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The socioeconomics of food crop production and climate change vulnerability: a global scale quantitative analysis of how grain crops are sensitive to drought

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Abstract Many studies warn that climate change may undermine global food security. Much work on this topic focuses on modelling crop-weather interactions but these models do not generally account for the ways in which socio-economic factors influence how harvests are affected by weather. To address this gap, this paper uses a quantitative harvest vulnerability index based on annual soil moisture and grain production data as the dependent variable in a Linear Mixed Effects model with national scale socio-economic data as independent variables for the period 1990–2005. Results show that rice, wheat and maize production in middle income countries were especially vulnerable to droughts. By contrast, harvests in countries with higher investments in agriculture (e.g. higher amounts of fertilizer use) were less vulnerable to drought. In terms of differences between the world's major grain crops, factors that made rice and wheat crops vulnerable to drought were quite consistent, while those of maize crops varied considerably depending on the type of region. This is likely due to the fact that maize is produced under very different conditions worldwide. One recommendation for reducing drought vulnerability risks is coordinated

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development and adaptation policies, including institutional support that enables farmers to take proactive action.

Keywords Drought vulnerability index · Crop failure · Soil moisture · Food security · Transition economies · Linear model · Adaptive capacity

Introduction

According to a range of policy and scientific figures, global food security is challenged by many factors including population growth, water scarcity, increased demand for livestock products and high energy costs, as well as climate change. These challenges represent a "perfect storm" of problems (Beddington 2009) which can be expected to trigger public unrest and international conflict unless food production is boosted by approximately 70% by 2050 (UK Government 2011). Of particular concern on a global scale is the effect that climate change may have. While estimates vary, most crop and climate modellers agree that climate change will reduce global cereal production due to a combination of heat and water stress caused by higher temperatures and longer droughts.

While these projections suggest that farmers will face significant environmental constraints, much can be learnt from the way that large-scale droughts affected harvests in the recent past (Mishra and Singh 2010). In particular, a large body of work demonstrates how the socio-economic context of farming can have huge effects on farmers' capacity to maintain harvests in years with climatic stress (IPCC 2007; Ericksen et al. 2011). For instance, Fraser (2007) showed that social, institutional and agro-ecological factors can make food systems vulnerable to even small droughts. Similarly, other studies specifically demonstrate how institutional factors can promote or undermine farming systems that are resilient to environmental challenges (Devereux 2009; Fraser and Stringer 2009). For example, the work of Patt and Gwata (2002) showed that when farmers in rural Africa attended workshops with weather forecasters they were better able to maintain harvests during droughts than farmers who had not been to these workshops.

There is a challenge, however, in that most of the research that has explored how socio-economic factors help (or inhibit) whether farmers can adapt to droughts tends to be small scale, authored by social scientists, and qualitative. This contrasts with the large scale, usually quantitative and natural science based modelling work that shows global food security is threatened (e.g. Foley et al. 2011). As a result, a range of scientists are trying to bridge the gap between the natural-science dominated work on the impact of climate change on crop growth, and the social-science dominated work that looks at socio-economic barriers to farmer adaptation.

This interdisciplinary research agenda is illustrated by a recent study published by Challinor et al. (2010) where a crop model was used to simulate the effect of climate change on north east China's wheat production under different adaptation scenarios. Under "no adaptation", climate change was projected to cause between 20 and 30% of the wheat crops to "fail" over the 21st century. However, when the socio-economic parameters of the model were changed to simulate different farm management scenarios, they discovered that the effect of climate change dropped dramatically. This exercise was an important step towards more insightful inclusions of socio-economic conditions in larger-scale crop-modelling. However, much remains unknown about what socio-economic conditions might lead to different harvest outcomes.

The need for more quantitative analysis on the contextual factors that make harvests vulnerable to climate change is also demonstrated by recent studies that use a mixture of socio-economic and environmental variables to "map vulnerability", thereby attempting to identify where food production (or other aspects of food security and sustainable livelihoods) is vulnerable to climate change. A brief sample of this body of work includes Pandey et al. (2011) who built an adaptive capacity index using a series of socio-economic variables to evaluate water resource system vulnerability in Nepal. Gbetibouo and Ringler (2009) developed a sub-national vulnerability framework to explore climate vulnerability in South Africa. The report of Ericksen et al. (2011) is probably the most ambitious of these studies: this team of researchers used a large number of data sets and a huge range of indicators to present a number of vulnerability maps for the global tropics. In each of the studies just cited, factors such as GDP, rural population density and access to water were included in vulnerability assessments. However, in each of these pieces of research, the relation between these variables and vulnerability is assumed to be constant regardless of the social, ecological or political contexts.

The purpose of this paper, therefore, is to help contribute to our understanding of how socio-economic factors and climatic conditions interact to create vulnerability. In particular, we analyse global data sets to identify what socio-economic factors are significant in making cereal crop production vulnerable to drought. Ultimately, our goal is to provide preliminary answers to three questions: (1) Where in the globe is cereal production most vulnerable to drought? (2) What are some of the underlying socio-economic conditions that make harvests vulnerable to drought? (3) What implications might these results have for policies aiming to enhance adaptive capacity in order to ensure food security?

Methods

Background and approach

In terms of our broad methodological approach, our definition of vulnerability builds on work by Fraser (2007) and Fraser et al. (2011), which proposes that the vulnerability of an agricultural system to adverse weather can be observed when relatively small weather anomalies have disproportionately large impacts on crop production. One reason for this may be that underlying socio-economic factors could have inhibited adaptation. Such "vulnerable" cases may be contrasted with situations where large weather anomalies seem to have caused little production loss. In these cases, Fraser et al. (2011) hypothesize that underlying socio-economic factors may have enhanced adaptive strategies, therefore, buffering harvests from the effects of adverse weather. This definition and approach relates to the earlier work of the IPCC (2001) that defines vulnerability as a function of exposure, impact and adaptive capacity but takes a step forward from the IPCC's definition by using data to identify and quantify the way that the socio-economic context of farming may either enhance or reduce adaptive capacity (thereby affecting overall vulnerability).

To operationalize this approach to vulnerability, we began by using global data sets to (1) identify regions in the world that have been exposed to drought over the past 20 years; (2) identify which of these regions had poor harvests and which had abundant harvests during these droughts; (3) combine step 1 and 2 to quantify vulnerability: where low vulnerability cases are defined as those areas that had good harvests despite having major droughts and high vulnerability cases are those where harvests were low despite there only being minor droughts; (4) use statistical analysis to determine what socio-economic factors were significant in explaining trends in vulnerability.

In conducting these steps, we built on the foundation laid by Brooks et al. (2005) who used statistical methods to identify national indicators of climate vulnerability. However, in this research, we employed a well established methodological framework that has already been used to identify the characteristics of vulnerability in case studies that were on a much smaller scale in Ghana (Antwi-Agyei et al. 2011); Ethiopia (Fraser 2007) and China (Fraser et al. 2008 and Simelton et al. 2009). These studies concluded that farm inputs and variables, representing land, labour or capital, were associated with vulnerability to drought (Fraser et al. 2008; Simelton et al. 2009).

For the purpose of the current paper, two further methodological advances have been made to this body of work. First, the drought index is based on soil moisture instead of rainfall to account for the capacity of soils to buffer variation in rainfall. Secondly, linear mixed-effects models are used to describe crop-drought vulnerability on a national scale as a function of specific socio-economic conditions. In our opinion, this is a considerable advance as it accounts for different agro-ecological zones, types of governance and income levels. While analyses at this scale are by necessity crude, this work provides important steps towards understanding how combined socio-economic and environmental changes influence food production.

The paper proceeds by first outlining the available data (Background and approach), then justifying the methods and describing the methodological steps undertaken to derive the vulnerability index (Data and data preparation) and then outlines the data analysis procedures (Method for calculating the vulnerability index).

Data and data preparation

Soil moisture data

In the hydrological literature, there are dozens of indices proposed for estimating drought (e.g. Mishra and Singh 2010). For this study, the choice of a drought index was governed by our need for data that was global, country scale, and had annual resolution. Furthermore, while published hydrological and vulnerability studies in the past often use rainfall data (e.g. Fraser et al. 2008; Simelton et al. 2009; Lobell and Field 2007), it was decided that for this study, soil moisture would be more appropriate as it accounts for rainfall, soil moisture storage and to some extent temperature (Mishra and Singh 2010).

