Climate Change, Adaptation, and Agricultural Output

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Abstract: Recent studies have estimated that climate generated extreme weather disasters have reduced crop yields globally by up to 10%. By incorporating measures of adaptive capacity, we develop a model of the relationship between climate change induced extreme weather disasters and agricultural output between 1995 and 2010. To our minds this is the first systematic effort to account for agricultural outcomes by controlling for social capabilities to counteract the pressures from the climate. Using panel data models, we find that at the national level, the greater the adaptive capability of a country the more attenuated are the expected agricultural losses from climate events. In effect climate related agricultural consequences vary as a function of the heterogeneity across countries. Much of this heterogeneity in adaptive capacity is a result of policy choices structural preparedness. We use our results to draw inferences about crop yields under different levels of adaptive capacity in the context of climate change.

Keywords: adaptive capacity; climate change adaptation; extreme weather disasters; sensitivity

1. Introduction

The international community is committed to addressing climate change impacts through adaptation. For example, Article 4.1b of the United Nations Framework Convention on Climate Change (UNFCCC) states that parties are, “committed to formulate and implement national and, where appropriate, regional programs containing measures to facilitate adequate adaptation to climate change” (UNFCCC 1992) and the recent Paris, 2016 accord codified the importance of adaptation. There are numerous climate change adaptation studies that scale up our understanding of existing vulnerabilities, climate adaptation, and the role of adaptation action at global, national, and local levels (e.g., Dunlap and Brulle 2015). Evidence suggests that climate change may lead to armed conflict (Caruso et al. 2016; Hsiang et al. 2013; Miguel et al. 2004), that climate change will affect the spread of infectious diseases and challenge local responses (Alitzer et al. 2013; Ostfeld 2009), and that agricultural deficits will increase with increasing climate pressures (Ewert 2012; Smit et al. 1999). Moreover, paleoanthropologists demonstrate that climate adaptation may account for some of the observed evolution of hominin species (Potts 2012).

A recent study estimated a 9-10% net crop yield reduction due to the excess temperature and drought at the global level (Lesk et al. 2016) and the Intergovernmental Panel on Climate Change (IPCC) predicted that crop yield reductions will be increasingly severe in the coming decades (IPCC 2014). Although evidence points to systematic relationships between climate change and agricultural output, they generally fail to demonstrate the significance of sociological and political processes and take into account efforts to forestall the effects of the climate risk on agricultural outcomes. In this study, we fill the void by investigating the role of adaptation in models of agricultural outputs from a theoretical and empirical perspective.

We build on established definitions of adaptation by IPCC (2001) and Adger et al. (2005) that "adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities" and adaptive capacity as tangible and intangible resource availabilities (e.g., Brooks et al. 2005; Cinner et al. 2015; Eakin and Lemos 2006; Smit and Wandel 2006; Yohe and Tol 2002), to extend a recent study by Lesk et al. (2016) that examines the effects of climate on global crop yields. Our objectives include (1) integrating adaptation to climate change into conceptual models of agricultural outputs, (2) estimating the impact of adaptive capacity and extreme weather disasters on crop yields, and (3) demonstrating the substantive impact adaptive capacity, sensitivity, and extreme weather events in Sudan and Cambodia.

2. Modeling adaptation to climate pressures in agricultural studies

Lesk et al. (2016) provide the first national level evidence that climate driven extreme weather disasters by reported data on the International Disaster Database (EM-DAT) systematically reduce crop yields. Figure 1 represents a parameterization of the general trend in their results. The main driver of their result is drought and drought leads to increased water scarcity, which in turn reduces available inputs in agricultural sectors. In the absence of sustained rainfall communities must choose between lower yields or proactive steps to offset reductions imposed by climate pressures. Results from Lesk et al. (2016) and others (Garibaldi et al. 2010; Liang et al. 2017) point to a rather direct effect between climate pressures and agricultural productivity.

However, most studies homogenize the impact of climate risk across diverse physical and social conditions and neglect the role of societal efforts to minimize the consequences of climate change. We argue that climatic pressures impact both physical and social systems and that much of the homogeneity observed across physical systems is masking heterogeneity across social systems. In the process of adapting to climate pressures social systems have retroactive responses or proactive responses in an effort to moderate the impact. While retroactive responses serve to offset climate-imposed consequences, proactive responses are designed to minimize expected future consequences.

