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Vulnerability, Resilience, and Disaster Response in a Warming World:
Considering Climate Adaptation Finance and Humanitarian Aid in Tandem

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An abstract of
a thesis submitted to the faculty of the
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Abstract

Vulnerability, Resilience, and Disaster Response in a Warming World:
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Human emissions of greenhouse gases (GHGs) are causing the climate to change. These changes impact temperature and precipitation and are increasing the frequency and intensity of extreme weather events, including cyclones, droughts, heatwaves, and floods. These disasters can cause or exacerbate a myriad of health problems. Due to the amount of GHGs that have already been released into the atmosphere, even a sudden reduction in emissions would not immediately stop climate change. Therefore, efforts to increase readiness for such disasters is and will continue to be crucial to protect people, communities, and livelihoods. Currently, many countries, especially low- and middle-income countries rely on international humanitarian aid to respond and rebuild following a disaster. International investment in adaptation efforts may be able to lessen future demand for humanitarian aid and save lives if communities are better prepared for disasters before they happen. Previous research suggests that both adaptation funding and humanitarian aid are related to country-level vulnerability to climate hazards, but these two international funding streams have not been considered together. Using data from the Notre Dame Global Adaptation Initiative, Organization for Economic Co-operation and Development, United Nations, International Federation of Red Cross and Red Crescent Societies, and World Bank, this study evaluated the relationships between country-level vulnerability, adaptation funding investments, and humanitarian aid allocations together from 2013 to 2019. Linear mixed models revealed that countries with high vulnerability and high readiness receive the most adaptation funding, but humanitarian aid is not a significant predictor of adaptation funding. Similarly, results indicated that countries with greater vulnerability are more likely to receive humanitarian aid, but adaptation funding is not a significant predictor of aid. Sub-analyses that focused on health and water showed that countries with high health vulnerability receive the most health-related adaptation funding, but water vulnerability is not a significant predictor of water-related adaptation funding. Based on these results, a country’s vulnerability is an important driver of adaptation funding and humanitarian aid, as expected. It is unclear if adaptation funding follows humanitarian aid or vice versa. These relationships are complex and require further study to understand.

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Introduction

In 2019, atmospheric carbon dioxide concentrations were greater than 400 parts per million (ppm), and over 100 ppm higher than at any other point in the previous 800,000 years.[1] The precipitous increase in carbon dioxide and other greenhouse gases (GHG) has been driven by human-caused emissions, and these GHGs are causing the planet to warm.[2] As of 2020, the planet had warmed about 1.09°C since pre-industrial times (1850-1900).[2] Beyond the temperature increases themselves, warming contributes to a host of downstream effects, including changes in precipitation and extreme events.[3]

Climate change is linked to increased intensity and frequency of cyclones, heavy rainfall events, agricultural and ecological droughts, and heatwaves.[2,4] These climate-related disasters can cause or worsen a myriad of health problems.[5] Especially in coastal areas that have experienced sea level rise, cyclones and heavy rainfall events often cause flooding. Common hazards of floods include drowning, electrocution, viral or bacterial infections, and mosquito-borne illnesses. [6,7] Flooding can also cause or exacerbate mental health problems and displace people from their homes temporarily or permanently.[6,7] Storms can also damage key infrastructure and make getting needed healthcare, food, or safe water difficult. Through various pathways, droughts can pose a threat to food security and nutrition and lead to vector-borne, water-related, and airborne disease.[8] Because droughts can cause loss of crops or livelihood, economic losses, mental health issues, and migration for work are also concerns.[8] In addition to increasing mortality and morbidity, heatwaves can have negative effects on mental health and reduce the amount of time people can work outside.[5]

The impacts that climate hazards have on human health, livelihoods, and infrastructure are largely dependent on communities' vulnerability and preparedness. Geographical location, expected disaster type and frequency, and socio-economic development all impact a country's vulnerability to climate disasters while preparedness depends on existing systems' abilities to disseminate information and protect communities.[9] Countries that are vulnerable and underprepared, particularly developing countries, often rely on the global community to provide humanitarian assistance following extreme events. The United Nations (UN) is a key, multilateral provider of disaster aid. UN allocations have been shown to be responsive, following disasters with allocation amounts proportionate to the severity of the extreme event and level of need left in its aftermath.[10] The International Federation of Red Cross and Red Crescent Societies (IFRC), the world's largest volunteer-based humanitarian network, estimated that 108 million people needed humanitarian aid for a climate-related extreme event in 2018 and that by 2050, this number will nearly double to 200 million people worldwide.[11] While the cost to help the 108 million people in need in 2018 was between $3.5 billion and $12 billion, as climate change worsens and more people are exposed to extreme, climate-related events, the cost to help all those in need in 2030 could be $20 billion.[11] The IFRC argues that investing in more adaptation to increase resilience could reduce the number of people who require international humanitarian assistance.

