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Climate Change and the Socioeconomics of Global Food Production: A Quantitative Analysis of how Socio-Economic Factors Influence the Vulnerability of Grain Crops to Drought

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Abstract

The impact of climate change on agriculture depends on the environmental and socio-economic contexts in which the changes occur. However, current tools to anticipate climate change impacts focus almost entirely on biological and environmental processes. For example, most large-scale crop models can identify where yields are sensitive to new temperatures and CO₂ concentrations but do not include any socio-economic factors that may enable (or inhibit) farmers' abilities to adapt. To address this gap, this paper uses national scale socio-economic, meteorological and agricultural data to identify socio-economic factors that have made rice, maize and wheat production resilient and sensitive to past droughts. Results suggest that cereal harvests in countries undergoing economic and political transition are most vulnerable to droughts and that factors related to investments in the agriculture sector (such as the amount of fertilizer used by farmers or the amount of Gross Domestic Product produced by a nation's agricultural sector) help reduce vulnerability. While results are limited by data quality and availability, this study provides preliminary quantitative insights that highlight important areas for further research on the socio-economic factors that create vulnerability to climate change.

Keywords

Global food production, vulnerability to climate change, food security, adaptive capacity, resilience, sensitivity, climate change impacts, climate adaptability, crop failure

1. Introduction

A large and growing body of research shows that socio-economic factors can be as important as the magnitude of a climatic event in determining the impact of environmental change on agriculture (Fraser et al., 2003; Patt and Gwata, 2002). However, there are no clear-cut procedures to characterise human coping and adaptation mechanisms as these vary from place to place. For example, droughts are slow-onset phenomena with a relatively high level of predictability compared to most other environmental stressors (e.g. flood or storm events that emerge relatively quickly and with little – if any – warning). This means that many drought impacts, such as crop failures, could, theoretically, be avoided with preparedness and appropriate response mechanisms. As a result, to anticipate where climate change may affect yields, impact models should integrate environmental factors, such as available water and temperature that directly affect yield, with socio-economic factors that encourage pro-active adaptation.

At the farm level, this means researchers need to identify those human factors that allow farmers the opportunity to overcome periods of drought. This may include things such as access to labour or capital that a farmer may use to adapt to climatic problems. At larger spatial scales, research on human factors includes identifying the economic and governance systems that help enhance (or undermine) the adaptive capacity of entire regions (Devereux, 2009). The importance of human factors in determining climate impacts is highlighted in the literature on climate vulnerability that views vulnerability as a dynamic concept defined in relation to an external stressor or an undesirable outcome (Füssel and Klein, 2006). More specifically, climate vulnerability is defined by the Intergovernmental Panel on Climate Change (2001) as arising when some ecosystem service, such as 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. Smit and Wandel (2006), Adger (2006), and Folke (2006) all develop these ideas and stress that in addition to exposure, sensitivity and adaptive capacity, vulnerability is also a function of a system's resilience, i.e. its ability to both absorb a shock as well as its ability to recover after being exposed to a stress.

Despite the wide spread awareness in the literature that socio-economics is important in determining the resilience, sensitivity and adaptive capacity of production systems, human factors do not feature strongly in many discussions on impacts of climate change on agriculture production (Yearley, 2009). For example, in the IPCC's report "Impact, Adaptation and Vulnerability", the chapter on food and fibre presents crop yield-projections that are based on modelling the biological potential of crops to grow under future climates. The results do not include the capacity of farmers to adapt to such changes (Easterling et al., 2007; Füssel and Klein, 2006). There are several practical and intellectual challenges that must be overcome before scholars will effectively be able to integrate the socio-economic and environmental factors that affect crop yield. Firstly, crop-climate and socio-economic data exist on different spatial and temporal scales (Adger et al., 2005; Hulme et al., 1999; Vincent, 2008). For example, crop and climate data are generally quantitative as compared with socio-economic data that are typically more qualitative. In contrast, when quantitative socio-economic (census) data are available, indicators are usually aggregated to administrative scales at an annual resolution, averaging out regional inter-annual variability. Therefore, while a single-level (census) data may provide an entry point for examining the contextual issues that are associated with vulnerability (Brooks et al., 2005), more than one resolution is required to characterise the multilevel and multi-scale natures of vulnerability or adaptation (Janssen et al., 2007).

Secondly, crop, climate and socio-economic models make different assumptions about the behaviour of economic actors. In the crop models used to estimate the impact of climate change on yields, farmers' adaptation is usually treated guite simply (See Challinor et al., 2009a for a review of current trends in crop-climate models). Generally speaking, crop-climate models either assume that farmers will not make any changes in crops/cultivars grown (thus over-estimating the impact of changes in climate) or assume that farmers will use management practices that are ideally suited to new climatic conditions (this under-estimates the impact of climate change) (Füssel and Klein, 2006; Kandlikar and Risbey, 2000). Similarly, in most integrated socio-economic models of climate and agriculture, land managers are viewed as profit-maximisers (Cooke et al., 2009) in markets at equilibrium (Mendelsohn, 2007). From this perspective, harvests' sensitivity to climate is indirectly reflected in price or income volatility (Ahmed et al., 2009). Again, this approach fails to capture the way in which socio-economic factors may encourage or inhibit farmer adaptation. As such, some recent work has begun by examining the effects of climate change if farmers switch to "non-ideal" crops as a way of estimating the impact of climate change depending on a range of possible farmer responses (e.g. Challinor et al., 2009b).