Monthly soil moisture data was obtained from an established global hydrological model, Mac-PDM.09 (Arnell 1999; Gosling and Arnell 2011; Gosling et al. 2010). Mac-PDM.09 was driven with $0.5°\times0.5°$gridded monthly CRU TS3 meteorological inputs for the period 1989/90 to 2004/05. A gridded map of the earth's landmass was used to select only those grid cells that had >1% of the land base devoted to producing rice, wheat or corn (Leff et al. 2004). At first, a 10%-limit was used but this resulted in many countries appearing with no agricultural land. The 1%-limit thus represents both intensively cultivated regions and more extensively cultivated areas.

For each selected grid cell, the soil moisture was accumulated for a growing period from October of one year through to October the following year. These gridded time-series were then averaged to one national time-series (see Drought Index below) to match the national level harvest data. The selection of the October to October period is crude but was deliberately chosen for three reasons. First, results from Lobell and Field (2007) demonstrate that empirical/statistical model results were insensitive to choice of growing season months. More specifically, Lobell and Field ultimately defined a `global growing season' for each crop based on the continuous months within the growing seasons for the major growing regions, using the same landuse data as was used in our study (Leff et al. 2004). Furthermore, we tested a number of different combinations of months to calculate soil moisture but found that this had little effect on the overall results (thus confirming Lobell and Fields' work that showed their results were insensitive to the selection of growing season months). Secondly, there is a significant disagreement in the literature on the most relevant time period for assessing drought with different studies recommending different lengths of drought-periods. For example, soil moisture fluctuates so much in tropical areas that droughts may emerge and dissipate in less than six months, while droughts may take over twelve months to emerge in parts of semi-arid Sub-Saharan Africa and in high northern latitudes (Erigayama et al. 2009). Third, working with national annual harvest data makes it impossible to account for double cropping, hence, the period October to October was chosen to represent a uniform growing season that captures both northern and southern growing seasons in one calculation and to ensure that only the long lasting droughts were captured (hence our approach was conservative from a methodological perspective).

With regards to the use of simulated versus observed soil moisture, while there are a number of regional datasets of observed soil moisture (e.g. Hollinger and Isard 1994), there is no spatially coherent global observation database of soil moisture that covers a long (several years) historic period at annual or monthly resolution. Although monitoring from satellites allows for large spatial coverage, data collected in this way only captures soil water storage that is limited to the uppermost soil layer and to areas free of dense vegetation cover (Wagner et al. 2003). It is often argued that these limitations have hampered efforts to improve physical representation of soil moisture in global hydrological models (Nijssen et al. 2001). To this end, we used soil moisture simulations from a global hydrological model and must note that these results have not been validated. However, the hydrological response of the model has been validated and it has been shown that it simulates well the global pattern of runoff (Gosling and Arnell 2011). Moreover, a recent global hydrological model intercomparison exercise (Haddeland et al. 2011) showed that the model applied here performs as well as other global hydrological models in terms of simulating runoff, snowfall, and potential evapotranspiration at the global scale (the analysis did not cover soil moisture). Therefore, while lack of data availability has precluded validation of simulated soil moisture, the model does simulate the global hydrological cycle robustly. So, and in common with other recent assessments that have required soil moisture data for exploring droughts at the global scale, this analysis applied soil moisture from a global hydrological model (Corzo Perez et al. 2011; Sheffield et al. 2009).

Crop production data

National level crop production data was obtained for rice, wheat and maize harvests from the United Nations Food and Agriculture Organization's FAOSTAT online database (FAO 2008) for each year between 1986 and 2005.

Socio-economic data

To analyse the socio-economic factors that explain drought impacts on harvests the following data were used:

(1) To test hypotheses that access to farm inputs explains trends in harvest vulnerability, national socio-economic data was downloaded from a number of online databases (EarthTrends 2008; FAO 2008; The World Bank Group 2008). Six continuous variables were selected to represent access to land, labour, and capital based farm inputs (see Table 1). As crop specific annual irrigation data are not available we did not include this variable. Similarly, incomplete time series and comparatively slow-moving indicators were excluded, such as education, Gini-coefficient, and investment in agricultural research.

(2) Each country was grouped based on its average income, type of governance and key agro-environmental zone. Each of these three indicators has four levels. The income groupings follow the World Bank's classification of average GDP per capita in 2008: low income, lower middle income, upper middle, or high income (World Bank 2009). Governance categories were taken from the Economist Intelligence Unit's 2008 assessment that divides countries into authoritarian regimes, hybrid regimes, flawed democracies or full democracies (The Economist 2009). Finally, countries were categorized as belonging to one of Köppen's climate zones (Kottek et al. 2006) based on whether the largest share of the cropland area fell into tropical, arid, temperate or cold climate conditions. (Note: the choice of using the Köppen classification system was deliberate because this classification is still used as a basis for spatial aggregation in hydrological modelling (e.g. Haddeland et al. 2011) and observation studies (e.g. McMahon et al. 2007). As the simulated global soil moisture data in our analysis was from a global hydrological model, we decided to use the same baseline data that is most common in this field of scholarship.)

Table 1 Explanatory variables used in the linear mixed-effects models for vulnerability to drought

Type of indicator	Data	Unit	Source	Proxy for
Discrete variables	Governance *Authoritarian regimes (A), Hybrid regimes (B), Flawed democracies (C), Full Democracies (D)*	n/a	Economist Intelligence Unit 2008[a]	Governance style
	Agroenvironment *Tropical (A), Dry (B), Temperate (C), Cold (D)*	n/a	Köppen[b]	Climatic suitability, associated meteorological disturbance, agro-environment
	Income level *Low Income (A), Lower Middle Income (B), Upper Middle Income (C), High Income (D)*	n/a	World Bank[c]	Stage in economic development
Continuous population/ labour variables	Population density per ha permanent cropland	People/ha	Earth Trends[d], FAOSTAT[e]	Population pressure; domestic demand
	Rural population	%	Earth Trends[d]	Potential available rural labour
Continuous land variables	Permanent cropland per capita	Ha/per capita	FAOSTAT[e]	Land use intensity
	Cereal intensity *Cereal area/harvested area*	Area of rice, wheat and maize of total harvested area	FAOSTAT[e]	Importance of cereal crops of agricultural production
Continuous economic variables	Fertiliser intensity	Hg/ha	FAOSTAT[e]	Degree of technical development, access to agricultural inputs
	GDP in agriculture	US$/capita	World Development Indicators[f]	Potential investments in agriculture, importance of agriculture

[a] The Economist 2009, [b] Kottek et al. 2006, [c] World Bank 2009, [d] EarthTrends 2008, [e] FAO 2008, [f] The World Bank Group 2008

Data quality and data preparation

The lack of complete high quality socio-economic time-series data is well acknowledged in the literature. The United Nations databases are the only ones available that have time-series data of agricultural and socio-economic indicators. However, data quality varies as countries may use different approaches for compiling and reporting data (Hafner 2003; Rudel et al. 2009). These limitations influenced the selection of variables. For instance, only data from the past 16 years was used because the data quality for many developing countries is assumed to have improved over time, and with many new states emerging around 1990 this period marks a new era. Hence, analysing older data may not contribute further to the understanding of current vulnerability. However, the number of meteorological stations included in the CRU-data set declined after the 1980s, which is a particular limitation for analysis of sub-Saharan Africa where stations are already sparsely distributed (Conway et al. 2009). In addition, the investigated period is limited to years before 2005 due to available climate data (for more details see "Explaining the vulnerability of crops to drought").

Even by restricting the analysis to 16 years, datasets still had occasional missing values. These were replaced using spline interpolation procedure in R statistical software, whereby a locally weighted regression produces a smooth shape in the vicinity of the missing data and the missing value is estimated from this function (Crawley 2007). Data points that were missing from either the beginning or end of the time series were replaced by linear back-/forecasted values when fewer than four years were missing and no more than one extrapolated data point exceeded the observed data range.

All variables were log-transformed to reduce heteroscedasticy and the influence of extreme values.

