Quantifying Vulnerability to Climate Change: Implications for Adaptation Assistance

David Wheeler

Abstract

This paper attempts a comprehensive accounting of climate change vulnerability for 233 states, ranging in size from China to Tokelau. Using the most recent evidence, it develops risk indicators for three critical problems: increasing weather-related disasters, sea-level rise, and loss of agricultural productivity. The paper embeds these indicators in a methodology for cost-effective allocation of adaptation assistance. The methodology can be applied easily and consistently to all 233 states and all three problems, or to any subset that may be of interest to particular donors. Institutional perspectives and priorities differ; the paper develops resource allocation formulas for three cases: (1) potential climate impacts alone, as measured by the three indicators; (2) case 1 adjusted for differential country vulnerability, which is affected by economic development and governance; and (3) case 2 adjusted for donor concerns related to project economics: intercountry differences in project unit costs and probabilities of project success. The paper is accompanied by an Excel database with complete data for all 233 countries. It provides two illustrative applications of the database and methodology: assistance for adaptation to sea level rise by the 20 island states that are both small and poor and general assistance to all low-income countries for adaptation to extreme weather changes, sea-level rise, and agricultural productivity loss.

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1. Introduction

The recent history of extreme weather events suggests that significant climate change may have begun. Severe drought lurks behind the Darfur conflict;[1] a rising sea level has combined with subsidence and cyclone activity to drive thousands of people off islands in the Sundarbans of India and Bangladesh;[2] and a World Meterological Organization report issued in August, 2007 linked global warming to unprecedented rainfall and flooding in South Asia and China.[3] Warmer seas and greater atmospheric moisture seem to have increased the power of hurricanes, magnifying their destructive coastal impacts in Central America, the Caribbean, East Asia and South Asia.[4] In a possible indicator of this trend, the year 2007 witnessed the first documented hurricane landfalls in Brazil and the Arabian Sea.[5] The current year is tied with 1998 as the warmest on record, [6] with a notable surge of extremely damaging weather in Pakistan,[7] Russia,[8] China[9] and elsewhere.

Individual weather events can easily be ascribed to natural variation, so credible inferences about climate change require tests for significant shifts in the historical pattern of weather-related variables. In developed countries, temperature and rainfall data are available from thousands of weather stations for periods as long as a century. They permit rigorous analysis of climate stability, both at individual weather station sites and across broader areas. Drawing on this information, a comprehensive assessment by the US National Oceanic and Atmospheric Administration (NOAA) concludes that significant climate change is occurring in the US (Karl, et al., 2009). This finding is bolstered by IPCC (2007): "At continental, regional, and ocean basin scales, numerous long-term changes in climate have been observed. These include … aspects of extreme weather including droughts, heavy precipitation, heat waves and the intensity of tropical cyclones."

[1] Faris (2007)
[2] Sengupta (2007)
[3] WMO (2007b)
[4] Emmanuel (2005) and Webster (2006)
[5] WMO (2007b)
[6] NOAA (2010b)
[7] New York Times (2010a)
[8] Rionovosti (2010)
[9] New York Times (2010b)

While scientific tests of weather data are clearly necessary for policy analysis, they are insufficient for two main reasons. First, they cannot be replicated in many countries—particularly developing countries—where historical data are sparse. Second, even where such assessments are possible, their conclusions are limited to statements about the distribution of potentially-damaging weather events. These statements may tell us little about the consequences for particular communities, whose ability and willingness to invest in protective measures depends on local geographic conditions, incomes, discount rates, social norms, perceptions of local climate risk, and the costs of risk-mitigation measures. Complete insulation from climate risk is infeasible, even for the wealthiest communities, and affordable adaptive measures may leave poor communities exposed to recurrent losses in hazard-prone areas.

Things may get much worse when the climate changes, as hundred-year floods become ten-year floods; coastal storm surges are amplified by sea level rise and more frequent, powerful hurricanes; destructive tornados increase in frequency and magnitude; drought-induced wildfires become larger and more widespread; and farmers are forced to cope with unfamiliar weather regimes. Where large numbers of people have settled in "safe" areas on the periphery of historical hazard zones, rapid expansion of those zones may lead to huge losses before settlement patterns adapt. And the effect may be compounded if the climate keeps changing in fits and starts, rather than slowly and predictably.

In short, understanding vulnerability requires information on potential human impacts as well as scientific assessments of weather data. The potential for quantifying such impacts is illustrated by the EM-DAT database, which is maintained by the Centre for Research on the Epidemiology of Disasters (CRED) at the Université Catholique de Louvain. This database contains information on human losses from natural disasters in 222 countries since 1900. Among the disaster categories tracked by EM-DAT, five are particularly relevant for climate change analysis: floods, droughts, extreme heat, wind storms and wild fires.

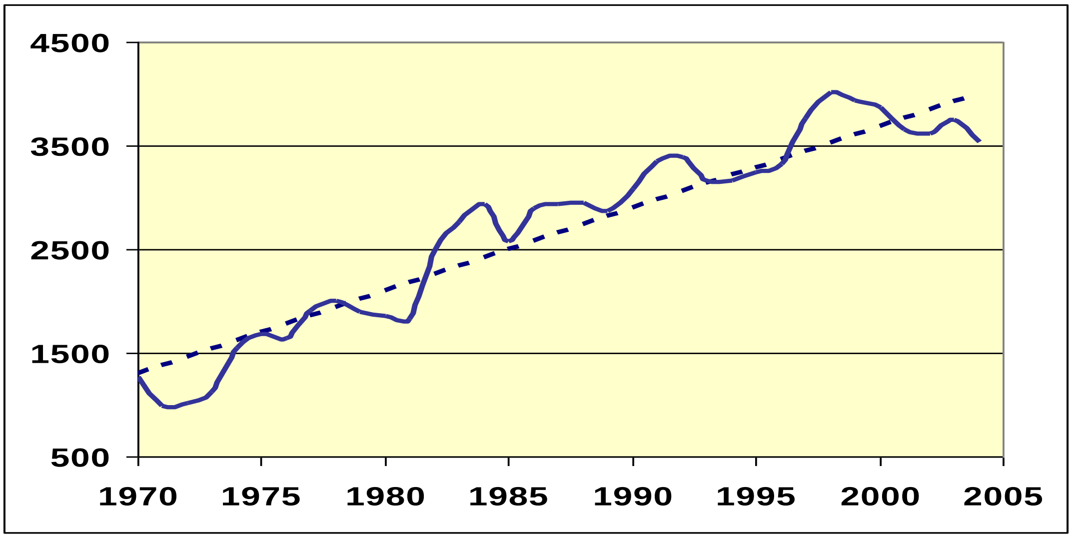
Figures 1 and 2 illustrate overall trends in EM-DAT from 1970 to 2008. Figure 1 displays the global probability of being affected by an event in one of the five climate-related disaster categories. The data are smoothed using an 11-year centered moving average and accompanied by the regression trend line.[10] They suggest a steady upward trend, with an annual increase of about 80 per 100,000. Reported risk has roughly tripled since 1970, from 1,300 per 100,000 (or 1.3%) to 4,000 (or 4%).

Figure 2 presents regional trends in the annual number of countries with climate-related disasters in the five categories. The figure displays country numbers as percents of regional totals for ease of comparison. Numerically, total affected countries increased from 39 in 1970 to 103 in 2008: from 4 to 16 in Europe, 12 to 25 in Asia, 5 to 28 in

[10] Estimated by Prais-Winsten (AR 1): Trend coefficient 79.61; t-statistic 8.16 (significant at .001)

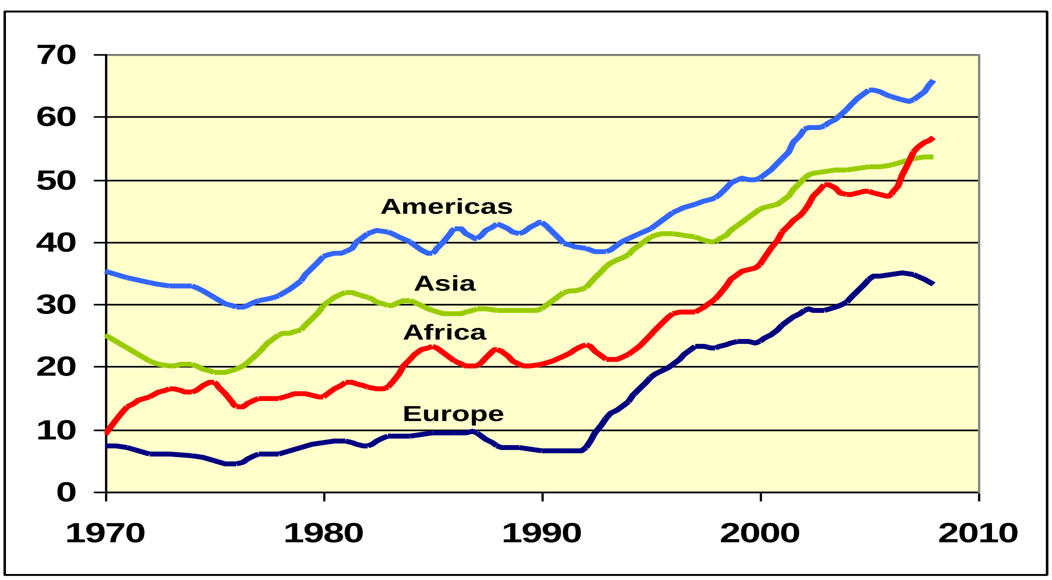
Africa, and 18 to 34 in the Americas. In all four regions, the time lines suggest particularly rapid increases after 1990.

Figure 1: Global Climate Risk, 1970–2008: Probability of Being Affected by an Extreme Climate Event* (Per 100,000)



* Eleven-year centered moving average; trend estimated by Prais-Winsten (AR 1)
Data source: EM-DAT (2010)

Figure 2: Percent of Countries with Extreme Weather Impacts, 1970–2008*



***** Five-year moving average
Data source: EM-DAT (2010)

Although the patterns displayed in Figures 1 and 2 are certainly consistent with climate change, there are other possible explanations. The first is better coverage of extreme weather events, as registration of local weather disasters has improved. The second possible explanation is population growth, which has increased the number of people who are potentially subject to extreme weather events.[11] The third potential factor is rapid urbanization -- movement from traditional settlements that are adapted to their local environments to relatively unprotected sites in urban areas. Governance may be a related factor, particularly the ability of public authorities to enforce restrictions on settlement in high-risk areas. All four of these potentially-confounding factors – better information about disasters, population growth, rapid urbanization and weak regulation – may be most significant in developing countries. And taken together, they might suffice to explain the patterns in Figures 1 and 2 even if no climate change had occurred.

While these confounding factors may account for part of the increase in reported weather impacts since 1970, growth in per capita income has undoubtedly pushed in the opposite direction. Extensive research suggests that income growth has a significant risk-reducing impact, via greater willingness to pay for personal security, a lower discount rate, and greater support for public investments in risk reduction.[12] This factor might cause reported losses to hold steady or even decline in the face of rapid climate change, as income growth reduced the vulnerability of affected communities. And, to reverse the argument of the previous paragraph, the same "masking" effect might characterize societies where improving governance promotes more climate resilience.

In summary, we cannot understand the implications of climate change without quantifying its human impacts. This requires extending research beyond weather pattern analysis to observed human impacts and the geographic and socioeconomic factors that influence them. But this extension places additional demands on research, because it requires statistical analysis to separate the possible role of climate change from the effects of changes in other variables – income, governance, urbanization – that influence the human impact.

Ultimately, such research is important for two reasons. First, we cannot accurately assess the impact of climate change without quantitative analysis that controls for the concurrent influence of other factors. And uncertainty about the magnitudes of impacts, and related costs, hinders intelligent collective action to control global carbon emissions. Second, our ability to cope with climate change depends critically on specific knowledge about where, when, and how much it will affect human communities. Without such information, we cannot make rational decisions about allocating scarce resources for adaptation.

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[11] Although the trend in Figure 1 normalizes by population, growth in the latter might still produce a disproportionate number of settlements where extreme weather events produce casualties beyond CRED's reporting thresholds of 10 people killed or 100 affected.

[12] See for example Blankespoor, et al. (2010).

This paper responds on both fronts with a global exercise that spans 233 states. In Section 2, I marshal the available evidence to develop country impact indicators for three critical dimensions of climate change: more extreme weather; sea level rise (SLR) and loss of agricultural productivity. The extreme weather exercise requires new econometric work that focuses on two objectives: separating the effects of climate change, income and governance, and estimating the effect of the latter two variables on vulnerability to climate change. In the SLR exercise, the foundation is my previous work with co-authors for a subset of developing countries (Dasgupta, et al., 2009a,b). This paper extends coverage to the full set of coastal and island states. Similarly, my agricultural productivity exercise extends the ground-breaking work of Cline (2007) to the full set of 233 states.

After the impact indicators are constructed, Section 3 incorporates them in a methodology for cost-effective allocation of adaptation assistance. The methodology can be applied easily and consistently to the entire set of 233 countries, or to any subset that may be of interest to particular donors. It can address one problem (e.g., sea level rise alone) or all three. Because institutional perspectives and priorities differ, I develop resource allocation formulas for three cases: (1) Potential climate impacts alone, as measured by my indicators; (2) Case (1) adjusted for differential country vulnerability, which I estimate from my econometric results for extreme weather impacts; (3) Case (2) adjusted for donor concerns related to project economics: inter-country differences in project unit costs and probabilities of project success.

In Section 4, I demonstrate the scope and flexibility of the methodology with separate illustrations for two contrasting cases: specific assistance for adaptation to sea level rise by the 20 island states that are both small and poor; and general assistance to all low income countries for adaptation to extreme weather changes, sea level rise, and agricultural productivity loss. I provide a summary, conclusions and discussion of potential implications in Section 5.