Climate-driven extreme weather disasters such as drought in the U.S. West and floods in the U.S. Midwest and South, or the 2004 heat wave in Europe directly decrease crop yields. The mechanism can involve the reduction in inputs such as water, the destruction of planted crops, such as by a flood, or the inefficiency of different crop varieties under specific temperature ranges. The net result is lower yields per hectare for a given year(s) in which climate imposed harsh growing conditions. This type of model assumes no societal intervention.

We argue that this direct effect model masks underlying social efforts to respond to climatic pressures on crop yields. Many scholars assume a certain level of adaptation is taking place, but omit explicit theoretical or empirical approaches. Indicators to measure adaptive capacity are widely developed but only marginally included in output modeling (Haddad 2005). Smit and Skinner (2002) suggest four main categories of agricultural adaptation such as farm production practices, farm financial management, technological developments, and government programs and insurance.

Adaptation to climate change is a response to actual or anticipated impacts from climate pressures, and reflect social efforts to minimize risk to assets of value (Dow et al. 2013; Moser et al. 2010; Moser and Boykoff 2013). As a process to cope with the consequences of climate change (Lim and Spanger-Siegfried, 2005), adaptation that is associated with the ability of communities to provide agricultural inputs under most conditions would be an asset of value at a local and national level. Local or individual level adaptation – at the level of the farmer – may offset risk to the family, leaving the broader risk to the community or country unacceptably high. The greater the reach of adaptive capacity, the greater the requirements on capacity to facilitate and implement adaptive strategies. At the extreme, national level adaptive capacity flows through to local communities such that the broader risk is minimized through adroit national planning. One economic rationale for adaptive capacity at national level could be the expected reduction in the need for food or agricultural-input imports.

These adaptation strategies involve the interaction of micro and macro level initiatives. The centrality of adaptation is evident in the concept of water scarcity as a driver of agricultural output. Water scarcity is a function of the hydrological cycle and, ceteris paribus, sustained drought will lead to severe water scarcity. But water scarcity can be minimized by irrigation. If drought is measured by the Palmer Drought Severity Index (PDSI) or soil moisture content (ESA), both can be manipulated by adding water via ground water irrigation systems or developing water retention programs (Elliott et al. 2013). Each is a form of adaptation to climate change, and implementation is often a function of national level capacity.

Current studies from agronomy, climatology, and environmental science suggest that adaptation policies can not only mitigate the effects of climate change on crop yields but also they can transform what would be anticipated declines in yields into increases. For example, Wang et al. (2012) found that by utilizing a "double-delay" method of farming —a planned adaptation strategy—which staggers both the harvesting and planting of winter wheat and maize over a growing year, Chinese farmers not only compensated for some of the negative impacts of climate change, but realized significant crop yield increases as a result of this adaptation strategy

(Jorgensen and Termansen 2016). From this perspective models of the climatic impact on crop yields should account for the potential positive as well as negative impacts by climate change.

As depicted in Figure 2, we articulate a conceptual model of the effect of extreme weather disasters on crop yields mediated through the lens of adaptive capacity. Within the model, vulnerability to climate change refers to the potential for losses given exposure to climate-driven stressors, sensitivity is the level of risk under conditions of exposure and adaptive capacity reflects the social and structural conditions available to protect the level of risk. We hypothesize that under conditions of climate generated extreme weather disasters, greater levels of agricultural adaptive capacity will reduce expected declines in crop yield as a result of extreme weather disasters alone.

National level support for and local level implementation of adaptation strategies are functions of the sensitivity to climate change. These are related to a combination of geophysical conditions and social endowments. Social endowments can be distributed from the national to the local in accordance with the capabilities and incentives of the government. More specifically, if a country has high levels of sensitivity and large adaptive social endowments, social resources could be distributed in a way that minimizes the impact of climate stressors on agricultural output. On the other hands, if social endowments are lower than the sensitivity to climate stressors, the limited resources will have only a marginal effect on preventing crop yield reductions. Adaptive capacity in general will not reverse the deleterious consequences of extreme weather disasters but rather moderate those down-side consequences. From a broadly cross national perspective extreme weather disasters will suppress agricultural output but in environments where adaptation resources are more readily available, weather-related deficits should be minimized relative to a country with less adaptive capacity and similar sensitivity.

Based on the conceptual model of adaptive capacity and agricultural outputs, we estimate the role of adaptive capacity in mitigating climate risk on crop yields using country-level panel data.