Therefore, given the (1) spatial and temporal incompatibility of available socioeconomic, biological and environmental data, and the (2) difficulties with generalising human behaviour, most integrated studies on food security and climate change rarely stretch outside community-levels (Patt and Siebenhüner, 2005). This discussion has led Brooks et al. (2005) to call for scholars working on vulnerability to distinguish between "context specific" and "generic" vulnerability. Considerable effort has already been invested in "context specific vulnerability" and there are many published studies that illustrate how climatic impacts will depend on specific local contexts (E.g. Misselhorn, 2005). By contrast, to date there have been only a few attempts to employ mathematical or statistical methods to identify indicators of generic vulnerability at larger spatial scales (Allison et al., 2009; Brooks et al., 2005; Fraser et al., 2008; Liu et al., 2008; Reidsma et al., 2009). The main aim of the current paper is to examine these issues at the global scale using national data to identify the socio-economic factors that are statistically significant in indentifying the relation between cereal (rice, wheat and maize) losses and drought. Specifically, this paper builds on previous work done on "generic vulnerability" by Simelton et al. (2009). The previous work was carried out at subnational scale using data from Chinese provinces as an early attempt to bring together both the environmental and socio-economic factors that made crop production vulnerable to drought. This previous work concluded that farm inputs, i.e. variables representing land, labour or capital, were associated with vulnerability to drought where drought was defined as occurring in years when the rainfall during the growing season was below average (Fraser et al., 2008; Simelton et al., 2009). For the purpose of the current paper, two methodological advances have been made to previous work. Firstly, the drought index has been refined and is now based on soil moisture to account for the capacity of soils to buffer variations in rainfall. Secondly, the vulnerability index is used to construct linear mixed-effects models of vulnerability to drought at the national scale as a function of specific socio-economic conditions accounting for different governance, income and agro-ecological zones. While analyses at this scale are by necessity crude, this work represents an important step towards understanding the combined effects of socio-economic context and environmental changes on crop productivity.

2. Data & Methods

The availability of data at the global scale to address climate change vulnerability is limited. This paper, therefore, proceeds by first outlining the available data (section 2.1), then justifying the methods and describing the methodological steps undertaken to derive the vulnerability index (section 2.2) and, finally, outlines the data analysis procedures (section 2.3).

2.1 Data and data preparation

Soil moisture data

Monthly soil moisture data was obtained from an established global hydrological model (GHM), Mac-PDM.09 (Gosling and Arnell, 2010; Gosling et al., 2010; Arnell, 1999). Mac-PDM.09 was driven with 0.5%0.5 °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 mask out soil moisture for only those grid cells that had >1% of the land base devoted to producing rice, wheat or corn (Leff et al., 2004). For each selected grid and for each year, total soil moisture was determined for the period October of one year to October of the following year. Using this data, the average national-scale soil moisture was computed for each growing season from

the selected grids cells. With regard to our selection of the October to October period, it is important to note that some studies recommend different lengths of drought-periods. For example, soil moisture fluctuates so much in the tropics that droughts may emerge and dissipate in less than six months, while droughts many take over twelve months to emerge in Sub-Saharan Africa and in high northern latitudes (Erigayama et al., 2009). To address this issue, we tested a number of different combinations of months to calculate soil moisture but found that this had little effect on the overall results (This is similar to what was found by Lobell and Field, 2007). Therefore, the period October-October was chosen since it combines the southern and northern hemisphere growing seasons for harvests to be recorded for the same year (Leff et al., 2004).

Harvest 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 1986-2005.

Socio-economic data

To analyse the socio-economic factors that explain drought impacts on harvests we made use of the following types of data (Alcamo et al., 2008; Brooks et al., 2005):

- To test hypotheses that access to farm inputs explain trends in harvest vulnerability, national socio-economic data were obtained 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).
- (2) Each country was grouped based on average income, type of governance and agro-environmental zone. Each of these three indicators has four levels. The income groupings follow the World Bank's classification based on the average GDP per capita in 2008: Iow income, Iower 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 and full democracies (The Economist, 2009). 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 in either tropical, arid, temperate or cold climate conditions.
- < Table 1. Data used in this analysis >

Data quality and data preparation

The lack of complete time-series high quality socio-economic data is well acknowledged in the literature. The United Nations databases, such as those used in this study, are the only databases available that have time-series data of agricultural and socio-economic factors. Data quality vary as countries may use different approaches for compiling data (Hafner, 2003; Rudel et al., 2009). These limitations influenced the selection of variables used in this study. For instance, we only used data from the past 16 years because: 1) the data quality for many developing countries is assumed to have improved over time, and, 2) this period marks a new era with many new states emerging around 1990. Hence, analysing older data may not contribute to understanding of current vulnerability.

Even by restricting our analysis to the last 16 years, data sets still had occasional missing values that were replaced using the spline interpolation procedure 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 heteroscedasticity and the influence of extreme values.