Even a substantial and rapid reduction of GHGs would not immediately stop global warming because of the amount of GHGs that have already been emitted, so adaptation efforts are crucial to protect people and communities in the coming decades. Adaptation strategies are location specific. They rely on the climate hazards likely to affect the area, vulnerabilities and risks in communities, level of development, and the current status of any adaptation efforts. Depending on the context, entities might consider early warning systems, building levees or flood walls, protecting wetlands or marshes, increasing tree cover, switching to drought-resistant crops, designing or redesigning infrastructure with climate projections in mind, or a host of other adaptation strategies. Low- and middle-income countries that face climate hazards often receive support for adaptation projects from high-income countries and multilateral institutions. Several studies have investigated the forces that drive adaptation funding allocations, finding vulnerability of the recipient country, cost-effectiveness of the project, and trade considerations of the donor entity all to be factors that influence allocations.[12–15]

If countries can be better prepared for future cyclones, floods, droughts, and heatwaves, it is thought that there may be less need for disaster aid following an extreme event. As such, investment in adaptation activities and climate-sensitive development could protect communities and result in long-term financial savings for international funders. Despite research into the impact of climate vulnerability on humanitarian aid and adaptation allocations separately,[10,12–15] there has been no serious consideration of how these two separate financial streams may influence each other. This is a key gap in understanding international, climate-related finance and considering future approaches to allocations. To address this gap, this study evaluated the relationships between country-level vulnerability, adaptation funding investments, and humanitarian aid allocations together from 2013 to 2019. We investigated both the potential impact of vulnerability and humanitarian aid on adaptation funding and the potential impact of vulnerability and adaptation funding on humanitarian aid.

We hypothesized that countries with higher vulnerability and lower readiness would receive higher adaptation funding and humanitarian aid allocations, and that the receipt of humanitarian aid would be correlated with lower adaptation funding.

Methods

Data sources

We collected and synthesized country-level data from five publicly available sources for the seven-year period from 2013 to 2019:

(1) To quantify **vulnerability to climate hazards**, we used the Notre Dame Global Adaptation Initiative (ND-GAIN) Country Index.[16] Each year, most countries are assigned a score from ND-GAIN that is based on their vulnerability to climate change and readiness to improve resilience. Scores can range from 0 to 100 with low scores indicating a combination of high vulnerability and poor readiness. Total ND-GAIN scores are calculated from several vulnerability sub-scores that include indicators related to food, water, health, ecosystem service, human habitat, and infrastructure, and readiness sub-scores that considers each country's economic, governance, and social factors (Figure 1).[9] A high ND-GAIN vulnerability score indicates a high level of vulnerability, so we anticipated a positive relationship between vulnerability score and adaptation funding. A high ND-GAIN readiness score indicates a high level of readiness, so we anticipated a negative relationship between readiness score and adaptation funding. Overall, we hypothesized that countries with high vulnerability scores and low readiness scores would require the most adaptation funding.

Figure 1: Graphic explaining components and calculation of ND-GAIN score. The readiness and vulnerability boxes include the sectors that contribute to the overall score. Vulnerability sectors with (*) indicate those included in a sub-analysis. Adapted from Notre Dame Global Adaptation Initiative (https://gain.nd.edu/our-work/country-index/methodology/).

(2) **Adaptation finance data** were taken from the Organization for Economic Co-operation and Development's (OECD) Development Assistance Committee (DAC) Rio Markers for Climate.[17] The OECD is an international organization with 38 member countries from around the world that seeks to inform policy and standard making through voluntary collaboration, monitoring, and reporting.[18] The DAC is an OECD committee that focuses on providing aid. It currently includes 30 member countries that have robust systems in place to provide development assistance, participating countries, and observers, mostly multilateral development banks.[19] The Rio Markers for Climate dataset includes climate-related commitments from OECD countries (DAC countries and some non-DAC countries), multilateral development organizations, and private donors (mostly foundations) to developing countries.[20] All allocations are marked as mitigation and/or adaptation related. We only included public allocations (excluded private donors) that included adaptation objectives, inclusive of amounts that were cross listed for mitigation and adaptation. Our analyses used OECD-provided financial data that were adjusted for

inflation to 2019 levels. Each allocation also included information about the designated use for the money by sector (e.g., health, water, agriculture, education, disaster preparedness) and the year that the allocation was made.[20] We used the year and sector information in our analyses.

