The impact of climate change on global tropical cyclone damage

The emission scenario used here is the SRES A1b scenario²¹. In this emission scenario, the concentration of greenhouse gases peaks at 720 ppm in 2100 and is constant thereafter. Global temperatures are predicted to increase between 2.5° and 4.5° C by 2100 depending on the climate model³. Sea level rise is expected to increase by about 40cm by 2100³ but this analysis does not consider the effects of melting land ice. Changes to the climate and to sea level are expected to continue to increase beyond 2100 but this is not examined in this study.

Using this emission scenario, four climate models are used to predict climate conditions for both the current climate, represented by the years 1981-2000, and the future climate, represented by the years 2081-2100. The four climate models used are: CNRM CM3 ¹⁵, ECHAM 5 ¹⁶, GFDL CM2.0 ¹⁷, and MIROC 3.2 ¹⁸. For each model, we compare the climate in 1981-2000 from their 20th century simulations to the climate in 2081-2100 from their 21stcentury simulations. CNRM predicts a global warming of 2.9°C, ECHAM predicts 3.4°C, GFDL predicts 2.7°C, and MIROC predicts 4.5°C. We report results by climate model in order to reveal how sensitive the results are to these climate predictions. Because the models predict very different regional climatology, there is a large range of effects predicted by the models.

Sea level temperature, atmospheric temperatures and humidities at different elevations, and wind patterns at two levels are all downloaded from a global general circulation model output repository. Tropical cyclones are generated by randomly seeding each ocean with nascent storms. Given local climate conditions, these seeds either dissipate or grow into tropical cyclones. This process generates the probability (annual number) of storms in each ocean basin. A large set of synthetic storms is then generated in order to estimate the intensity and tracks of tropical cyclones in each ocean basin. Previous research suggests that the tail of this distribution is very important. In order to get a better estimate of this tail, we generate 3,000 storms in every ocean basin and 5,000 storms in the North Atlantic for a total of 17,000 storms. We do this with and without climate change for each climate model. The entire synthetic set of storms is equal to 136,000 storms. Budget limitations prevented us from looking at more storms. However, each of these sets is equivalent to having about 300 years worth of observations for each climate scenario.

We then examine the path of these storms to determine where they make landfall. Storms passing over islands are examined to see if they pass close enough (50 km) to cause damage. Which country is struck and the intensity (wind speed and minimum pressure) of the storm at landfall are also recorded.

Since we do not have detail concerning the population and income of spatially detailed areas within countries, the unit of analysis is the country. The global study is at a national level, so that landfalls anywhere in a country are assumed to have identical impacts. Ideally, we want to know the size and income of the local population hit by the storm. At the country level, the best proxy for the affected population is the population density of the country. If we used the absolute population, physically large countries would appear to have higher damages per storm.

The frequency and intensity of storms is predicted by the atmospheric model. The next step is to predict the damage per storm. The damage function predicts the damage a storm of a given intensity causes if it strikes a location with a specific income and population density. Historic data from 1960 to 2008 were gathered to estimate three tropical cyclone damage

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functions. US data were collected on a county basis that included storm intensity²². Global data were available on a country basis but did not include storm intensity¹³. We consequently use the US study to measure the sensitivity of damage to storm intensity and the global study to measure the sensitivity of damage to income and population.

Damage per storm (D) was regressed on intensity (Z) (for the US data), population density Pop, and income (Y) using storms since 1960. The functional form of the regression is

$$lnD = B_0 + B1lnPop + B2lnY + B3lnZ + \varepsilon \tag{1}$$

where (ε) is the error term and (B_i) are the estimated coefficients. Exponentiating both sides of the equation:

$$D = B_0 * Pop^{B_1} * Y^{B_2} * Z^{B_3} * \varepsilon$$

$$\tag{2}$$

Note that this functional form implies a constant elasticity relationship between the independent variables and damage equal to the coefficients. For example, 100 percent increase in income leads to a B_2 increase in damage. This functional form fits the data more closely than alternative semi-log or linear functional forms.

Note that damages were not identified by whether they were caused by wind, storm surge, or fresh water flooding so that these effects could not be separately estimated. For the US analysis, both wind speed and minimum barometric pressure were tried as measures of storm intensity (wind speed is not significant when included with minimum pressure). Note that using wind speed leads to a very different income elasticity coefficient in the US data.