2.2 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 by Fraser who analyzed the relationship between food security and drought (see: Fraser, 2007; Fraser et al., 2008; Simelton et al., 2009). Briefly, this work 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 losses (the Crop Failure Index, CFI). Cases where relatively severe droughts are not associated with significant crop losses are considered "resilient" to the drought and cases where minor droughts are associated with major crop losses are considered "sensitive" to the drought. Taken together, the impact of a drought relative to the size 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' "adaptive capacity". 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* (eqn 1):

$$VI_{i} = \frac{CFI_{i}}{DI_{i}} = \frac{\left(\frac{\hat{H}_{i}}{H_{i}}\right)}{\left(\frac{S\hat{M}C_{i}}{SMC_{i}}\right)}$$

[eq. 1]

(1) There were two steps in calculating the crop failure index (CFI). First, harvest data for each country was smoothed using an fourth order auto-regression model (Schneider and Neumaier, 2001; Simelton et al., 2009). Three year-lags was used for a few countries with limited time series to increase the number of countries included in the analysis. As four years are lost to the smoothing procedures the remaining period 1990-2005 refers to the effective dataset. 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 produced an estimate of the "expected" value of the harvest, \hat{H} , taking into account multi-year temporal trends. Second, for each country and for each crop, the smoothed harvest, \hat{H} , were divided by actual harvests, H, recorded by the FAO data. 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 larger crop failures.

(2) The drought index (DI) was computed in a similar manner. First, for each country in each year soil moisture content, SMC, was estimated from averaging the October-October soil moisture for all the grid cells in a given country that had been identified as cultivating more than 1% of the particular crop. 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, and since there were no long-term trends, soil moisture data was smoothed using a linear regression model. Third, for each country and each year the smoothed soil moisture, $S\hat{MC}$, 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 available for each crop.

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

2.3 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 of these years, the following steps were undertaken:

(1) To compare differences in mean vulnerability among the different groups of countries, we undertook Duncan's post-hoc test to determine homogeneity in mean

vulnerability within-groups. This was done for all crops taken together and separately for each crop. The significance level was set to α <0.05.

(2) 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, agroenvironment (tropical, arid, temperate, cold), income (low, lower middle, upper middle, high) and governance (autocratic, hybrid, flawed, full). 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 affects on interactions and the intercept. To obtain estimates of coefficients, the minimal adequate model was then fitted using 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 "rworldmap" packages.

3. 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, we present the LME models of vulnerability to drought for rice, wheat and maize.

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

The average VIs during years with below normal rainfall during the growing season for rice, wheat and maize are shown in Figure 1a-c. The maps point out three possible regions of particular concern: a vulnerable triangle between southern, eastern and northwest Africa, some former Soviet Union-states along the borders of Europe and central Asia, and northern parts of South America.

In terms of the characteristics of different countries with different levels of vulnerability the following results stand out:

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 arid

zones also had the highest standard deviation in terms of the vulnerability index.

- 2. For governance, countries with authoritarian and hybrid 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 rice vulnerability, authoritarian and cold agro-environments were most vulnerable while hybrid regimes and low income countries had the lowest mean vulnerability.
- 2. For wheat, flawed democracies and cold agro-environments had the highest mean vulnerability, while low income countries had the lowest vulnerability.
- 3. For maize, flawed democracies, low and upper middle income countries had the highest mean vulnerability, and tropical agro-environments the lowest vulnerability.

Additional details on the interactions between variables and the significance of different variables is available in supplementary table 1 and supplementary figure 1.

<Figure 1.>

3.2 Linear mixed-effects models of vulnerability for rice, wheat and maize

Table 2 summarises the overall significant effects of the LME models, including the interactions between variables (see also the last two columns of Supplementary table 1). In particular, the following socio-economic factors were identified as significant in explaining trends in rice wheat and maize harvest vulnerability to drought:

- In the case of rice, the overall effect of the amount of GDP generated by a country's agricultural sector and the intensity of cereal cultivation were both significant in reducing vulnerability. The way that cereal intensity affected vulnerability, however, varied depending on the country's agro-ecological zone. Cereal intensity had the strongest effect on reducing vulnerability in cold countries, whereas in tropical countries, the effect of cereal intensity on vulnerability was negligible (these interactions are indicated in the bottom rows and last column of Supplementary table 1a).
- 2. In the case of wheat, the amount of GDP generated by a country's agricultural sector was significant in reducing vulnerability. The exact nature of this effect, however, depended on the country's government type and agro-ecological zone. In particular, agricultural GDP increased vulnerability in flawed and full

democracies while it decreased vulnerability in autocratic and hybrid regimes. Similarly, agricultural GDP increased the vulnerability of wheat harvests to drought in tropical and cold climates while it decreased vulnerability in arid and temperate countries.

- 3. For maize a large number of significant effects and interactions were observed. Key results include that maize harvests were significantly less vulnerable to drought in countries where fertilizer use, agricultural GDP and cereal intensity were all high but were more vulnerable in countries where rural populations were low. Notable exceptions to these trends include countries with flawed or full democracies. In these countries, GDP in agriculture, rural populations and cereal intensity are all associated with increased vulnerability. These same three factors are, however, associated with decreased vulnerability in countries with autocratic or hybrid governments. To further illustrate this, figure 3 presents the impact of GDP on maize vulnerability alone, keeping the other variables constant. This demonstrates that GDP in agriculture has an overall negative effect on vulnerability but that this effect is strongest in full democracies (significant decrease in vulnerability) and hybrid regimes (significant increase in vulnerability). For flawed democracies there is no significant difference from the overall mean relationship with GDP.
- < Table 3. >
- < Figure 3. >

4. Discussion

This paper provides insights into three empirical questions: (1) Where in the globe are cereal crops most vulnerable to drought? (2) What are some of the underlying socio-economic conditions that contribute to drought-harvest vulnerability? And (3) what implications might these results have in terms of policy to enhance adaptive capacity? Finally, the methods used in this paper point towards how socio-economic and crop-climate models may be integrated in future research.