(3 & 4) To quantify **humanitarian aid allocations**, we combined data from two sources: a) the United Nations (UN) Central Emergency Response Fund (CERF) and b) the International Federation of Red Cross and Red Crescent Societies (IFRC).[21,22] Both datasets included the type of disaster, the amount allocated, and an indication of when the allocation was made (a start or approval date). As we were specifically interested in climate-related and climate change exacerbated disasters, we only included allocations that were related to cold waves, cyclones, droughts, fires, floods, food insecurity, heat waves, pluvial/flash floods, or storms.

Due to differences in size and mandate, CERF generally made relative few, large allocations for disaster aid while IFRC generally made more numerous, relatively small allocations. We combined these two datasets in order to capture both the scale and breadth of climate-related humanitarian aid. Because the date provided in the dataset may have corresponded with the beginning of its disbursement, it is probable that some allocations that were made near the end of a year had impacts that may have been felt most strongly in the following year. We were not able to quantify timing of impact, so we relied on the listed start or approval date for our analyses. Because the humanitarian data were combined from two data sources with different scopes and resource allocations, we used humanitarian aid as a binary variable in our analyses (1 for a year that a country received any humanitarian aid, 0 for any year that a country did not receive any humanitarian aid).

(5) In order to compare countries of different sizes, we pulled annual **population data** from the World Bank.[23] These data were used to put adaptation funding allocations into per capita values for use in models.

Data preparation

This study focused on countries that had ND-GAIN scores and population data available and received public adaptation funding at some point from 2013 to 2019. Because we used humanitarian aid as a binary variable, receipt of such aid was not a limiting factor for inclusion in analysis. Some countries could not be included in one or more analysis or sub-analysis because they were missing a key component.

For example, while most countries in the world receive an overall ND-GAIN score every year, there are notable absences. In particular, some island nations in Oceania and the South Pacific (Cook Islands, Kiribati, Marshall Islands, Nauru, Palau, and Tuvalu) and in the Caribbean (Saint Vincent and the Grenadines) were not assigned ND-GAIN scores during our period of study. Without ND-GAIN scores, these countries could not be included in the analyses, despite the distinct and dire risks that climate change poses to small island nations. Given our focus on countries that received public adaptation funding, by design we largely included low- and middle-income countries, as defined by the World Bank. High-income countries were often the providers of the adaptation funding and humanitarian aid, and thus these countries fell out of this analysis.

Finally, Eritrea did not have population data available from the World Bank and was therefore removed from analysis.

Originally, 141 countries were considered for inclusion because they had received public adaptation funding at least once during 2013-2019. See Appendix I for a breakdown of countries included in each analysis described below. Between the five data sources, numerous discrepancies in country names had to be resolved to facilitate merging of datasets. The list in Appendix I includes the final names of countries as we included them in our analyses. In order to compare countries of vastly different sizes, we transformed the raw adaptation funding amounts into amounts per capita using annual population data from the World Bank, and we log transformed this amount to meet model-related assumptions of normality.

Statistical analyses

Models Predicting Adaptation Funding

There were two key objectives of this study. We set out to explore the impact of country-level vulnerability and receipt of humanitarian aid on adaptation funding and the impact of country-level vulnerability and adaptation funding on receipt of humanitarian aid. We began with simple correlations to assess if our key variables were monotonically related to each other. We also tested the relationship between log adaptation dollars per capita with a country's humanitarian aid from the previous year to see if receiving any humanitarian aid in one year was correlated with that country's amount of adaptation funding received the next, but use of humanitarian aid in the current year provided a better fit to the data.