Method for calculating the vulnerability index

To bring these data together and evaluate how different socio-economic factors affect the vulnerability of cereal crops to drought, we followed an approach developed previously to analyse the relationship between food security and drought (Fraser 2007; Fraser et al. 2008; Simelton et al. 2009). Briefly, this work defines climate vulnerability as arising when food production, is (1) exposed to changing climatic conditions; (2) limited in its ability to adapt to these conditions; and (3) sensitive to these changes (IPCC 2001). Building on this approach, the study presented here conceptualises vulnerability in terms of "exposure to climatic events", measured in this paper as drought severity (the Drought Index, DI), versus the "impact of the drought", measured in terms of crop production losses (the Crop Failure Index, CFI). Cases where relatively severe droughts are not associated with significant crop losses are considered less sensitive to the drought and cases where minor droughts are associated with major crop losses are considered more sensitive to drought. Taken together, the impact of a drought relative to the severity of the drought becomes the "vulnerability index". We hypothesise that different levels of vulnerability may be due to the underlying socio-economic conditions in a specific region, as these conditions may influence farmers' and institutions' ability to respond to the drought. Therefore, the crop-specific vulnerability index (VI) is defined as a crop failure index (CFI) divided by a drought index (DI), and was calculated for each country in each year, i (eq 1):

$$VI_i = \frac{CFI_i}{DI_i} = \frac{\left(\frac{\widehat{H}_i}{H_i}\right)}{\left(\frac{\widehat{SMC}_i}{SMC_i}\right)} \tag{1}$$

(1) The crop failure index (CFI) was calculated in two steps. First, the crop production time series for each country were smoothed using a fourth order auto-regression model (Schneider and Neumaier 2001; Simelton et al. 2009). For a few countries with limited data, three year-lags were used to increase the number of data-points included in the analysis. As four years (1986–1989) are lost to the smoothing procedures the remaining period 1990–2005 refers to the effective dataset. This procedure for de-trending was done to take away the technical increase in yields, and the reason for choosing 4 lags rather than linear de-trending was based on our previous work on China that showed harvests underwent stepwise rather than linear change. Third or fourth order auto-regression modelling thus gives a smoother de-trending and captures cases where trends are both linear and nonlinear. This process, therefore, provides an estimation of, all other things being held constant, what sort of harvest a region could reasonably expect. This is the same approach that was used in previously published studies including those by Antwi-Agyei et al. (2011); Fraser et al. (2008), Fraser (2007) and Simelton et al. (2009). In total, this meant that the harvest data covered 102 rice producing countries, 112 wheat producing countries, and 127 maize producing countries. This smoothed harvest time-series produced an estimate of the "expected" value of the harvest, $\widehat{H}$, taking into account multi-year temporal trends. Second, for each country and for each crop, the smoothed harvests, $\widehat{H}$, were divided by the actual harvest, H. This means that a CFI of 1 refers to a year in which the actual harvest was the same as expected, or the harvest was "normal". Higher CFIs indicate degrees of crop failure.

(2) The drought index (DI) was computed in a similar manner as the CFI. First, soil moisture content, SMC, was estimated as the country mean for October-October soil moisture of all the grid cells in a given country that had been identified as cultivating more than 1% of the particular crop (see section on soil moisture for details). This, therefore, resulted in different SMC values for rice, maize and wheat as each of these crops has different spatial distribution in each country. Second, soil moisture data was detrended using a linear regression model (i.e. the long-term mean). Third, for each country and each year, the smoothed soil moisture, $\widehat{SMC}$, was divided by the actual soil moisture, SMC. This created a drought index (DI) where a year with "normal soil moisture" has a DI of 1, and the higher the DI, the lower the soil moisture for each crop.

(3) The vulnerability index (VI, Eq. 1) was constructed by dividing the CFI by the DI so that higher the VI value, the higher the vulnerability to drought.

Explaining the vulnerability of crops to drought

To determine if socio-economic factors influenced the vulnerability of each of the three crops' harvests to drought, only those years when the cumulative October - October soil moisture was below average were selected for this analysis (i.e. when DI>1).

For each crop, a separate Linear Mixed Effects Model (LME) was designed with the log-transformed vulnerability index (VI, Eq. 1) as the dependent variable. The model variables included the fixed effects: population density, rural population, fertiliser, GDP in agriculture, cropland per capita, cereal intensity, agro-environment (tropical, arid, temperate, cold), income (low, lower middle, upper middle, high) and governance (autocratic regime, hybrid regime, flawed democracy, full democracy). 'Country' was included as a random effect to take into account random differences between countries on the overall intercept. The model was fitted with all fixed effects and up to two-way interactions. Model simplification was undertaken by comparing models (fitted using maximum likelihood) with and without the terms using Likelihood Ratio Tests. In this, we removed insignificant interactions and main effects until all remaining terms (or their marginal interaction effects) were significant.

Factor levels were merged when the coefficients for both were non-significant and had similar effects on interactions and the intercept. To obtain estimates of coefficients, the minimal adequate model was then fitted using the restricted maximum likelihood (REML) method. The contrast coefficients for each factor and group interactions add up to zero. The models were tested for heteroscedasticy. Autocorrelation in residuals was not considered a problem as only the years with DI>1 were used, hence the time series are incomplete. ‘Year’ was included as a factor but was non-significant for each of the crops. Statistical analyses and mapping were carried out in R using the “LME” and “rworld-map” packages.

Limitations of the study

Global-scale analyses, such as that conducted here, are inevitably undertaken within the constraints and limitations of available global climate, agricultural and socio-economic data. These data pose serious challenges on the nature of the analysis and the robustness of the results. Nevertheless, while these limitations must be acknowledged, this type of work is still worth undertaking. Other academics seem similarly inspired to use existing datasets and see what can be learned from them (e.g. see Nelson et al. 2010 and Hazell and Wood 2007). This is particularly an issue when dealing with data from developing countries. For example, sometimes there are gaps in the climate time series, or the time series may be short in length. To some extent, the Regional Workshop Programme run by the WMO Global Climate Observing System (GCOS) is seeking to address this for climate data. However, this should not preclude any type of analysis that requires data at the global-scale. As a result, in our analysis, we consistently used the highest quality data that was available. For instance, in terms of climate data, we applied the CRU-TS3 gridded observational dataset. This has been widely used in previous climate-impact assessments (Xu et al. 2010; Gosling and Arnell 2011; Thorne 2011). However, we do acknowledge that the relationships we define are contingent upon the reliability of the data.

In addition to the general issue posed by data quality, there are three specific limitations of this study.

1. This study only accounts for one single stressor, drought, without considering other factors that might affect yield such as heat or cold spells. After careful consideration of a range of options, it was decided that soil moisture would be the most appropriate metric for the crops that are considered in our study. While extra hydrometeorological variables could have been included (e.g. precipitation, temperature, relative humidity), this would have likely resulted in severe model over-parameterisation. Moreover, the soil moisture was from a global hydrological model that had been forced with climate data that included temperature, precipitation, wind speed, and relative humidity. To this end, several of the explanatory hydrometeorological variables that could have been included separately, are in fact inherently considered through the application of simulated soil moisture, which itself was used for computation of the drought index.
2. The omission of irrigation in this study is unfortunate but unavoidable because global scale irrigation data are limited in terms of seasonal availability of irrigation, what crop was irrigated and quality of data (See Siebert et al. 2005; Thenkabail et al. 2008). In most cases, there are no annual time-series data on irrigation, hence there is no way of knowing what share of the harvest gain/loss was due to irrigation. Moreover, 80% of the world’s irrigated areas are found in a few countries in Asia where relatively few data are available (Thenkabail et al. 2008).
3. The spatial scale of this analysis means that many contextual factors that influence vulnerability cannot be covered. Data aggregated at national level do not capture the variability at sub-national scales. The crop failure index is likely to be biased towards the more productive regions of a country, while the drought index is based on the location of meteorological stations and the explaining socioeconomic variables represent the whole country. The compatibility of the three scales therefore vary by country. Furthermore, only finer scale sub-national studies can identify what regions contribute to national food insecurity in the event of droughts (Antwi-Agyei et al. 2011; Conway and Schipper 2011; Simelton et al. 2009), and the role of temporal lag effects of adaptive measures. While it is argued that a diversity of adaptation strategies is going to make people less vulnerable to climate change, finer resolution contextual studies are needed to identify those strategies (Fazey et al. 2010). The six variables used in this study, therefore, can only be seen as proxies of different effects in different contexts.

Results

First, we report on the geographical distribution of vulnerability to drought and show what types of countries are more vulnerable and where they are located. Second, the LME models of vulnerability to drought for rice, wheat and maize are presented.

Geographic distribution of vulnerability to drought by crop, income, governance and agro-environmental group

The average vulnerability index during years with below normal rainfall and during the growing season for rice, wheat and maize are shown in Fig. 1a–c. These maps point out a couple of possible regions of particular concern for global food production: southern, eastern and northwest Africa and some former Soviet Union-states along the borders of Europe and central Asia.