4.1 Where are cereal harvests most vulnerable to drought?

This study shows that the lowest mean crop-drought vulnerability is found in tropical agro-environments, hybrid regimes, and low income levels, such as Cambodia, Guatemala and Ghana. 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. The high vulnerability of cold countries may 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 grain cultivation in countries at low latitudes typically is irrigated (e.g. the Nile). Hence, tropical cereal crops may be better buffered against droughts in these regions as long as water is available for irrigation. Arid zones are more vulnerable than tropical zones and also had the highest variability in vulnerability for all crops, in particular for maize. Again, this may be due to the fact that cultivation in these countries is close to an ecological threshold so relatively minor changes in soil moisture have commensurately large effects. The high vulnerability to drought in tropical zones where water resource management may be more crucial than water deficits (Evers and Benedikter, 2009).

4.2 What are the underlying socio-economic conditions that contribute to drought-vulnerability?

Overall, high levels of GDP in agriculture, cereal intensity and fertiliser use are associated with lower vulnerability to drought. Since these are proxy indicators for the capital resources available to a farmer, one interpretation of these results is that financial capital is significant in enhancing adaptive capacity. An alternative explanation is that weather forecasts are better in countries with high capital input in agriculture and this helps buffer harvests from drought. The findings also indicate more subtle and complex relationships, particularly in the case of maize that is grown under very diverse circumstances across the world. For example, higher levels of GDP in agriculture were associated with increased vulnerability in low income countries but reduced vulnerability in hybrid regimes. Moreover, large rural populations are significantly associated with reduced vulnerability in hybrid regimes. One interpretation of this is that high vulnerability countries may be undergoing an agricultural transition. In particular, it may be that in these countries farmers still rely on labour-intensive agricultural management but that labour is not available because it has been drawn away from agriculture and into industry. 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 soil moisture.

As a result, we feel that one of the most striking results of this research is that vulnerability is low in both rich and poor countries but high for the middle income countries. 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. The highest income countries may have low vulnerability because they may have ample financial reserves with which to adapt. The middle income countries, however, may neither have the financial nor traditional coping strategies in place. Exploring this issue is a likely avenue for future research and suggests that it is farmers in countries in

economic transition - and not the poorest (as suggested by the Millennium Development Goals (2008)) - who may be most vulnerable to droughts.

4.3 What implications does this have for policy?

Results presented here suggest it is misguided to assume that programmes to reduce poverty, make farm inputs more accessible, or increase democracy will necessarily reduce vulnerability to climate change. Rather the effect of any of such programmes will depend on the political and economic context of the country. More specifically, the socio-environmental context can change the sign of a relationship (e.g. Fig 3), suggesting that policy interventions may have reversed outcomes depending on the situation. These results, therefore, are somewhat at odds with community-scale work that has explored vulnerability and concluded that the poor are necessarily the most vulnerable (Gbetibouo and Ringler, 2009). Instead, the results presented here suggest that - at a national scale - it seems to be countries in transition that are most vulnerable. If institutional support is unpredictable in such regions then harvests may be especially vulnerable to a "double exposure" of economic/political and climatic uncertainty (Eakin, 2005; O'Brien and Leichenko, 2000). If this is true (and more research is needed to demonstrate this point conclusively) climate change adaptation policy needs to be built on debates around social vulnerability and entitlement that explores how people in different contexts adapt to the same climatic exposure (Adger, 2006). Taken together, therefore, results suggest that policy geared at reduced harvest vulnerability to drought needs to, at the very least, be sensitive to the wealth, ecology, and government as well as the type of crop that is being considered.

5. Conclusion

One likely effect of climate change is that many regions around the world are projected to experience more frequent and more intense droughts. Predicting whether these new droughts will impact harvests, however, is difficult. Oftentimes, rainfall deficits are one of many factors that contribute to crop failure, because farmers operate within socioeconomic structures that increase to their vulnerability to such weather anomalies. As a result, it is important to understand the socio-economic contexts that make harvests vulnerable droughts. Results show that countries with low populations and wealthy economies had lower vulnerability to drought and that upper middle income countries were more vulnerable than both low and high income countries. Furthermore, 'authoritarian' and 'flawed' democracies (as defined by "The Economist") 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 a growing population, one implication of this

research is that being prepared for future droughts means ensuring stable agricultural development to reduce vulnerability.

Economist Intelligence Unit 20081Governance styleKöppen2Climatic suitability, associated meteorological disturbance, agro-environmentWorld Bank3Stage in economic
meteorological disturbance, agro-environment
World Bank ³ Stage in economic
development
Earth Population pressure; Trends ⁴ , domestic demand FAOSTAT ⁵
Earth Potential available rural Trends ⁴ labour
bita FAOSTAT ⁵ Land use intensity
e, FAOSTAT ⁵ Importance of cereal crops of
agricultural production otal area
FAOSTAT ⁵ Degree of technical development, access to agricultural inputs
World Potential investments in Development agriculture, importance of Indicators ⁶ agriculture
e, ota ai

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

Sources: 1) The Economist, 2009. 2) Kottek et al., 2006. 3) World Bank, 2009. 4) EarthTrends, 2008. 5) FAO, 2008. 6) The World Bank Group, 2008.