To address our primary objective, we considered two main models, one for predicting adaptation funding and the other for predicting humanitarian aid. For adaptation funding, we ran linear mixed models in which country was a random effect, according to *Equation 1*.

$$\text{Equation 1: } ADF_{ij} = (\beta_0 + b_{0i}) + (\beta_1)NDGAIN_{ij} + (\beta_2)HA_{ij} + (\beta_3)Year_{ij} + e_{ij}$$

where "ADF" is the log transformed per capita amount of public adaptation funding that a country received in a year, adjusted to 2019 inflation levels; "NDGAIN" is the ND-GAIN score assigned to that country that year; "HA" is a binary variable that represents whether or not the country received any humanitarian aid that year; "Year" represents the corresponding year; and "e" is an error term. The model controlled for repeated measures data by country by including a random effect for country (represented by b_{0i}). The indices i and j represent country and year, respectively. β_0 is the overall mean, and β_1 and β_2 are the coefficients of interest indicating the effect of NDGAIN and HA on ADF. A country's overall ND-GAIN score is calculated using two sub-scores, one for vulnerability and one for readiness. In supplemental analyses, we adapted the model from *Equation 1* to explore the relationship between each of these two scores to overall adaptation dollars received.

<u>Health- and Water-specific Analyses</u>

The ND-GAIN's vulnerability score is calculated using six sub-scores, including one for health and one for water. Additionally, the OECD Rio Markers data includes information on the sector to which adaptation dollars were allocated. Health and water were two common sectors for projects. Health adaptation dollars went towards basic health care, infrastructure, and nutrition; health education; medical services; and health policy and administrative management.[17] Water adaptation dollars went towards basic water supply, sanitation, waste management, and education and training related to water supply or sanitation.[17] Again adapting *Equation 1*, in additional analyses, we used the health and water sub-scores from ND-GAIN to map to adaptation funds allocated specifically to those sectors. Because humanitarian aid did not include specific information about sector allocations, it was not included in these analyses.

<u>Model Predicting Humanitarian Aid</u>

To explore if ND-GAIN score and adaptation dollar allocations were predictors of a country receiving humanitarian aid, we ran a logistic regression model with repeated measures, as seen in *Equation 2*.

Equation 2: $\ln(\text{odds of HA})_{ij} = \alpha + (\beta_1)\text{NDGAIN}_{ij} + (\beta_2)\text{ADF}_{ij} + (\beta_3)\text{Year}_{ij} + e_{ij}$

where "HA" corresponds to a country receiving any humanitarian aid in a given year, α represents the intercept, "NDGAIN" is the ND-GAIN score for the year, "ADF" corresponds to the log transformed adaptation funding per capita that the country received that year, "Year" represents the corresponding year, and *e* is an error term. Indices i and j again refer to country and year. We used a compound symmetry correlation matrix on the assumption that the odds of HA for a given country were correlated across years with a constant correlation. β_1 and β_2 are the coefficients of interest, indicating the effect of NDGAIN and ADF on HA.

Results

For our analyses, we only included years during which a country had an overall ND-GAIN score available and received adaptation funding. Table 1 highlights key statistics for each of the variables in the aggregate from 2013 to 2019. We used 891 unique data points from 130 countries for the overall analysis and for the analyses of the ND-GAIN vulnerability and ND-GAIN readiness sub-scores. Figure 2 presents the overall distribution of adaptation funding across ND-GAIN quartiles and stratified by presence or absence of humanitarian aid. Figure 3 shows the same distribution after the adaptation funding was converted to log transformed adaptation funding per capita values.

The sub-analyses that focused on the health and water sector only included years during which a country had a health or water sub-score from ND-GAIN and received adaption funding for the associated sector. The health analysis included several countries that were not in the initial analyses because they had the necessary health-specific data available despite not having overall ND-GAIN score. As indicated in Table 1, we included 418 unique data points from 109 countries for the health analysis and 693 unique data points from 119 countries for the water analysis.

Table 1: Key statistics for key variables used throughout analyses. ND-GAIN scores can range from 0 to 100 (higher scores are better). ND-GAIN sub-score (vulnerability, health, water, and readiness) can range from 0 to 1. See Figure 1 for more information. Adaptation finance values across years were adjusted to 2019 inflation rates.