The damages measured are the direct damages of each storm. They do not include indirect damages or long term impacts (other than lost capital) because none of these effects are

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measured. Some authors argue this leads to an underestimate of damages. Empirical evidence suggests that small disasters do not have noticeable indirect effects or long term damages. Large disasters may cause both indirect and long term damages. Some empirical studies suggest that there are long term damages whereas others suggest that large disasters stimulate local economies²⁶. Long term effects can be confused with other events temporally correlated with a storm such as a revolution. It is also true that large disasters attract relief funds which stimulate economic activity.

Fatalities are not included in this study because almost 80% of fatalities from tropical cyclones are concentrated in two countries Myanmar and especially Bangladesh. Global fatality results are largely just capturing what happens to these two countries. The tropical cyclone model used in this analysis suggests a reduction of storm power in the Indian Ocean which would reduce fatalities in these two countries. However, this effect depends on the climate model.

The damage function results are shown in Table 1. The first and second columns display the results for the US data. The US results suggest that damages are a highly nonlinear function of storm intensity. The first column coefficient on wind speed reveals an elasticity of 5 which implies that a 20% increase in wind speed would double damages. The 95% confidence interval for this variable is between 4 and 6. The second column results for the US suggests a minimum pressure elasticity coefficient of -86 which implies that a 1.2% reduction in minimum pressure doubles damages. The 95% confidence interval of the minimum pressure coefficient is between - 68 and -104. Comparing the significance of the intensity coefficients and the R squared results in columns 1 and 2, it is evident that minimum pressure provides a more accurate measure of damage than maximum wind speed.

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The US coefficient on income is near 1 in column 1 where wind speed is used but is equal to 0.4 in column 2 where minimum pressure is used. The population density coefficient is close to 0.5 in both columns 1 and 2. However, the coefficients are not statistically significant. The results in column 3 with the global data suggest that the elasticity of income is 0.42 with a 95% confidence interval between 0.30 and 0.54. Damages increase less than proportionately with income. This may be because higher income countries spend more to protect themselves from storms 23,24,25 . The elasticity of population density is -0.20 with a 95% confidence interval between -0.07 and -0.35. High population density may reduce damages because, although it implies more people are affected, cities may be more hardened against storms than rural areas. In this analysis, we rely on the US elasticity of minimum pressure in column 2 and the global elasticity of population and income in column 3. We consequently assume that the US damage sensitivity applies to the world. The sensitivity may be too high because subsidies in the US encourage development along the coast and so more gets damaged as storm surge increases. Alternatively, the sensitivity may be too low because US structures are more hardened than global structures.

Because the damage function is critical, we present a sensitivity analysis of the damage coefficients. The analysis explores the effect of using the 95% confidence interval instead of the estimated coefficient. That is, we examine the results with a value of -68 for the minimum pressure coefficient, a value of -0.07 for the population density coefficient, or a value of 0.54 for the income elasticity.

There are potential biases introduced by relying on countries as the unit of analysis because of systematic differences within countries. Coastal areas are generally denser and wealthier than the country average. In large countries, the regions affected by tropical cyclones

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may have larger or smaller populations. To correct for this source of bias, current baseline predicted storm damage in each country is adjusted to match long term observed damage. This correction, however, does not address changes within countries that might occur over time. Relying on countries as the unit of observation remains a source of uncertainty.

Some storms were projected to have very low minimum pressure. Coupled with the highly nonlinear damage function, these storms were projected to damage more than what is in harm's way. Damage was truncated at \$1 trillion per storm. We assume this is the maximum damage per storm in each country. Some truncations were necessary in both the current climate and future climate.

The expected damage from climate change is measured as the difference in the expected value of global damage from tropical cyclones in 2100 with and without climate change. The expected value takes into account changes in the frequency, location, and intensity of storms as well as the vulnerability in each scenario.

We use projected population and income in 2100 by country for both the baseline and the climate change calculation. Using fertility and mortality rates, demographic experts predict global population will be 9 billion in 2100²⁰. We calculate the 2100 Global World Product (GWP) assuming that developed countries grow at 2%, emerging countries grow at 3.3%, and least developed countries grow at 2.7%. The resulting GWP is \$550 trillion in 2100. Income per capita is calculated by dividing GDP by population. These projections are uncertain so a sensitivity analysis was done for a future population of 10 billion and a 20% higher future income.