In terms of the characteristics of different countries with different levels of vulnerability, the following results stand out (see Fig. 2 for additional details):

1. In terms of climate, tropical agro-environments had the lowest mean vulnerability index across all three crops. The most vulnerable crops were rice and wheat in cold countries and maize in arid agro-environments. The high standard deviation of the vulnerability index for arid zones suggests great variation between years and countries within this group.
2. For governance, countries with authoritarian and flawed regimes had the overall highest average vulnerability.
3. For income levels, the two middle income groups were the most vulnerable.

In terms of crop-specific results, the following observations stand out:

1. In terms of vulnerability of rice production to drought, authoritarian and cold agro-environments had the highest mean vulnerability score while hybrid regimes and low income countries had the lowest mean vulnerability.
2. For wheat production, flawed democracies and cold agro-environments had the highest mean vulnerability to drought, while low income countries had the lowest vulnerability.
3. For maize production, flawed democracies and lower and upper middle income countries had the highest mean vulnerability to drought, while tropical agro-environments and full democracies had the lowest vulnerability score.

More details on the interactions between variables and the significance of different variables are available in supplementary Table 1 and supplementary Figure 1.

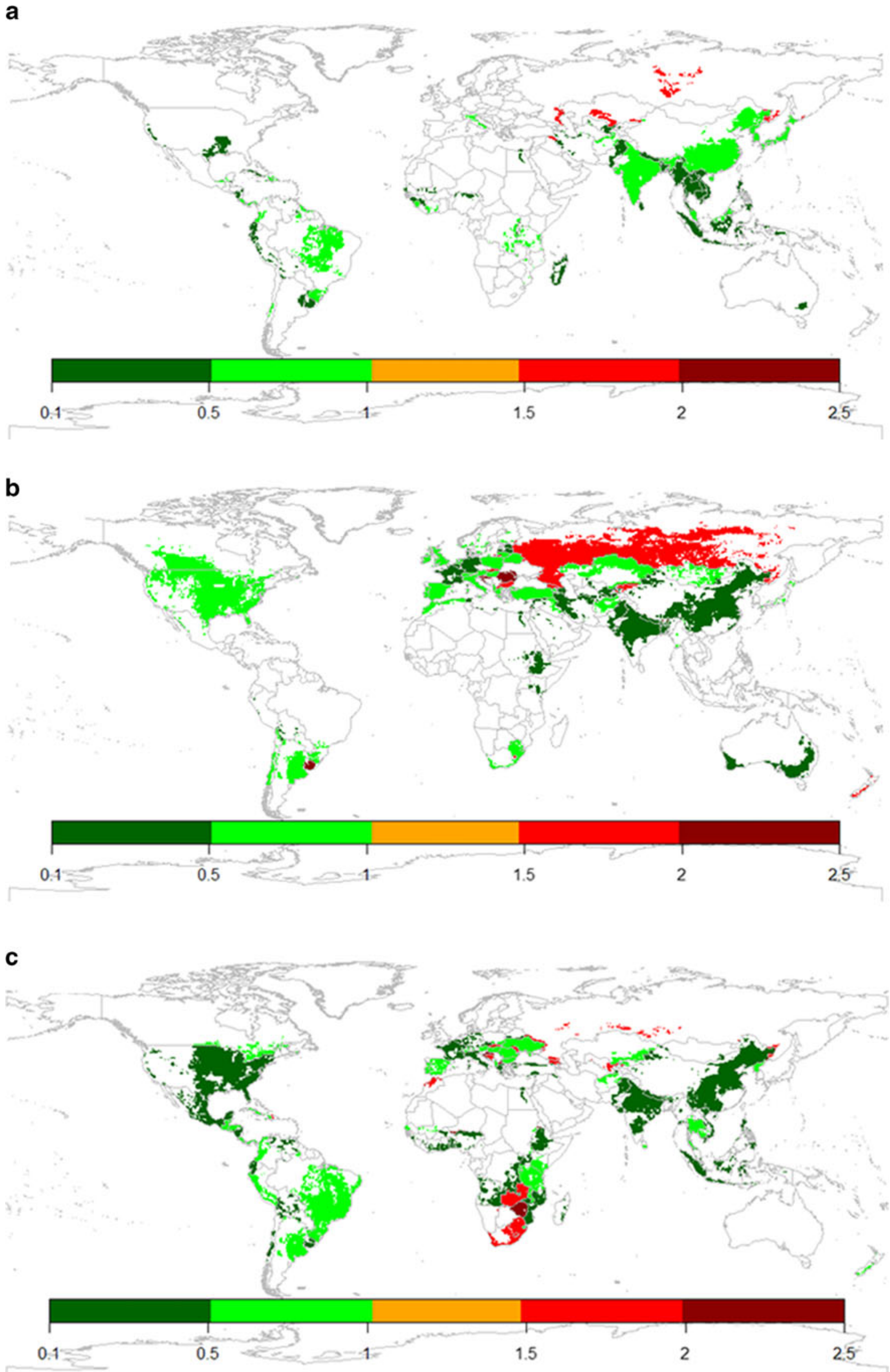
Linear mixed-effects models of vulnerability to drought for rice, wheat and maize production

Table 2 shows the detailed coefficients for the linear mixed-effects models with interactions between variables in the two right hand columns. The Supplementary Table 1 summarises the overall significant effects of the linear mixed-effects models. In particular, the following socio-economic factors were identified as significant in explaining trends in rice, wheat and maize harvest vulnerability to drought:

1. For rice, the overall effect of the amount of GDP generated by a country's agricultural sector and the agroenvironment were both significant in reducing vulnerability to drought (Table 2a). The way that agroenvironment affected vulnerability varied with the intensity of cereal cultivation, i.e. the share of cereal crops of the total harvested area. Although drought vulnerability of rice was highest in cold climates, cereal intensity had a significant effect on reducing vulnerability to drought in cold countries. As expected, drought vulnerability was lowest in the tropics where the effect of cereal intensity on vulnerability was negligible (these interactions are indicated in the bottom rows and last column of Table 2a).
2. For wheat production, the amount of GDP generated by a country's agricultural sector was significant in reducing vulnerability to drought. The exact nature of this effect, however, depended on the government type and agro-ecological zone. Autocratic regimes had the highest vulnerability, while GDP significantly reduced vulnerability in these countries and in arid countries (Table 2b).
3. For maize production, a large number of significant effects and interactions were observed, including fertiliser use, GDP in agriculture, the size of rural population, intensity of cereal cultivation and governance. Maize harvests were most vulnerable to drought in in flawed democracies and in low income countries. In flawed democracies, cereal intensity was associated with a signficant reduction in vulnerability. In low income countries, GDP reduced vulnerability while in hybrid regimes, GDP increased vulnerability and rural populations reduced vulnerability (Table 2c).

Governance interaction effects with GDP in agriculture were complex in the case of maize. For example, Fig. 3 demonstrates that, if all other variables are kept constant, an increase in GDP from agriculture typically results in reduced vulnerability (main effect). Furthermore, in flawed and full democracies, vulnerability starts at a higher level with the steepest slope of reduced vulnerability in full democracies. For flawed democracies and autocratic regimes, there is no significant difference from the overall mean relationship with GDP. Vulnerability in hybrid regimes, in contrast, starts at lower levels but show a significant increase with increasing GDP in agriculture. The situation was less complex for rice as governance style was insignificant for drought vulnerability outcomes. For wheat, high drought vulnerability in autocratic regimes was reduced through GDP (for wheat and rice see Table 2a and b).

