranean, and parts of central Asia. For maize, our analysis suggests that vulnerability hotspots are: southeastern South America, parts of southern Africa, and the northeastern Mediterranean.

1. Introduction

Crop models demonstrate that food production is vulnerable to climate change in many regions through a combination of temperature change, water stress and extreme weather (Challinor et al., 2009, 2010; Lobell and Field, 2007). Although there is considerable uncertainty in these models, and some debate way that ozone pollution, carbon dioxide fertilization, and water shortages may interact with climate change to affect productivity, there is a general concern in the literature that these problems are likely to cause food production to fall over the next 100 years (Jaggard et al., 2010; Long et al., 2005; Royal Society, 2008; Sitch et al., 2007). These concerns sit alongside economic and demographic models that project a rising demand for food thanks to population growth (Foley et al., 2011; Lutz and KC, 2010), urbanization (Satterthwaite et al., 2010), and a shift towards more meat consumption (Kearney, 2010). This leads some to argue that global food security is threatened unless production increases by as much as 70% (Bruinsma, 2009; Godfray et al., 2010a,b). Therefore, new technologies (Brown and Funk, 2008), and in particular biotechnologies (Tester and Langridge, 2010), may be needed to create more productive crops and ensure food security during the 21st century.

In addition, the socio-economic, ecological, and institutional context of farming has a tremendous influence on whether a producer can adapt to environmental stressors and remain productive

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http://dx.doi.org/10.1016/j.agrformet.2012.04.008

(Adger, 2006; Brooks et al., 2005; Patt et al., 2005; Smit and Skinner, 2002; Thomas et al., 2007; Watts and Bohle, 1993). For example, degraded soils, a lack of off-farm employment, social upheaval, and a dysfunctional government prevented the Ethiopian population from adapting to drought in the 1980s (Comenetz and Caviedes, 2002). As a result, it only took a very minor drought (measured in terms of rainfall) to trigger a famine (Fraser, 2007). By contrast, there are cases where even major climatic problems were adapted to without serious losses in agricultural productivity or human life (DeRose et al., 1998). The implication of this is that institutional reform, poverty reduction, and gender equality will help boost adaptive capacity and that this may be as important as developing new crops to meet the challenges of feeding future generations (Fraser et al., 2003; Paavola and Adger, 2006).

Overall, therefore, the vulnerability of crop production to climate change is seen by many scholars as a function of both an exposure to a climatic stress, such as a drought, as well as an ability to adapt to that stress (Fraser et al., 2011b; Intergovernmental Panel on Climate Change, 2001; Watts and Bohle, 1993). To date, however, most quantitative and global scale projections of how food crop production is vulnerable to climate change have focused on the ways in which new temperature and rainfall patterns will affect plant growth (Zhang and Cai, 2011). Those studies that do include socio-economic factors in future projections are most often based only on two socio-economic variables, GDP and population, and there is limited or no assessment as to whether, or under what context, these variables are significant (Diffenbaugh et al., 2007).

The aim of this paper is to better integrate socio-economic and meteorological data to conduct a global scale quantitative assessment that identifies which of the world's cereal producing regions may become vulnerable to climate change over the 21st century. We do this by identifying those regions that will be both exposed to climatic stresses and will not have the capacity to adapt to these problems. The climate impact we focus on is declining cereal harvests since these provide the world with approximately 90% of its calories and are likely to be affected by changing weather patterns (International Development Research Council, 1992). In terms of climate change exposure, we have chosen to focus our attention on droughts as many climate models project that droughts will be a major factor in limiting future crop growth (Intergovernmental Panel on Climate Change, 2007). To assess adaptive capacity, we use a range of socio-economic and ecological data and employ statistical methods to identify proxy indicators of adaptive capacity. We then use different socio-economic and climate projections to identify regions that, given current trends, are likely to be both exposed to worse droughts in the future as well as have a diminishing capacity to adapt. While this project does not provide conclusive results, this nonetheless represents an important step in the field of research devoted to better understanding when, where, and why food systems are likely to be vulnerable to climate change in the future.

2. Data and methods

2.1. Quantifying and modeling exposure to drought

To identify regions likely to be exposed to worse droughts in the future, we used soil moisture simulations from Mac-PDM.09, which is an established global hydrological model. Mac-PDM.09 simulates soil moisture and runoff across the world at a spatial resolution of $0.5^\circ \times 0.5^\circ$. A detailed description and validation of the model is provided by Gosling and Arnell (2011) and the model has been applied in several recent studies of the global hydrological cycle (e.g. Haddeland et al., 2011; Gosling et al., 2010, 2011). Mac-PDM.09 requires the following climate variables as input: precipitation, temperature, vapor pressure, net radiation, and wind speed (the latter four to calculate Penman Monteith potential evapotranspiration, PE).

Mac-PDM.09 was forced with the pattern of climate change from a single global climate model (GCM) run under the SRES A1B and B2 emissions scenarios for the 2050s and 2080s (see Table 2 for details on the scenarios). We acknowledge that climate change projections could have been obtained from other GCMs, and that to some extent this could produce different results. However, given the exploratory nature of this research, we adopted the same approach employed by other recent assessments of the impact of climate change on global food production (Cheung et al., 2010; Iglesias and Rosenweig, 2009; Rockström et al., 2009) and applied a single version of the well-established Met Office Hadley Centre coupled ocean-atmosphere GCM: HadCM3. The climate change forcing scenarios were created using ClimGen (Mitchell and Osborn, 2005), a spatial climate scenario generator that uses the pattern-scaling approach (Mitchell, 2003) to generate downscaled spatial climate change information for a given GCM (in this case HadCM3), following the procedures outlined by Todd et al. (2011). Mac-PDM.09 was also forced with CRU-TS3 data for a present-day simulation (1990–2005). The pattern-scaling technique employed by ClimGen ensures that the Mac-PDM.09 climate change and present day simulations are directly comparable.