3. Methods and data

As described in Table 1, we use selected variables as independent, dependent, or instrumented variables to secure appropriate empirical models. We use annual data by country, with logged *Cropyield*, as a dependent variable. The crop yields are equivalent to total country level production divided by acres harvested, similar to the work by Schlenker and Roberts (2009) on the U.S. crop yields under climate change. Our temporal range covers the period 1995-2010 which corresponds to data availability. Extreme weather disasters data are reported disasters and include annual drought events (*Singleyeardrought*, *Multiyeardrought*), heat (*Heat*), cold (*Cold*), and flood events (*Flood*). These data are recoded dichotomously (1= yes, 0 = no) and were obtained from EM-DAT.

We add indicators of the theoretical conditions of climate sensitivity and adaptive capacity, which jointly contribute to conditions of climate vulnerability (*Sensitivity* and *Agricultural capacity*). These data come from Notre Dame Global Adaptation Initiative (ND-GAIN) (http:// index.gain.org) and cover the same 167 countries and span the years 1995-2015. Sensitivity captures the extent to which a country is dependent upon a sector or the proportion of the population that is negatively affected by climate-related disasters; adaptive capacity captures the availability of social resources for sector-specific adaptation. ND-GAIN records a sectorally constrained measure of agricultural adaptive capacity, which we use in our primary models. For our instrumental model we use the *Readiness* indicator from ND-GAIN which represents a country's investment capability for adaptation actions and includes economic conditions, governance support, and social capacities, and the *Infrastructure* variable to capture the capacity to mitigate negative effects of climate change on infrastructure.

We use the primary data on extreme weather disasters and agricultural outputs from Lesk et al. (2016) to directly replicate and extend their analysis. We proceed systematically by first replicating within a parametric framework the results of Lesk et al. (2016). We follow this with a series of cross sectional time series models that address the effect of adaptive capacity on agricultural output over 15-year period (from 1995 to 2010). A Hausman test result (Chi-square (7) =55.52, p = 0.000) suggests that a fixed effect model is appropriate. Since the distribution of the dependent variable, *Cropyield*, was positively skewed (skewness 1.39), we logged our outcome variable. Our analysis, then, employs fixed effects panel models such as a linear model and an instrumental variable model. We replicate the Lesk et al. (2016) results using a linear OLS model. We test the robustness of results with an instrumental variable model with over identification tests of all instruments, instrumenting national level agricultural adaptive capacity. Our instruments include *Sensitivity*, *Lagged Singleyeardrought, Lagged Multiyeardrought, Cropharvested area, Infrastructure,* and *Readiness* for climate investment.

To test panel-level heteroscedasticity and autocorrelation, we use a Wald test for groupwise heteroscedasticity in fixed effect regression model and Wooldridge test for autocorrelation in panel data. These tests demonstrate that there is no heteroscedasticity (Chi-square (165) = 74,558.72, p = 0.000) or serial correlation (F (1, 164) = 1.313, p <0.253). To take into account robustness, we use Huber and White robust standard errors. Our test for the over identification for instrumented variables, Sargan statistic (Chi-square (5) = 48.59, p=0.000) suggests that our model is identified. Our primary explanatory variable of agricultural adaptive capacity is comprised of 12 indicators from which ND-GAIN calculates Adaptive Capacity (AC) index as:

$$AC_{\mathrm{Y}}^{\mathrm{N}} = \frac{1}{\sum_{r=1}^{m} \alpha_r} \sum_{r=0}^{m} \alpha_r \left| d_r - \mathrm{I}_{Y,r}^{\mathrm{N}} \right| \qquad \text{Eq. (1)}$$

where r is the index of the AC. AC has 12 indicators, thus $r = 1,2,3 \dots ,12$, m is the number of indicators, in this case 12, α_r is the equally weighted indicator, d_r is the direction adjustment for AC indicator r, $\mathrm{I}_{Y,r}^{\mathrm{N}}$ is the scaled score for indicator r for nation N and year Y. Those 12 indicators that can be obtained from ND-GAIN index include agriculture capacity, child malnutrition, dam capacity, access to reliable drinking water, medical staff, access to improved sanitation facilities, protected biome, engagement in international environmental conventions, quality of trade and transport infrastructure, paved roads, electricity access, and disaster preparedness.