Fig. 1 Mean vulnerability to drought 1990–2005 for **a** rice, **b** wheat, and **c** maize production. Vulnerability to drought is low (*high*) when crop failures are small (*big*) despite a major (*minor*) drought, indicated by colours from green to red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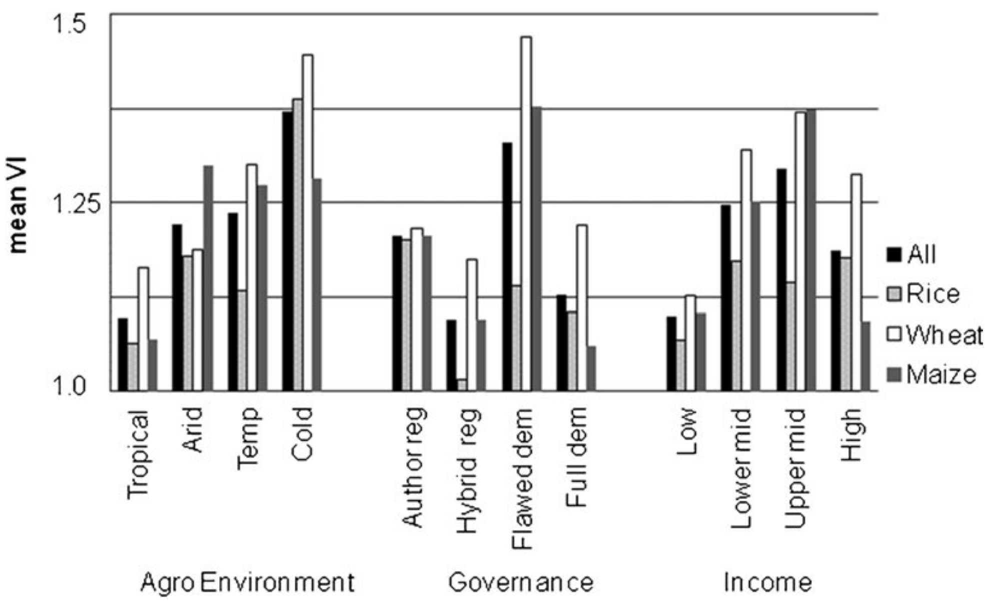

Fig. 2 Mean vulnerability to drought (VI) for all three crops together and separately, by (1) agro-environment, (2) governance and (3) income level groupings. For mean values, significant differences between groups and total number see supplementary table 1 and for box plot distributions for this graph see supplementary figure 1

In summary, average vulnerability to drought increased progressively by latitude, from tropical, arid, temperate to cold; peaked in middle income countries and in flawed democracies. For maize in particular, GDP in agriculture in combination with other factors, was significantly associated with vulnerability to drought in both low income countries (where GDP generally reduces vulnerability) and hybrid regimes (where it increases vulnerability).

Discussion

This paper provides partial answers to three empirical questions: (1) Where in the globe is cereal production most vulnerable to drought? (2) What are some of the underlying socio-economic conditions that contribute to harvest vulnerability to drought? (3) What implications might these results have for policies aiming to enhance adaptive capacity in order to ensure food security?

Where is cereal production most vulnerable to drought?

Average vulnerability to drought was comparatively high in key wheat and maize producing regions, e.g. Central Asia and Southern Africa (Fig. 1a–c) and comparatively low in tropical agro-environments, in countries with low income levels, and in hybrid regimes (such as Cambodia, Guatemala and Ghana). The low vulnerability in the tropics may be related to ample water supply. In contrast, the highest mean vulnerability to drought is found in cold agro-environments, middle income level countries, and flawed democracies such as the Ukraine and Moldova where droughts, sometimes in combination with cold spells, are well documented, (e.g. USDA 2004) and where vulnerability may have been exacerbated by the collapse of the Soviet Union that destroyed many agricultural institutions (FAO 2003; Ohno 2009). The high vulnerability of cold countries may also be due to the fact that grain cultivation in higher latitudes is closer to the ecological margins tolerated by these crops. In addition, high latitude countries have predominantly rainfed agriculture while key grain cultivation areas in regions at low latitudes are typically irrigated (OECD-FAO 2009; Siebert et al. 2005). For example, Asia has nearly 80% of the world's irrigated areas, and this is dominated by China (33%, a key area is North China Plain) and India (28%, in particular northern and west central parts), while Southeast and Central Asian countries have smaller shares (1–3% each), especially Pakistan, Russia, Thailand, Bangladesh, Kazakhstan, Myanmar, Uzbekistan and Viet Nam (see: Thenkabail et al. 2008, p 32). However, this type of irrigation map does not separate irrigation supply into seasonality or specify by crop nor does it reflect the actual access to water. For example, in the case of China, the impacts of irrigation and droughts vary with provinces and depend more on investments and institutional arrangements (Simelton et al. 2009; Simelton 2011). Nevertheless, it indicates regions where irrigation overlaps with some of the low vulnerability areas shown in this study and suggests regions where vulnerability to drought could be lower than our maps indicate.

What are some of the underlying socio-economic conditions that contribute to harvest vulnerability to drought?

Overall, our results show that high levels of GDP in agriculture (rice, wheat and maize), cereal intensity (rice) and fertiliser use (maize) are associated with lower vulnerability to drought (Table 2). As these may be proxy indicators for

Table 2 Coefficients for linear mixed effects models of vulnerability to drought for a) rice, b) wheat and c) maize production

	Value	Standard Error	DF	t-value	p-value	Overall intercept	Slope modified by interaction
a) Rice							
Intercept	2.614	0.170	525	15.383	<0.001		
GDP in agriculture	−0.054	0.027	525	−1.998	0.046	2.561	
Cereal intensity	−0.220	0.078	525	−2.907	0.004	2.394	
Tropical	−0.426	0.145	81	−2.935	0.004	2.188	
Arid	−0.420	0.151	81	−2.784	0.007	2.194	
Temperate	−0.351	0.148	81	−2.363	0.020	2.263	
Cold	1.197	0.148	81	8.074	<0.001	3.811	
Cereal *tropical	0.224	0.079	525	2.830	0.005		0.004
Cereal*arid	0.211	0.083	525	2.549	0.011		−0.009
Cereal*temperate	0.167	0.081	525	2.059	0.040		−0.053
Cereal*cold	−0.602	0.081	525	−7.427	<0.001		−0.822
b) Wheat							
Intercept	2.278	0.122	563	18.703	<0.001		
GDP in agriculture	−0.065	0.040	563	−1.638	0.102	2.213	
Tropical	−0.404	0.252	89	−1.602	0.113	1.874	
Arid	0.341	0.180	89	1.904	0.060	2.619	
Temperate	0.199	0.153	89	1.298	0.198	2.477	
Cold	−0.136	0.195	89	−0.697		2.142	
Autocratic regimes	0.538	0.204	89	2.638	0.010	2.816	
Hybrid regimes	−0.023	0.240	89	−0.095	0.925	2.255	
Flawed democracies	−0.254	0.195	89	−1.303	0.196	2.024	
Full democracies	−0.261	0.213	89	−1.225		2.017	
GDP*autocratic	−0.164	0.064	563	−2.555	0.011		−0.229
GDP*hybrid	0.007	0.073	563	0.098	0.922		−0.058
GDP*flawed	0.090	0.064	563	1.405	0.161		0.025
GDP*full	0.066	0.067	563	0.988			0.001
GDP*tropical	0.116	0.076	563	1.522	0.129		0.051
GDP*arid	−0.128	0.057	563	−2.250	0.025		−0.193
GDP*temperate	−0.061	0.049	563	−1.240	0.216		−0.126
GDP*cold	0.073	0.061	563	1.200			0.008
c) Maize							
Intercept	2.376	0.242	600	9.838	<0.001		
Fertiliser	−0.047	0.017	600	−2.771	0.006	2.329	
GDP in agriculture	−0.108	0.051	600	−2.106	0.036	2.268	
Rural population	0.138	0.074	600	1.868	0.062	2.514	
Cereal intensity	−0.034	0.074	600	−0.455	0.649	2.342	
Autocratic regimes	−0.408	0.292	97	−1.340	0.165	1.968	
Hybrid regimes	−0.617	0.253	97	−2.440	0.016	1.759	
Flawed democracies	0.598	0.228	97	2.626	0.010	2.974	
Full democracies	0.428	0.258	97	1.661		2.804	
Low income	0.808	0.322	97	2.504	0.014	3.184	
Lower middle income	−0.321	0.235	97	−1.365	0.175	2.055	
Upper mid+High inc	−0.487	0.272	97	−1.791		1.889	
Tropical	−0.024	0.112	97	−0.218	0.828	2.352	
Arid	0.452	0.112	97	4.031	<0.001	2.828	
Temperate	0.289	0.116	97	2.478	0.015	2.665	
Cold	−0.717	0.113	97	−6.321	<0.001	1.659	
GDP*autocratic	−0.064	0.092	600	−0.693	0.488		−0.172
GDP*hybrid	0.267	0.097	600	2.757	0.006		0.159
GDP*flawed	−0.021	0.072	600	−0.292	0.770		−0.129
GDP*full	−0.182	0.087	600	−2.086			−0.29

Table 2 (continued)