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

a) Rice	Numerator DF	Denominator DF	F-value	p-value
Intercept	1	525	42249.71	<0.0001
GDP in agriculture	1	525	4.19	0.0411
Cereal intensity	1	525	0.45	0.5015
Agroenvironment	3	81	2.73	0.0492
Cereal intensity*Agroenvironment	3	525	2.90	0.0344

b) Wheat	Numerator DF	Denominator DF	F-value	p-value
Intercept	1	563	26282.520	<0.0001
GDP in agriculture	1	563	5.826	0.0161
Agroenvironment	3	89	1.453	0.2328
Governance	3	89	3.028	0.0336
GDP*governance	3	563	2.803	0.0393
GDP*agroenvironment	3	563	2.821	0.0383

c) Maize	Numerator DF	Denominator DF	F-value	p-value	
Intercept	1	600	42160.71	<0.0001	
Fertiliser	1	600	5.79	0.0164	
GDP in agriculture	1	600	6.80	0.0093	
Rural population	1	600	12.14	0.0005	
Cereal intensity	1	600	8.10	0.0046	
Governance	3	97	3.59	0.0164	
Income level ¹	2	97	1.71	0.1864	
Agroenvironment	3	97	1.09	0.3583	
GDP*governance	3	600	0.19	0.9063	
RuralPop*governance	3	600	4.67	0.0031	
Cereal*governance	3	600	6.57	0.0002	
GDP*income ¹	2	600	5.47	0.0044	
Cereal*income ¹	2	600	1.47	0.2318	
Cereal*agroenv	3	600	7.89	<0.0001	

¹ Upper middle and high income levels were merged.

a) Rice	Value	Standard Error	DF	t-value	p-value	Overall intercept	Slope modified by interaction
Intercept	2.6144	0.1700	525	15.3827	0.0000		
GDP in agriculture	-0.0535	0.0268	525	-1.9980	0.0462	2.561	
Cereal intensity	-0.2202	0.0757	525	-2.9072	0.0038	2.394	
Tropical	-0.4264	0.1453	81	-2.9347	0.0043	2.188	
Arid	-0.4200	0.1508	81	-2.7837	0.0067	2.194	
Temperate	-0.3506	0.1484	81	-2.3626	0.0205	2.263	
Cold	1.1966	0.1482	81	8.0742	0.0000	3.811	
Cereal *tropical	0.2240	0.0792	525	2.8298	0.0048		0.004
Cereal*arid	0.2114	0.0829	525	2.5486	0.0111		-0.009
Cereal*temperate	0.1669	0.0811	525	2.0592	0.0400		-0.053
Cereal*cold	-0.6023	0.0811	525	-7.4266	0.0000		-0.822

Supplementary Table 1. Coefficients for linear mixed effects models of vulnerability to drought for a) rice, b) wheat and c) maize.

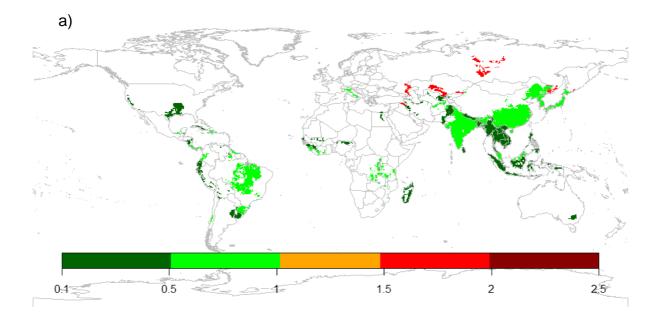
b) Wheat	Value	Standard Error	DF	t-value	p-value	Overall intercept	Slope modified by interaction
Intercept	2.2776	0.1218	563	18.7031	0.0000		
GDP in agriculture	-0.0651	0.0398	563	-1.6380	0.1020	2.213	
Tropical	-0.4043	0.2523	89	-1.6024	0.1126	1.874	
Arid	0.3412	0.1792	89	1.9039	0.0602	2.619	
Temperate	0.1989	0.1532	89	1.2980	0.1977	2.477	
Cold	-0.1358	0.1949	89	-0.6968		2.142	
Autocratic regimes	0.5379	0.2039	89	2.6375	0.0099	2.816	
Hybrid regimes	-0.0228	0.2403	89	-0.0948	0.9247	2.255	
Flawed democracies	-0.2542	0.1950	89	-1.3034	0.1958	2.024	
Full democracies	-0.2610	0.2131	89	-1.2248		2.017	
GDP*autocratic	-0.1636	0.0640	563	-2.5548	0.0109		-0.229
GDP*hybrid	0.0071	0.0728	563	0.0976	0.9223		-0.058