The differences in observations reflect the different time frames used by Lesk et al. (1960-2010) and the ND-GAIN index (1995-2015). Developing several fixed effects estimations with balanced panel models that accounts for the role of climate sensitivity and agricultural adaptive capacity generates the following specification:

$$\begin{aligned} \log Cropyield_{it} = {} & \beta_1 Singleyeardrought_{it} + \beta_2 Heat_{it} + \beta_3 Multiyeardrought_{it} + \beta_4 Cold_{it} \\ & + \beta_5 Flood_{it} + \beta_6 Sensitivity_{it} + \beta_7 Agriculturalcapacity_{it} \\ & + \alpha_i + \mu_{it} \end{aligned} \qquad \text{Eq. (2)}$$

where i denotes spatial units (countries in the study), t indicates time series dimensions (1995 to 2010 in this study), α_i is the unknown intercept for each study area i , and μ_{it} is the error term. Building on Eq. (2) and responding to the moderate effects of extreme weather events and climate sensitivity and agricultural capacity, we add interaction effect variables like *Heat×Agricultural capacity, Multiyeardrought×Agricultural capacity*, *Heat×Sensitivity*, and *Multiyeardrought×Sensitivity*. Based on the panel data specification, we propose three different empirical equations. In all three equations agricultural adaptive capacity (*Agricultural capacity* variable) enters additively with respect to the extreme weather disasters.

Next, in order to estimate "the presence of unobserved effects and endogeneity in one or more time-varying explanatory variables," we employ an instrumental variables estimation with panel data (Wooldridge 2006, p.538). As noted before, we used several variables including sensitivity (*Sensitivity*), one year lagged multi and single year drought (*Lagged Multiyeardrought* and *Lagged Singleyeardrought*), crop harvested area (*Cropharvested area*), readiness for climate investment (*Readiness*), and the country's infrastructure (*Infrastructure*) as instrumental variables. Based on Eq. (2), a fixed effects-instrumental variable panel model can be given:

$$\log Cropyield_{it} = f(Singleyeardrought_{it}, Heat_{it}, Multiyeardrought_{it}, Cold_{it}, Flood_{it}, Sensitivity_{it}, Agriculturalcapacity_{it})$$

Eq. (3)

$$Agriculturalcapacity_{it} = g(LaggedMultileyeardrought_{it}, LaggedSingleyeardrought_{it}, Cropharvestedarea_{it}, Readiness_{it}, Infrastructure_{it},)$$

4. Results

Table 2 presents empirical estimations of the role of adaptive capacity on agricultural output by comparing to the Lesk et al.'s (2016) approach to the relationships between extreme weather disasters and agricultural output. Our initial effort is to confirm the broad outlines of their results, albeit using a parametric form of estimation. By our modeling the results reported by Lesk and colleagues (2016) are confirmed. Extreme weather disasters associated with drought generate decreased crop yields. Other forms of extreme weather disasters are associated with yield increases. We can attribute these differences to model specification.

In subsequent models we add sophistication to the theoretical and empirical specifications by employing cross-sectional and temporal designs, and including national level indicators of climate sensitivity and agricultural adaptive capacity. These results support both the initial argument about climate disasters and the influence of country level capacity. In a panel model with both climate sensitivity and agricultural adaptive capacity the implication for country level capacity is quite strong (b= 0.305; robust se=0.103 Model 3 and b=0.302; robust se=0.103 Model 4). In Models 2-4 the seemingly confounding signs associated with non-drought extreme weather disasters are now negative and the more sensitive a country to climate pressure the greater the reductions in crop yields (b=-2.729; robust se= 0.428 Model 3 and b=-2.719; robust se=0.432 Model 4). One could question whether a general level of adaptive capacity or an agricultural-specific measure provides the best theoretical traction on understanding the mediating effect on crop yields. Primarily we emphasize agricultural adaptive capacity because it portends to give greater purchase on the capability to offset agricultural loses, but we provide in an appendix comparing results using the broader measure of national adaptive capacity. These results confirm our findings using agricultural-specific measure.

Given interaction effects of extreme weather events and climate sensitivity or adaptive capacity, there remain unexpected results (Model 4). Our empirical results stand up across various model specifications and indicators of adaptive capacity. Whether we use a general indicator of national adaptive capacity, an agricultural specific indicator, or indicators that capture specific forms of agricultural adaptive capacity, our results demonstrate that human social adaptation can attenuate the debilitating consequences of climate driven extreme weather disasters on agricultural productivity.

We extend our linear model in Table 2 to include an instrumental variable model. Reflecting on the statistically significant effect of crop yield (p=0.000), Model 5 captures the positive outcome of agricultural adaptive capacity and negative influence of sensitivity level on agricultural output in the context of climate change. As with our empirical results, these more robust specifications confirm that extreme weather disasters tend to have deleterious effects on agricultural outputs, but that country level adaptive capacity can offset some of those effects.