	Value	Standard Error	DF	t-value	p-value	Overall intercept	Slope modified by interaction
Rural pop*autocratic	0.244	0.150	600	1.632	0.103		0.382
Rural pop*hybrid	−0.299	0.116	600	2.585	0.010		−0.161
Rural pop*flawed	0.074	0.103	600	0.717	0.474		0.212
Rural pop*full dem	−0.019	0.123	600	−0.155			0.119
Cereal*autocratic	0.125	0.092	600	1.352	0.177		0.091
Cereal*hybrid	0.155	0.094	600	1.650	0.099		0.121
Cereal*flawed	−0.324	0.104	600	−3.101	0.002		−0.358
Cereal*full	0.044	0.097	600	0.454			0.01
GDP*low inc	−0.214	0.093	600	−2.300	0.022		−0.322
GDP*lower mid inc	0.015	0.066	600	0.231	0.817		−0.093
GDP*(upper+high inc)	0.199	0.078	600	2.492			0.091
Cereal*low inc	−0.086	0.063	600	−1.367	0.172		−0.12
Cereal*lower mid inc	0.134	0.065	600	2.066	0.039		0.1
Cereal*(upper+high) inc	−0.047	0.064	600	−0.742			−0.081
Cereal*tropical	0.012	0.061	600	0.195	0.845		−0.022
Cereal*arid	−0.271	0.064	600	−4.234	<0.001		−0.305
Cereal*temperate	−0.151	0.066	600	−2.304	0.022		−0.185
Cereal*cold	0.410	0.064	600	6.440	<0.001		0.376

the relative importance of agriculture in a country's economy and the capital resources available to farmers, one interpretation of these results is that financial capital is significant in enhancing adaptive capacity. Many large-scale, high-impact droughts are associated with ENSO and other predictable weather phenomena (Chen et al. 2002; Mishra and Singh 2010). Therefore, investment in seasonal weather forecasting may help farmers prepare for soil moisture deficits (Chen et al. 2002; Patt and Gwata 2002).

The findings also reflect the complexity of maize production, which is grown under very diverse circumstances across the world. For example, our results show that higher levels of GDP in agriculture were associated with reduced maize vulnerability in low income countries but increased vulnerability in hybrid regimes. Moreover, large rural populations are significantly associated with reduced maize vulnerability in hybrid regimes. Several of the countries identified as hybrid regimes underwent structural

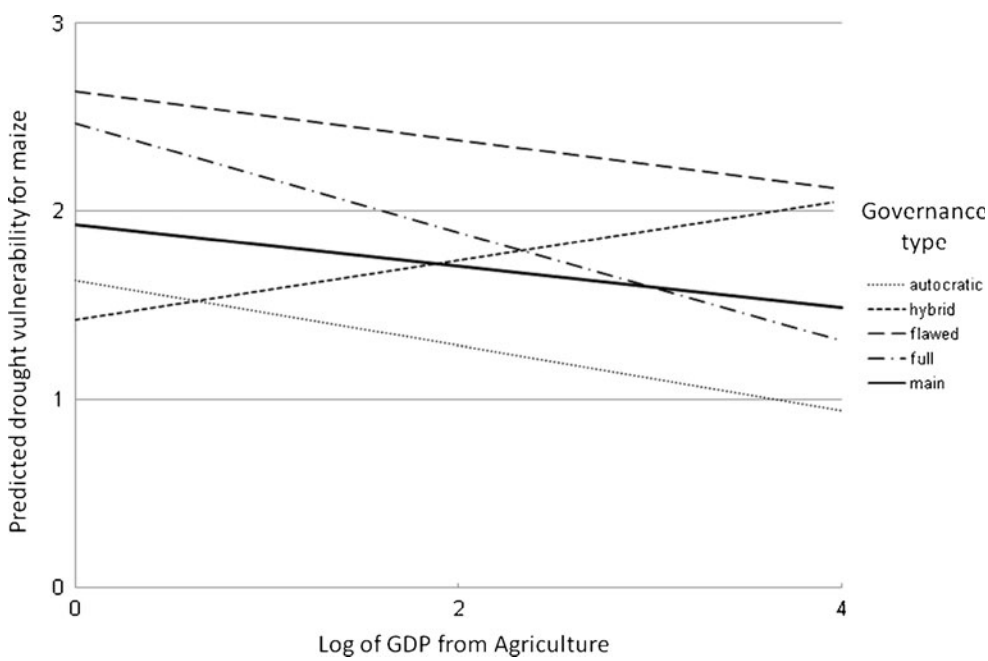

Fig. 3 Main effect and interaction effects of GDP from agriculture on vulnerability to drought for maize production when all other variables are kept constant

adjustment programs and trade liberalization policies in the 1980s that had significant impacts on agriculture, land use, and labour (FAO 2003). These changes may have had the effect of reducing traditional drought coping strategies making harvests more vulnerable to drought. More specifically, it may be that farmers in this category of country still rely on labour-intensive agricultural management but that labour was not available because it had been drawn away to urban or industrial sectors of the economy. Similarly, the high vulnerability observed in middle income countries may be because agricultural modernisation is not yet fully implemented in such regions and this makes it difficult for farmers to adapt to changes in weather alongside other societal changes (see Fraser and Stringer 2009 for an example of this taken from Romanian history).

One of the most striking results of this research is that vulnerability to drought is lower in both rich and poor countries than for the middle income countries. We note similarities to what is referred to as middle-income trap in the macro economic literature (Ohno 2009). In these cases, failures to modernize the agricultural sector to meet new quality standards as the country moves from low to middle income, may impact on drought vulnerability. Similar observations have been indicated in studies that create future food security scenarios (Nelson et al. 2010). From this we hypothesize that the low vulnerability of the poorest countries may be because farmers in these countries are still using traditional farming practices and have well-established adaptation strategies, such as mixing traditional and hybrid seeds (for examples from southern Africa see Stringer et al. 2009). These trends further reflect how the roles of natural, human, social, financial and physical capitals for adaptation shift as farming systems continuosly adapt, and depend on spatial scale (Verchot et al. 2007). For example, the high income countries may have low vulnerability because they may have ample financial reserves with which to adapt, such as by investing in seasonal weather forecasting. The middle income countries, however, may neither have the financial investment nor traditional coping strategies in place. Moreover, many of these countries are undergoing market and trade liberalisation reforms with variable success (Ohno 2009). The generally low vulnerability in China and Viet Nam as compared to large parts of the former Soviet Union may partly be explained by investments in agriculture development and slower institutional changes (FAO 2003). Thus, this study shows one important difference between the role of governance status and income levels: among the transitioning countries, governance (rather than income level) has a key role for avoiding drought vulnerability in states where agriculture plays an important role for GDP as well as domestic food security, i.e. China, India, Viet Nam. Although it is possible to quantitatively derive similarities in drought vulnerability among categories of countries, the discussion also builds on the results from a largely qualitative and case-based body of literature (e.g. see: Fraser et al. 2011).

What implications might these results have for policies aiming to enhance adaptive capacity in order to ensure food security?

In the 1960s, between 5 and 10% of the world's grain producing regions were affected by drought. Since then, this area has more than doubled and today between 15 and 25% of grain fields are suffering from water deficits (Li et al. 2009). Many expect this trend to continue under climate change (Foley et al. 2011) and if this happens, understanding the underlying socio-economic factors that enhance or reduce vulnerability to drought becomes ever more important.

Results presented here provide some insight into the sorts of policy that may help farmers adapt. In particular, by highlighting the socio-economic factors that influence why grain production is vulnerable to drought we can infer how different types of policy may affect drought vulnerability in different types of region. For instance, the results presented in Fig. 3 suggest that boosting a country's GDP from agriculture can help reduce the vulnerability of grain harvests to drought. In particular, this study suggests that this strategy will have the most effect in countries with autocratic governments but may actually cause vulnerability in what the Economists Intelligence Unit describes as “hybrid regimes”. Similarly, a number of potential policy implications emerge from the results presented in Fig. 2. This figure, suggests that if a poor country grows richer then farmers may become more vulnerable to drought before becoming less vulnerable at the highest income levels. While this conclusion needs to be taken cautiously, if the observation is confirmed in other research (notably from other scales such as at district-level within countries), then policy makers need to be aware that promoting economic growth in low income countries may increase drought vulnerability. The implication of this work is that policies to boost economic growth need to be coordinated with multi-level adaptation strategies including land use and agricultural extension policies to promote water-saving farming practices. If such institutional support is unpredictable then our results suggest that harvests may be especially vulnerable to the “double exposure” of economic/political and climatic uncertainty (Eakin 2005; O'Brien and Leichenko 2000).