2.2. Quantifying and modeling adaptive capacity

To identify regions likely to have low adaptive capacity we built on the approach developed in Simelton et al. (2009). Their work is based on the assumption that regions where cereal harvests are sensitive to droughts, i.e. cases when relatively minor droughts in the past generated large reductions in cereal harvests, will have a low adaptive capacity. We developed this approach by hypothesizing that we would be able to quantify adaptive capacity by using socio-economic and biophysical data to identify proxy indicators of drought sensitivity. We then used the identified proxy indicators to create models of adaptive capacity to map areas of high potential for adaptation for the same two scenarios (A1B and B2, see Table 2) as used in the hydrological model. This involved five steps:

1. Using crop distribution and simulated soil moisture data for 1990–2005, we calculated a "drought severity index" for each country and each year. Two data sets were used for this. First, we used Leff et al. (2004)'s data on crop distribution as a fraction of the landbase devoted to rice, wheat and maize production in each 5 min (~10 km) grid cell. Second, we used simulated soil moisture data from Mac-PDM.09 (0.5° grid; ~55 km) for 1990–2005. The crop distribution data were aggregated over the 36 neighboring cells to obtain the same 0.5° resolution as used in the hydrological model. For each 0.5° grid cell where at least $\geq$1% of the land base was devoted to rice, wheat or maize respectively, we calculated the total soil moisture for the period of October to October for each year between 1990 and 2005. Therefore, using the period of October to October, we calculated the average amount of soil moisture that was available in each country's rice, wheat and maize land between 1990 and 2005 and divided this by the total amount of soil moisture that was available in each year. This returned a "drought severity index" where a drought is defined as a score >1, i.e. a year with below average soil moisture. The choice to use the October-to-October time period was deliberate. First, we tested a number of different periods of time with which to calculate the drought index. Similar to Lobell and Field (2007), we found that final results were relatively insensitive to choice of months. Second, since one goal of this project was to conduct a global assessment, the October to October period is useful as this captures both northern and

Table 1
Socio-economic variables used to create adaptive capacity models.

Variable	Unit	Source
Rural population	% of population	IF, 2009
Cropland per capita	ha/capita	IF, 2009
Safe water	%	IF, 2009
Gini coefficient	0–1	IF, 2009
Agriculture value added to GDP per ha	$/ha Cropland	IF, 2009
GDP per capita	$PPP/capita	IF, 2009
Fertiliser intensity	kg/ha	FAO, 2008 (fertiliser); IF, 2009 (cereal yield)

southern hemisphere growing seasons. Finally, using an annual (rather than a seasonal) period of time to assess rainfall made our results more conservative in that this under-represented many droughts because good rainfall in one of the calendar years had the effect of reducing the drought severity index for the other year.

2. Using harvest data from 1990 to 2005, we calculated a "harvest loss" index that shows how significant harvests losses were in regions and years where droughts occurred. This harvest loss index was based on crop production data obtained from FAOSTAT (FAO, 2008) for rice, wheat and maize and included 102 rice producing countries, 112 wheat producing countries, and 127 maize producing countries. First, missing data was interpolated with a smoothing spline function restricted within the range of existing values (Crawley, 2007). Missing data points at the beginning or end of the time series were linearly extrapolated if less than four consecutive years were missing or left as missing values if more years were missing. For each crop, the expected harvest was calculated as a de-trended crop production using an auto-regression model with four-year lags (Schneider and Neumaier, 2001; Simelton et al., 2009). A three year-lag was used in order to increase the number of data points for a few countries with limited time series. For each year with a drought, we calculated the crop failure index by dividing the expected (or detrended) harvest by the actual observed harvest. In this way, a high harvest loss index indicates that the harvest in a particular year was below expected.
3. For each crop, we calculated an adaptive capacity index by dividing the drought index by the harvest loss index for each year and country where there was a drought. This meant that a high adaptive capacity score indicated countries and years when harvests were good relative to the size of the drought.
4. To model adaptive capacity, all countries were categorized in terms of what climatic zone the crop land in the country fell into (temperate, tropical, arid, and cold following Köppen's climate zones (Kottek et al., 2006)), the level of Gross National Income per capita in 2008 (poor, lower middle, upper middle and high income following World Bank categories (World Bank, 2009)), and type of government (authoritarian regime, hybrid regime, flawed democracy, and full democracy following the Economist's Intelligence Unit's classification system (The Economist, 2009)). While this meant there were 64 hypothetical "types" of country, in reality, this resulted in 32 different types of rice producing country, 36 types of wheat producing country and 34 types of maize producing country. Using these different types of cereal producing country as the basis of our analysis, we developed linear models of adaptive capacity for rice, maize and wheat where the adaptive capacity index was regressed against seven country-level socio-economic, political, and ecological variables (Table 1).
5. For the last step, we ran the adaptive capacity models developed in step 4 for the IPCC's SRES A1B and B2 scenarios at the 0.5° grid level. Data for these scenarios came from the International Future's Database (version 6.18) that provides socio-economic projections at country-level that are consistent with all the IPCC's SRES scenarios (International Futures, 2009). These scenarios, and the data used in them, are presented in Table 2. To do this, we first identified each 0.5° grid cell where >1% of the landscape is currently planted with rice, wheat and maize and categorized each grid cell in terms of its climatic zone, income level, and government type using the same categorization system as was used to create the adaptive capacity models described above. Then, we used the adaptive capacity models to estimate a baseline level of adaptive capacity for 1990–2005. Finally, we used the linear models with the socio-economic data for the A1B and B2 scenarios to project gridded adaptive capacity in the future for the same time periods as the hydrological model outputs: 2045–2060 (2050s) and 2075–2090 (2080s). (In doing this, we assumed that scenario changes in the global Gini coefficient listed in Table 2 mirrors changes at the individual country-level, although there remains no clear relationship between trends in the global inequality between countries and changes in inequality within any country.)