Variable	N	Mean (SD)	Minimum	Maximum
ND-GAIN	891	43.95 (7.27)	27.38	62.61
Vulnerability	891	0.47 (0.08)	0.32	0.69
Health	418	0.58 (0.16)	0.18	0.85
Water	693	0.38 (0.12)	0.01	0.78
Readiness	891	0.35 (0.09)	0.12	0.60
Adaptation finance (USD)	891	148,635,204 (251,605,030)	2,786	3,122,100,923
Per Capita	891	22.49 (66.83)	0.0017	1,120.69
Health	418	5,981,768 (16,267,706)	241	125,392,733
Health Per Capita	418	1.61 (13.09)	0. 000013	257.87
Water	693	40,847,640 (94,602,759)	119	1,017,750,188
Water Per Capita	693	3.86 (15.03)	0. 000012	287.25
Variable	**N**	**Yes (%)**	**No (%)**	
Humanitarian aid	891	322 (36%)	569 (64%)	

Figure 2: Distribution of all data from 2013-2019 showing adaptation funding and overall ND-GAIN score, stratified by receipt of humanitarian aid.

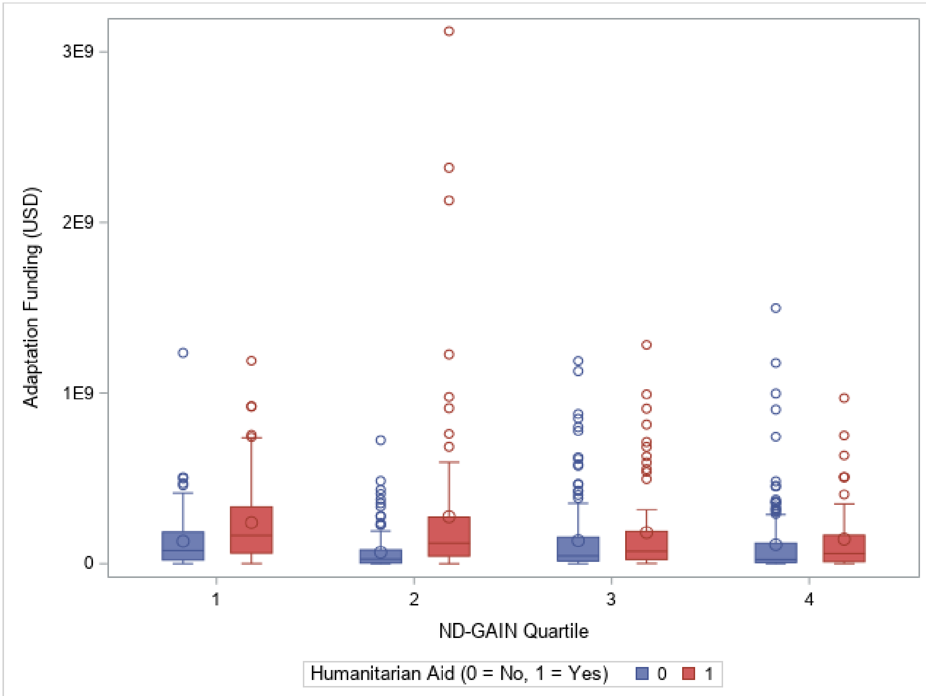
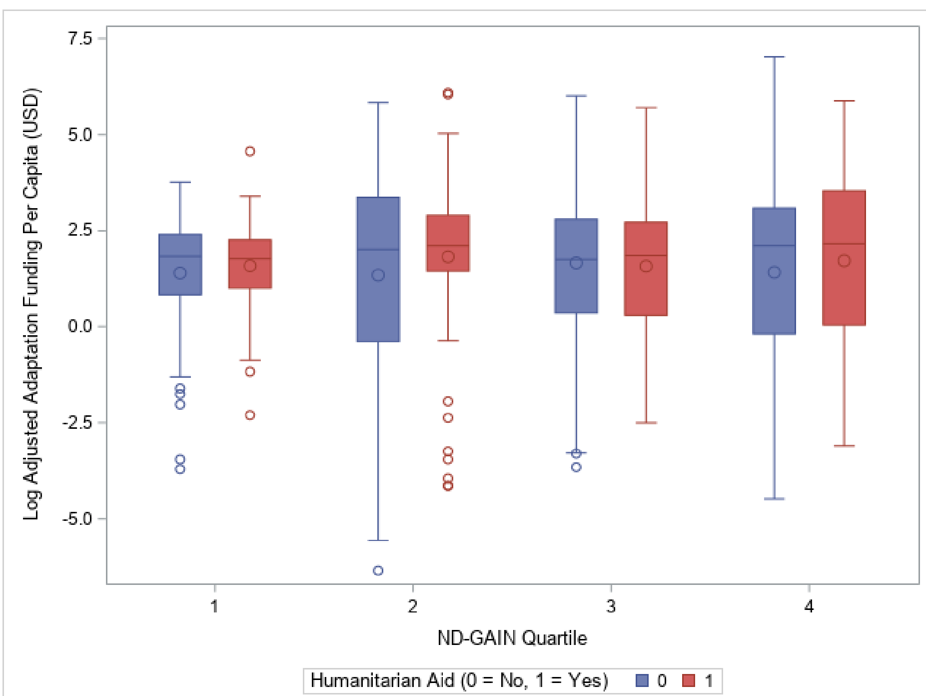