Seen in this light, the current crisis of food price inflation (2007–2011) provides us with two important lessons. First, natural hazards, including droughts, can trigger problems that spread and multiply. For instance, the Russian droughts in the summer of 2010 destroyed about 25% of Russia's wheat harvest. This prompted an export ban that may have contributed to destabilizing political regimes in Northern Africa (Fraser and Rimas 2011). Therefore, we must acknowledge that an inability to adapt to drought can cause far reaching consequences for our global food system. Second, while we have little control over when, where or how severe droughts will be, policy makers do have some influence on whether or not farmers have access to the tools they need to anticipate and adapt to drought, such as through drought tolerant seed varieties, early warning systems, funds for irrigation or subsidized labour.

Conclusion

To fully address the implications that climate change may have on future food security an enhanced understanding of how socio-economic conditions increase or reduce the vulnerability of key food crops to drought is necessary. To help address this need, the study presented here has attempted to use national level data to identify what factors were significant in influencing the way that drought affected cereal harvests between 1990 and 2005. The key conclusion is that the socio-economic factors that increase or decrease the vulnerability of cereal crops to drought vary, depending on the type of cereal and the type of region. For instance, countries with small populations and wealthy economies had lower average vulnerability to drought and upper middle income countries were more vulnerable than both low and high income countries. Furthermore, 'authoritarian' and 'flawed' democracies were more vulnerable than 'hybrid regimes' and 'full democracies'. Since many of the world's countries are in economic transition and depend on self-sufficiency in grain for growing populations, one implication of this research is that maintaining agricultural support institutions is an important step in reducing vulnerability to droughts and enhancing national food security.

This paper however needs to close with a strong caveat. Rather than seeing these empirical observations as definitive, they should be viewed as building on the conclusions of a largely qualitative and case study based body of literature which demonstrates that the impact of extreme weather is contingent on local contextual factors. Our paper provides a preliminary quantification and a refined set of hypotheses of what these contextual factors might be at the national level. As global scale data improves in quality, resolution and completeness researchers may be able to piece together a more comprehensive understanding of the interactions between changes in environmental challenges and human societies' ability to cope.

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References

Antwi-Agyei, P., Fraser, E. D. G., Dougill, A., Stringer, L., & Simelton, E. (2011). Mapping food system vulnerability to drought using rainfall, yield and socioeconomic data for Ghana. *Applied Geography, 32*, 324–334.

Arnell, N. W. (1999). A simple water balance model for the simulation of streamflow over a large geographic domain. *Journal of Hydrology, 217*, 314–335. doi:10.1016/S0022-1694(99)00023-2.

Beddington, J. (2009). Food, energy, water and the climate: A perfect storm of global events? Government Office for Science. Full text available at: http://www.bis.gov.uk/assets/bispartners/goscience/docs/p/perfect-storm-paper.pdf.

Brooks, N., Adger, N. W., & Kelly, M. P. (2005). The determinants of vulnerability and adaptive capacity at the national level and the implications for adaptation. *Global Environmental Change Part A, 15*(2), 151–163.

Challinor, A. J., Simelton, E. S., Fraser, E. D., Hemming, D., 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*, doi:10.1088/1748-9326/5/3/034012.

Chen, C. C., McCarl, B., & Hill, H. (2002). Agricultural value of ENSO information under alternative phase definition. *Climatic Change, 54*, 305–325.

Conway, D., Persechino, A., Ardoin-Bardin, S., Hamandawana, H., Dieulin, C., & Mahe, G. (2009). Rainfall and water resources variability in sub-Saharan Africa during the 20th century. *Journal of Hydrometeorology, 10*, 41–59. doi:10.1175/2008JHM1004.1.

Conway, D., & Schipper L. E. F. (2011). Adaptation to climate change in Africa: Challenges and opportunities identified from Ethiopia. *Global Environmental Change, 21*, 227–237.

Corzo Perez, G. A., van Huijgevoort, M. H. J., Voß, F., & van Lanen, H. A. J. (2011). On the spatio-temporal analysis of hydrological droughts from global hydrological models. *Hydrology and Earth System Sciences, 15*, 2963–2978.

Crawley, M. J. (2007). *The R Book*. Chichester: Wiley.

Devereux, S. (2009). Why does famine persist in Africa? *Food Security, 1*, 25–35.

Eakin, H. (2005). Institutional change, climate risk, and rural vulnerability: cases from Central Mexico. *World Development, 33*(11), 1923–1938.

EarthTrends (2008). The environmental information portal. World Resources Institute. http://earthtrends.wri.org/searchable_db/index.php?theme=4.

Ericksen, P. et al. (2011). *Mapping hotspots of climate change and food insecurity in the global tropics*. Copenhagen: CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS).

Erigayama, N., Smakhtin, V., & Gamage, N. (2009). *Mapping drought patterns and impacts: a global perspective*. Colombo: International Water Management Institute.

FAO (2003). Trade reforms and food security. Conceptualizing the linkages, Commodity Policies and Projections Service, Commodities and Trade Division. Rome, Italy. 296pp.

FAO (2008). FAOSTAT Online database. Food and Agriculture Organization of the United Nations. http://faostat.fao.org/default.aspx.

Fazey, I., Gamarra, J. G. P., Fischer, J., Reed, M. S., Stringer, L. C., & Christie, M. (2010). Adaptation strategies for reducing vulnerability to future environmental change. *Frontiers in Ecology and the Environment, 8*(8), 414–422. doi:10.1890/080215.

Foley, J. A., et al. (2011). Solutions for a cultivated planet. *Nature*. doi:10.1038/nature10452.

Fraser, E. (2007). Travelling in antique lands: Studying past famines to understand present vulnerabilities to climate change. *Climate Change, 83*, 495–514.

Fraser, E. D. G., Rimas, A. (2011). The psychology of food riots. Foreign Affairs, January 30, http://www.foreignaffairs.com/articles/67338/evan-fraser-and-andrew-rimas/the-psychology-of-food-riots.

Fraser, E. D. G., & Stringer, L. C. (2009). Explaining agricultural collapse: macro-forces, micro-crises and the emergence of land use vulnerability in southern Romania. *Global Environmental Change, 19*(1), 45–53.

Fraser, E. D. G., et al. (2008). Quantifying socioeconomic characteristics of drought-sensitive regions: evidence from Chinese provincial agricultural data. *Comptes Rendus Geoscience, 340*(9–10), 679–688.

Fraser, E. D. G, Dougill, A. J., Hubacek, K., Quinn, C. H., Sendzimir, J., Termansen, M. (2011). Assessing vulnerability, resilience and adaptive capacity to climate change in arid/semi-arid social ecological systems. *Ecology and Society 16*(3), Art. 3.

Gbetibouo, G., Ringler, C. (2009). Mapping South African farming sector vulnerability to climate change and variability: A subnational assessment. IFPRI Discussion Paper 885. International Food Policy Research Institute Washington, DC.

Gosling, S. N., & Arnell, N. W. (2011). Simulating current global river runoff with a global hydrological model: model revisions, validation, and sensitivity analysis. *Hydrological Processes, 25*, 1129–1145.

Gosling, S. N., Bretherton, D., Haines, K., Arnell, N. W. (2010). Global hydrology modelling and uncertainty: running multiple ensembles with a campus grid. *Philosophical Transactions of the Royal Society A, 368*, 4005–4021. doi: 10.1098/rsta.2010.0164.

Haddeland, I., et al. (2011). Multimodel estimate of the global terrestrial water balance: setup and first results. *Journal of Hydrometeorology, 12*, 869–884.

Hafner, S. (2003). Trends in maize, rice, and wheat yields for 188 nations over the past 40 years: a prevalence of linear growth. *Agriculture, Ecosystems and Environment, 97*, 275–283.

Hazell, P., & Wood, S. (2007). Drivers of change in global agriculture. *Philosophical Transactions of the Royal Society B*. doi:10.1098/rstb.2007.2166.

Hollinger, S. E., & Isard, S. A. (1994). A soil moisture climatology of Illinois. *Journal of Climate, 7*, 822–833.

IPCC (2001). Glossary, Fourth Assessment Report, Working Group 2. Intergovernmental Panel on Climate Change. Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press. http://www.ipcc.ch/pdf/glossary/ar4-wg2.pdf

IPCC. (2007). *Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge: Cambridge University Press.

Kottek, M., Grieser, J., Beck, C., Rudolf, B., & Rubel, F. (2006). World Map of the Köppen-Geiger climate classification updated. *Meteorologische Zeitschrift, 15*(3), 259–263. doi:10.1127/0941-2948/2006/0130.

Leff, B., Ramankutty, N., Foley, J. A. (2004). Geographic distribution of major crops across the world. *Global Biogeochemical Cycles 18*, GB 1009.