3. Results

3.1. Hydrological model

Fig. 1 presents changes from baseline (1990–2005) in two of the main climatic drivers of soil moisture (precipitation and temperature) for 2045–2060 and 2075–2090, under each scenario (A1B and B2). The climate projections show that changes in precipitation are slightly greater under the A1B emissions scenario than under the B2 emissions scenario. Likewise, warming is higher under A1B than under B2. The largest declines in precipitation with climate change are for northern Brazil, North Africa, southern Africa, the Arabian Peninsula, and Western Australia. Large increases in precipitation are simulated by the GCM for northern India, north-eastern China and the high northern latitudes. Warming is highest in the northern hemisphere. Relative changes in temperature with time are greater than the relative changes in precipitation; e.g. the pattern of precipitation change for Australia is similar for the two time horizons, whereas for temperature, the pattern of warming changes from 2045–2060 to 2075–2090.

Fig. 2 displays the results of the hydrological model showing changes to available soil moisture between the baseline period (1990–2005) and 2045–2060 and 2075–2090. Results are also displayed for the A1B and B2 scenarios. Generally, these outputs suggest that there could be less available soil moisture across many of the world's grain producing regions and that, as the 21st century continues, problems could gradually worsen. There are subtle differences between the A1B and B2 scenarios, with the changes from baseline slightly greater under A1B. For example, a larger extent of southern Africa experiences a decrease in soil moisture greater than 25%, under A1B than B2. Changes from baseline increase with time into the future as well. For example, note the substantial declines in soil moisture across the central United States under both scenarios, from 2045–2060 to 2075–2090.

The changes in soil moisture largely reflect changes in precipitation up to the middle of the 21st century. For instance, the largest declines in soil moisture for 2045–2060 are generally for areas that experience substantial declines in precipitation. However, as warming continues into the latter half of the 21st century, and at a greater rate than precipitation change for some regions (e.g. western Europe and northern Australia; see Fig. 1), potential evaporation increases relative to baseline and, as a result, soil moisture declines further. For some regions, even though precipitation changes little, or increases with time into the future, soil moisture

Table 2
Description of the scenarios used to model the vulnerability of cereal crops to drought.

Scenario Name	Description	Cropland per Capita	Rural Population	Gini coefficient	Safe water	Fertiliser intensity	Agriculture Value Added to GDP per ha	GDP per capita
		Global average % Change compared to baseline period (1990–2005)						
A1B–2020s	A future world of very rapid economic growth, global population that peaks in mid-century and declines thereafter, and rapid introduction of new and more efficient technologies. Balanced used of energy sources.	−72%	−19%	1%	−21%	17%	3%	36%
A1B–2050s		−73%	−32%	10%	−50%	24%	6%[a]	141%
A1B–2080s		−69%	−47%	18%	−75%	33%	5%[b]	342%
B2–2020s	A world in which the emphasis is on local solutions to economic, social, and environmental sustainability, with continuously increasing population and intermediate economic development.	−72%	−20%	1%	−21%	18%	15%	36%
B2–2050s		−75%	−33%	10%	−51%	28%	22%[a]	147%
B2–2080s		−74	−48%	18%	−77%	63%	25%[b]	376%

Source: http://www.ipcc.ch/ipccreports/tar/wg1/029.htm.
[a] Average for the period 2045–2050.
[b] Average for the year 2050 only.

declines relative to baseline because of large warming and subsequently high potential evapotranspiration (e.g. north-eastern China and north Australia).

3.2. Adaptive capacity model

In terms of modeling adaptive capacity, we did not find statistically significant results to explain adaptive capacity in the world's rice harvest. This may be because much of the world's rice crop is irrigated and, therefore, not as affected by changes in available soil moisture that are driven by precipitation (note, testing this sort of hypothesis is beyond the scope of this paper). We did, however, find evidence of statistically significant relations between maize and wheat adaptive capacity and a range of socio-economic characteristics. In our baseline analysis, we observed that regions with the lowest overall adaptive capacity for wheat include much of western Russia, northern India, southeastern South America, and southeastern Africa. In terms of maize, regions with the lowest adaptive capacity include the northeastern USA, southeastern South America, southeastern Africa, and central/northern India. These results are displayed on the top row of figure three.

In terms of the socio-economic factors that influenced adaptive capacity in the world's wheat and maize producing regions, the data suggest a number of complex relations. The analysis has not identified general relationships between socio-economic characteristics and adaptive capacity. Rather, the analysis presented here suggests that many of the socio-economic factors that influence adaptive capacity are context-specific. For instance, the amount of crop land per capita was found to be a significant predictor of adaptive capacity in a number of the wheat models. But the income of the country in question determines the nature of this relation. More specifically, data show that there is often a positive relation between cropland per capita and adaptive capacity for wheat harvests but that this relation is stronger in some poorer countries than in most rich countries. One explanation for this result is that having access to cropland is more important in determining adaptive capacity in poor parts of the world where farmers may adapt to drought by planting larger areas, leaving fields fallow to conserve moisture, or reducing planting density to lessen moisture competition between plants (see Dougill et al., 2010 for a review of these kinds of adaptation strategies as related to pastoral Botswana). Access to land may be less important for farmers in wealthier regions where adaptation may be based around access to farm inputs such as purchasing drought tolerant seed varieties. For the groups of countries where the Gini coefficient was found to have a significant effect, results show that the greater the inequity in wealth, the lower the adaptive capacity in wheat harvests, suggesting that inequality undermines adaptive capacity in the world's wheat producing areas. Fertilizer use was found to be most often negatively associated with adaptive capacity in cold and temperate regions. By contrast, fertilizer use was, when significant, found to be positively associated with adaptive capacity in tropical and arid countries. This provides some suggestive evidence that increasing fertilizer use in tropical and arid countries may help buffer wheat yields from drought but that this same strategy may not have the same effect in different ecological zones.