Additional Results

It was not possible to include all the results in the paper. Table 2 provides country level results. Table 2shows the predicted baseline and the climate change damage from tropical cyclones in each country for each climate model. It is important to stress that the country estimates are highly uncertain and the reader is advised not to place too much confidence in national estimates. However, there are some general results worth noting at the country level. First, two countries are responsible for 75% of the damage from climate change: the United States and China. Second, tropical island countries tend to have the highest damage per GDP. This is because they are in the path of severe storms and a greater fraction of their nation is damaged by each storm. At the country level it is quite clear that some climate models predict increases in damage whereas others predict a reduction in damage.

Supplemental References

26. Cavallo, E., Galiani, S., Noy, I., & Pantano, J. Catastrophic natural disasters and economic growth. *IDB Working Paper Series*, IDP-WB- 183, Inter-American Development Bank, Washington DC (2010).

Table 1: Multiple Regressions of Tropical Cyclone Damage Per Storm Using a Log-Log Functional Form.

	US	US	International
Constant	12.19	607.5	15.17
	(8.58)	(58.5)	(0.67)
Log (Wind Speed)	4.95		
	(0.63)		
Log(Minimum		-86.3	
Pressure)		(8.66)	
Log(income)	0.90	0.37	0.42
	(0.94)	(0.82)	(0.06)
Log(Population	0.46	0.49	-0.21
Density)	(0.36)	(0.32)	(0.07)
Adj Rsq	0.371	0.501	0.158
F Statistic	22.61	35.76	103.2
Observations	111	111	807

Note: standard error in parentheses. Source of US data is NOAA 2009 and the source of the international data is EMDAT 2009.

	Future		Climate	Climate	Climate
	Baseline	Climate	Damage	Damage	Damage
	Damage	Damage			
		CNRM	ECHAM	GFDL	MIROC
Afghanistan	0.0	0.0	0.0	0.0	0.0
Albania	0.0	0.0	0.0	0.0	0.0
Algeria	0.0	0.0	0.0	0.0	0.0
American Samoa	15.7	66.9	-2.4	-14.3	-15.6
Andorra	0.0	0.0	0.0	0.0	0.0
Angola	0.0	0.0	0.0	0.0	0.0
Anguilla	0.0	0.1	0.0	0.1	0.0
Antigua & Barbuda	62.0	515.0	2.2	285.0	76.0
Argentina	0.0	0.0	0.0	0.0	0.0
Armenia	0.0	0.0	0.0	0.0	0.0
Aruba	10.4	-1.3	-10.0	-10.3	-5.4
Australia	263.0	79.0	-1.0	-255.9	-9.0
Austria	0.0	0.0	0.0	0.0	0.0
Azerbaijan	0.8	-0.8	-0.8	-0.8	-0.8
Bahrain	0.0	0.0	0.0	0.0	0.0
Bangladesh	447.0	-254.0	-347.5	-444.1	-241.0
Barbados	0.8	10.1	-0.4	12.8	-0.4
Belarus	0.0	0.0	0.0	0.0	0.0
Belgium	0.0	0.0	0.0	0.0	0.0
Belize	63.8	-60.3	-48.0	1.5	-49.4
Benin	0.0	0.0	0.0	0.0	0.0
Bermuda	25.2	-16.6	113.8	3.8	37.2
Bhutan	0.0	0.0	0.0	0.0	0.0
Bolivia	0.0	0.0	0.0	0.0	0.0
Bosnia & Herzegovina	0.0	0.0	0.0	0.0	0.0
Botswana	0.0	0.0	0.0	0.0	0.0
Brazil	0.0	0.0	0.0	0.0	0.0
British Virgin Is.	209.0	102.7	227.7	4706.6	2243.0
Brunei	8.0	-7.6	3.6	-6.7	-1.1
Bulgaria	0.0	0.0	0.0	0.0	0.0
Burkina Faso	0.0	0.0	0.0	0.0	0.0
Burundi	0.0	0.0	0.0	0.0	0.0
Cambodia	0.0	0.0	0.0	0.0	0.0
Cameroon	0.0	0.0	0.0	0.0	0.0
Canada	22.5	6.8	-3.5	13.9	28.1