Li, Y. P., Ye, W., Wang, M., & Yan, X. D. (2009). Climate change and drought: a risk assessment of crop-yield impacts. *Climate Research, 39*, 31–46.

Lobell, B. D., & Field, C. B. (2007). Global scale climate-crop yield relationships and the impacts of recent warming. *Environmental Research Letters, 2*, 014002.

McMahon, T. A., Peel, M. C., Vogel, R. M., & Pegram, G. G. S. (2007). Global streamflows—Part 3: Country and climate zone characteristics. *Journal of Hydrology, 347*, 272–291.

Mishra, A. K., & Singh, V. P. (2010). A review of drought concepts. *Journal of Hydrology, 391*(1–2), 202–216.

Nelson, G., et al. (2010). Food security, farming, and climate change to 2050: Scenarios, results, policy options. IFPRI. Washington DC. 155 pp http://www.ifpri.org/sites/default/files/publications/rr172.pdf.

Nijssen, B., Schnur, R., & Lettenmaier, D. P. (2001). Global retrospective estimation of soil moisture using the variable infiltration capacity land surface model, 1980–93. *Journal of Climate, 14*, 1790–1808.

O'Brien, K., & Leichenko, R. M. (2000). Double exposure: assessing the impacts of climate change within the context of economic globalization. *Global Environmental Change, 10*, 221–232.

OECD-FAO (2009). OECD-FAO Agricultural outlook Highlights No1 Feb 2009. OECD/FAO.

Ohno, K. (2009). Avoiding the middle-income trap: renovating industrial policy formulatoin in Vietnam. *ASEAN Economic Bulletin, 26*(1), 25–43.

Pandey, V. P., Babel, M. S., Shrestha, S., & Kazama, F. (2011). A framework to assess adaptive capacity of the water resources system in Nepalese river basins. *Ecological Indicators, 11*(2), 480–488.

Patt, A., & Gwata, C. (2002). Effective seasonal climate forecast applications: examining constraints for subsistence farmers in Zimbabwe. *Global Environmental Change, 12*(3), 185–195.

Rudel, T. K., et al. (2009). Agricultural intensification and changes in cultivated areas, 1970–2005. *Proceedings of the National Academy of Sciences of the United States of America, 106*(49), 20675–20680. doi:10.1073/pnas.0812540106.

Schneider, T., & Neumaier, A. (2001). Algorithm 808: ARfit—A Matlab package for the estimation of parameters and eigenmodes of multivariate autoregressive models. *ACM Transactions on Mathematical Software, 27*(1), 58–65.

Siebert, S., Doll, P., Hoogeveen, J., Faures, J. M., Frenken, K., & Feick, S. (2005). Development and validation of the global map of irrigation areas. *Hydrology and Earth System Sciences, 9*, 535–547.

Sheffield, J., Andreadis, K. M., Wood, E. F., & Lettenmaier, D. P. (2009). Global and continental drought in the second half of the Twentieth Century: severity-area-duration analysis and temporal variability of large-scale events. *Journal of Climate, 22*, 1962–1981.

Simelton, E., Fraser, E. D. G., Termansen, M., Forster, P. M., & 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). *Environmental Science and Policy, 12*(4), 438–452.

Simelton, E. (2011). Food self-sufficiency and natural hazards in China. *Food Security, 3*(1), 35–52.

Stringer, L. C., Dyer, J. C., Reed, M. S., Dougill, A. J., Twyman, C., & Mkwanbisi, D. (2009). Adaptations to climate change, drought and desertification: local insights to enhance policy in southern Africa. *Enironmental Science and Policy, 12*, 748–765.

The Economist (2009). The Economist Intelligence Unit's Index of Democracy 2008. http://graphics.eiu.com/PDF/Democracy%20Index%202008.pdf.

Thenkabail, P. S., et al. (2008). A Global Irrigated Area Map (GIAM) Using remote sensing at the end of the last millennium. Colombi. Sri Lanka: International Water Management Institute. 63 pp. http://www.iwmigiam.org/info/gmi-doc/GIAM-world-book.pdf.

The World Bank Group (2008). World Development Indicators Online database. http://data.worldbank.org/indicator

Thorne, R. (2011). Uncertainty in the impacts of projected climate change on the hydrology of a subarctic environment: Liard River Basin. *Hydrological and Earth System Sciences, 15*, 1483–1492.

Government, U. K. (2011). *Global food and farming futures*. London: Foresight Government of the United Kingdom.

USDA (2004). Ukraine: Average harvest prospects for winter grains, production estimates and crop assessment division, foreign agricultural service. United States Department of Agriculture.

Verchot, L. V., et al. (2007). Climate change: linking adaptation and mitigation through agroforestry. *Mitigation and Adaptation Strategies for Global Change*. doi:10.1007/s11027-007-9105-6.

Wagner, W., Scipal, K., Pathe, C., Gerten, D., Lucht, W., Rudolf, B. (2003). Evaluation of the agreement between first global remotely sensed soil moisture data with model and precipitation data, *Journal of Geophysical Research*, *108*(D19), 4611, doi:10.1029/2003JD003663.

World Bank (2009). Country classification 2008. http://go.worldbank.org/K2CKM78CC0.

Xu, H., Taylor, R. G., Kingston, D. G., Jiang, T., Thompson, J. R., & Todd, M. C. (2010). Hydrological modeling of River Xiangxi using SWAT2005: a comparison of model parameterizations using station and gridded meteorological observations. *Quaternary International, 226*, 54–59.

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Mette Termansen obtained her PhD from the University of York, UK, in Environmental Economics, working on spatio-temporal modelling approaches to forest economics in order to enable environmental interactions to be taken into account. After working as a research fellow at York, she took up a position as Lecturer and later on Senior Lecturer in Ecological Economics at the Sustainability Research Institute at Leeds. In 2009 she was appointed Professor in Environmental Economics at the Department of Policy Analysis, Aarhus University, Denmark. Her main research areas are in integrated ecological economic modelling and ecosystems services valuation. She has worked on a range of environmental issues related to modelling of land use. These include land use and climate change impacts on species distribution patterns, quantification of adaptation capacity to climate change in agriculture, recreation modelling, and evaluation of policy schemes for land use in order improve water quality.

Tim Benton is Professor of Population Ecology at the Institute of Integrative and Comparative Biology and Chair of Africa College at the University of Leeds. His primary research areas are biodiversity and population management under scenarios of environmental change and the ecology of agricultural land. He works in the field and uses model species in the laboratory in order to elucidate fundamental biological mechanisms from which he develops statistical models. Much of his work concerns understanding systems.

Simon Gosling's main interests are in understanding the impacts of climate change on natural and human systems and bridging the boundary between physical science and impact and policy-related areas. Much of his current research investigates the potential impact of climate change on global- and catchment-scale hydrology and water resources. Simon is interested in understanding how average conditions and extremes (floods and droughts) might be affected by climate change. He applies a variety of climate and hydrological numerical models to achieve this. Simon also has strong interests in modeling the relationship between climate and human health; specifically, on the association between extreme temperature events (heat waves and cold snaps) and temperature-related mortality. A key element throughout his research is exploring the inherent uncertainties of the impact of climate change projections, due for instance, to uncertainties associated with the current state of science on the modelling of climate, hydrology and health.

Andy South is a biologist with an interest in the communication of global information, particularly about climate change. As a part of the NERC QUEST project he developed the open-source software 'rworldmap' for creating maps in R. The aim is to provide a free software tool that can be used across disciplines to produce maps of gridded and country level information.

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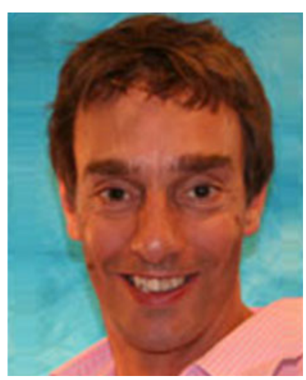
Andrew Dougill is an applied environmental researcher who has developed a range of integrated approaches for combining local and scientific knowledge in assessment of dryland degradation. His work has focused on Southern Africa and routes to ensure that pastoral and mixed-farming communities are involved in projects to assess degradation problems and to develop management and policy solutions for these. His recent work is funded by the ESRC Centre for Climate Change Economics and Policy investigating ways to 'close the loop' between climate science, development practice and policy interactions in dryland agro-ecological systems. He is currently Professor of Environmental Sustainability and Head of the School of Earth and Environment at the University of Leeds.



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