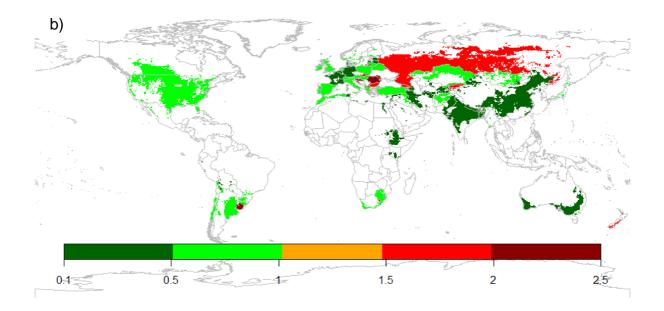
GDP*flawed	0.0903	0.0643	563	1.4046	0.1607	0.015
GDP*full	0.0662	0.0670	563	0.9880		0.001
GDP*:tropical	0.1163	0.0764	563	1.5218	0.1286	0.051
GDP*:arid	-0.1284	0.0571	563	-2.2494	0.0249	-0.193
GDP*temperate	-0.0610	0.0492	563	-1.240	0.2157	-0.126
GDP*cold	0.0731	0.0609	563	1.2003		0.008

c) Maize	Value	Standard Error	DF	t-value	p-value	Overall intercept	Slope modified by interaction
Intercept	2.3762	0.2415	600	9.8378	0.0000		
Fertiliser	-0.0471	0.0170	600	-2.7713	0.0058	2,423	
GDP in agriculture	-0.1077	0.0511	600	-2.1061	0.0356	2,268	
Rural Population	0.1376	0.0737	600	1.8682	0.0622	2,514	
Cereal intensity	-0.0337	0.0742	600	-0.4549	0.6493	2,342	
Autocratic regimes	-0.4084	0.2918	97	-1.3995	0.1649	1.968	
Hybrid regimes	-0.6174	0.2530	97	-2.4400	0.0165	1.759	
Flawed democracies	0.5983	0.2278	97	2.6260	0.0100	2.974	
Full democracies	0.4276	0.2575	97	1.6606		2.804	
Low income	0.8075	0.3225	97	2.5045	0.0139	3.184	
Lower middle income	-0.3209	0.2350	97	-1.3653	0.1753	2.055	
Upper mid + High inc	-0.4866	0,2717	97	-1.7909		1.889	
Tropical	-0.0243	0.1115	97	-0.2176	0.8282	2.352	
Arid	0.4523	0.1122	97	4.0311	0.0001	2.828	
Temperate	0.2888	0.1165	97	2.4784	0.0149	2.665	
Cold	-0.7168	0.1134	97	-6.3210	0.000	1.659	
GDP*autocratic	-0.0640	0.0922	600	-0.6933	0.4884		-0.516
GDP*hybrid	0.2667	0.0967	600	2.7570	0.0060		-0.725
GDP*flawed	-0.0212	0.0724	600	-0.2923	0.7702		0.490
GDP*full	-0.1817	0.0871	600	-2.0861			0.320
RuralPop*autocratic	0.2443	0.1497	600	1.6318	0.1032		-0.270
RuralPop*hybrid	-0.2991	0.1157	600	2.5848	0.0100		-0.479
RuralPop*flawed	0.0738	0.1029	600	0.7169	0.4737		0.736
RuralPop*full	-0.0190	0.1228	600	-0.1547			0.566
Cereal*autocratic	0.1246	0.0922	600	1.3519	0.1769		-0.442

Cereal*hybrid	0.1551	0.0940	600	1.6503	0.0994	-0.651
Cereal*flawed	-0.3236	0.1044	600	-3.1011	0.0020	0.564
Cereal*full	0.0440	0,0969	600	0.4541		0.394
GDP*low inc	-0.2144	0.0932	600	-2.2997	0.0218	0.700
GDP*lower mid inc	0.0154	0.0665	600	0.2314	0.8171	-0.429
GDP*upper+high inc	0.1991	0.0799	600	2.4919		-0.595
Cereal*low inc	-0.0862	0.0631	600	-1.3669	0.1722	0.774
Cereal*lower mid inc	0.1336	0.0647	600	2.0660	0.0393	-0.355
Cereal*upper+high inc	-0.0474	0.0639	600	-0.7418		-0.521
Cereal*tropical	0.0120	0.0614	600	0.1952	0.8453	-0.058
Cereal*arid	-0.2711	0.0640	600	-4.2345	0.0000	0.418
Cereal*temperate	-0.1511	0.0656	600	-2.3044	0.0215	0.255
Cereal*cold	0.4102	0,0637	600	6.4400	0.0000	-0.751







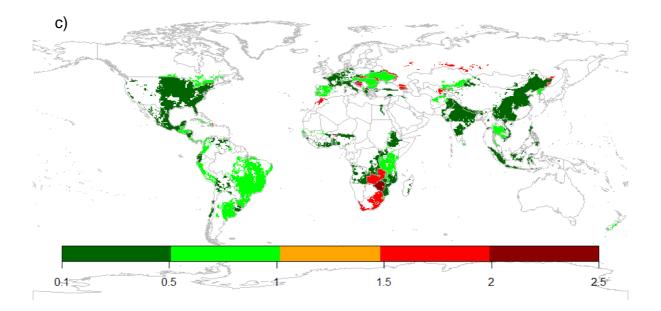


Figure 1. Mean vulnerability 1990-2005 for a) rice, b) wheat, and c) maize.