Figure 3: Distribution of all data from 2013-2019 showing log transformed adaptation funding per capita and overall ND-GAIN score, stratified by receipt of humanitarian aid.



Initial Correlations

In initial exploration of relationships between key variables using Spearman correlations, we found that ND-GAIN score was significantly negatively correlated with raw adaptation funding ($r = -0.18$, p-value < 0.01). ND-GAIN score and raw adaptation funding were also each significantly correlated with a binary variable representing the presence or absence of humanitarian aid ($r = -0.16$, p-value < 0.01 and $r = 0.26$, p-value < 0.01, respectively). The negative correlations with ND-GAIN score suggested that an increase in ND-GAIN score is correlated with a decrease in raw adaptation funding and a decreased likelihood of receiving humanitarian aid. The positive correlation between raw adaptation funding and presence or absence of humanitarian aid suggests that as adaptation funding increases, so does the likelihood of receiving humanitarian aid. There were no statistically significant correlations when using adaptation funding per capita or log transformed adaptation funding per capita.

Additionally, we assessed the relationship between ND-GAIN and adaptation funding variables in a given year and the presence of absence of humanitarian aid in the prior year. Similar to same-year correlations, prior year humanitarian aid was significantly correlated with ND-GAIN score and raw adaptation funding ($r = -0.10$, p-value $= 0.01$, $r = 0.23$, p-value <0.01, respectively) but not with adaptation funding per capita or log transformed adaptation funding per capita. In our subsequent analyses, we used humanitarian aid from the same year as the ND-GAIN score and adaptation funding because it fit the data better.

Table 2: Results from linear mixed models and logistic regression model. ADF represents log transformed adaptation funding per capita, NDGAIN represents a score from the ND-GAIN index, HA represents humanitarian aid as a binary variable, and Year represents the corresponding year.

Variable	Estimate	SE	t	p-value
Model 1: $ADF_{ij} = (\beta_0+b_{0i}) + (\beta_1)NDGAIN_{ij} + (\beta_2)HA_{ij} + (\beta_3)Year_{ij} + e_{ij}$				
NDGAIN	0.00060	0.018	0.03	0.97
HA	0.13	0.10	1.24	0.22
Year	0.20	0.02	9.42	<0.01
Model 2: $ADF_{ij} = (\beta_0+b_{0i}) + (\beta_1)Vulnerability\text{-}NDGAIN_{ij} + (\beta_2)HA_{ij} + (\beta_3)Year_{ij} + e_{ij}$				
Vulnerability-NDGAIN	5.40	1.86	2.90	<0.01
HA	0.11	0.10	1.10	0.27
Year	0.20	0.02	9.70	<0.01
Model 3: $ADF_{ij} = (\beta_0+b_{0i}) + (\beta_1)Readiness\text{-}NDGAIN_{ij} + (\beta_2)HA_{ij} + (\beta_3)Year_{ij} + e_{ij}$				
Readiness-NDGAIN	2.62	1.29	2.03	0.04
HA	0.13	0.10	1.27	0.20
Year	0.19	0.02	9.16	<0.01
Model 4: $Health\text{-}ADF_{ij} = (\beta_0+b_{0i}) + (\beta_1)Health\text{-}NDGAIN_{ij} + (\beta_2)Year_{ij} + e_{ij}$				
Health-NDGAIN	3.86	1.34	2.89	<0.01
Year	0.19	0.058	3.34	<0.01
Model 5: $Water\text{-}ADF_{ij} = (\beta_0+b_{0i}) + (\beta_1)Water\text{-}NDGAIN_{ij} + (\beta_2)Year_{ij} + e_{ij}$				
Water-NDGAIN	-1.19	1.68	-0.71	0.48
Year	0.075	0.043	1.75	0.08
Variable	**Estimate**	**SE**	**Z**	**p-value**
Model 6: $\ln(\text{odds of HA})_{ij} = \alpha + (\beta_1)NDGAIN_{ij} + (\beta_2)ADF_{ij} + (\beta_3)Year_{ij} + e_{ij}$				
NDGAIN	-0.04	0.014	-2.94	0.0033
ADF	0.049	0.043	1.14	0.26
Year	0.086	0.030	2.88	0.0039