2. Quantifying Vulnerability to Changes in Extreme Weather, Sea Level Rise and Agricultural Productivity Loss

2.1 Vulnerability to Changes in Extreme Weather

2.1.1 Introduction to the CRED Database

Cross-country econometric work on the impacts of climate-related disasters depends critically on the EM-DAT database, maintained by the Centre for Research on the Epidemiology of Disasters (CRED) at the Université Catholique de Louvain, Brussels. To be entered in CRED's EM-DAT database, a natural disaster must involve at least 10 people reported killed; 100 people reported affected; the declaration of a state of emergency; or a call for international assistance. Recorded deaths include persons confirmed as dead and persons missing and presumed dead. Total affected persons include people suffering from disaster-related physical injuries, trauma or illness requiring medical treatment; people needing immediate assistance for shelter; or people requiring other forms of immediate assistance, including displaced or evacuated people.[13]

CRED characterizes its methodology and information sources as follows:

> The database is compiled from various sources, including UN agencies, non-governmental organizations, insurance companies, research institutes and press agencies. Priority is given to data from UN agencies, governments and the International Federation of Red Cross and Red Crescent Societies. …The entries are constantly reviewed for redundancy, inconsistencies and incompleteness. CRED consolidates and updates data on a daily basis. A further check is made at monthly intervals. Revisions are made annually at the end of each calendar year.[14]

As I noted previously, the rapid increase in CRED-reported disasters since 1970 may reflect several factors besides climate change. CRED itself provides a cautionary note (Revkin, 2009):

> CRED is fully aware of the potential for misleading interpretations of EM-DAT figures by various users … We believe that the increase seen in the graph until about 1995 is explained partly by better reporting of disasters in general, partly due to active data collection efforts by CRED and partly due to real increases in certain types of disasters. We estimate that the data in the most recent decade present the least bias and reflect a real change in numbers. This is especially true for floods and cyclones. Whether this is due to climate change or not, we are unable to say.[15]

CRED's disclaimer has two clear implications for the use of EM-DAT data. First, the likelihood of confounding effects from improved information is high for the period before 1995. Second, any credible attempt to impute climate change effects from recorded disasters must incorporate such confounding factors. Accordingly, I limit my econometric assessment to the period since 1995 and introduce explicit controls for the four confounding factors noted in the introduction -- better information about disasters, population growth, rapid urbanization and weak regulation.

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[13] For more information, see the EM-DAT glossary at http://www.emdat.be/criteria-and-definition.

[14] Statement by EM-DAT/CRED, available online at http://www.emdat.be/frequently-asked-questions

[15] Cited online at http://dotearth.blogs.nytimes.com/2009/02/23/gore-pulls-slide-of-disaster-trends/

2.1.2 Model Specification and Data

My core model specifies climate impact risk as a function of radiative forcing from atmospheric accumulation of CO2. I define climate impact risk in year t as the probability that a representative individual will be affected by an extreme weather event in that year. The radiative forcing attributable to a particular concentration level of atmospheric CO2 is "...the rate of energy change per unit area of the globe as measured at the top of the atmosphere" (Rockström, et al., 2009). By convention, radiative forcing is expressed in watts per square meter and measured relative to the pre-industrial atmospheric concentration of CO2 in 1750 (277 ppm). Equation (1) provides a standard approximation to the relationship between radiative forcing and CO2 accumulation (IPCC 2001, Myhre, et al., 1998):

$$(1)\quad \Delta F_t = \theta \ln \frac{C_t}{C_0}$$

where ΔF_t = Radiative forcing (W/m^2) in year t
C_t = Atmospheric CO2 concentration in year t
C_0 = Atmospheric CO2 concentration in reference year

I embed this relationship in an estimating equation (2) that also incorporates income per capita and the confounding factors identified in the previous section. In (2), β_1 can be derived from estimation results once θ is specified (the standard approximation for θ is 5.35 (IPCC 2001, Table 6.2)); B_0 can be estimated once θ and C_0 are specified (the standard reference date for C_0 is 1750, when the atmospheric CO2 concentration was 277 ppm (Neftel et al., 1994)).

(2)

$$l(p_{it}) = [\beta_0 - \theta \ln C_0] + \beta_1 \theta \ln C_t + \beta_2 \ln Y_{it} + \beta_3 \ln N_{it} + \beta_4 \ln U_{it} + \beta_5 I_{it} + \beta_6 R_{it} + v_i + \varepsilon_{it}$$

Expectations: $\beta_1, \beta_3, \beta_4, \beta_5 > 0$; $\beta_2, \beta_6 < 0$

where $l(p_{it})$ = The logit of the reported probability that a representative individual will be affected by an extreme climate-related event. The logit of p is log[p/(1-p)]. I use the logit transformation to impose natural [0,1] constraints on the probability.

N_{it} = Population
U_{it} = Percent of the population in urban areas
I_{it} = A measure of information transparency
R_{it} = A measure of regulation quality
v_i = Unobserved country- and region-specific effects
ε_{it} = A random error term

Prior expectations are positive effects on reported risk for the atmospheric CO2 concentration, population, urban population percent and information transparency; and negative effects for income per capita and quality of regulation.

To calculate reported risk for country i in year t, I divide total persons affected in the five disaster categories by total population. I have drawn time series data on atmospheric CO2 concentrations from Neftel, et al. (1994) and Keeling, et al. (2007; updated to 2010). Annual data on population and percent urban are from the World Bank's World Development Indicators database.[16] Consistent time series measures for information transparency and regulation are difficult to obtain; I have used two indicators from Kaufmann, Kraay and Mastruzzi (KKM, 2009): Regulatory Quality (RQ) and Voice and Accountability (VA). KKM construct VA from a number of indicators that "captur[e] perceptions of the extent to which a country's citizens are able to participate in selecting their government, as well as freedom of expression, freedom of association, and a free media."[17] Neither variable is perfect for my purposes. RQ focuses on private-sector development concerns, but I adopt it as a measure of regulatory capacity more generally. VA certainly captures key elements of transparency, which should positively affect the completeness of disaster reporting. At the same time, the democratic governance components of VA might have countervailing effects by encouraging governments to invest in climate resilience (which would reduce risk, ceteris paribus). My results for VA should therefore be interpreted as conservative estimates of transparency's impact on disaster reporting.

2.1.3 Panel Estimation Results

Table 1 reports panel estimates for several versions of the model. Prior experimentation revealed that the estimated coefficients for log(population) and log(percent urban) are not significantly different, so I have consolidated the two terms into the log of urban population (percent urban x population) for the estimates reported in Table 1. I have also checked the robustness of the two KKM indicators, VA and RQ, through joint estimation with the other KKM indicators – Political Stability and Absence of Violence, Government Effectiveness, Rule of Law, and Control of Corruption. None of the other KKM indicators is significant in any estimate. I incorporate controls for 24 world subregions (listed in Appendix C) that I use for two purposes: checking for significant regional variation in climate responses to CO2 accumulation, and short-term forecasting for development of the risk indicator for extreme weather.[18] I have checked for first-

[16] Available online at http://databank.worldbank.org/ddp/home.do?Step=12&id=4&CNO=2
[17] KKM (2009), p. 6.
[18] Estimation by random effects continues to incorporate country effects in the models that include regional dummies.

order autoregressive error in the panel estimates, and in no case is the autocorrelation parameter significant.

Table 1: Determinants of Climate Risk, 1995-2008

Dependent Variable - Logit Probability: Affected by Extreme Weather Event

	(1) Random Effects	(2) Fixed Effects	(3) Random Effects	(4) Random Effects	(5) Random Effects	(6) Random Effects
Log CO2 Concentration	33.806 (7.44)**	34.729 (3.93)**	28.869 (6.55)**	34.123 (7.61)**	31.387 (6.89)**	32.244 (7.10)**
Log GDP Per Capita PPP	-1.223 (5.76)**	-2.379 (2.98)**		-0.988 (6.24)**	-0.705 (3.28)**	-.779 (3.76)**
Log Urban Population	0.424 (4.15)**	1.694 (1.29)			0.365 (3.63)**	0.360 (3.59)**
KKM Voice and Accountability	1.209 (4.38)**	1.646 (3.39)**			1.089 (3.75)**	2.693 [log] (3.85)**
KKM Quality of Regulation	-0.609 (2.04)*	-0.736 (1.93)			-0.763 (2.73)**	-1.641 [log] (2.11)*
Constant	-208.484 (7.84)**	-223.887 (6.16)**	-181.910 (6.97)**	-204.620 (7.78)**	-196.106 (7.38)**	-200.648 (7.57)**
Tests						
	Hausman:	χ^2 6.90 (p=.2282)				
Regional Dummies					χ^2 175.79** (p=.0000)	
Regional Interactions With Log CO2 Concentration			χ^2 34.90** (p=.0290)	χ^2 34.16** (p=.0349)	χ^2 28.17 (p=.1354)	
Observations	2223	2223	2223	2223	2223	2223
Countries	175	175	175	175	175	175

Absolute value of z statistics in parentheses
* significant at 5%; ** significant at 1%

The first two columns of Table 1 present random and fixed effects estimates for a model that incorporates the potential impacts of CO2 radiation-forcing, income per capita, urban population, information transparency and quality of regulation. Random effects is preferable because it is more efficient, but its use depends on failure of the appropriate Hausman test to reject the null hypothesis of equal parameters in random and fixed effects estimation. Failure occurs in this case (χ^2 = 6.90, p=.228), so I adopt the random effects estimator.

Column (1) provides random effects estimates. All signs conform to expectations, and all coefficients are estimated with high levels of significance.[19] As expected, I find a very strong negative impact of income per capita on climate vulnerability: For each 1% increase in income, extreme weather risk for the representative individual falls by 1.2%. Conversely, urbanization increases vulnerability, as expected: For each 1% increase in urban population, risk rises by 0.4%.

Table 2: Distributions of VA and RQ

	VA	RQ
Min	-2.35	-3.13
Q1	-0.83	-0.66
Median	-0.01	-0.06
Q3	0.90	0.77
Max	1.83	3.41

Table 2 presents basic distributional information for the two KKM variables, Voice and Accountability (VA) and Regulatory Quality (RQ). The best and worst performers are separated by 4.2 units for VA and 6.5 units for RQ. In Table 1, an increase of one unit in VA increases the *log* of reported extreme weather risk by 1.2, which is obviously a large impact. This result seems quite important for interpreting the CRED data, because it assigns a large, significant role to reporting quality even during the most recent period, which CRED has deemed most reliable for disaster reporting. For RQ, an increase of one unit decreases the log of reported risk by 0.6. This result increases in both size and significance in column (5), the full specification of the model that also incorporates regional fixed effects.[20]

The result for CO2 concentration is the most important of the set, so it is worth considering in some detail. I should begin by stressing the conservative underpinnings of this estimate. First, I have limited the sample to the period 1995-2008, which has been judged most reliable by CRED itself. Second, I have explicitly controlled for the effect of income and three variables – urbanization, reporting quality and regulatory quality – that are frequently cited as confounding factors in the interpretation of the CRED data. Finally, I have employed panel estimation techniques that explicitly control for

[19] While logit estimation is both theoretically and practically appropriate (particularly for forecasting), estimation using the log of probability yields estimates that are effectively identical within the sample range. The estimates are identical at two decimal places for urban population, information transparency and quality of regulation; and identical at one decimal place for CO2 concentration and income per capita. Column (6) of Table 1 presents log-log estimates to facilitate discussion of impacts and development of the resource allocation methodology in Section 3.

[20] In this context, it is also worth noting that the KKM variables are scaled to a uniform mean across years. This means that they can account for country differences over time, but not for overall trends (e.g., generalized improvement in voice and accountability across all countries).

unobserved country effects. This means that my results relate *changes* in risk to *changes* in the righthand variables, including the CO2 concentration.

After introduction of these adjustments, the estimated CO2 parameter remains strikingly large and significant. Controlling for other factors, the results indicate that a 1% increase in the atmospheric CO2 concentration has been associated with an increase in extreme weather risk of about 30%. When I hold the other factors constant at their sample mean values, the actual increase in CO2 concentration from 1995 to 2008 is associated with a 9.6-fold increase in risk.

Columns (3) – (5) present results for alternative versions of the model. The result in (3) is the bivariate estimate for CO2 concentration. The estimated elasticity (28.9) is slightly lower than others because it incorporates the "masking" effect of income growth without an explicit control for that variable. Models (3) – (5) introduce regional interactions with CO2 concentration to test whether the climate change impact of atmospheric accumulation has differed significantly across regions[21] The appropriate χ^2 tests reject the null hypothesis (no geographic variability) with very high confidence in (3) and (4), which exclude the effects of urban population growth, information quality and regulatory quality. However, inclusion of these variables in (5) eliminates the significance of regional differences in climate change impacts, while confirming the importance of regional fixed effects in the determination of weather-related risk.[22]

In summary, my results are strongly consistent with one global pattern of response to CO2 accumulation, once I account for country and regional differences in income growth, urbanization, information quality and regulatory quality. This global response is both very large and basically stable across a variety of specifications. The other righthand variables add to the explanatory power of the model, but in somewhat surprising ways. Incorporating income actually increases the estimated effect of CO2 accumulation, while adding the three "confounding" variables eliminates apparent regional variability in climate response without significantly reducing the estimated CO2 elasticity.

The sheer size of this elasticity is alarming, because it bodes very ill for climate change as CO2 accumulation continues. But it remains a challenge for interpretation, despite my explicit introduction of potentially-confounding factors. Could a seemingly-modest change in atmospheric CO2 concentration really promote such a sharp increase in weather-related risk? To lend additional insight, Appendix A uses data from the US National Oceanic and Atmospheric Administration (NOAA) to analyze the relationship between CO2 accumulation and exposure of the US population to extreme precipitation since 1970. This analysis relies entirely on weather and population data, not reported impacts, but I find an exposure response elasticity that is very close to the impact

[21] I use 24 world subregions, which are listed with constituent countries in Appendix C.

[22] These fixed effects are also significant in (3) and (4), along with the interaction effects. But the latter constitute the critical differentiating factor, so the table focuses on χ^2 tests for regional interactions.

elasticities in Table 1. The similarity may well be fortuitous, since the appendix covers only one climate variable for one country, but the magnitude of the estimate suggests that the elasticities in Table 1 are indeed plausible.