Results were different when we considered adaptive capacity in maize harvests. In cases where GDP per capita was significant, it generally had a positive relation with adaptive capacity. Data from arid countries showed that the size of the rural population was negatively associated with adaptive capacity for maize, suggesting that high population densities may hinder adaptation to drought in dry regions. By contrast, the analysis presented here provides some evidence that high rural populations help buffer maize harvests from the impacts of drought in temperate regions. This may be because arid regions cannot support high population densities and,

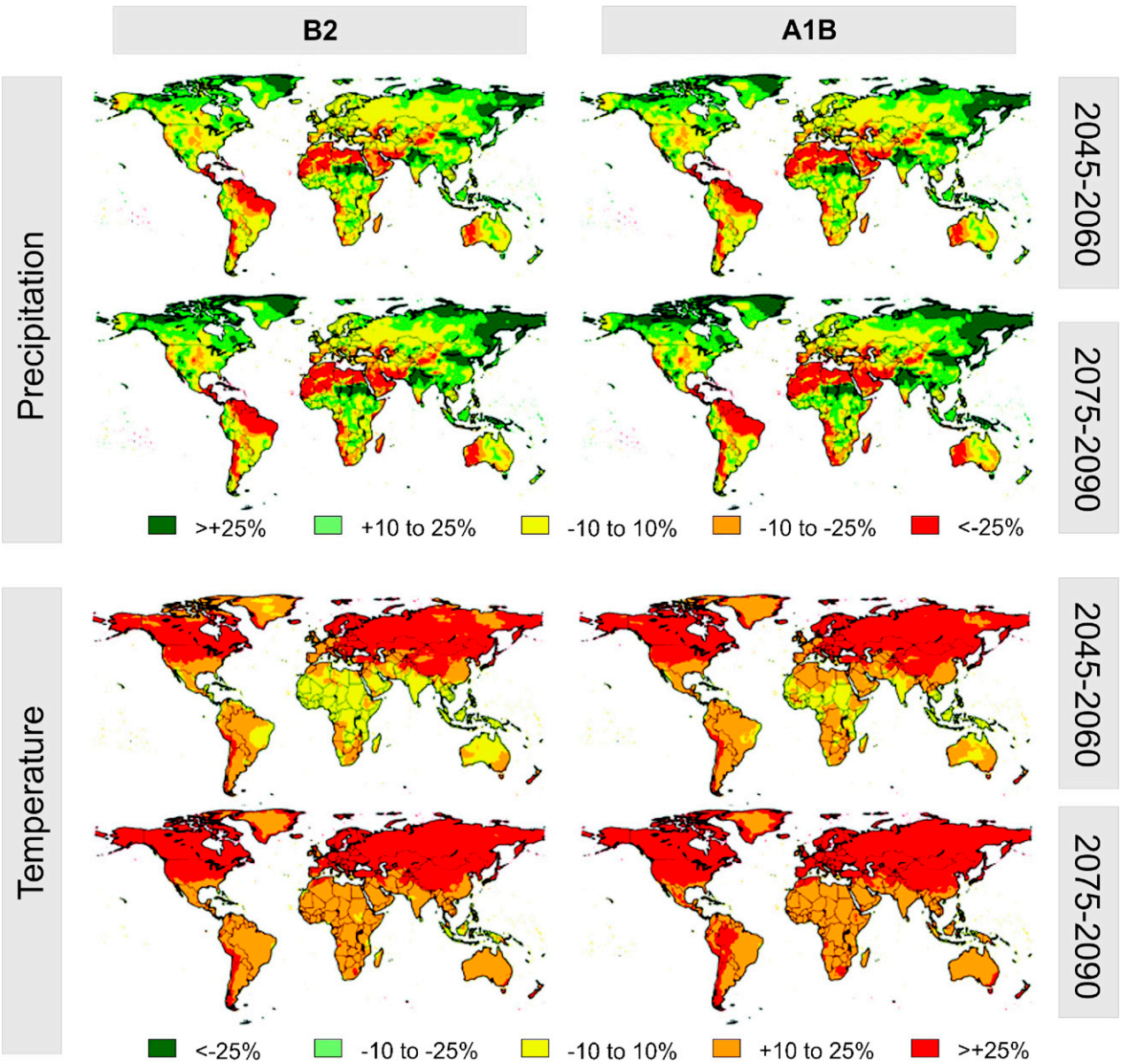

Fig. 1. Change (%) in mean annual precipitation and temperature relative to baseline (1990–2005) for two future time horizons under the SRES B2 (left panels) and A1B (right panels) scenarios.

therefore, the extra people in such regions hurt farmers' ability to adapt to drought. By contrast in temperate regions, the extra people may be used in labor intensive adaptation strategies. The size of a country's Gini coefficient was also observed to have a negative relation with adaptive capacity in maize crops for arid regions, but a weaker (and positive) relation in temperate regions and a stronger positive relation in tropical countries.

Such details aside, the general point from this analysis is that the effect of socio-economic variables on adaptive capacity depends on the type of region. Tables 3A and 3B provide the statistics details for the different adaptive capacity models for wheat and maize.

When the adaptive capacity models were used to project changes in adaptive capacity for the A1B and B2 scenarios, results show that regions with the largest declines in wheat and maize adaptive capacity are in areas with authoritarian regimes and arid ecosystems. In particular, Russian wheat and South American maize farmers are projected to lose adaptive capacity. Overall, adaptive capacity is projected to increase in tropical and cold areas that have high incomes and hybrid regimes or democratic governments (e.g. eastern China and central North America). Finally, there were only small changes between the 2050s and 2080s and very little in the way of any differences between the A1B and B2 socio-economic scenarios. Details on these modeled changes are presented in Fig. 3.

3.3. Vulnerability "hotspots"

When the outputs of the hydrological and adaptive capacity models are taken together, data suggest there are perhaps five wheat and three maize growing regions likely to be both exposed to worse droughts and a reduced capacity to adapt. We refer to these areas as "vulnerability hotspots." For wheat, these are: southeastern USA, southeastern South America, the northeastern Mediterranean, and parts of central Asia. For maize, our analysis suggests that vulnerability hotspots are: southeastern South America, parts of southern Africa, and the northeastern Mediterranean (see Fig. 4).