Table 2: Future Baseline and Climate Damage From Tropical Cyclones in 2100 by Country and Climate Model (million USD/yr)

Cape Verde	0.0	0.0	0.0	0.0	0.0
Cayman Is.	283.0	59.0	-151.0	887.0	-9.0
Central African					
Republic	0.0	0.0	0.0	0.0	0.0
Chad	0.0	0.0	0.0	0.0	0.0
Chile	2.8	1.1	-2.8	-1.5	0.0
China	8080.0	51420.0	320.0	-7871.0	14920.0
Colombia	0.1	0.0	-0.1	-0.1	-0.1
Comoros	29.2	-14.9	22.6	-15.9	91.3
Congo	0.0	0.0	0.0	0.0	0.0
Congo, DRC	0.0	0.0	0.0	0.0	0.0
Cook Is.	24.1	102.7	-3.7	-21.9	-24.0
Costa Rica	39.8	14.6	-25.7	325.2	25.0
Cote d'Ivoire	0.0	0.0	0.0	0.0	0.0
Croatia	0.0	0.0	0.0	0.0	0.0
Cuba	1530.0	1560.0	830.0	7000.0	-1280.0
Cyprus	0.0	0.0	0.0	0.0	0.0
Czech Republic	0.0	0.0	0.0	0.0	0.0
Denmark	0.0	0.0	0.0	0.0	0.0
Djibouti	0.0	0.0	0.0	0.0	0.0
Dominica	26.6	-24.4	-12.2	45.1	22.3
Dominican Republic	342.0	340.0	-31.0	3378.0	78.0
Ecuador	0.0	0.0	0.0	0.0	0.0
Egypt	0.0	0.0	0.0	0.0	0.0
El Salvador	78.2	30.8	116.8	-75.2	16.9
Equatorial Guinea	0.0	0.0	0.0	0.0	0.0
Eritrea	0.0	0.0	0.0	0.0	0.0
Estonia	0.0	0.0	0.0	0.0	0.0
Ethiopia	0.0	0.0	0.0	0.0	0.0
Faroe Is.	0.0	0.0	0.0	0.0	0.1
Fiji	69.3	491.7	45.7	765.7	207.7
Finland	0.0	0.0	0.0	0.0	0.0
France	0.0	0.0	0.0	0.0	0.0
French Guiana	0.0	0.0	0.0	0.0	0.0
French Polynesia	32.0	136.4	-4.9	-29.1	-31.9
Gabon	0.0	0.0	0.0	0.0	0.0
Gaza Strip	0.0	0.0	0.0	0.0	0.0
Georgia	0.0	0.0	0.0	0.0	0.0
Germany	0.1	-0.1	0.4	0.2	0.1
Ghana	0.0	0.0	0.0	0.0	0.0
Gibraltar	0.0	0.0	0.0	0.0	0.0
Greece	0.0	0.0	0.0	0.0	0.0
Greenland	0.3	-0.2	1.8	0.9	0.3
Grenada	94.7	-17.0	-91.3	-92.9	101.3
Guadeloupe	37.6	59.3	37.6	445.4	31.5
Guam	79.8	-30.3	-46.1	292.2	1290.2