2.1.4 Forecasting Near-Term Impacts

The results in Table 1 shed useful light on several questions that have complicated the policy dialogue on adaptation assistance:

- Where will significant impacts occur, how large will they be, and how quickly will they emerge? Without an answer, we have no systematic basis for allocating assistance aid.
- How can we distinguish problems attributable to historical weather patterns from problems caused by climate change? Without some kind of distinction, we cannot credibly determine the "additional" component that qualifies for assistance beyond standard development aid.
- Should adaptation assistance distinguish between "exogenous" vulnerability attributable to weather changes and "endogenous" vulnerability that can be affected by policy? The income elasticity results in Table 1 indicate that countries with successful economic growth strategies become far less climate-vulnerable than their less-successful counterparts over time. The results suggest that vulnerability also decreases markedly in countries whose urban development strategies incorporate effective control of land use in high-risk areas. Ignoring endogenous vulnerability will introduce perverse incentives for aid recipients, because countries whose policies reduce vulnerability will receive significantly less adaptation assistance than countries with ineffective policies.

Ultimately, the significance of these issues depends on orders of magnitude in measurement. In this section, I use a short-term forecasting exercise to assess the relevant magnitudes. Using Table 1 and trend extrapolation for the righthand variables, I estimate weather-related risks for all countries in 2015, and calculate the impact of changing climate vulnerability as the change in the probability of being affected (paffected) by a climate-related disaster from 2008 to 2015. I perform this calculation for three cases:[23]

[23] I forecast using the results summarized in Table 1, column (5), including results for country and regional effects. I forecast by country for two periods; 2008 and 2015; calculate the difference in the estimated probability of being affected by a weather-related disaster (paffected); and then add the difference to the median country value of paffected for 2000-2008 in EM-DAT. Using median paffected ensures that each country forecast is anchored by observations in the dataset.

1. Trend change in CO_2 accumulation; all other variables constant at 2008 levels;
2. Addition of forecast change in real income per capita (at purchasing power parity)[24];
3. Addition of trend changes in urbanization and regulatory quality.[25]

Table 3 summarizes the distributions of results across 233 countries for paffected in 2008; the three change cases; the estimated contribution of each factor to the forecast change for case 3 (all determinants included); and the % contribution to Δ paffected of the same factors.[26] The most striking result in the table is the order-of-magnitude shift in median vulnerability, from 1.3 per 100,000 in 2008 to the range 9-10 in 2015. This reflects the CO_2 result in Table 1, with continued steady growth in accumulated CO_2 through 2015. Inclusion of the other righthand variables affects the distribution, but much less than CO_2. My calculation of % contributions also reflects the dominance of accumulated CO_2: Its median contribution to change in risk is 74.1%, compared to 12.1% for income and 14.6% for urbanization and regulation. For clarity, I should note that the % contributions to risk change in Table 3 are presented in absolute terms for comparison of effect magnitudes. The signed effect of income is actually negative, for example, since increasing income reduces risk.

[24] I forecast from 2008 real GDP per capita at PPP, from the World Bank's World Development Indicators. (WDI). I draw forecast growth rates from Hughes (2009), who draws on a critical assessment of the IPCC's SRES scenarios by Tol, et al. (2005). Hughes develops a consensus economic projection by taking an average growth rate from five integrated assessment models. The Hughes estimates are similar to income growth estimates for the IPCC A2 Scenario (IPCC 2007a). For countries excluded from WDI and Hughes, I convert UN current income data to purchasing power parity and forecast from average regional forecast growth rates for included countries, using the 24 subregions listed in Appendix C.

[25] I hold information quality (KKM Voice and Accountability) constant at its 2008 level because I am interested in actual, not reported, change in climate risk.

[26] I calculate the percent attribution serially for cases 1-3 in the following steps: (1) I calculate the absolute value (abs) of Δ paffected for the CO_2-only case; (2) I calculate abs (Δ paffected) for the addition of income per capita and subtract abs (Δ paffected) for CO_2 only. (3) I calculate abs (Δ paffected) for the addition of urbanization and regulation quality and subtract abs (Δ paffected) for CO_2 and income. I normalize by the sum of the three increments to obtain percent contributions. These results are not invariant to the sequence of calculations. Reversing the sequence (first urbanization/regulation, then income, then CO_2) shifts the allocation toward CO_2 even more. For comparison, the paired distribution medians for the original (in Table 3) and reversed sequences are CO_2 (74.1, 88.5); income (12.1, 5.3), urbanization/regulation (14.6, 6.5). Reversing the order of calculations does not change the results in the final column of Table 3 (% of 2015 vulnerability due to climate change during 2008-2015, based on inclusion of all righthand variables).

Table 3: Distributions of Vulnerability Change Results

	Risk (Probability of Extreme Weather Impact) (Per 100,000 Population)				Percent Contribution to Risk Change, 2008-2015			
Country	2008	2015 Climate Only	2015 Climate + Income	2015 Climate + Income + Urbanization + Regulation	Climate	Income	Urbanization + Regulation	2015 Risk % Due to Climate Change (2008-2015)
Min	0.001	0.044	0.036	0.026	21.56	0.94	0.06	0.00
10th Pct.	0.013	0.424	0.352	0.331	56.96	4.14	3.12	16.52
Q1	0.050	2.070	1.841	1.498	64.42	8.46	6.31	45.17
Median	1.270	10.204	9.155	9.917	74.09	12.12	14.57	74.24
Q3	45.848	109.450	102.463	106.877	79.93	15.22	23.52	94.78
90th Pct.	442.818	875.569	800.145	964.163	85.10	17.24	31.83	99.01
Max	13,708.860	25,072.160	19,932.540	17,719.590	94.73	22.21	77.50	99.97

The large jump in median risk is also reflected in the final column of Table 3: Across 233 countries, the median percent of 2015 weather risk attributable to climate change after 2007 is 74.2%. For the top quartile, it increases to nearly 95%. This result provides an important perspective on the question that crops up after each climate catastrophe: was it “normal,” or a reflection of climate change? My evidence suggests strongly that, for many countries, the likelihood is now very high that an extreme weather event reflects climate change, not a random draw from the historical distribution of weather events.

Table 4 illustrates results in the same format for the 20 most vulnerable countries in 2015. I have added rankings for the most complete specification of vulnerability (including CO2, income, urbanization and regulation) to facilitate comparison. The most striking feature is the status of China and India (respectively 1st and 3rd among 233 countries) which rank at the top in risk (the probability of impact from an extreme weather event) as well as population. China’s risk increases fourfold, from 6% (6,772 per 100,000) to 25%, while India’s increases more than fourfold, from 2.6% of the population to 11.7%. Sandwiched between China and India is tiny Djibouti, whose risk remains roughly stable (13.7% in 2008, 14.3% in 2015). Inspection of the remaining 17 countries reveals a very broad regional distribution, with 7 in Africa, 6 in Asia and 4 in Latin America and the Caribbean. Of the top 20 countries in 2015, only one (Bolivia) was outside the top 20 in 2008, and it was 21st. Within the top 20, however, there is considerable movement, with relatively rapid increases in risk for Bangladesh and Bolivia, and slower increases for Ethiopia, Cuba, Zambia and Zimbabwe. These patterns reflect the general pattern displayed by the distributional information in Table 3: The main driver behind changed climate risk has been atmospheric CO2 accumulation, whose global impact does not differ significantly across regions. This acts like a common multiplier for all countries (dampened somewhat for higher-risk countries by the logit specification), so the countries with highest risk in 2008 remain so in 2015, at substantially higher levels of risk in many cases. At the same time, second-order effects from changes in income, urbanization and regulatory quality cause positions to shift somewhat among neighboring countries in the 2008 rankings.

Table 4: Extreme Weather Risk: Top 20 Countries in 2015

	Vulnerability: Probability of Extreme Weather Impact (Per 100,000 Population						Percent Contribution to Vulnerability Change, 2008-2015			
Country	Rank 2008	Rank 2015	2008	2015 Climate Only	2015 Climate + Income	2015 Climate + Income + Urbanization + Regulation	Climate	Income	Urbanization + Regulation	2015 Risk % Due to Climate Change (2008-2015)
China	3	1	6,772	25,072	19,933	17,720	71.3	20.0	8.6	61.78
Djibouti	1	2	13,709	14,281	14,167	14,331	67.3	13.4	19.3	4.34
India	7	3	2,599	11,704	9,531	9,153	78.1	18.6	3.2	71.61
Kenya	2	4	6,807	7,752	7,620	7,617	87.5	12.3	0.2	10.64
Somalia	8	5	2,382	4,011	3,807	5,482	46.4	5.8	47.7	56.55
Mozambique	4	6	4,576	5,133	5,028	5,269	61.6	11.7	26.7	13.14
Philippines	10	7	2,134	5,161	4,607	5,102	74.2	13.6	12.2	58.18
Bangladesh	19	8	823	5,487	4,611	4,844	80.8	15.2	4.0	83.01
Sri Lanka	6	9	3,458	4,304	4,072	4,558	54.1	14.8	31.1	24.12
Ethiopia	5	10	3,791	4,892	4,747	4,540	75.8	10.0	14.2	16.51
Vietnam	11	11	1,904	4,696	4,121	3,834	76.4	15.7	7.9	50.33
Bolivia	21	12	638	1,508	1,362	3,573	27.0	4.5	68.5	82.14
Hong Kong (China)	17	13	1,251	3,877	3,147	2,413	64.2	17.8	18.0	48.13
Cuba	9	14	2,190	2,221	2,213	2,227	59.0	15.2	25.8	1.63
Madagascar	14	15	1,314	2,203	2,076	2,122	83.6	12.0	4.4	38.09
Honduras	18	16	1,237	2,303	2,148	2,104	84.2	12.2	3.5	41.19
Thailand	16	17	1,271	1,996	1,813	1,863	75.7	19.1	5.2	31.77
Zambia	12	18	1,718	1,877	1,847	1,853	81.5	15.3	3.2	7.32
Colombia	15	19	1,299	2,026	1,892	1,781	74.8	13.8	11.4	27.08
Zimbabwe	13	20	1,692	1,714	1,709	1,721	55.3	13.2	31.5	1.69

2.1.5 Policy Implications

In the recent policy dialogue on adaptation to climate change, much attention has focused on the distinction between the current climate regime and future changes in that regime attributable to atmospheric CO2 accumulation. Coping with the current regime is understood to be a standard development problem, and it is obviously an important one for many countries. Coping with a future CO2-induced change in that regime, on the other hand, is widely understood to lie in the domain of "additionality" for aid donors.

The results in Table 1 have a number of implications for this discussion. First, they suggest that *the future has already arrived*: Controlling for other factors, my results imply a nearly-tenfold increase in extreme weather risk during the past fifteen years. Clearly, the domain of additionality is already quite large, and promises to continue growing rapidly as CO2 accumulates in the atmosphere. Second, my results suggest that aid donors face an inescapable strategic choice between two approaches to judging climate vulnerability, and therefore additionality. As the results in column (5) show, changes in extreme weather risk have a powerful exogenous component because the CO2 elasticity is very large and invariant across regions. But the endogenous component is also large, because national policies can have major effects on income growth, urbanization, and regulatory quality.[27]

Should donors interested in adaptation to changes in extreme weather base allocation decisions only on the common CO2 effect, or should they also incorporate the effects of the endogenous determinants? The former case is much simpler, because no regional distinctions apply: Tomorrow's rank ordering of countries will be the same as today's, and the current climate regime provides adequate information for determining adaptation assistance.[28] But the latter case seems compelling, because the endogenous components obviously do matter a lot. If donors respond to both the endogenous and exogenous components of vulnerability, then there will be an unavoidable, perverse effect: Countries whose policy regimes increase vulnerability will receive more assistance than countries with more effective policies, ceteris paribus. Whether this is a very important factor depends entirely on the measured effects of the relevant variables. An additional contribution of the results in Table 1 is to make such quantification and comparison possible. I will return to this issue on a more general plane after presenting results for sea level rise and agricultural productivity loss, which reveal significantly different patterns across countries.

2.2 Vulnerability to Sea Level Rise

This section extends previous work with co-authors (Dasgupta et al., 2009a,b) to much broader coverage of coastal and small island states. Climate change will increase coastal risk for two reasons. First, coastal inundation and heightened storm surges will accompany a rising sea level as thermal expansion and ice cap disintegration continue. Recent evidence suggests that sea level rise could exceed 1 meter during this century

[27] I exclude reporting quality from this list because it relates to disaster reporting, rather than the actual incidence of disasters.

[28] Although the rank-ordering will remain the same if the endogenous factors are ignored, the relative size of CO2 effects will change because the model is logistic: The marginal risk impact of CO2 accumulation declines as the risk grows. So cross-country risks will tend to converge over time, while preserving the same rank order (because the underlying relationship is monotone-increasing).

(Dasgupta, et al. 2009a; Rahmstorf 2007; Rahmstorf, 2010). Second, a warmer ocean is likely to intensify cyclone activity and heighten storm surges.[29] Greater surges will move further inland, threatening larger areas than in the past. In addition, both natural increase and internal migration are increasing vulnerable populations in coastal regions. Table 5 shows that global population in low-elevation coastal zones grew from 544 million in 1990 to 636 million in 2000 -- 17% in a single decade. The increase has been particularly rapid in Africa (27%) and Asia (18%).

Table 5: Population in Low-Elevation Coastal Zone (LECZ), 1990 – 2000

	LECZ Population (Million)		
Region	1990	2000	Increase
Africa	46.2	58.5	12.2
Asia	394.7	465.8	71.2
Europe	49.0	50.2	1.3
Latin America & Caribbean	28.6	33.2	4.6
North America	21.8	24.2	2.3
Oceania	3.6	4.2	0.6
Total	543.9	636.2	92.3

Source: CIESIN (2010)

To quantify vulnerability for 192 coastal and small island states, I have drawn on several sources: estimated areas and populations of storm surge zones in 83 countries from Dasgupta, et al. (2009b); estimated areas and populations of low-elevation coastal zones in 181 countries from CIESIN (2010) and McGranahan, et al. (2007); topographical information from WorldAtlas.com (2010) and the US Central Intelligence Agency (2010); and national population data from the US Census Bureau (2010), the United Nations (2010), the US Central Intelligence Agency (2010), the Government of Australia (2010), the Tokelau Statistics Unit (2010), and reports for other small island principalities. I estimate risk indices for 2008 and 2050 in a multi-stage exercise that sequentially estimates the areas of low-elevation coastal zones (LECZs); areas of storm surge zones within LECZs; and populations within the storm surge zones.