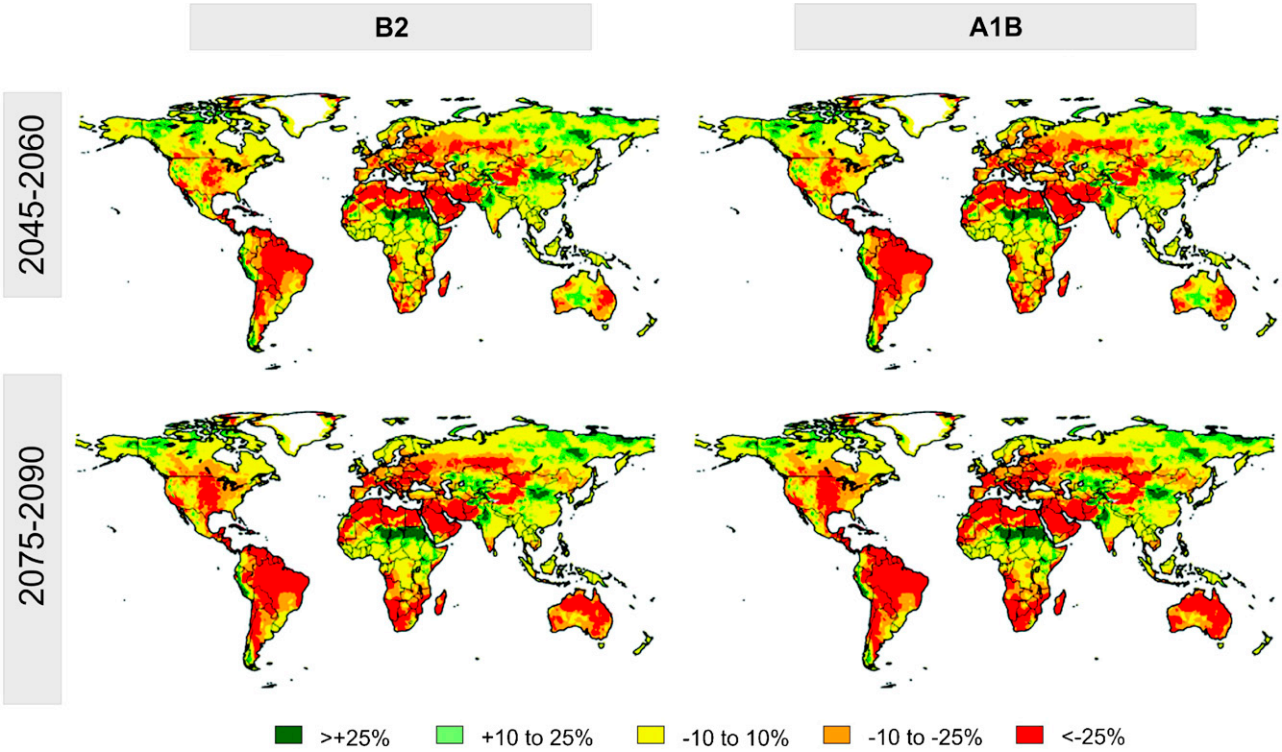

Fig. 2. Percentage change in growing season (October-to-October) soil moisture from baseline (1990–2005) for two scenarios (A1B and B2) and two time horizons (2045–2060 and 2075–2090).

4. Discussion and conclusion

In terms of empirical results, the following observations stand out:

(1) Results from the hydrological model project significant drying in many parts of the world overt the 21st century.
(2) Results from the adaptive capacity models show that regions with the lowest overall adaptive capacity for wheat include much of western Russia, northern India, southeastern South America, and southeastern Africa. In terms of maize, regions with the lowest adaptive capacity include the northeastern USA, southeastern South America, southeastern Africa, and central/northern India.
(3) When taken together, this study identifies five wheat and three maize growing regions likely to be both exposed to worse droughts and a reduced capacity to adapt. For wheat, these are: southeastern USA, southeastern South America, the northeastern Mediterranean, and parts of central Asia. For maize, our analysis suggests that vulnerability hotspots are: southeastern South America, parts of southern Africa, and the northeastern Mediterranean.

More generally, while there are a number of challenges with adopting the approach used here, this paper represents an important step in the body of research currently attempting to assess where harvests are vulnerable to climate change. Therefore, this paper should be seen as contributing explicitly to the work of those scholars who use a mixture of socio economic and environmental variables to map current patterns of vulnerability. Representing this body of literature are Pandey et al. (2011) who use a range of variables to construct an adaptive capacity index to assess water resource systems in Nepal. Gbetibouo and Ringler (2009)'s work is similar. They use a vulnerability framework to conduct a sub-national climate vulnerability assessment in South Africa. Ericksen et al.'s (2011) work is, in our opinion, the most ambitious and comprehensive of these studies. They use a large range of indicators to compile a series of vulnerability maps for the global tropics. In each of the studies cited here, socio-economic variables such as GDP, rural population density, access to water, etc., are included in vulnerability assessments. But in each of these studies, the relation between these variables and vulnerability is assumed to remain the same regardless of the social, ecological or political context. Also, none of these studies attempt to model future patterns of vulnerability. Our paper, therefore, builds on the foundation established by these scholars but here we have tried to test the significance of different socio-economic variables in different "types" of food producing region. We then used this knowledge as the basis for some preliminary models to identify where adaptive capacity may change in the future.

This does not mean that regions projected by our results to have declining levels of soil moisture but also high levels of adaptive capacity are resilient to drought (e.g. according to our results, the central USA is likely to experience worse droughts but has a relatively high adaptive capacity). There may be a host of other factors not included in this assessment that may yet undermine food crop production in such areas. For example, this analysis did not consider the effects of available ground water on adaptive capacity and one likely reason that farmers in the Great Plains of the USA and Northern China have been able to adapt to drought over the past 20 years (which is the period used to create the adaptive capacity models presented here) is that they had access to ground water for irrigation. If, however, these resources become unavailable in the future (and evidence is mounting that the water table is dropping in both the US (Sophocleous, 2005) and northern China (Foster et al., 2004)), then farmers in these regions may find themselves unable to cope with large-scale droughts. Including an assessment of ground water resources and ground water management, therefore, represents a logical next step in this research.