Table 3 presents the predicted crop yields based on the results of our empirical analysis. We draw these results from Model 4. The predicted yields demonstrate two critical aspects of a country's climate vulnerability with regard to agricultural output. First, the degree of climate sensitivity has a large impact on crop yields in the face of multiyear droughts. Under drought conditions a highly sensitive country at the lower end of adaptive capacity suffers crop yields losses that are five times those of a less sensitive country with the same adaptive capacity (yields: 6,011 vs. 32,700). At the higher end of adaptive capacity those losses are still significant but amount to less than half of the predicted agricultural output (yields: 35,050 vs. 61,762). Second, adaptive capacity has a significant impact on expected output that is non-linear. Countries with low adaptive capacity and high sensitivity are estimated to lose 47% of their yields due to drought, whereas countries with higher capacity are estimated to lose only 13% as a result of multiyear droughts. Clearly the attributes of a country with regard to social and structural conditions that influence outcomes from climate stressors have a large impact. We present this predicted change in yields graphically in Figure 3.

To demonstrate the practical implications we use our model to estimate the outcome in specific countries (Table 4). Sudan is a resource constrained country that has suffered from drought conditions, desertification, and war. They also fall at the lower end of the adaptive capacity indicator and in the middle of our sensitivity measure. Under drought conditions in 2001, the predicted loss in yields from a multi-year drought is roughly 90%. But if Sudan were to increase its adaptive capacity by a factor of three (still leaving it on the lower end of global averages), the expected loss from a drought would be less than 50%. Alternatively, Cambodia has a much wetter climate, low socio-economic development, and low levels of adaptive capacity; it suffered from a multiyear drought ending in 1996. The expected loss from that drought would amount to 32% crop yields relative to non-drought conditions. If they were to increase their adaptive capacity by a factor of two (0.11 to 0.22), yields would be expected to drop by only 11%.

5. Conclusions and discussion

Biophysical evidence supports the notion that climate change is causing reductions in agricultural outputs. This augurs poorly for a planet with a growing population, a changing climate, and great disparities in social endowments across countries. But the evidence to date does not adequately take into account the role of human social efforts to offset the damaging impacts from climate change. Evidence from China suggests that farmers are changing their methods of farming in response to declining yields (Wang et al. 2012), and individual case studies confirms this across a wider swath of political and social systems (Jorgensen and Termansen 2016; Wirehn et al. 2017). We present the broad evidence that national level adaptive capacity can offset the negative impacts of climate, at least as it pertains to agricultural output. In the study, we provide insights about the interface between national wealth, exposure to severe climate, and adaptive agricultural capacity to the physical impacts of extreme weather events in the agriculture sector. Manipulating national level adaptive capacity is a social choice among possible tradeoffs as to where to spend limited resources. To the extent that the international community can support the development of adaptive capacity, our evidence suggests that climate induced human trauma can be minimized. In this sense our results have broad policy implications.

Analysis relies on the assumption that if the country has greater adaptive capacity this will ‘trickle down’ at higher amounts to a local level and in effect, farm-level capacity to offset climate pressure is mirrored in national level policy. While national level agricultural policy is almost by definition designed to influence local level strategies, systematic evidence at the local level would go a long way to helping to merge biophysical evidence about climate and its consequences to policy research that might help design ways to offset climate consequences. As farm-level adaptation strategies, numerous economic models (e.g., Forest and Agricultural Sector Optimization Model, Farm Aquaculture Resource Management Model) allow farms in different regions to select new crop rotation systems in response to climate conditions. In the new systems, farms adapt agricultural production systems to accommodate new climate conditions by changing in input mix and use like nutrient management, tillage, and irrigation. Ground water irrigation provides one form of proactive or reactive adaptation in response to expected or actual drought conditions. Estimates are that on the African continent only 6% of agriculture is irrigated through ground water sources (Liangzhi et al. 2010), leaving ample room for increased adaptive capacity to be developed. Policy, whether internationally supported or otherwise, can shape agricultural consequences from drought by increasing irrigation initiatives. These can be through broad regional projects or farmer level access to small irrigation pumps. Alternatively, national level support for local level adaptation in the form of access to more responsive seed varieties could reduce the impact from drought on local crop yields. Either strategy would reflect an increased level of adaptive capacity.