Models Predicting Adaptation Funding

Table 2 presents the results of all models. Our initial linear mixed model (model 1 in Table 2) showed that year was a significant predictor of log transformed adaptation funding per capita, but ND-GAIN and the presence or absence of humanitarian aid were not. From 2013 to 2019, there was a consistent, upward trend in the amount of log transformed adaptation funding per capita over time, but there was no significant difference between funding levels across ND-GAIN quartiles. The intraclass correlation coefficient (ICC) to measure variance within and between countries indicates that 66% of the variance in the model was due to variance between countries.

We separated the ND-GAIN variable into its component parts, vulnerability and readiness, and reran our linear mixed model (models 2 and 3, respectively). We hypothesized that countries with high vulnerability scores would require the most adaptation funding, and the vulnerability score analysis (model 2) matched our expectations. ND-GAIN vulnerability score was significantly, positively associated with log transformed adaptation funding per capita (estimate = 5.40, p-value < 0.01), indicating that those countries with greater vulnerability received greater funding. This represents an average increase in funding per capita by $1.72 with each 0.1 increase in vulnerability sub-score. There was a steady increase in log adaptation funding per capita across vulnerability sub-score quartiles, with the third and fourth quartiles receiving significantly more funding than the first.

We expected countries with low readiness scores to receive greater funding, as they are the most in need, but the analysis (model 3) showed the opposite. ND-GAIN readiness score was significantly, positively associated with log transformed adaptation funding per capita (estimate = 2.62, p-value = 0.04, model 3). This indicates that, on average, adaptation funding per capita increased by $1.30 for every 0.1 increase in readiness sub-score. The quartile with the lowest readiness scores received the least funding, while countries in the third and fourth quartiles received the most. As with the overall analysis, humanitarian aid was not significantly associated with adaptation funding in the vulnerability or readiness analyses, but adaptation funding steadily increased over time.

Health- and Water-specific Analyses

To further our analyses of the relationship between a country's vulnerability and the adaptation funding it receives, we focused on two specific sectors: health and water. Using sub-scores from the ND-GAIN index and sector information from the adaptation funding data, we ran additional linear mixed models. Because the humanitarian aid allocations did not include sector-specific information, these models used only ND-GAIN sub-score and year as predictors, and sector-specific log transformed adaptation funding per capita as the outcome. The health and water sub-scores are both vulnerability scores, meaning they are part of a country's overall vulnerability score. As such, higher scores indicate higher vulnerabilities related to health or water. As with overall vulnerability scores, we hypothesized that vulnerability sub-scores would have a positive association with adaptation funding. This would show that countries with greatest need are receiving the most funding.

We observed a positive relationship between health vulnerability and log transformed health adaptation funding per capita (estimate = 3.86, p-value < 0.01, model 4). On average, each 0.1 increase in health vulnerability sub-score was associated with a $1.47 increase in health funding per capita. The two most vulnerable quartiles for health received significantly more health adaptation funding than the least vulnerable quartile. Unlike the overall analysis, there was no steady trend across time, with fluctuations over the 7-year time period. In the water analysis, water vulnerability was not a significant predictor of sector-specific adaptation funding (estimate = -1.19, p-value = 0.48, model 5). There was also no trend over time or across quartiles.

Model Predicting Humanitarian Aid

We considered humanitarian aid as a binary outcome (yes or no) with ND-GAIN score, log transformed adaptation funding per capita, and year in the model (model 6). We saw that each one unit increase in ND-GAIN score reduced the odds of receiving humanitarian aid by 4% (OR = 0.96, CI: 0.93, 0.99), in line with our expectation. Over the seven-year period, the odds of receiving humanitarian aid increased by about 9% each year (OR = 1.09, CI: 1.03, 1.15), but log transformed adaptation funding per capita was not associated with humanitarian aid.