[29] A sea-surface temperature of 28° C is considered an important threshold for the development of major hurricanes of categories 3, 4 and 5 (Michaels et al 2005; Knutson and Tuleya 2004).

2.2.1 Low-Elevation Coastal Zones[30]

CIESIN (2010) provides area estimates for LECZs in 181 countries. For the remaining 11 of 192 coastal countries, I develop estimates from a regression model that relates the LECZ share of total area to two variables: the insularity index (total coastline length/total area), which should be positively related to the LECZ share; and maximum elevation in the country, which should be negatively related to the LECZ share. The Caribbean states of Dominica and the Bahamas provide a useful illustration of the latter factor. The two countries have similar insularity indices (Bahamas 25.5; Dominica 19.2) but Bahamas is very low-lying (maximum height 63 meters) while Dominica rises steeply from the coast to mountainous terrain (maximum height 1,447 meters). Dominica's steep rise causes its LECZ share (4.6%) to be far lower than the Bahamas' (88.4%).

Table 6: Determinants of Coastal Zone Area Shares

Dependent Variable:	Logit Low-Elevation Coastal Zone Share of Total Area
Log Insularity	0.543
	(11.66)**
Log Insularity Squared	-0.044
	(3.30)**
Log Maximum Elevation	-1.358
	(4.16)**
Log Maximum Elevation Squared	0.067
	(2.48)*
Constant	3.112
	(2.99)**
Observations	181
R-squared	0.68

Absolute value of t statistics in parentheses
* significant at 5%; ** significant at 1%

My regression model relates the logit of LECZ share to log insularity and log maximum height. I include squared terms to allow for diminishing marginal effects. The regression result for 181 countries (Table 6) is robust ($R^2 = .68$), has the expected parameter signs, and has high levels of significance for both variables. Both second-order terms are significant, with signs that indicate diminishing marginal effects. I use

[30] Following CIESIN (2010), I define the low-elevation coastal zone as the coastal area that is less than 10 meters above sea level.

the results to estimate LECZ shares for the 11 coastal and island states that are excluded from the CIESIN database.[31]

2.2.2 Storm Surge Zones

This exercise builds on results for 83 countries by Dasgupta, et al. (2009b), who estimate present and future areas that are vulnerable to storm surges. The future estimates assume 1 meter of sea level rise and a 10% increase in average storm intensity. For the remaining 109 coastal and island states, I develop estimates from a regression model that relates the surge zone share (SZS) of total area to the LECZ share of total area and the insularity index. I use a second-order approximation, regressing the logit of SZS on the logs of LECZ share and insularity, their interaction, and their squares. I also incorporate fixed effects for the 24 regions listed in Appendix C. Table 7 reports the results, which are robust for both present and future areas (R^2 = .94 in both cases) and highly significant, except for the log of the insularity index. I use these results to estimate SZS for the 109 coastal and island countries excluded by Dasgupta, et al.

Table 7: Determinants of Future Storm Surge Zone Shares

Dependent Variable: Logit Future Storm Surge Zone/Total Area

	(1) Future	(2) Present
LA: Log(LECZ Area/Total Area)	1.039	1.042
	(7.29)**	(7.02)**
LI: Log Insularity Index	-0.099	-0.060
	(0.80)	(0.46)
LA x LI	0.221	0.208
	(2.84)**	(2.56)*
LA Squared	-0.099	-0.103
	(2.36)*	(2.36)*
LI Squared	-0.135	-0.123
	(3.26)**	(2.87)**
Constant	-4.944	-5.408
	(10.55)**	(11.08)**
Observations	83	83
R-squared	0.94	0.94

Absolute value of t statistics in parentheses * significant at 5%; ** significant at 1%

[31] The excluded countries and principalities are Gaza, Guernsey, Saint Barthelemy, Pitcairn, Svalbard and Jan Mayen, Jersey, Saint Helena, Norfolk Island, Tokelau, Kiribati and Saint Martin.

2.2.3 Population Densities in Low Elevation Coastal Zones

CIESIN (2010) provides population density estimates for LECZs in 181 coastal countries. For the remaining 11 countries, I develop estimates from a regression model that relates LECZ population density to national population density, the LECZ share of national area, and maximum elevation. I also incorporate fixed effects for the 24 regions listed in Appendix C. Table 8 presents the results of the log-log estimation exercise. Prior experimentation with second-order effects revealed significance only for the squared log of the LECZ share in national area. The results are robust ($R^2 = .86$), and all variables are highly significant. The parameter estimates indicate a high positive elasticity for national population density; a negative elasticity (with diminishing marginal effect) for LECZ area share; and a negative elasticity for maximum elevation (i.e., LECZ density is lower in countries whose territory rises more rapidly into the interior). I use these results to estimate LECZ population densities in 2008 for the 11 states that are excluded from the CIESIN database.[32] Then I project LECZ densities in 2050 by assuming that LECZ populations change at the same rate as projected national populations.

Table 8: Determinants of LECZ Population Density

Dependent Variable: Log LECZ Population Density	
Log Country Population Density	0.842 (20.29)**
LA: Log (LECZ Area/Total Area)	-0.163 (3.55)**
LA^2	-0.039 (3.12)**
Log Maximum Elevation	-0.137 (2.57)*
Constant	2.513 (3.29)**
Observations	181
R-squared	0.86

Absolute value of t statistics in parentheses
* significant at 5%; ** significant at 1%

[32] See the previous footnote for the list of excluded states.

2.2.4 Quantifying Risk

Following the extreme-weather approach, I define risk from sea level rise (SLR) as the probability that an individual resides in a zone threatened by storm surges. To estimate SLR risk in 2008, I multiply LECZ population density in 2008 (from 2.2.3 above) by storm surge zone area (obtained by multiplying national area by the LECZ share (from 2.2.2 above). Then I divide by national population to obtain the probability of residence in a threatened area in 2008.

For the future estimate, I assume changes by 2050 that are half those forecast for 2100 by Dasgupta, et al. (2009b). I use national population forecasts for 2050 from the US Census Bureau (2010) and the UN (2010). For countries without forecasts, I apply average population growth rates for their regions (using the 24 regions listed in Appendix C). Then I compute future LECZ population densities and replicate the calculations described above to obtain vulnerability estimates for 2050.

Table 9: Top 20 Countries: Risk From Sea Level Rise, 2008 and 2050

	Rank		Population % at Risk	
Country	2008	2050	2008	2050
Qatar	3	1	28.3	35.1
Bahamas	4	2	24.4	33.3
Bahrain	2	3	30.6	32.7
Kuwait	1	4	32.4	29.8
Tuvalu	6	5	20.9	27.7
Cook Islands	8	6	16.4	27.4
Guinea-Bissau	5	7	23.0	26.3
Turks and Caicos Islands	7	8	17.0	21.1
Marshall Islands	9	9	16.4	20.3
Saint Pierre and Miquelon	11	10	13.3	20.3
Denmark	14	11	12.7	18.6
Cayman Islands	10	12	14.9	18.2
Falkland Islands	16	13	12.1	17.8
Pitcairn	12	14	13.0	17.0
Maldives	15	15	12.7	16.1
Svalbard and Jan Mayen	24	16	10.4	15.7
Wallis and Futuna	20	17	11.1	15.3
Monaco	22	18	10.6	15.2
Tunisia	17	19	12.0	15.0
United Arab Emirates	13	20	12.8	14.0

Tables 9 and 10 illustrate my results for the top 20 countries, ranked by risk (probability of residence in a threatened zone) and population at risk. In Table 9, 12 of the 20 highest-risk countries are small island states or principalities; 4 are small Persian Gulf states; 2 are in Europe (Denmark, Monaco); and 2 in Africa (Guinea-Bissau, Tunisia). Future risk incorporates both projected sea level rise and projected population change, which is negative in some cases. Among the top 20 countries, however, only Kuwait has a projected population decrease sufficient to offset the effect of a larger storm surge zone. The results indicate substantial increases in risk for many countries, particularly Qatar (from 28.3% to 35.1% of the population in threatened areas), the Bahamas (24.4% to 33.3%), the Cook Islands (16.4% to 27.4%), Saint Pierre and Miquelon (13.3% to 20.3%) and Denmark (12.7% to 18.5%). The storm surge results resemble the extreme weather results in the stability of rankings over time. Of the top 20 countries in 2050, only 2 are ranked lower than 20th in 2008, and they are near-neighbors at 22 (Monaco) and 24 (Svalbard and Jan Mayen).

When my results are summarized for all 192 coastal states and principalities, they indicate total vulnerable populations of 156.4 million in 2008 and 266.9 million in 2050. In contrast to the dominance of small states in Table 9, the states with the greatest vulnerable populations in Table 10 are large coastal countries in Asia (12), Africa (3), Europe (3), Latin America (1) and North America (1). Again, the rankings are quite stable over time: Of the top 20 states in 2050, 19 have the same status in 2008. And the sole exception, Mozambique, ranks 25th in 2008.

Table 10: Top 20 Countries – Population at Risk From Sea Level Rise, 2008 and 2050

	Rank		Vulnerable Population (Million)	
Country	2008	2050	2008	2050
India	1	1	20.6	37.2
Bangladesh	3	2	13.2	27.0
China	2	3	16.2	22.3
Indonesia	4	4	13.0	20.9
Philippines	6	5	6.5	13.6
Nigeria	9	6	4.3	9.7
Vietnam	7	7	5.7	9.5
Japan	5	8	9.8	9.1
United States	10	9	3.8	8.3
Egypt, Arab Rep.	17	10	2.1	6.3
United Kingdom	11	11	3.3	5.6
Korea, Rep.	8	12	4.8	5.3
Myanmar	12	13	2.8	4.6
Brazil	14	14	2.6	4.5
Turkey	13	15	2.6	3.9
Malaysia	18	16	1.9	3.5
Germany	15	17	2.3	3.3
Italy	16	18	2.1	2.9
Mozambique	25	19	1.2	2.8
Thailand	19	20	1.8	2.6

2.3 Agricultural Productivity Loss

I supplement the new results on extreme weather and sea level rise with estimates of future agricultural productivity change based on the results of Cline (2007). The Cline dataset includes single estimates with and without carbon fertilization for many countries, and estimates for multiple regions in large countries. For large countries, I use median regional values for this exercise. I use Cline's preferred estimates, without carbon fertilization.[33]

After drawing agricultural productivity change forecasts for 113 countries from the Cline dataset, I complete my 233-country dataset as follows: I calculate median agricultural productivity changes for the 24 geographic subregions listed in Appendix C. Wherever possible, I use these median values to replace missing country values within subregions. Cline's results are broadly distributed geographically, so this procedure provides estimates for an additional 84 states. The remaining 36 states are all islands in the Atlantic, Indian and Pacific Oceans that have no natural comparators. For those states, I use the global median agricultural productivity loss forecast by Cline (20.5%).

Cline forecasts for the period through 2080. For this exercise, I match the forecast interval for storm surge threats and assume that half the forecast agricultural productivity change occurs by 2050. Table 11 provides median forecasts of agricultural productivity loss through 2050, by subregion. I have ordered the data from highest to lowest productivity loss. Cline's forecasts are based on midrange IPCC emissions forecasts; central tendencies in temperature and precipitation across a number of Global Circulation Models; and combined estimates from technical and economic models of farmers' responses to changing weather conditions. The extreme weather trends cited in this paper, coupled with recent global carbon emissions estimates, provide ample evidence that the assumptions underlying Cline's estimates are realistic. The implications for many developing countries are clearly serious, with forecast losses greater than 10% in all developing regions outside of Asia, and substantial losses in all Asian regions except China. Here I should note that the forecast for China is the median: Significant productivity losses are forecast for some regions, but these are largely balanced by forecast productivity gains in others.

[33] Cline's preferred estimates (without carbon fertilization) have an effectively-perfect linear association with the estimates with carbon fertilization for the 114 countries in his dataset (R^2=1.00, t=2,137) because they differ by a constant amount. The significance of my choice of Cline's preferred estimates is case-specific. The methodology developed in this paper uses relative, not absolute, indicator values to allocate shares of resources for adaptation assistance. Therefore, the choice of fertilization mode has a negligible effect on allocations when all countries have forecast productivity losses for both modes, because their relative losses are nearly identical. However, allocation results are affected in cases where some countries have productivity gains forecast with carbon fertilization and losses forecast without fertilization. For those countries, my use of Cline's preferred (non-fertilization) estimates results in larger assistance allocations than in the converse case.

Table 11: Forecast Agricultural Productivity Losses by Region: 2008–2050

Region	Median Forecast Agricultural Productivity Loss, 2008-2050 (%)
Central Africa	19.80
Caribbean Islands	19.65
Southern Africa	18.95
North Africa	18.00
Sahelian Africa	17.05
Coastal West Africa	16.35
Andean South America	14.85
Middle East	13.50
Madagascar	13.10
Northern South America	12.83
Southern South America	12.20
Central America	11.85
Southeast Asia	11.70
Southern Asia	10.45
East Africa	10.25
Australia / New Zealans	5.30
Western Asia	4.50
Eastern Europe	4.08
Northeast Asia	3.65
Western Europe	2.50
North America	1.65
China	1.50

3. Implications for Resource Allocation

3.1 Vulnerability Indicators and Efficient Resource Allocation

In this paper, I construct risk indicators for 233 states that combine short- and long-term factors: changes in extreme weather risks from 2008 to 2015, and risks associated with storm surges and agricultural productivity loss from 2008 to 2050. As I noted in the introduction, actual vulnerability to climate change depends on the interaction of these risks with determinants of resilience: economic development, demographic change, and governance.