Guatemala	149.0	500.0	-53.1	-146.6	498.0
Guernsey	0.0	0.0	0.0	0.0	0.0
Guinea	0.0	0.0	0.0	0.0	0.0
Guinea-Bissau	0.0	0.0	0.0	0.0	0.0
Guyana	0.0	0.0	0.0	0.0	0.0
Haiti	41.4	11.8	-16.9	132.6	10.3
Honduras	412.0	231.0	-369.9	-123.0	-2.0
Hungary	0.0	0.0	0.0	0.0	0.0
Iceland	0.0	3.6	0.0	2.6	0.0
India	1020.0	-85.0	280.0	-945.3	950.0
Indonesia	5.2	-4.9	2.3	-4.3	-0.7
Iran	0.0	0.0	0.0	0.0	0.0
Iraq	0.0	0.0	0.0	0.0	0.0
Ireland	0.1	-0.1	0.2	0.8	0.0
Isle of Man	0.0	0.0	0.0	0.0	0.0
Israel	0.0	0.0	0.0	0.0	0.0
Italy	0.0	0.0	0.0	0.0	0.0
Jamaica	151.0	101.0	-4.0	4269.0	397.0
Japan	7790.0	-1250.0	-4720.0	-6320.0	12310.0
Jersey	0.0	0.0	0.0	0.0	0.0
Jordan	0.0	0.0	0.0	0.0	0.0
Kazakhstan	0.0	0.0	0.0	0.0	0.0
Kenya	9.9	-2.9	2.7	-3.1	65.8
Kiribati	0.0	0.0	0.0	0.0	0.0
Kuwait	0.0	0.0	0.0	0.0	0.0
Kyrgyzstan	0.0	0.0	0.0	0.0	0.0
Laos	32.0	41.6	2.3	-30.2	63.0
Latvia	0.0	0.0	0.0	0.0	0.0
Lebanon	0.0	0.0	0.0	0.0	0.0
Lesotho	0.0	0.0	0.0	0.0	0.0
Liberia	0.0	0.0	0.0	0.0	0.0
Libya	0.0	0.0	0.0	0.0	0.0
Liechtenstein	0.0	0.0	0.0	0.0	0.0
Lithuania	0.0	0.0	0.0	0.0	0.0
Luxembourg	0.0	0.0	0.0	0.0	0.0
Macedonia	0.0	0.0	0.0	0.0	0.0
Madagascar	38.3	-19.5	29.7	-20.8	119.7
Malawi	0.6	-0.2	0.2	-0.2	3.8
Malaysia	6.5	-6.1	2.9	-5.4	-0.9
Maldives	0.0	0.0	0.0	0.0	0.0
Mali	0.0	0.0	0.0	0.0	0.0
Malta	0.0	0.0	0.0	0.0	0.0
Marshall Is.	0.0	0.0	0.0	0.0	0.0
Martinique	49.7	95.3	-12.8	1950.3	55.3
Mauritania	0.0	0.0	0.0	0.0	0.0
Mauritius	28.1	-3.0	101.9	-19.6	30.2

Mayotte	65.2	-33.2	50.6	-35.4	203.8
Mexico	2470.0	-60.0	20.0	2180.0	90.0
Micronesia	0.1	0.0	0.1	0.0	1.3
Moldova	0.0	0.0	0.0	0.0	0.0
Monaco	0.0	0.0	0.0	0.0	0.0
Mongolia	0.0	0.0	0.0	0.0	0.0
Montenegro	0.0	0.0	0.0	0.0	0.0
Montserrat	2.5	0.3	2.0	13.1	1.3
Morocco	0.0	0.0	0.0	0.0	0.0
Mozambique	7.5	-2.2	2.0	-2.4	50.2
Myanmar	423.0	271.0	-32.0	-416.4	527.0
Namibia	0.0	0.0	0.0	0.0	0.0
Nauru	0.0	0.0	0.0	0.0	0.0
Nepal	0.0	0.0	0.0	0.0	0.0
Netherlands	0.0	0.0	0.0	0.0	0.0
Netherlands Antilles	144.0	-18.0	-138.9	-142.3	-74.8
New Caledonia	4.3	0.3	-1.7	-0.1	9.7
New Zealand	6.5	-3.4	-2.0	-3.1	-2.6
Nicaragua	94.0	-5.7	-69.8	30.0	1816.0
Niger	0.0	0.0	0.0	0.0	0.0
Nigeria	0.0	0.0	0.0	0.0	0.0
North Korea	924.0	196.0	-604.0	-40.0	1066.0
Northern Mariana Is.	65.0	-24.7	-37.6	238.0	1050.9
Norway	0.4	-0.3	2.3	1.2	0.4
Oman	244.0	545.0	312.0	195.0	60.0
Pakistan	117.0	165.0	63.0	-46.7	674.0
Palau	92.9	-35.3	-53.7	340.2	1502.0
Panama	0.0	0.0	0.0	0.0	0.0
Papua New Guinea	0.2	0.4	0.1	-0.1	-0.1
Paraguay	0.0	0.0	0.0	0.0	0.0
Peru	1.9	0.8	-1.9	-1.0	0.0
Philippines	432.0	-103.0	48.0	-341.8	878.0
Poland	0.0	0.0	0.0	0.0	0.0
Portugal	36.7	-14.1	38.5	29.3	15.3
Puerto Rico	384.0	216.0	1776.0	2806.0	562.0
Qatar	0.0	0.0	0.0	0.0	0.0
Reunion	4.8	-4.4	-3.4	14.4	-0.5
Romania	0.0	0.0	0.0	0.0	0.0
Russia	23.6	-1.6	-11.2	-2.3	45.0
Rwanda	0.0	0.0	0.0	0.0	0.0
Samoa	61.0	1459.0	180.0	-59.9	-60.4
San Marino	0.0	0.0	0.0	0.0	0.0
Sao Tome & Principe	0.0	0.0	0.0	0.0	0.0
Saudi Arabia	0.0	0.0	0.0	0.0	0.0
Senegal	0.0	0.0	0.0	0.0	0.0
Serbia	0.0	0.0	0.0	0.0	0.0