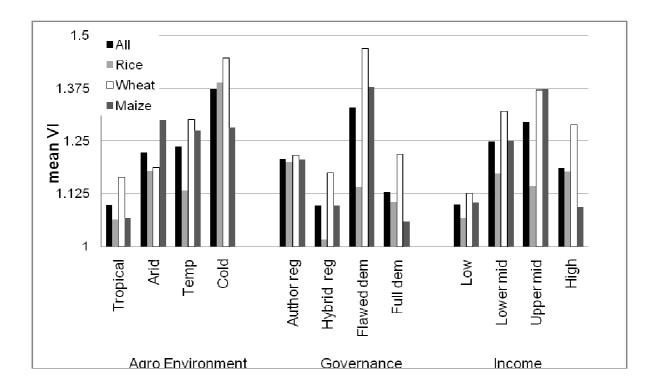


Figure 2. Mean vulnerability during droughts for all three crops together and separately, by (1) agro-environment, (2) governance and (3) income level groupings. For mean values, significant differences between groups and total number see supplementary table 1 and for box plot distributions for this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

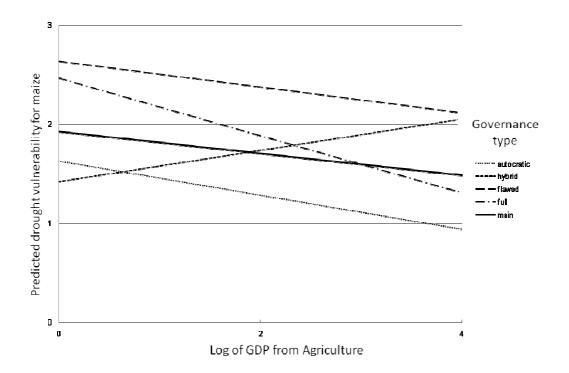
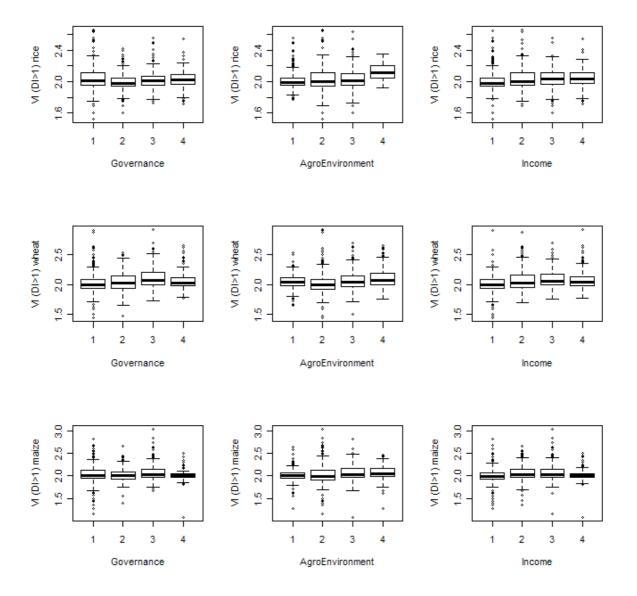


Figure 3. Main effect and interaction effects of GDP from agriculture on vulnerability to drought for maize when all other variables are kept constant.

Supplementary Figure 1. Distribution of the vulnerability index for rice (top row), wheat (middle row) and maize (bottom row) during droughts separated by governance type (left), agro-environment zone (centre) and income category (right) levels. The levels 1, 2, 3, 4 correspond to A, B, C, D and go from A for autocratic governance, tropical agro-environment, low income to D for full democracy, cold agro-environment, high income. See table 1 for descriptions of these variables and supplementary table 1 for differences between the groups. The boxplots show the median (horizontal line), 25th and 75th percentile (box), 1.5 times the inter-quartile range (~2 standard deviations) or minimum/maximum values of the data, whichever is smaller (whiskers) and outliers (circles).



References

Adger, N.W. (2006) Vulnerability. Global Environmental Change 16, 268-281.

Adger, W.N., Arnell, N.W., Tompkins, E.L. (2005) Adapting to climate change: perspectives across scales. Global Environmental Change Part A 15, 75-76.

Ahmed, S.A., Diffenbaugh, N.S., Hertel, T.W. (2009) Climate volatiliy deepens poverty vulnerability in developing countries. Environmental Research Letters 4, doi: 10.1088/1748-9326/1084/1083/034004.

Alcamo, J., Acosta-Michlik, L., Carius, A., Eierdanz, F., Klein, R., Krömker, D., Tänzler, D. (2008) A new approach to quantifying and comparing vulnerability to drought. Regional Environmental Change 8, 10.1007/s10113-10008-10065-10115.

Allison, E.H., Perry, A.L., Badjeck, M.-C., Adger, W.N., Brown, K., Conway, D., Halls, A.S., Pilling, G.M., Reynolds, J.D., Andrew, N.L., Dulvy, N.K. (2009) Vulnerability of national economies to the impacts of climate change on fisheries. Fish and Fisheries, DOI: 10.1111/j.1467-2979.2008.00310.x.

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

Challinor, A., Ewert, F., Arnold, S., Simelton, E., Fraser, E. (2009a) Crops and climate change: progress, trends, and challenges in simulating impacts and informing adaptation. Journal of Experimental Botany 60, 2775-2789.

Challinor, A.J., Wheeler, T.R., Hemming, D., Upadhyaya, H.D. (2009b) Crop yield simulations using a perturbed crop and climate parameter ensemble: sensitivity to temperature and potential for genotypic adaptation to climate change. Climate Research 38, 117-127.

Cooke, I.R., Queenborough, S.A., Mattison, E.H.A., Bailey, A.P., Sandars, D.L., Graves, A.R., Morris, J., Atkinson, P.W., Trawick, P., Freckleton, R.P., Watkinson, A.R., Sutherland, W.J., (2009) Integrating socio-economics and ecology: a taxonomy of quantitative methods and a review of their use in agro-ecology, pp. 269-277.