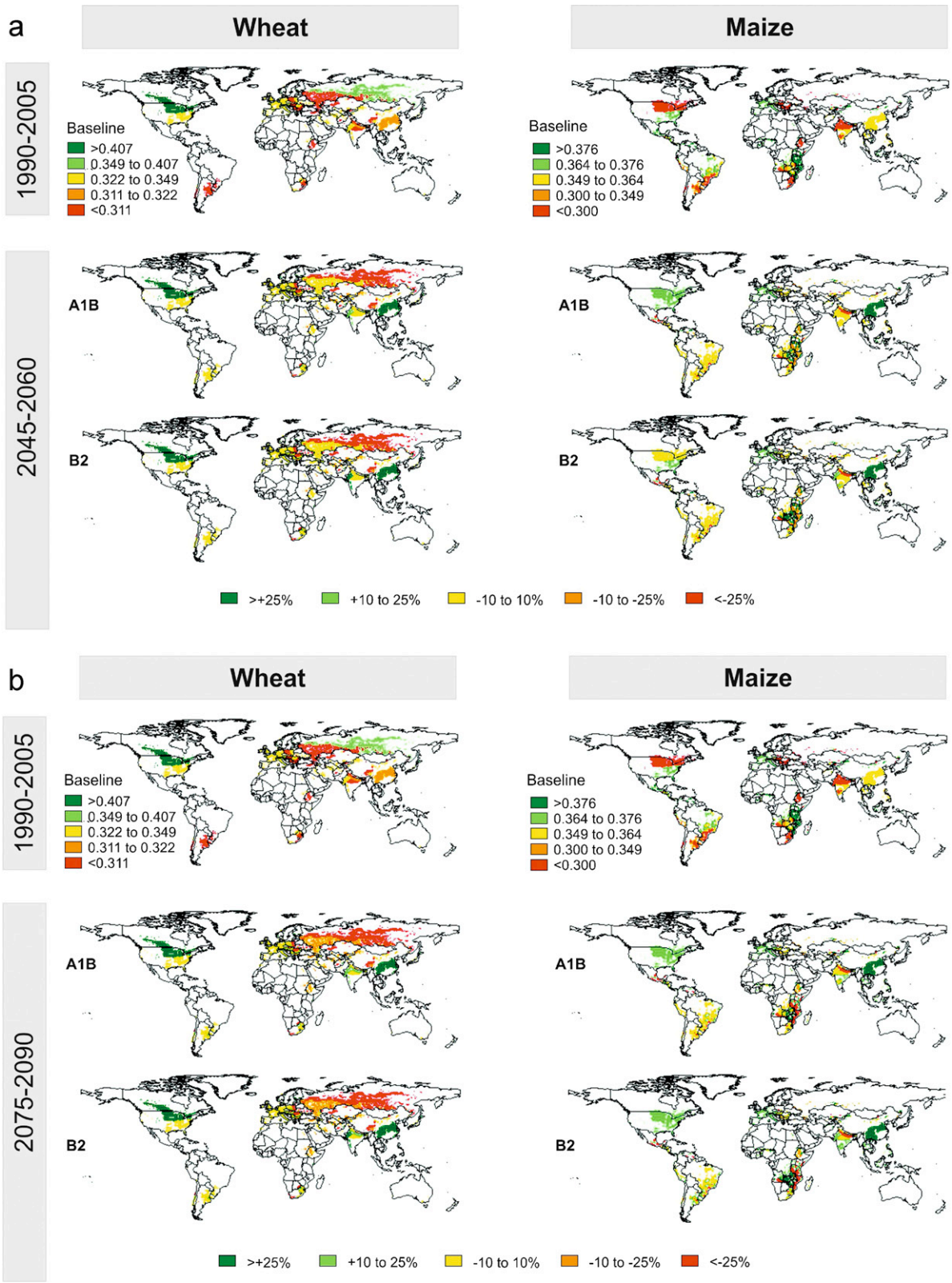

Fig. 3. (a) Modeled adaptive capacity levels for the 2000s and the % change in adaptive capacity by the 2050s (based on SRES A1B and B2 scenarios). The top. row refers to the baseline levels of adaptive capacity in the 2000s for wheat (left) and maize (right). (b) Modeled adaptive capacity levels for the 2000s and the % change in adaptive capacity by the 2080s (based on SRES A1B and B2 scenarios). The top row refers to the baseline levels of adaptive capacity in the 2000s for wheat (left) and maize (right). In both figure 3a and 3b, the colors display the interquartile range. In all cases, red indicates low adaptive capacity and green high adaptive capacity. (Note: these maps do not include all regions where wheat and maize are produced as we did not find significant results for our adaptive capacity models for all parts of the globe.)