Seychelles	0.0	0.0	0.0	0.0	0.0
Sierra Leone	0.0	0.0	0.0	0.0	0.0
Singapore	0.0	0.0	0.0	0.0	0.0
Slovakia	0.0	0.0	0.0	0.0	0.0
Slovenia	0.0	0.0	0.0	0.0	0.0
Solomon Is.	0.4	0.2	-0.2	-0.4	-0.4
Somalia	0.0	0.0	0.0	0.0	0.0
South Africa	0.0	0.0	0.0	0.0	0.0
South Korea	1270.0	320.0	-562.0	-647.0	1350.0
Spain	48.6	-18.8	46.0	-40.2	3.7
Sri Lanka	31.7	-2.6	8.7	-29.4	29.5
St. Helena	0.0	0.0	0.0	0.0	0.0
St. Kitts & Nevis	77.3	428.7	67.7	751.7	426.7
St. Lucia	5.3	8.0	15.3	72.2	10.8
St. Pierre & Miquelon	0.6	0.2	-0.1	0.4	0.7
St. Vincent & the					
Grenadines	2.1	52.6	0.1	539.9	1.0
Sudan	0.0	0.0	0.0	0.0	0.0
Suriname	0.0	0.0	0.0	0.0	0.0
Swaziland	0.0	0.0	0.0	0.0	0.0
Sweden	0.0	0.0	0.0	0.0	0.0
Switzerland	0.0	0.0	0.0	0.0	0.0
Syria	0.0	0.0	0.0	0.0	0.0
Tajikistan	0.0	0.0	0.0	0.0	0.0
Tanzania	6.3	-1.9	1.7	-2.0	42.2
Thailand	66.1	-48.1	15.8	0.2	-40.2
The Bahamas	263.0	564.0	193.0	1137.0	-219.5
The Gambia	0.0	0.0	0.0	0.0	0.0
Timor-Leste	0.0	0.0	0.0	0.0	0.0
Тодо	0.0	0.0	0.0	0.0	0.0
Tonga	7.0	316.0	-5.6	20.2	2.3
Trinidad & Tobago	0.1	-0.1	-0.1	-0.1	0.0
Tunisia	0.0	0.0	0.0	0.0	0.0
Turkey	0.0	0.0	0.0	0.0	0.0
Turkmenistan	0.0	0.0	0.0	0.0	0.0
Turks & Caicos Is.	47.3	28.4	10.8	112.7	-23.6
Tuvalu	0.0	0.0	0.0	0.0	0.0
Uganda	0.0	0.0	0.0	0.0	0.0
Ukraine	0.0	0.0	0.0	0.0	0.0
United Arab Emirates	0.0	0.0	0.0	0.0	0.0
United Kingdom	34.7	-27.1	204.3	106.3	37.3
United States	26300.0	20000.0	16200.0	65100.0	-300.0
Uruguay	0.0	0.0	0.0	0.0	0.0
Uzbekistan	0.0	0.0	0.0	0.0	0.0
Vanuatu	0.6	0.3	-0.3	-0.5	-0.6
Venezuela	0.6	17.4	0.1	-0.6	-0.3

Vietnam	465.0	605.0	33.0	-438.9	915.0
Virgin Is.	179.0	88.0	195.0	4031.0	1921.0
Wallis & Futuna	0.0	0.0	0.0	0.0	0.0
Western Sahara	0.0	0.0	0.0	0.0	0.0
Yemen	0.0	0.0	0.0	0.0	0.0
Zambia	0.0	0.0	0.0	0.0	0.0
Zimbabwe	0.1	0.0	0.0	0.0	1.0

Note: Results from 4 climate models using future baseline for 2100.