Appendices

Primarily we emphasize agricultural adaptive capacity because it portends to give greater purchase on the capability to offset agricultural loses, but we provide comparative results using the broader measure of national adaptive capacity. Table A.1 reproduces the results presented in the main paper with a general indicator of national level adaptive capacity using the same model specifications. Results are supported. Moreover, in an effort to generate policy specific inferences about agricultural adaptive capacity, we extract a sectoral agricultural capacity index that reflects specific input capabilities. The composite agricultural capacity indicators are categorized into structural and non-structural capacity. Structural agricultural capacity (*Structural agricultural capacity*) includes the area equipped with irrigation and tractor usage, non-structural capacity (*Nonstructural agricultural capacity*) involves the extent of fertilizer use and pesticide use. Our empirical results stand up across various model specifications and indicators of adaptive capacity. Whether we use a general indicator of national adaptive capacity, an agricultural specific indicator, or indicators that capture specific forms of agricultural adaptive capacity, our results demonstrate that human social adaptation can attenuate the debilitating consequences to agricultural productivity from climate driven extreme weather disasters.

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Table 1. Descriptive statistics

Variable name		Obs	Mean	SD	Min	Max	
Singleyeardrought	(index)	8,450	0.037	0.188	0	1	IV
Heat	(index)	8,450	0.015	0.123	0	1	IV
Multiyeardrought	(index)	8,450	0.064	0.245	0	1	IV
Cold	(index)	8,450	0.020	0.140	0	1	IV
Flood	(index)	8,450	0.238	0.426	0	1	IV
Sensitivity	(index)	2,704	0.430	0.146	0.125	0.811	IV/IS
Agricultural capacity	(index)	2,656	0.364	0.329	0	1	IV
Cropharvested area	(10,000m^2)	7,536	4,083,373	1.25e+07	2	1.07e+08	IS
Infrastructure	(index)	2,704	0.347	0.141	0.058	0.808	IS
Readiness	(index)	2,672	0.409	0.167	0.090	0.883	IS
Cropyield	(0.1 kg/10,000m^2)	7,536	21,536.96	15,417.92	542	97,108	DV
Log Cropyield	(logged *Cropyield*)	7,536	9.732	0.721	6.292	11.483	DV

Note : units are in parentheses, IV : independent variable, IS : instruments variable, DV: dependent variable

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Table 2. Crop yields as a function of climatic condition and vulnerability

	Lesk et al. (2016)'s replication OLS	Panel design w/vulnerability measures			
		cross-section, time series OLS, fe			instrumental
	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	9.704*** (0.009)	11.148*** (0.177)	11.010*** (0.188)	11.007*** (0.189)	8.782*** (0.303)
Singleyeardrought	-0.146*** (0.040)	-0.077** (0.030)	-0.073** (0.030)	-0.072** (0.030)	-0.042 (0.036)
Heat	0.490*** (0.054)	-0.065** (0.020)	-0.064** (0.020)	-0.097 (0.064)	-0.067** (0.027)
Multiyeardrought	-0.585*** (0.029)	-0.074** (0.023)	-0.070** (0.023)	-0.073 (0.101)	-0.059** (0.028)
Cold	0.399*** (0.041)	-0.023* (0.014)	-0.019 (0.013)	-0.017 (0.013)	0.014 (0.028)
Flood	0.219*** (0.017)	0.025** (0.009)	0.025** (0.009)	0.024** (0.009)	0.023* (0.011)
Sensitivity		-2.775*** (0.413)	-2.729*** (0.428)	-2.719*** (0.432)	
Agricultural capacity			0.305** (0.103)	0.302** (0.103)	3.291*** (0.839)
Heat×Agricultural capacity				0.117 (0.089)	
Multiyeardrought×Agricultural capacity				-0.056 (0.098)	
Heat×Sensitivity				-0.127 (0.187)	
Multiyeardrought×Sensitivity				0.029 (0.202)	
Number of observations / groups (nations)	7,536	2,661/168	2,613 /165	2,613/165	2,581/163
F	155.37***	16.88***	12.99***	9.97***	
R-squared	0.682				
Wald Chi-square					56.91***

Note: *: $P<0.1$, **: $P<0.05$, ***: $P<0.001$ (two-tailed test), robust standard errors in parentheses , dependent variable is log *crop yield*