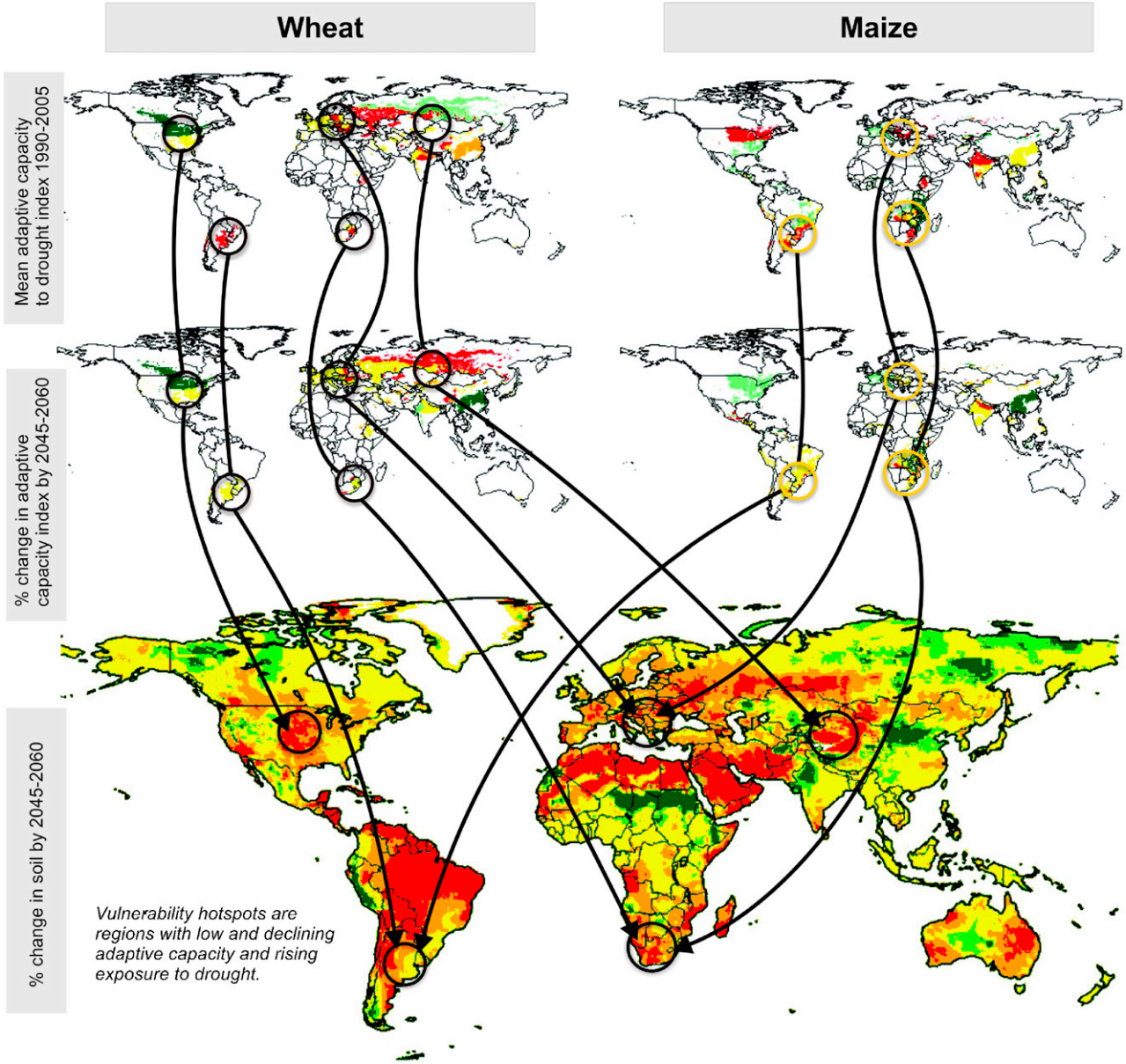

Fig. 4. Vulnerability hotspots for wheat (black circle), and maize (yellow circle) defined in terms of areas where adaptive capacity and soil moisture are both projected to be low and decline in the 2050s. The top row refers to the baseline adaptive capacity of each region where colors are displayed as interquartile range, with values for wheat (on the left): <0.3112 (red), 0.3113–0.3310 (orange), 0.3311–0.3510 (yellow), 0.3511–0.4054 (light green), >0.4054 (dark green). For maize (on the right) values are: <0.2926 (red), 0.2927–0.3234 (orange), 0.3235–0.3434 (yellow), 0.3435–0.3760 (light green), >0.3760 (dark green), with red indicating low adaptive capacity and green high adaptive capacity. The second row refers to the percent change in adaptive capacity by the 2050s. The bottom row refers to chances in soil moisture by the 2050s. In both the bottom two rows red indicates a 25% reduction in adaptive capacity or soil moisture relative to the baseline, orange indicates a 10–25% reduction, yellow indicates a −10% to +10% change, light green indicates a 10–25% increase, and dark green indicates a >25% increase. Models are run for the A1B SRES scenario (please see Table 2 for details). Note: These maps do not include all regions where wheat and maize are produced as we did not find significant results for our adaptive capacity models for all parts of the globe.

Consequently, the results of this analysis should not be seen as providing a definitive assessment of the vulnerability of crops to drought. Rather, by linking hydrological and socio-economic assessments together, we have provided a way of identifying different types of vulnerability. The areas projected by our models as likely to have low adaptive capacity in the future should be targeted by policy aimed at creating the socio-economic conditions that will enable farmers to adapt. Such interventions, of course, would need to be guided by an understanding of local on-the-ground conditions and here our analysis provides a preliminary level of insight. For example, our results suggest that helping farmers access fertilizer may be more effective in helping promote adaptive capacity to drought in arid and tropical regions than temperate or cold regions. In contrast, the areas identified as likely to lose soil moisture may be vulnerable due to being exposed to future climatic change. In such regions, an appropriate policy response may be to find ways of better conserving water. Therefore, both the hydrological and adaptive capacity model results should be seen as ways of highlighting at-risk areas and providing an initial level of guidance on interventions: any specific programs or policies should be developed in participatory ways with local farmers (Fraser et al., 2011a; Tywyman et al., 2011).

Finally, by integrating socio-economic and biophysical models, this study represents an attempt to overcome a significant limitation in current ways of projecting climate change impacts. Currently, our best tools to anticipate the effect of new climate patterns are driven by downscaled global circulation models. These computer models provide a reasonable way of identifying regions

Table 3A
Models of adaptive capacity for wheat.