Risk and vulnerability indicators can contribute to efficient allocation of resources for increasing climate resilience.[34] Resource-constrained donor institutions are interested in promoting significant resilience improvements for the group of countries they choose to assist, while striking a balance between maximizing overall gains, ensuring at least some support for all countries in the group, and incorporating the likelihood of diminishing returns to investment in each country.[35] These objectives can all be served by constructing a composite vulnerability indicator that assigns weight to both climate risks and the determinants of resilience. Equipped with this indicator, donor institutions can achieve a reasonably efficient allocation by assigning per-capita project resources to countries in proportion to their indicator values, with adjustments for country differences in average project costs and the likelihood of project success. I provide a formal demonstration of this proposition in Appendix B.

In recent years, donor institutions such as IDA, the Asian Development Bank (ADB) and the African Development Bank (AfDB) have adopted this approach to resource allocation.[36] All four institutions allocate development assistance in proportion to country scores computed from the following formula (IDA, 2007):

(3)

$$[\text{Problem Index (V)}]^{\beta 1} \text{ x } [\text{Project Success Probability Index (G)}]^{\beta 2} \text{ x } [\text{Population (P)}]^{\beta 3} = V^{\beta 1} G^{\beta 2} P^{\beta 3}$$

The essential problem is poverty for the development banks,[37] so their problem index is income per capita (and β_1 is given a negative exponential weight: -0.125 for IDA and AfDB; -0.25 for ADB). Various combinations of governance indicators are used as

[34] For an introduction to this approach in a broader environmental context, see Buys, et al. (2003).

[35] Technically, the donor's objective function cannot realistically be characterized as linear (infinite elasticity of substitution across countries) because sole allocation to one country within the set is not desirable on a priori grounds, whatever the relative scale of its problems. Some representation for all countries in the qualifying set is implied by the original choice of countries to be assisted. At the same time, the donor's objective function is not purely fixed-coefficient (zero elasticity of substitution across countries), because nothing forces it to maintain cross-country parity in per-capita allocation. This is undeniably a good thing because the distribution of climate vulnerability across countries is very different than the distrubtion of population. For resource allocation, then, an intermediate assumption appears warranted: a positive, finite elasticity of substitution across countries, which implies a CES (constant elasticity of substitution) donor welfare function. I have opted for a Cobb-Douglas (unit-elastic) function because it implies a simple allocation formula that is easy to compute and intuitively plausible to practitioners.

[36] Recent parallel work at the World Bank by Barr, et al. (2010) has investigated how adaptation assistance can be allocated in a transparent, efficient and fair way. The authors propose an approach based on three criteria: climate change impacts, adaptive capacity, and implementation capacity.

[37] The GEF has adopted a similar approach for its allocation of resources to biodiversity conservation programs. In the GEF case, the problem index is specified using a cross-country biodiversity measure. .

proxies for project success probability, and all three MDBs assign the same positive weight to this factor (2.0). Population provides the scaling factor; IDA and the African Development Bank assign it full weight ($\beta_3 = 1$), while the Asian Development Bank uses a partial weight ($\beta_3 = 0.6$).

For this paper the problem is climate vulnerability, whose critical components in the extreme weather case are given by econometric equation (2) in anti-log form:

(4) $V = C^{\alpha 1} Y^{\alpha 2} G^{\alpha 5}$[38]

where C = Atmospheric CO2 accumulation

Y = Income per capita

G = KKM Regulatory Quality

Translating (4) to change in vulnerability, the climate driver is the change in atmospheric CO2 concentration, holding Y and G constant:

$$(5)\ \Delta V = [C_t^{\alpha_1} - C_{t-1}^{\alpha_1}] Y_{t-1}^{\alpha_2} G_{t-1}^{\alpha_3}$$

In a more general expression, the climate driver is the difference in environmental conditions (D) attributable to carbon emissions:

$$(6)\ \Delta V = D Y_{t-1}^{\alpha_2} G_{t-1}^{\alpha_3}$$

This paper focuses on three climate-driven variables with per-capita scaling: the change from 2008 to 2015 in the probability that an individual will be affected by an extreme weather-related event (W), holding other vulnerability factors constant in (5); the change from 2008 to 2050 in the probability that an individual will be a resident of a coastal area threatened by sea level rise (R); and the percent change in productivity from 2008 to 2050 for an individual engaged in agriculture (A). The three variables are not measured in comparable units, and I have no basis for weighting their relative importance for welfare. Accordingly, I rescale each variable to an indicator with a maximum value of 100 for parity in computations.

Each of the three indicators – W, R, A – can be used for a separate allocation exercise when a donor institution focuses on one problem. For combined exercises, it seems reasonable to aggregate with weights proportional to the sizes of directly-affected groups: the national population (P_T) for extreme weather, the population of the coastal storm surge zone (P_R) for sea level rise, and the rural population (P_A) for agricultural

[38] I also incorporate two other variables: the KKM Voice and Accountability index, but as a control for completeness of disaster reporting, not for climate vulnerability; and urban population, which I hold constant for the allocation exercise.

productivity change. Weighting by group size relative to national population, the aggregate climate change index is:

(7) $D = W + \rho_R R + \rho_A A$, where $\rho_R = P_R/P_T$ and $\rho_A = P_A/P_T$

Replicating the MDB allocation formula requires an appropriate measure of G (governance, the proxy for likelihood of project success). For the KKM governance indicators, Table 12 reports correlations for four relevant measures: Regulatory Quality (already a determinant of climate vulnerability in this paper), Government Effectiveness, Rule of Law and Control of Corruption. The correlation coefficients are calculated from nearly 2000 observations for 209 countries during the period 1996-2008. The correlations are all very high, and highly significant, so any of the variables is a reasonable governance proxy in this context. For simplicity and convenience, I opt for Regulatory Quality.

Table 12: Correlations of KKM Governance Measures, 209 countries, 1995-2008

	Regulatory Quality	Government Effectiveness	Rule of Law
Government Effectiveness	0.923		
Rule of Law	0.885	0.934	
Control of Corruption	0.874	0.941	0.943

I also explicitly incorporate a unit project cost index based on differential wages, using income per capita as a proxy and an exponential weight (0.6) that reflects the findings of Harrison (2002) on the labor share of income in low- and middle-income countries.[39]

For climate vulnerability, then, the full formula for country scoring is given by

(8) $S = [\text{Climate Change Vulnerability}]^{\beta 1} [\text{Governance}]^{\beta 2} [\text{Population}]^{\beta 3} [\text{Cost Index}]^{\beta 4}$
$= [D\, Y^{\alpha 2}\, G^{\alpha 3}]^{\beta 1}\, G^{\beta 2}\, P^{\beta 3}\, Y^{\beta 4}$

It is expositionally useful to separate this score into three components:

Per-capita vulnerability: $[D\, Y^{\alpha 2}\, G^{\alpha 3}]^{\beta 1}$

Project concerns: $G^{\beta 2}\, Y^{\beta 4}$

Population scaling: $P^{\beta 3}$

[39] Formally, this index assumes a Cobb-Douglas (unit-elastic) cost function, internationally-traded capital and non-traded labor. The cost elasticity of the average wage (proxied by income per capita) in this function is the labor share of national income.

Per-capita vulnerability already incorporates exponential weighting, so I set β_1 =1.0. I use estimated vulnerability weights from column (6), Table 1: $\alpha_2 = -0.78$; $\alpha_3 = -1.64$. For the governance parameter (β_2), I adopt the IDA's 2007 weighting scheme that sets an effective value of 3.0.[40] I follow IDA and the AfDB in setting the population weight β_3 at 1.0 and, as previously noted, I set the cost index β_4 at 0.6.

Re-arranging terms in the scoring equation, the full formula is[41]

(9) $$S = DY^{\alpha_2+\beta_4}G^{\alpha_3+\beta_2}P^{\beta_3}$$

In some cases, donor institutions may want to allocate adaptation assistance by vulnerability alone, without incorporating the project concerns of organizations like the MDBs. In other cases, they may want to ignore both resilience factors and project concerns, focusing exclusively on climate drivers. Accordingly, I develop allocation formulas for climate drivers only ($\alpha_2 = 0$; $\alpha_3 = 0$, $\beta_2 = 0$, $\beta_4 = 0$), addition of vulnerability factors ($\beta_2 = 0$, $\beta_4 = 0$); and addition of project concerns (all parameters non-zero).

Climate Drivers: (10a) $S_C = D\ P$
Vulnerability: (10b) $S_V = D\ Y^{-0.78}\ G^{-1.64}\ P$
Project concerns: (10c) $S_P = D\ Y^{-0.18}\ G^{1.36}\ P$

Interpretation of these formulas is case-specific. For composite allocation exercises, D is the group-weighted sum in (7) and P is national population (P_T). For exercises that focus on one problem, D is the appropriate indicator (W, R, A) and P is the directly-affected population group (P_T, P_R, P_A).

These three formulas have very different policy implications. In the first case (10a), resilience factors make no difference: Equal shares will go to two countries with the same climate drivers, even if one is much more resilient because it is significantly richer and/or better governed. In the second case (10b), differences in income and governance

[40] In the IDA formula, the exponent of the overall governance measure (G) is 2. But G itself is the product of two interior measures: A weighted combination of World Bank CPIA and other performance indicators, and a separate governance indicator raised to the power 1.5. Combining these factors, I set the equivalent exponent for my single governance measure (KKM Regulatory Quality) at 3.0 (1.5 x 2.0). More recently, IDA has revised its weighting formulation to promote ease of interpretation by the Bank's client countries (IDA, 2007).

[41] The formulation in (9) uses additive parameters α_3 and β_2 to incorporate the effects of governance on climate vulnerability and project implementation capability. With this specification, I take a direct, empirically-based approach to incorporating the countervailing effects of governance. In contrast, IDA uses a two-stage approach. In the first stage, it ensures minimum commitments to countries regardless of their governance status. Then it distributes the remaining funds using its allocation formula.

may alter the climate-driver allocation significantly. Introduction of project concerns (10c) will reduce the high negative weight on income to a very moderate value, and switch the governance effect from strongly negative to strongly positive. By implication, relatively poor, ineffectively-governed countries will get significantly lower allocation scores (and allocations) from (10c) than (10b).

3.2 The Supporting Database

Formulas 10a, 10b and 10c yield country scores whose relative values are also the countries' relative funding shares when they qualify for assistance from a donor fund.

The accompanying Excel spreadsheet for 233 states includes all the data necessary for applying the three formulas to each of the three adaptation problems (extreme weather change, sea level rise, agricultural productivity change) separately, and to the composite case. For practitioners' convenience, I have also computed indicated country shares for individual problems and the composite case. In the database, all entries are global shares, as if all 233 countries are candidates for allocation. Computation of shares for any subset of countries requires only one additional step: Calculate the total of shares in the subset of countries and divide each share by that total. The results are the appropriate shares for countries within the subset.

In the following section, I present illustrative applications for two contrasting cases: assistance for adaptation to sea level rise by the 20 developing states that are small islands, and assistance for general adaptation to climate change by the 68 states that qualify for low-income status.

4. Illustrations of the Methodology

4.1 Developing Small Island States

From the 64 small islands in the database (those with areas less than 20,000 sq. km.), I select the 20 states that qualify for IDA lending or have low or lower-middle income status. For this illustration, I assume that a donor institution is only interested in assistance for adaptation to sea level rise. The critical indicator is the forecast change in storm surge risk during the period 2008-2050. My measure of risk is the probability of residence in the coastal area that is threatened by storm surges.

The first four columns of Table 13 provide information on geography, area and population. The 20 island states are scattered across the oceans, with 3 in the Atlantic (Cape Verde, St. Helena, Sao Tome and Principe); 5 in the Caribbean (St. Vincent and the Grenadines, Dominica, Montserrat, Grenada, St. Lucia); 2 in the Indian (Maldives, Comoros) and 10 in the Pacific (Tuvalu, Marshall Islands, Wallis and Futuna, Kiribati, Nauru, Tonga, Tokelau, Samoa, Vanuatu, and Federated States of Micronesia). They vary in size from 12,189 sq. km. (Vanuatu) to 12 sq. km. (Tokelau); in population from 731,775 (Comoros) to 1,467 (Tokelau); and in income per capita from $4,349 (Wallis and Futuna) to $591 (Kiribati). The islands' diverse topographies and settlement patterns are reflected in 2008 probabilities of residence in coastal storm surge areas that range from 22.3% in Tuvalu to 0.9% in St. Lucia. Many probabilities are forecast to change substantially by 2050, as the sea level rises, average storm intensity increases, and population changes in the storm surge areas. Table 13 presents the data in descending order of forecast change in probability. Tuvalu has the most change (4%), while St. Lucia and the Federated States of Micronesia have the least (0.1%). From the general database, I extract the 20 states' pre-calculated global assistance shares for cases 10a (climate drivers), 10b (vulnerability) and 10c (project concerns).[42] Then I apply the previously-described adjustment, totaling the pre-calculated global shares for the 20 states and dividing each share by that total. The results (which add to 100%) are the indicated assistance shares for the 20 small island states.

Column (8) of Table 13 uses formula 10a to calculate indicated shares for the climate driver -- change in storm surge probability -- weighted by population. Maldives has the greatest share (46.01%), which reflects both a high probability change (2.3%) and the largest threatened population in the group (49,250). The relatively large shares of the Marshall Islands (11.03%) and Kiribati (7.93%) also reflect both factors, while relatively large threatened populations provide the main factor for Samoa (6.04%), Cape Verde (5.54%) and Comoros (6.30%). Conversely, the smallest shares are indicated for countries that have small threatened populations and small forecast probability changes (Montserrat (0.005%), St. Lucia (0.07%), Federated States of Micronesia (0.04%).

Column (9) uses formula 10b, which includes the effects of income and regulatory quality on resilience. Indicated shares increase sharply for Kiribati (7.93% to 26.46%) and Comoros (6.30% to 17.25%), which have both the lowest incomes in the group ($591 and $1,010, respectively) and the lowest regulatory quality scores (-1.22, -1.51). Conversely, Maldives' share drops from 46.01% to 24.16% because its income is in the group 90th percentile while its regulatory quality score (-0.42) is near the group median (-0.46). Smaller gains or losses by other islands also reflect their relative incomes and regulatory quality scores.