Table 3. Estimated crop yields by adaptive capacity, sensitivity, and drought

	High sensitivity			Low sensitivity		
Adaptive capacity	Multi- year drought	No multi-year drought	%Loss yield	Multi- year drought	No multi-year drought	%Loss yield
0.10	6,011	11,265	46.65	32,723	37,977	13.84
0.20	9,237	14,491	36.26	35,950	41,203	12.75
0.30	12,464	17,718	29.68	39,176	44,430	11.83
0.40	15,691	20,944	25.09	42,403	47,657	11.03
0.50	18,917	24,171	21.74	45,629	50,883	10.33
0.60	22,144	27,398	19.18	48,856	54,110	9.71
0.70	25,370	30,624	17.16	52,083	57,336	9.17
0.80	28,597	33,851	15.53	55,309	60,563	8.68
0.90	31,823	37,077	14.18	58,536	63,790	8.24
1	35,050	40,304	13.04	61,762	67,016	7.84

Table 4. Comparisons of estimated crop yields between Sudan and Cambodia

Adaptive capacity	Sensitivity	Multi- year drought	No multi-year drought	Δ yield	Loss reduction
Sudan					
0.03	0.55	511	5,765	-5,254	
0.10	0.55	2,770		-2,995	43%
Cambodia					
0.11	0.34	11,263	16,517	-5,254	
0.22	0.34	14,813		-1,704	68%

Table A.1. Comparative estimates with and without adaptive capacity

	Cross sectional models w/adaptive capacity			Instrumental		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	11.148***	8.512***	9.584***	7.403***	8.301***	9.115***
	(0.177)	(0.146)	(0.255)	(0.347)	(0.521)	(0.259)
Singleyeardrought	-0.077**	-0.066**	-0.064**	-0.053*	-0.082**	-0.043
	(0.030)	(0.030)	(0.030)	(0.031)	(0.032)	(0.035)
Heat	-0.065**	-0.070**	-0.065**	-0.068**	-0.097**	-0.055**
	(0.020)	(0.020)	(0.020)	(0.021)	(0.029)	(0.025)

Multiyeardrought	-0.074** (0.023)	-0.069** (0.023)	-0.057** (0.022)	-0.058** (0.022)	-0.096*** (0.024)	-0.056* (0.030)
Cold	-0.023* (0.014)	-0.017 (0.014)	-0.016 (0.013)	-0.009 (0.015)	-0.022 (0.023)	0.034 (0.029)
Flood	0.025** (0.009)	0.014* (0.008)	0.015* (0.008)	0.004 (0.009)	0.017 (0.011)	0.021 (0.013)
Sensitivity	-2.775*** (0.413)		-1.958*** (0.410)			
Adaptive capacity		3.123*** (0.315)	2.620*** (0.322)	5.497*** (0.742)		
Structural agricultural capacity					6.832** (2.135)	
Nonstructural agricultural capacity						3.380** (1.034)
Number of observations / nations		2,661 /168			2,629/166	
F	16.88***	22.41***	21.27***			
Wald Chi-square				94.30***	42.63***	28.96**

Note: *: $P<0.1$, **: $P<0.05$, ***: $P<0.001$ (two-tailed test), robust standard errors in parentheses , dependent variable is log *crop yield*