Governance[a]	Agro environment[b]	Income level[c]	Intercept	Cropland/cap	Rural Pop	Gini	Safe Water	Fertiliser	Agr GDP/cropland	GDP/cap	Adjusted R[b]	*p*-value	DF	N of countries
Authoritarian regime	Tropical	Low	0.696		−0.297	−1.852	0.234	0.050	0.567		0.263	0.012	31	5
Authoritarian regime	Arid	Low	5.979	2.306	−3.235			0.127	−1.087	1.690	0.611	0.000	29	6
Authoritarian regime	Arid	Lower middle	1.448	0.341	−0.569	−1.969	0.078				0.300	0.000	73	10
Authoritarian regime	Arid	Upper middle	0.253	0.287							0.720	0.001	9	2
Authoritarian regime	Temperate	Low	0.670					−0.247			0.334	0.060	7	3
Authoritarian regime	Temperate	Lower middle	−1.180		1.165		−0.366	−0.036	−0.459		0.530	0.000	33	5
Hybrid regime	Arid	Lower middle	0.180	−0.223			0.375	0.059			0.831	0.001	8	3
Hybrid regime	Temperate	Low	1.931	−0.407	−0.690		−0.139		−0.326		0.641	0.000	28	4
Hybrid regime	Temperate	Lower middle	1.941		−0.849					−0.168	0.462	0.001	18	3
Flawed democracy	Tropical	Lower middle	0.220						0.164	0.075	0.162	0.039	26	4
Flawed democracy	Arid	Lower middle	1.906	−1.005	−0.828						0.412	0.016	12	2
Flawed democracy	Arid	Upper middle	0.442		0.674				−2.425		0.341	0.032	12	2
Flawed democracy	Temperate	Lower middle	1.107		−0.320				−0.487		0.688	0.000	26	4
Flawed democracy	Temperate	Upper middle	0.601			−1.188					0.155	0.005	42	6
Flawed democracy	Temperate	High	0.550	−0.988							0.097	0.158	11	2
Flawed democracy	Cold	Upper middle	2.857	0.262	−1.679				1.205	−0.242	0.665	0.004	10	3
Full democracy	Temperate	High	−0.022	0.159	0.113			0.106	−0.097		0.119	0.006	83	15
Full democracy	Cold	High	1.546		0.421	−9.533		−0.381			0.378	0.000	57	10

[a] The Economist (2009).
[b] Kottek et al. (2006).
[c] The World Bank (2009).

Table 3B
Models of adaptive capacity for maize.

Governance[a]	Agro environment[b]	Income level[c]	Intercept	Cropland/cap	Rural Pop	Gini	Safe Water	Fertiliser	Agr GDP/cropland	GDP/cap	Adjusted R^2	*p*-value	DF	N of countries
Authoritarian regime	Tropical	Low	−0.613		0.411	1.456			−0.292		0.296	0.000	81	12
Authoritarian regime	Arid	Low	8.100	1.322	−3.984			−0.081	−2.363	1.126	0.610	0.000	29	6
Authoritarian regime	Arid	Lower middle	0.855			−4.916	0.183	0.108	−0.317		0.318	0.000	52	9
Authoritarian regime	Arid	Upper middle	0.262	0.249							0.015	0.306	10	2
Authoritarian regime	Temperate	Low	0.832						−2.339		0.146	0.098	12	3
Authoritarian regime	Temperate	Lower middle	−0.234		0.334	2.423	−0.227	−0.054		−0.219	0.497	0.000	32	5
Hybrid regime	Tropical	Low	0.043				0.081		0.316	0.129	0.161	0.001	74	10
Hybrid regime	Tropical	Lower middle	0.503		0.323		−0.313	−0.242			0.274	0.033	18	3
Hybrid regime	Arid	Low	4.229	3.956	−2.836	−8.439	1.290	−0.450	3.926		0.239	0.085	18	3
Hybrid regime	Arid	Lower middle	−0.478			1.312	0.554		0.761		0.376	0.004	22	3
Hybrid regime	Temperate	Low	0.852				−0.205	−0.140		−0.304	0.363	0.003	24	4
Hybrid regime	Temperate	Lower middle	1.067		−0.410		0.077				0.710	0.000	18	3
Flawed democracy	Tropical	Lower middle	0.167	0.305				0.065			0.154	0.009	45	10
Flawed democracy	Tropical	Upper middle	1.390		−0.143	2.529		−0.197			0.421	0.001	26	5
Flawed democracy	Arid	Upper middle	0.846					−0.386			0.141	0.076	15	2
Flawed democracy	Temperate	Lower middle	0.591			2.627		−0.428			0.268	0.072	11	4
Flawed democracy	Temperate	Upper middle	−0.630	1.262	0.429	0.895			0.202		0.471	0.000	38	6
Flawed democracy	Temperate	High	−5.442	−2.870	2.429		14.205			2.090	0.638	0.014	8	2
Full democracy	Tropical	Upper middle	−1.464			7.560	0.269			0.602	0.621	0.001	13	2
Full democracy	Temperate	High	−0.160	0.374	0.174			0.074			0.226	0.000	69	12
Full democracy	Cold	High	−0.716					−0.281	0.369		0.317	0.018	16	4

[a] The Economist (2009).
[b] Kottek et al. (2006).
[c] The World Bank (2009).

that are, in the future, likely to be exposed to climate change. However, it has proven challenging to capture the socio-economic context in which a climate change event occurs into these models. The chapter on agriculture and food in the Fourth Assessment Report of the Intergovernmental Panel on Climate Change highlights this challenge in that it provides a sophisticated review of the way crops respond to changing moisture, carbon dioxide fertilization, and temperature (Easterling et al., 2007). The chapter also provides a brief review of adaptive capacity but while it argues that the social context of farming is very important, the conclusions of the chapter focus almost entirely on the ways crops respond to climate. As a result, our study provides a methodological template that demonstrates one way of integrating biological and socio-economic processes into a single integrated assessment of how cereal crops may be vulnerable to droughts in the future.

Acknowledgements

This work was supported by a grant from the Natural Environment Research Council (NERC), under the QUEST program (grant # NE/E001890/1), the Economics and Social Research Council, under the Centre for Climate Change Economics and Policy, through support from the Canada Research Chair program and through a Rural Economy and Land Use Fellowship. The climate change scenarios that were used as input to Mac-PDM.09 were created using ClimGen, which was developed by Tim Osborn at the Climatic Research Unit (CRU) at the University of East Anglia (UEA), UK. We are grateful for Andy Challinor, Jouni Paavola (University of Leeds), and two anonymous reviewers for their thoughtful critiques of this paper and to Marie Puddister from the University of Guelph for helping with the figures.

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