Column (10) uses formula 10c, which adds two project concerns: probability of success (proxied by regulatory quality) and unit cost (proxied by income per capita). As previously noted, these adjustments greatly moderate the negative overall weight on income and switch the weight on regulation quality from negative to positive. The result is near-neutralization of the resilience factors, and indicated shares in column (10) that are very close to those in column (8), relative to column (9). However, relative share decreases from (8) to (10) are still noticeable for island states with particularly low regulatory quality scores (Comoros (-1.51), Kiribati (-1.22), Tuvalu (-1.16), Nauru

[42] In the database, global shares are pre-calculated for all 233 countries.

Table 13: Results for Developing Small Island States

State	(1) Ocean	(2) Area (sq. km.)	(3) Pop 2008 ('000)	(4) Storm Surge Pop 2008 ('000)	(5) Surge Zone Prob. 2008 (/100K)	(6) Surge Zone Prob. 2050 (/100K)	(7) Chg. In Surge Zone Prob. 08-50 (/100K)	(8) Indicated Aid Share, Storm Surge Prob. Only	(9) Indicated Aid Share, Vulner. Only	(10) Indicated Aid Share, Proj. Concerns	(11) Income Per Capita 2008 ($US PPP)	(12) KKM Reg. Qual. 2008
Tuvalu	Pacific	26	10.339	2.30	22.3	26.3	4.0	3.80	4.12	2.86	2,360	-1.16
Marshall Islands	Pacific	181	63.174	9.70	15.4	18.1	2.8	11.03	9.98	11.03	2,010	-0.68
Wallis and Futuna	Pacific	142	15.237	2.27	14.9	17.6	2.7	2.50	1.10	2.4	4,349	-0.46
Maldives	Indian	298	385.925	49.25	12.8	15.0	2.3	46.01	24.16	47.22	3,363	-0.42
Kiribati	Pacific	811	96.858	10.25	10.6	12.5	1.9	7.93	26.46	7.4	591	-1.22
Nauru	Pacific	21	9.162	0.96	10.5	12.3	1.8	0.73	0.84	0.66	1,760	-0.91
Tonga	Pacific	747	119.009	11.31	9.5	11.2	1.7	7.84	7.07	7.51	2,124	-0.75
Tokelau	Pacific	12	1.467	0.13	8.9	10.5	1.6	0.08	0.10	0.1	1,223	-0.46
Samoa	Pacific	2,831	189.503	12.94	6.8	8.0	1.1	6.04	4.52	6.57	2,195	-0.46
Cape Verde	Atlantic	4,033	493.619	19.78	4.0	4.7	0.7	5.54	2.82	6.99	2,708	-0.02
St, Helena	Atlantic	308	7.601	0.30	4.0	4.6	0.7	0.08	0.02	0.16	3,197	1.44
Comoros	Indian	2,235	731.775	26.12	3.6	4.2	0.6	6.30	17.25	4.45	1,010	-1.51
St. Vincent & Grenadines	Caribbean	389	104.938	3.39	3.2	3.8	0.5	0.76	0.37	1.15	2,298	0.4
Sao Tome & Principe	Atlantic	964	168.415	7.70	4.6	4.8	0.3	0.81	0.79	0.8	1,884	-0.72
Dominica	Caribbean	751	72.514	1.27	1.7	2.0	0.3	0.13	0.07	0.18	2,270	0.16
Montserrat	Caribbean	102	5.082	0.07	1.3	1.5	0.2	0.005	0.002	0.008	3,448	0.58
Vanuatu	Pacific	12,189	215.446	2.66	1.2	1.4	0.2	0.22	0.23	0.21	1,754	-0.76
Grenada	Caribbean	344	106.555	1.31	1.2	1.4	0.2	0.10	0.04	0.14	2,593	0.31
St. Lucia	Caribbean	616	159.585	1.40	0.9	1.0	0.1	0.07	0.03	0.1	2,508	0.40
Micronesia, Fed. Sts.	Pacific	702	107.665	1.09	1.0	1.1	0.1	0.04	0.04	0.04	1,582	-0.63

(-.91)), while relative increases are evident for high-scoring islands (St. Helena (1.44), Montserrat (0.58), St. Lucia (0.40), St. Vincent and the Grenadines (.40)).

In summary, my results for 20 small island developing states highlight two allocation factors. First, the islands' heterogeneity produces large differences in indicated shares of an adaptation assistance fund, in both per capita and absolute terms. Second, the indicated shares are highly sensitive to the incorporated decision factors. Changing from a focus on climate drivers (formula 10a) to inclusion of resilience (10b) leads to sharply higher indicated shares for states with particularly low incomes and regulatory quality scores, and lower shares for states with the opposite characteristics. Addition of project concerns (10c) returns the results to the neighborhood of the climate driver shares (10a), but with differences that are largely due to regulatory quality scores.

4.2 Low Income States

To illustrate the generality of my approach, I switch from one problem dimension (sea level rise) to three (extreme weather change, sea level rise, agricultural productivity loss), and from the microcosm of small island developing states to the macrocosm of all low income states (those qualified for IDA lending, or with 2008 per capita incomes below $2,500 at purchasing power parity). From the general database for 233 countries, I extract the overall climate change risk index; risk indicators for extreme weather change, sea level rise, and loss of agricultural productivity; and indicated adaptation assistance shares for three overall cases: climate drivers (formula 10a); vulnerability (10b); and project concerns (10c).

As before, I recalculate shares for this country subset by totaling pre-calculated shares within the subset, and then dividing each pre-calculated share by that total. Table 14 (page 35) presents the results, with data ordered from the highest overall indicator of climate change risk. Per equation (7), this is the weighted average of the indicators for extreme weather change, sea level rise and agricultural productivity loss. The weights for the three indicators are proportional to total population, population threatened by coastal storm surges, and rural population, respectively. The three problem indicators are derived from the underlying measures of climate impact (respectively change in the probability of being affected by extreme weather; change in the probability of residence in a storm surge zone; percent change in agricultural productivity). I transform them to indicators with maximum values of 100 to establish parity for aggregation and facilitate comparisons. These scalar transformations have no effect on indicated aid shares.

Since the threat indicators are per-capita measures, it is not surprising to see great variation over the range of country sizes. Djibouti and Guyana have much higher sea level rise indicators than Bangladesh, and Congo Republic and Haiti have higher agricultural vulnerability indicators than Vietnam or Ethiopia. Similarly, Honduras and Somalia have much higher extreme weather indicators than Nigeria.

Column (1) presents overall climate change risk indicators in descending order. Sub-Saharan Africa clearly dominates the top range, with significant representation from all African subregions. In the top 25 states, 19 are from Sub-Saharan Africa, 4 from Asia (Bangladesh, Myanmar, Vietnam and Cambodia), and 2 from Latin America and the Caribbean (Guyana, Haiti). Overall, the weighting tends to be dominated by agricultural productivity loss because its cross-country distribution is much less skewed than the distributions for sea level rise and extreme weather change (particularly the latter). Examples are provided by the top two countries, Central African Republic and Burundi, which have maximum global indicator values (100) for agricultural productivity loss but no coastal threat (they are landlocked) and very small extreme weather indicators. However, many countries in the top 15 owe substantial parts of their rankings to threats from extreme weather change or sea level rise. Examples include Bangladesh, Senegal, Ethiopia, Myanmar, Malawi, Guinea-Bissau, Vietnam, Madagascar, Guyana, Mauritania and Sierra Leone.

Columns (5) – (7) present indicated aid shares for climate drivers only (formula 10a), vulnerability (10b, which adds the resilience factors), and inclusion of project concerns (10c). Among the countries with high indicated aid shares, Vietnam and Ethiopia provide an instructive comparison. Across threat indicators, the two countries are a study in contrasts: Vietnam's extreme weather change index (15.3) is over twice Ethiopia's (6.0), while the opposite is true for agricultural productivity loss (Ethiopia 52.1, Vietnam 25.1). Vietnam has a very high indicator value for sea level rise (37.2), while Ethiopia has no SLR vulnerability because it is landlocked. The two countries have similar total and rural populations, while Vietnam's population in the storm surge area is about 10 million. The net results produce similar indicated shares for climate threat only (Ethiopia 9.7%, Vietnam 7.8%). These results are changed substantially by addition of the resilience factors – income per capita and regulatory quality (formula 10b). Ethiopia's per capita income ($600) is far lower than Vietnam's ($2,349); Vietnam's regulatory quality score (-0.53) is around the 70^{th} percentile for the group, while Ethiopia's score (-.86) is well below the median. Incorporation of these resilience factors raises Ethiopia's indicated share to 11.4%, while reducing Vietnam's to 2.6%. As in the case of small island states, inclusion of project concerns (formula 10c) largely reverses the resilience adjustment, but with a modest relative shift to Vietnam because of its higher regulatory score.

In summary, the pattern of results for all poor countries resembles the pattern for developing small island states: Per-capita shares assigned for climate drivers alone (10a) change markedly with the addition of vulnerability factors (10b), and then shift back substantially with the inclusion of project concerns (10c). As before, cross-country differences in affected populations have large impacts on indicated aid shares. However, this case is differentiated from the small island illustration by its inclusion of all three climate problems. Relative weightings and results are strongly affected by differences in the relative sizes of the three affected population groups (total population for extreme weather change; population in storm surge areas for sea level rise; rural population for agricultural productivity loss). Although all three climate change risk indicators play significant roles, the indicator for agricultural productivity loss tends to dominate many overall indicator values because its cross-country distribution is much less skewed than the distributions for sea level rise and extreme weather change (particularly the latter).

5. Summary and Conclusions

In this paper, I have constructed, tested and applied indicators that incorporate factors related to climate change risk, vulnerability to climate change, and aid project economics. I have taken the broadest feasible view of climate change risk by including indicators for extreme weather, sea level rise and agricultural productivity loss. Similarly, I have taken the most inclusive possible approach to country representation. My database, included with this paper in an Excel spreadsheet, provides a complete set of indicators for 233 states that range in size from China to Tokelau, and in per capita income from Monaco to the Democratic Republic of the Congo.

In large part, this exercise has been driven by an immediate, practical objective: comprehensive information for donor institutions – MDBs, bilateral aid agencies, NGO's – that seek to provide financial assistance for adaptation to climate change. The paper develops and illustrates methods for cross-country allocation that incorporate climate drivers, resilience factors, and concerns related to project economics. The methods can be applied easily and consistently to any subset of the 233 states. To facilitate applications, the database includes relevant identifiers for each country: area, population, income per capita, island status, small island status, coastal status, region, subregion, World Bank region, World Bank lending class and income class. I have also included standard ISO3 codes for linking to other databases.

At first glance, my inclusion of 233 states might seem excessive. The richest states are in the database alongside the poorest; the tiniest island states alongside the mainland giants, and current "rogue states" (however and by whomever defined) alongside the states currently favored by the major multilaterals and bilaterals. My reasons for this all-inclusive approach are straightforward and, I hope, persuasive: First, all states are affected by climate change, and it makes sense to provide a comprehensive view of the risks they all face. I hope that an inclusive approach will encourage citizens of all countries to consider their stakes in this global problem. Second, all states may well be candidates for assistance in the uncertain, undoubtedly-turbulent world that awaits if we continue to dither on controlling carbon emissions. Finally, I hope that the information in this paper will promote recognition that conventional divisions (North/South, rich/poor, etc.) can impede understanding in this context. We are all in this together, and my results indicate that dangerous climate change is already upon us.

Table 14: Result for Low-Income Countries

	Threat Indicators				Indicated Aid Shares							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	
Country	Overall	Extreme Weather	Sea Level Rise	Ag. Prod. Loss.	Climate Only (10a)	Incl. Vulner. (10b)	Inc. Project Concerns	Income Per Capita 2008 ($US PPP)	KKM Reg. Qual. 2008	Total Pop. 2008 (‘000)	Storm Surge Pop 2008 (‘000)	Rural Pop. 2008 (‘000)	Region
Central African Rep.	61.5	0.071	0.00	100.0	0.67952	0.93996	0.58293	711	-1.28	4,641.3		2,850.7	Central Africa
Burundi	60.2	1.138	0.00	65.9	1.30942	3.07957	1.37777	326	-1.18	9,139.3		8,188.8	Central Africa
Sudan	59.2	6.437	0.46	93.3	5.87824	4.10589	4.05259	1,838	-1.36	41,680.8	88.6	23,574.7	East Africa
Bangladesh	55.0	25.485	31.26	36.1	19.79592	13.57820	20.10123	1,172	-0.82	151,290.0	15,312.7	110,229.9	Southern Asia
Rwanda	53.9	0.060	0.00	65.9	1.33905	1.09339	1.72840	736	-0.49	10,440.8		8,525.9	Central Africa
Senegal	50.3	0.082	11.89	86.4	1.40212	0.55022	1.71067	1,643	-0.29	11,698.3	491.5	6,740.6	Coastal West Africa
Ethiopia	49.2	6.016	0.00	52.1	9.67773	11.43805	10.88093	600	-0.86	82,544.8		68,512.2	East Africa
Myanmar	48.7	3.008	20.80	65.4	6.05669	17.02881	2.28081	945	-2.24	52,228.2	4,047.4	35,212.2	Southeast Asia
Malawi	48.3	5.983	0.00	52.1	1.68073	1.36687	2.29964	689	-0.39	14,623.7		11,874.4	East Africa
Niger	48.0	0.654	0.00	56.7	1.68622	1.58925	2.21875	623	-0.52	14,752.1		12,312.1	Sahelian Africa
Lesotho	47.1	0.085	0.00	63.1	0.21477	0.10992	0.22955	1,478	-0.63	1,915.5		1,427.8	Southern Africa
Zambia	43.4	0.870	0.00	65.9	1.31238	0.64337	1.64749	1,270	-0.33	12,694.2		8,197.9	Central Africa
Chad	41.6	0.017	0.00	56.7	1.00193	0.74333	0.75666	1,550	-1.26	10,111.3		7,413.6	Sahelian Africa
Mali	40.3	0.098	0.00	59.2	1.25613	0.71284	1.63095	1,053	-0.33	13,100.8		8,885.0	Sahelian Africa
Guinea-Bissau	40.3	0.042	22.54	54.4	0.14408	0.25883	0.13756	481	-1.22	1,503.2	136.1	1,054.6	Coastal West Africa
Zimbabwe	39.6	0.120	0.00	63.1	1.07106	1.88589	0.39657	1,542	-2.18	11,350.1		7,112.0	Southern Africa
Congo, Rep.	38.8	0.056	8.77	100.0	0.36117	0.13488	0.24575	3,500	-1.19	3,905.0	58.1	1,509.7	Central Africa
Vietnam	37.6	15.258	37.18	25.1	7.84844	2.64111	8.09469	2,349	-0.53	87,558.4	10,031.8	63,182.1	Southeast Asia
Cambodia	36.4	0.969	3.85	45.1	1.20943	0.53791	1.37353	1,581	-0.47	13,957.0	204.6	10,947.9	Southeast Asia
Guinea	36.0	0.014	6.27	54.4	0.83967	0.70467	0.71271	1,189	-1.15	9,806.5	434.7	6,429.1	Coastal West Africa
Madagascar	35.7	4.861	5.79	43.6	1.70482	1.10734	2.28702	884	-0.33	20,042.6	483.4	14,126.0	East Africa
Guyana	35.7	0.224	41.22	42.7	0.06448	0.01527	0.06068	3,735	-0.55	758.1	90.8	542.9	Northern South America
Haiti	35.7	0.658	9.94	65.4	0.81946	0.54848	0.79237	1,274	-0.89	9,639.1	277.7	5,124.1	Caribbean Islands
Mauritania	34.8	0.356	23.28	56.7	0.25317	0.10910	0.26593	1,793	-0.59	3,054.9	128.0	1,802.4	Sahelian Africa