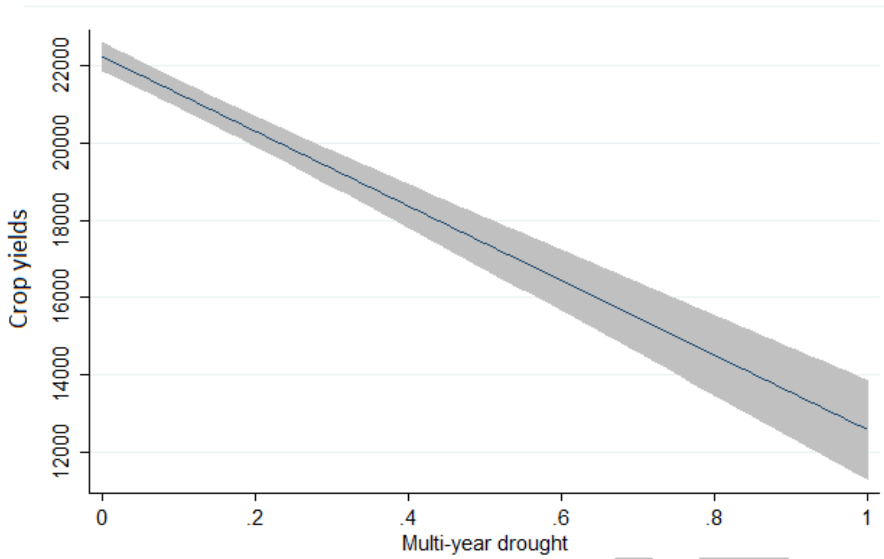

Figure 1. Estimated effect of drought on crop yields

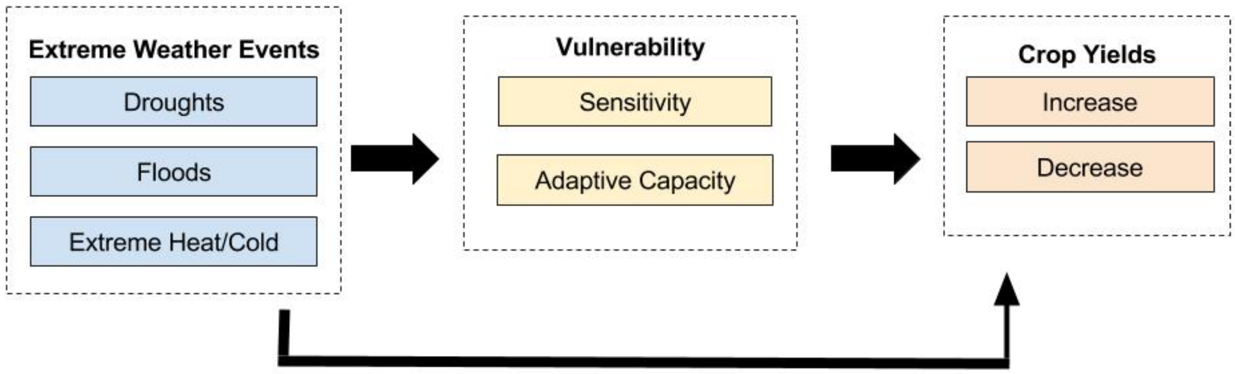

Figure 2. Model of agricultural adaptation to climate change

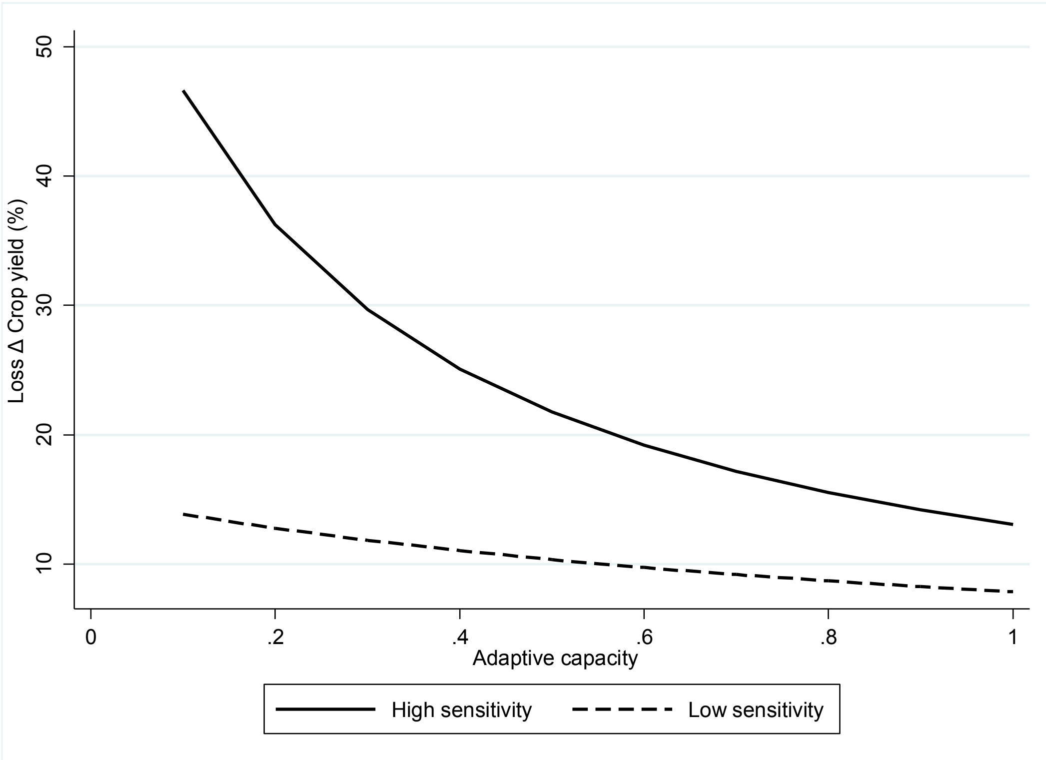

Figure 3. Predicted crop yields change by sensitivity, adaptive capacity under conditions of multiyear drought