Crawley, M.J. (2007) The R Book. John Wiley & Sons, Ltd, Chichester, UK.

Devereux, S. (2009) Why does famine persist in Africa? Food Security 1, 25-35 doi 10.1007/s12571-12008-10005-12578.

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

EarthTrends, (2008) The environmental information portal. World Resources Institute.

Easterling, W.E., Aggarwal, P.K., Batima, P., Brander, K.M., Erda, L., Howden, S.M., Kirilenko, A., Morton, J., Soussan, J.-F., Schmidhuber, J., Tubiello, F.N., (2007) Food, fibre and forest products, in: M.L. Parry, O.F.C., J.P. Palutikof, P.J.v.d. Linden and C.E. Hanson (Ed.), Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, UK, pp. 273-313.

Erigayama, N., Smakhtin, V., Gamage, N., (2009) Mapping drought patterns and impacts: a global perspective. International Water Management Institute, Colombo, Sri Lanka, p. 31.

Evers, H.-D., Benedikter, S. (2009) Hydraulic bureaucracy in a modern hydraulic society – strategic group formation in the Mekong Delta, Vietnam. Water Alternatives 2, 416-439.

FAO, (2008) FAOSTAT Online database. Food and Agriculture Organization of the United Nations.

Folke, C. (2006) Resilience: The emergence of a perspective for social-ecological systems analyses. Global Environmental Change 16, 253-267.

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

Fraser, E., Mabee, W., Slaymaker, O. (2003) Mutual dependence, mutual vulnerability: The reflexive relation between society and the environment. Global Environmental Change 13, 137-144.

Fraser, E.D.G., Termansen, M., Sun, N., Guan, D., Simelton, E., Dodds, P., Feng, K., Yu, Y. (2008) Quantifying socioeconomic characteristics of drought-sensitive regions: Evidence from Chinese provincial agricultural data Comptes Rendus Geoscience 340 679-688.

Füssel, H.-M., Klein, R.J.T. (2006) Climate change vulnerability assessments: an evolution of conceptual thinking Climatic Change 75, 301-329.

Gbetibouo, G.A., Ringler, C., (2009) Mapping South African farming sector vulnerability to climate change and variability. A Subnational Assessment, in: Institute, T.I.F.P.R. (Ed.), IFPRI Discussion Paper 00885. Environment and Production Technology Division.

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.

Hulme, M., Barrow, E.M., Arnell, N.W., Harrison, P.A., Johns, T.C., Downing, T.E. (1999) Relative impacts of human-induced climate change and natural climate variability. Nature 397, 688-691.

IPCC, (2001) Glossary, Fourth Assessment Report, Working Group 2, pp. http://www.ipcc.ch/pdf/glossary/ar4-wg2.pdf

Janssen, M.A., Anderies, J.M., Ostrom, E. (2007) Robustness of Socio-Ecological Systems to spatial and temporal variability. Society and Natural Resources 20, 307-322.

Kandlikar, M., Risbey, J. (2000) Agricultural impacts of climate change: if adaptation is the answer, what is the question? Climatic Change 45, 529-539.

Kottek, M., Grieser, J., Beck, C., Rudolf, B., Rubel, F. (2006) World Map of the Köppen-Geiger climate classification updated. Meteorologische Zeitschrift 15, 259-263. DOI: 210.1127/0941-2948/2006/0130.

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

Liu, J., Fritz, S., van Wesenbeeck, C.F.A., Fuchs, M., You, L., Obersteiner, M., Yang, H. (2008) A spatially explicit assessment of current and future hotspots of hunger in Sub-Saharan Africa in the context of global change. Global and Planetary Change, doi:10.1016/j.gloplacha.2008.1009.1007.

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

MDG, (2008) Millennium development goals report 2008.

Mendelsohn, R. (2007) Measuring climate impacts with cross-sectional analysis. Climatic Change 81, 1-7.

Misselhorn, A.A. (2005) What drives food insecurity in southern Africa? a metaanalysis of household economy studies. Global Environmental Change Part A 15, 33-43.

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.

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

Patt, A., Siebenhüner, B. (2005) Agent based modeling and adaptation to climate change. Vierteljahrshefte zur Wirtschaftsforschung 74, 310-320.

Reidsma, P., Lansink, A.O., Ewert, F. (2009) Economic impacts of climatic variability and subsidies on European agriculture and observed adaptation strategies Mitigation and Adaptation Strategies for Global Change 14, 35-59.

Rudel, T.K., Schneider, L., Uriarte, M., Turner II, B.L., DeFries, R., Lawrence, D., Geoghegan, J., Hecht, S., Ickowitz, A., Lambin, E.F., Birkenholtz, T., Baptista, S., Grau, R. (2009) Agricultural intensification and changes in cultivated areas, 1970–2005. Proceedings of the National Academy of Sciences of the United States of America 106, 20675-20680, doi: 20610.21073/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, 58-65.

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, 438-452

Smit, B., Wandel, J. (2006) Adaptation, adaptive capacity and vulnerability. Global Environmental Change 16, 282-292.

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

The World Bank Group, (2008) World Development Indicators Online database.

Vincent, K. (2008) Uncertainty in adaptive capacity and the importance of scale Global Environmental Change 17, 12-24.

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

Yearley, S. (2009) What roles for social science in understanding climate change? Current Sociology 57, DOI: 10.1177/0011392108101589.