Table 4, continued

	Threat Indicators				Indicated Aid Shares								
Country	(1) Overall	(2) Extreme Weather	(3) Sea Level Rise	(4) Ag. Prod. Loss.	(5) Climate Only (10a)	(6) Incl. Vulner. (10b)	(7) Inc. Project Concerns	(8) Income Per Capita 2008 ($US PPP)	(9) KKM Reg. Qual. 2008	(10) Total Pop. 2008 ('000)	(11) Storm Surge Pop 2008 ('000)	(12) Rural Pop. 2008 ('000)	Region
Sierra Leone	34.1	0.019	9.48	54.4	0.40826	0.46409	0.45494	631	-0.86	5,023.0	134.7	3,126.3	Coastal West Africa
Sri Lanka	33.6	4.620	13.46	33.4	1.69136	0.33262	1.76990	3,956	-0.28	21,128.8	953.0	17,938.3	Southern Asia
Benin	32.7	0.088	22.46	54.4	0.66473	0.34773	0.78944	1,273	-0.46	8,532.5	243.2	5,017.1	Coastal West Africa
Yemen, Rep.	32.6	0.022	1.83	46.9	1.72430	0.65712	1.64686	2,276	-0.70	22,222.9	262.8	15,413.8	Middle East
Burkina Faso	32.6	0.036	0.00	40.4	1.18338	0.63640	1.52962	1,117	-0.32	15,264.7		12,279.0	Sahelian Africa
Togo	32.2	0.042	17.17	54.4	0.47731	0.51866	0.46004	787	-1.05	6,220.3	227.5	3,607.8	Coastal West Africa
Afghanistan	31.9	0.729	0.00	41.1	2.10388	3.35149	1.44790	806	-1.58	27,658.9		21,009.7	Western Asia
Tanzania	31.8	1.808	2.52	40.3	3.04786	1.86384	3.89636	995	-0.39	40,213.2	553.8	29,950.8	East Africa
Uganda	28.5	4.183	0.00	28.0	2.12910	1.21819	3.17518	883	-0.08	31,368.0		27,296.4	East Africa
Solomon Islands	28.3	0.041	16.67	33.4	0.03597	0.02420	0.02559	1,839	-1.31	533.8	28.7	437.9	Pacific Islands
Tonga	28.2	0.132	31.04	33.4	0.00798	0.00329	0.00756	2,124	-0.75	119.0	11.3	89.5	Pacific Islands
Eritrea	27.3	0.299	1.33	34.1	0.35826	1.07315	0.16009	721	-2.13	5,502.0	27.8	4,362.0	East Africa
Samoa	27.2	0.113	20.89	33.4	0.01229	0.00421	0.01320	2,195	-0.46	189.5	12.9	145.9	Pacific Islands
Lao PDR	27.1	0.199	0.00	38.9	0.39667	0.23890	0.28931	1,993	-1.25	6,145.2		4,247.6	Southeast Asia
Somalia	26.5	8.903	2.94	27.6	0.60247	7.80872	0.12587	416	-2.77	9,558.7	115.9	6,067.8	East Africa
Honduras	26.5	5.825	5.97	39.4	0.48359	0.10351	0.51877	3,527	-0.27	7,675.8	106.0	4,000.7	Central America
Mozambique	26.4	3.044	12.26	36.1	1.33731	1.08107	1.74548	734	-0.47	21,284.7	938.1	13,443.4	Southern Africa
Maldives	26.1	0.065	41.83	33.4	0.02401	0.00577	0.02436	3,363	-0.42	385.9	49.2	239.8	Indian Ocean Islands
Djibouti	25.7	3.127	78.09	27.6	0.04340	0.01866	0.04145	2,017	-0.75	709.2	173.2	90.1	East Africa
Vanuatu	25.5	0.372	3.67	33.4	0.01309	0.00632	0.01274	1,754	-0.76	215.4	2.7	162.1	Pacific Islands
Nepal	25.1	1.322	0.00	28.8	1.68808	1.14890	1.89779	1,044	-0.66	28,197.0		23,335.8	Southern Asia
Liberia	24.6	0.022	39.63	54.4	0.20163	0.54206	0.19647	313	-1.32	3,440.4	252.3	1,371.3	Coastal West Africa
Comoros	24.4	0.034	10.81	33.4	0.04253	0.05323	0.02966	1,010	-1.51	731.8	26.1	526.3	Indian Ocean Islands
Timor-Leste	24.4	0.094	2.29	33.4	0.06433	0.04031	0.04192	2,195	-1.40	1,108.8	10.0	806.1	Pacific Islands
Gambia, The	23.8	0.052	3.70	54.4	0.09821	0.05510	0.12019	1,144	-0.44	1,732.1	24.2	754.8	Coastal West Africa
Bhutan	22.8	0.037	0.00	34.8	0.03708	0.00994	0.02954	4,032	-0.86	682.3		447.1	Southern Asia

Table 4, continued

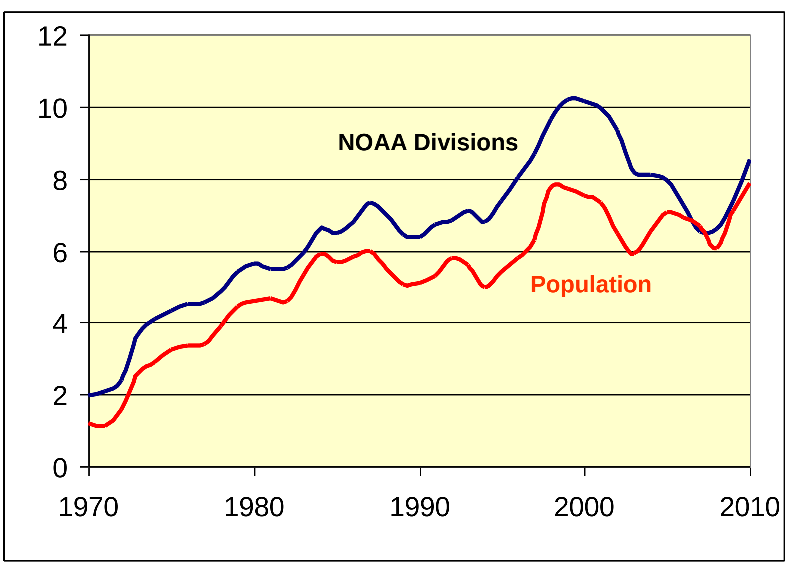
	Threat Indicators				Indicated Aid Shares							
Country	(1) Overall	(2) Extreme Weather	(3) Sea Level Rise	(4) Ag. Prod. Loss.	(5) Climate Only (10a)	(6) Incl. Vulner. (10b)	(7) Inc. Project Concerns	(8) Income Per Capita 2008 ($US PPP)	(9) KKM Reg. Qual. 2008	(10) Total Pop. 2008 ('000)	(11) Storm Surge Pop 2008 ('000)	(12) Rural Pop. 2008 ('000)	Region
Kiribati	22.6	0.197	34.64	33.4	0.00521	0.00795	0.00481	591	-1.22	96.9	10.2	54.4	Pacific Islands
Sao Tome & Principe	21.7	0.011	4.70	54.4	0.00870	0.00388	0.00851	1,884	-0.72	168.4	7.7	66.4	Atlantic Islands
Nicaragua	20.3	3.274	2.42	39.4	0.28027	0.07383	0.29977	2,874	-0.36	5,785.8	28.8	2,503.0	Central America
Nauru	19.7	0.152	33.90	33.4	0.00043	0.00023	0.00039	1,760	-0.91	9.2	1.0	4.4	Pacific Islands
Angola	18.9	0.127	6.97	42.9	0.56281	0.16189	0.43113	3,940	-0.94	12,531.4	267.4	5,426.1	Central Africa
Tokelau	18.6	0.039	28.96	33.4	0.00007	0.00004	0.00008	1,223	-0.46	1.5	0.1	0.7	Pacific Islands
Congo, Dem. Rep.	16.2	0.034	0.02	24.5	2.56343	8.20826	2.37721	279	-1.43	66,514.5	3.3	43,926.2	Central Africa
Nigeria	16.1	0.022	7.65	30.8	5.60603	2.64248	5.91313	1,631	-0.62	146,255.3	3,470.3	75,526.2	Coastal West Africa
Cameroon	14.5	0.004	4.26	33.3	0.63824	0.24777	0.62782	2,156	-0.66	18,467.7	529.5	7,985.4	Central Africa
Cote d'Ivoire	13.1	0.002	29.39	23.8	0.62953	0.33826	0.56090	1,754	-0.93	20,179.6	627.3	10,336.0	Coastal West Africa
Uzbekistan	12.7	0.003	0.00	20.1	0.82838	0.52490	0.53699	2,184	-1.41	27,345.0		17,276.6	Western Asia
Kenya	12.2	5.169	0.78	9.0	1.10396	0.42691	1.50460	1,459	-0.07	37,953.8	166.0	29,755.8	East Africa
Ghana	11.7	0.026	5.22	23.3	0.65535	0.26489	0.97499	1,255	0.08	23,434.6	345.9	11,712.6	Coastal West Africa
Tajikistan	8.0	0.787	0.00	9.8	0.13749	0.08070	0.12154	1,620	-0.97	7,211.9		5,303.6	Western Asia
Moldova	7.9	0.046	0.00	13.6	0.08179	0.02175	0.09569	2,555	-0.20	4,324.5		2,518.6	Eastern Europe
Kyrgyz Republic	6.3	0.009	0.00	9.8	0.07990	0.02839	0.09371	1,904	-0.32	5,356.9		3,413.4	Western Asia
Korea, Dem. Rep.	5.5	0.344	13.78	12.1	0.29661	0.42767	0.09140	2,353	-2.28	22,565.4	1,053.5	8,421.4	Northeast Asia
Mongolia	5.3	0.141	0.00	12.1	0.03810	0.00958	0.04193	2,909	-0.29	2,996.1		1,282.9	Northeast Asia

Appendix A: Atmospheric CO2 Accumulation and Exposure to Extreme Precipitation in the US, 1960–2010

This appendix analyzes the relationship between atmospheric CO2 accumulation and exposure of the US population to extreme precipitation. I divide the overall exposure change since 1960 into two components: heavier precipitation driven by CO2 accumulation (via radiative forcing), and population shifts toward wetter areas. My analysis draws on a long-term database maintained by the US National Oceanic and Atmospheric Administration (NOAA) for 344 geographic divisions in the continental United States. For the period January, 1970 to July, 2010, I analyze changes in the Palmer Hydrological Drought Index (PHDI), which indicates the severity of wet or dry periods in each NOAA division. I also weight divisional PHDI series by population to compute changes in the percent of Americans exposed to extreme precipitation.

For NOAA geographic divisions and the US population, Figures A1 and A2 present trend indicators of exposure to extreme precipitation (PHDI>=4).[43] The indicators in Figure A1 assign the following weights to divisional observations: 1 if PHDI>=4, 0 otherwise. In Figure A2, the assignment rule is (PHDI/4 if PHDI>=4, 0 otherwise). A1 and A2 would be identical if there were no trend in PHDI values. Inspection of A1 and A2 yields three conclusions. First, all exposure indicators trend sharply upward. Second, the slopes in A2 are steeper, indicating a trend increase in the value of PHDI measures above 4. Finally, some intertemporal divergence in trends for NOAA divisions and the US population suggests that heavier precipitation and geographic shifts have both played a role.

Figure A1: Extreme precipitation exposure, 1970–2010 (Unwgted)



[43] The trend lines are 10-year moving averages.

Figure A2: Extreme precipitation exposure, 1970–2010 (Wgted)

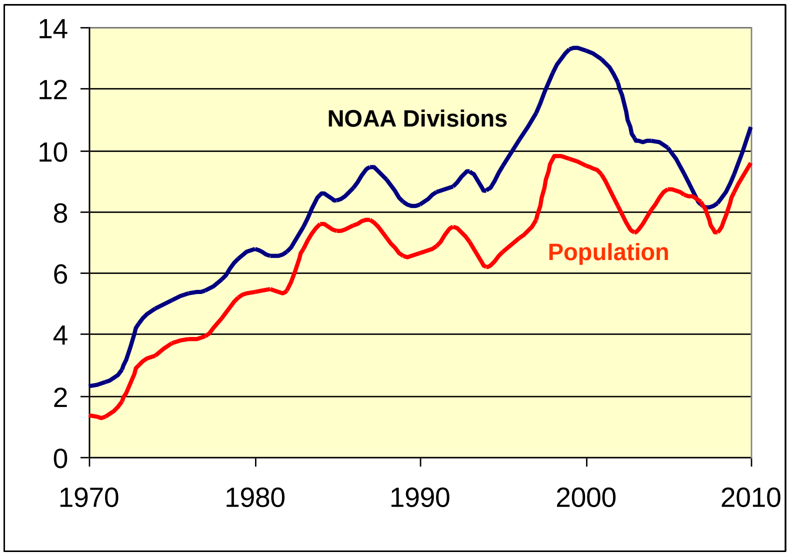


Table A1 presents elasticity calculations for the indicators in A1 and A2. They all exhibit large percent changes from 1970 to 2010: The PHDI weighted and unweighted indicators for NOAA divisions increase by 362% and 331%, respectively, while the corresponding indicators for the US population increase by 597% and 561%. When these are divided by the relatively modest increase in atmospheric CO2 concentration (19.5%), they yield very high elasticities: 18.6 and 17 for NOAA divisions; 30.6 and 28.8 for the US population. Comparison of the population exposure elasticities in Table A1 with the population impact elasticities in the paper's Table 1 shows that they are nearly identical. While this single result is undoubtedly fortuitous, it does suggest that the estimates in Table 1 have reasonable magnitudes.

Table A1: Exposure Elasticities

	Exposure Indicator Values				
	NOAA Divisions		US Population		
Weight (Figure)	PHDI/4 (A2)	1 (A1)	PHDI/4 (A2)	1 (A1)	CO2 (ppm)
1970	2.32	1.97	1.37	1.19	325.7
2010	10.73	8.51	9.57	7.88	389.2
	% Changes				
1970-2010	361.73	331.27	596.78	561.02	19.5
	Elasticities				
1970-2010	18.56	17.00	30.62	28.79	

The available data also permit decomposition of population exposure into two parts: the proportion due to change in extreme precipitation, holding each district's national population share constant, and the proportion due to change in each district's population share, holding its incidence of extreme precipitation constant. Mathematically:

$$\text{(A1) } P_{wt} = \sum_{i=1}^{344} r_{it}\, p_{it} \text{ ; (A2) } \frac{\Delta P_{wt}}{\Delta t} = \sum_{i=1}^{344} \left[r_{it} \frac{\Delta p_{it}}{\Delta t} + p_{it} \frac{\Delta r_{it}}{\Delta t} \right]$$

where P_{wt} = The probability of exposure to extreme precipitation
r_{it} = The incidence of extreme precipitation in division i, period t
p_{it} = The national population share of division i, period t

To apply equation (A2), I extract the subperiods 1960-75 and 1995-2010, and calculate the mean incidence of extreme wetness and mean population share in each subperiod. I calculate ($\Delta p/\Delta t$) and ($\Delta r/\Delta t$) from differences in the respective period means. For p and r, I use averages of the respective means for the two periods. I sum the two terms of (A2) separately across 344 divisions and calculate each sum as a proportion of the total for both. Table A2 presents results for the weighted and unweighted population exposure indicators. In both cases, the conclusion is clear: Heavier precipitation accounts for about 98% of the increase in indicator values, and population shifts account for about 2%.

Table A2: Contributions to Indicator Movement (%)

	Exposure Indicator Values				
	NOAA Divisions		US Population		
Weight (Figure)	PHDI/4 (A2)	1 (A1)	PHDI/4 (A2)	1 (A1)	CO2 (ppm)
1970	2.32	1.97	1.37	1.19	325.7
2010	10.73	8.51	9.57	7.88	389.2
	% Changes				
1970-2010	361.73	331.27	596.78	561.02	19.5
	Elasticities				
1970-2010	18.56	17.00	30.62	28.79	

In this appendix, my analysis has been confined to one data-rich country and one measure of extreme weather. My results indicate that population exposure incidence has been highly responsive to CO2 accumulation, and that almost all of the change has been due to heavier precipitation, not geographic shifts in the population. Of course, I cannot generalize my results to 233 countries and five types of weather-related disasters. Nevertheless, the near-equivalence of elasticity estimates in Tables A1 and 1 is at least suggestive. As I have noted in the paper, potential impacts are critically related to local adaptive settings: A rapid change in the climate regime may lead to disproportionately-heavy losses in settlements that are just outside the traditional boundaries of high-risk areas (near rivers, coastlines, arid zones, etc.).

Appendix B: Formal development of the resource allocation rule

Specify the donor's objective function for reducing vulnerability as:

(1) $W = \omega_0 \prod_{i=1}^{N} R_i$

where R_i = Reduction of vulnerability to climate change in country i

For each country, specify the vulnerability reduction function as:

(2) $R_i = \alpha_0 S_i^{\alpha_1 V_i p_i}$ ($\alpha_1 > 0$)

where S_i = Scale of donor activity in country i

V_i = Scale of vulnerability in country i

p_i = Probability that a project will succeed in country i

Equation (2) incorporates scale economies: The abatement productivity of donor activity rises with the scale of existing vulnerability. In (2) this is explicitly specified as expected productivity, with the probability of project success as a conditioning factor. The donor faces a fixed budget constraint and potentially-different internal administrative costs across countries:

(3) $\sum_{i=1}^{N} c_i B_i = I_T$

where c_i = Unit cost of donor activity in country i

I_T = Total sectoral budget

Substitution from (2) into (1) yields the following welfare function:

(4) $W = \omega_0 \prod_{i=1}^{N} \alpha_0 S_i^{\alpha_1 V_i p_i}$

Assuming equal internal administrative costs across countries, maximization of W subject to the overall budget constraint yields the following ratio of optimal allocations to countries i and j:

(5) $\frac{S_i^*}{S_j^*} = \frac{V_i p_i}{V_j p_j}$

Thus, allocations to countries i and j are proportional to their vulnerabilities if projects have equal success probabilities.

Appendix C: Subregions and Countries

Africa			Asia	
Subregion	Country		Subregion	Country
Central Africa	Angola		China	China
Central Africa	Burundi		China	Hong Kong SAR, China
Central Africa	Cameroon		China	Macao SAR, China
Central Africa	Central African Republic		Middle East	Bahrain
Central Africa	Congo, Dem. Rep.		Middle East	Iraq
Central Africa	Congo, Rep.		Middle East	Israel
Central Africa	Gabon		Middle East	Jordan
Central Africa	Rwanda		Middle East	Kuwait
Central Africa	Zambia		Middle East	Lebanon
East Africa	Djibouti		Middle East	Oman
East Africa	Eritrea		Middle East	Qatar
East Africa	Ethiopia		Middle East	Saudi Arabia
East Africa	Kenya		Middle East	Syrian Arab Republic
East Africa	Malawi		Middle East	Turkey
East Africa	Somalia		Middle East	United Arab Emirates
East Africa	Sudan		Middle East	West Bank and Gaza
East Africa	Tanzania		Middle East	Yemen, Rep.
East Africa	Uganda		Northeast Asia	Japan
East Africa	Madagascar		Northeast Asia	Korea, Dem. Rep.
North Africa	Algeria		Northeast Asia	Korea, Rep.
North Africa	Egypt, Arab Rep.		Northeast Asia	Mongolia
North Africa	Libya		Northeast Asia	Taiwan (China)
North Africa	Morocco		Southern Asia	Bangladesh
North Africa	Tunisia		Southern Asia	Bhutan
Southern Africa	Botswana		Southern Asia	India
Southern Africa	Lesotho		Southern Asia	Nepal
Southern Africa	Mozambique		Southern Asia	Sri Lanka
Southern Africa	Namibia		Southeast Asia	Brunei Darussalam
Southern Africa	South Africa		Southeast Asia	Cambodia
Southern Africa	Swaziland		Southeast Asia	Indonesia
Southern Africa	Zimbabwe		Southeast Asia	Lao PDR
Sahelian Africa	Burkina Faso		Southeast Asia	Malaysia
Sahelian Africa	Chad		Southeast Asia	Myanmar
Sahelian Africa	Mali		Southeast Asia	Papua New Guinea
Sahelian Africa	Mauritania		Southeast Asia	Philippines
Sahelian Africa	Niger		Southeast Asia	Singapore
Coastal West Africa	Benin		Southeast Asia	Thailand
Coastal West Africa	Cote d'Ivoire		Southeast Asia	Vietnam
Coastal West Africa	Equatorial Guinea		Western Asia	Afghanistan
Coastal West Africa	Gambia, The		Western Asia	Azerbaijan
Coastal West Africa	Ghana		Western Asia	Iran, Islamic Rep.
Coastal West Africa	Guinea		Western Asia	Kazakhstan
Coastal West Africa	Guinea-Bissau		Western Asia	Kyrgyz Republic
Coastal West Africa	Liberia		Western Asia	Pakistan
Coastal West Africa	Nigeria		Western Asia	Tajikistan
Coastal West Africa	Senegal		Western Asia	Turkmenistan
Coastal West Africa	Sierra Leone		Western Asia	Uzbekistan
Coastal West Africa	Togo			

Europe			Latin America and the Caribbean	
Eastern Europe	Albania		Andean South America	Bolivia
Eastern Europe	Armenia		Andean South America	Colombia
Eastern Europe	Belarus		Andean South America	Ecuador
Eastern Europe	Bosnia and Herzegovina		Andean South America	Peru
Eastern Europe	Bulgaria		Central America	Belize
Eastern Europe	Croatia		Central America	Costa Rica
Eastern Europe	Czech Republic		Central America	El Salvador
Eastern Europe	Estonia		Central America	Guatemala
Eastern Europe	Georgia		Central America	Honduras
Eastern Europe	Hungary		Central America	Mexico
Eastern Europe	Latvia		Central America	Nicaragua
Eastern Europe	Lithuania		Central America	Panama
Eastern Europe	Macedonia, FYR		Caribbean Islands	Anguilla
Eastern Europe	Moldova		Caribbean Islands	Antigua and Barbuda
Eastern Europe	Poland		Caribbean Islands	Aruba
Eastern Europe	Romania		Caribbean Islands	Bahamas, The
Eastern Europe	Russian Federation		Caribbean Islands	Barbados
Eastern Europe	Serbia and Montenegro		Caribbean Islands	Bermuda
Eastern Europe	Slovak Republic		Caribbean Islands	British Virgin Islands
Eastern Europe	Slovenia		Caribbean Islands	Cayman Islands
Eastern Europe	Ukraine		Caribbean Islands	Cuba
Western Europe	Andorra		Caribbean Islands	Dominica
Western Europe	Austria		Caribbean Islands	Dominican Republic
Western Europe	Belgium		Caribbean Islands	Grenada
Western Europe	Cyprus		Caribbean Islands	Guadeloupe
Western Europe	Denmark		Caribbean Islands	Haiti
Western Europe	Finland		Caribbean Islands	Jamaica
Western Europe	France		Caribbean Islands	Martinique
Western Europe	Germany		Caribbean Islands	Montserrat
Western Europe	Gibraltar		Caribbean Islands	Netherlands Antilles
Western Europe	Greece		Caribbean Islands	Puerto Rico
Western Europe	Guernsey		Caribbean Islands	Saint Barthelemy
Western Europe	Ireland		Caribbean Islands	Saint Martin
Western Europe	Italy		Caribbean Islands	St. Kitts and Nevis
Western Europe	Jersey		Caribbean Islands	St. Lucia
Western Europe	Liechtenstein		Caribbean Islands	St. Vincent and the Grenadines
Western Europe	Luxembourg		Caribbean Islands	Trinidad and Tobago
Western Europe	Malta		Caribbean Islands	Turks and Caicos Islands
Western Europe	Monaco		Caribbean Islands	Virgin Islands (U.S.)
Western Europe	Netherlands		Northern South America	Brazil
Western Europe	Norway		Northern South America	French Guians
Western Europe	Portugal		Northern South America	Guyana
Western Europe	San Marino		Northern South America	Suriname
Western Europe	Spain		Northern South America	Venezuela, RB
Western Europe	Sweden		Southern South America	Argentina
Western Europe	Switzerland		Southern South America	Chile
Western Europe	United Kingdom		Southern South America	Paraguay
			Southern South America	Uruguay

North America			Oceania	
North America	Canada		Atlantic Islands	Cape Verde
North America	Saint Pierre and Miquelon		Atlantic Islands	Faeroe Islands
North America	United States		Atlantic Islands	Falkland Islands
			Atlantic Islands	Greenland
			Atlantic Islands	Iceland
			Atlantic Islands	Isle of Man
			Atlantic Islands	Saint Helena
			Atlantic Islands	Sao Tome and Principe
			Atlantic Islands	Svalbard and Jan Mayen
			Indian Ocean Islands	Comoros
			Indian Ocean Islands	Maldives
			Indian Ocean Islands	Mauritius
			Indian Ocean Islands	Mayotte
			Indian Ocean Islands	Reunion
			Indian Ocean Islands	Seychelles
			Australia / New Zealand	Australia
			Australia / New Zealand	New Zealand
			Pacific Islands	American Samoa
			Pacific Islands	Cook Islands
			Pacific Islands	Fiji
			Pacific Islands	French Polynesia
			Pacific Islands	Guam
			Pacific Islands	Kiribati
			Pacific Islands	Marshall Islands
			Pacific Islands	Micronesia, Fed. Sts.
			Pacific Islands	Nauru
			Pacific Islands	New Caledonia
			Pacific Islands	Niue
			Pacific Islands	Norfolk Island
			Pacific Islands	Northern Mariana Islands
			Pacific Islands	Palau
			Pacific Islands	Pitcairn
			Pacific Islands	Samoa
			Pacific Islands	Solomon Islands
			Pacific Islands	Timor-Leste
			Pacific Islands	Tokelau
			Pacific Islands	Tonga
			Pacific Islands	Tuvalu
			Pacific Islands	Vanuatu
			Pacific Islands	Wallis and Futuna

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