Discussion

In this analysis, we observed that increased vulnerability and increased readiness are associated with higher levels of adaptation funding. These findings support those of Betzold and Weiler, 2017 and Weiler, Klöck, and Dornan, 2017 which used similar data and different methods but also found that countries with high vulnerability and high readiness generally receive more adaptation funding.[12,15] We were not surprised to see that countries with high vulnerability receive adaptation funding, as these are the places that have the greatest exposure to extreme climate hazards, high sensitivity to these hazards, and limited adaptive capacity.

Countries with low readiness are in greater need of funding to improve resilience, and we hypothesized that we would find a negative association between readiness and adaptation funding. However, the readiness portion of the ND-GAIN score includes factors related to economics and governance, both of which can impact a country's ability to receive and appropriately spend adaptation funds on designated projects. In our analysis, we observed those countries with higher readiness sub-scores, and therefore greater stability and rule of law, received more adaptation funding. This finding matches a larger trend. Over time, indicators of governance related to stability and rule of law have had increased influence on allocations of aid.[24] Previous studies have argued that cost-effectiveness and trade agreements may also play into donor decision making.[13,14]

In addition to adding to the limited body of research on adaptation funding and vulnerability, a major strength of this work was its addition of new considerations in this area. This study included humanitarian aid and focused on health and water to see if relationships differed by sector. In our models, adaptation funding and humanitarian aid were not associated with each other. However, as expected, we saw that as overall ND-GAIN score increases, countries are less likely to receive humanitarian aid. This suggests that increasing a country's readiness may be an effective way to reduce disaster response costs.

Sub-scores for health and water are part of a country's overall vulnerability score, so we expected to see both positively associated with sector-specific adaptation funding. While health met this expectation, water did not. Instead, water had a negative, though not statistically significant, relationship with water-related adaptation funding. It is possible that countries with high water vulnerability also have governance or rule of law issues, preventing them from receiving more funding, but more research is needed to investigate this specific relationship.

This study had limitations. The inclusion criteria for analysis required countries to have an ND-GAIN score and have received adaptation funding that was tracked through OECD. Certain countries were not included because of their lack of an ND-GAIN score. This included countries in the South Pacific, Oceania, Caribbean, and Africa—regions known to be at high risk of severe climate events. Other countries were excluded from analysis because they did not receive any adaptation funding throughout the seven-year time period. We were correct that OECD and high-income countries were not adaptation fund recipients, but it was unexpected that some Caribbean nations that are highly vulnerable to climate hazards had not received any funding. This may point to the limitation of the data sources used. Reporting to OECD is not mandated, meaning the data may be incomplete or inconsistently reported across donor countries and entities. Additionally, funding allocated near the end of a year may have been used in the following year, but we relied on the allocation dates included in reporting.

Another limitation was the inability to focus on geographical areas within countries. Similar to other research in this area, this study relied on country-level information, though we know that many countries have differential vulnerability and readiness across areas. Different methods might be necessary to complete a global analysis that considers smaller geographical areas. Alternative methods may also be useful in expanding the scope of this study to better understand the relationship between humanitarian aid and adaptation funding. In addition, this study does not investigate whether allocations were sufficient to meet needs or effective in meeting goals. Future research may compare requested to allocated funds, include additional predictors or confounders, or dive into sectors other than health and water. Similarly, additional work may focus on the impact of finance allocations on ND-GAIN score to see if investments are, in fact, lowering vulnerability and increasing readiness.

Our analysis showed that countries with higher ND-GAIN scores are less likely to receive humanitarian aid. The indirect goal of most adaptation projects is to increase a country's ND-GAIN score through better readiness and resilience. The findings of this study could be helpful to decision-makers in government or multilateral organizations when thinking about their funding allocations. As climate change causes natural disasters to grow in frequency and severity, humanitarian aid needs will grow. As the IFRC's "Cost of Doing Nothing" report suggests, investment in adaptation now may save on humanitarian aid costs in the future. Increasing a country's readiness for such disasters could not only save money through lessening the need for humanitarian aid; it could also save lives and livelihoods.

Conclusions

This study evaluated the complex relationships between vulnerability, adaptation funding, and humanitarian aid. We hypothesized that countries with higher vulnerability to and lower readiness for climate hazards would receive greater adaptation funding and humanitarian aid allocations. We also hypothesized that the receipt of humanitarian aid would be correlated with lower adaptation funding. Our analyses showed that high vulnerability and high readiness were associated with adaptation funding allocations. We also observed that receiving humanitarian aid is not a significant predictor of adaptation funding nor is adaptation funding a significant predictor of receiving humanitarian aid. In our sector-specific analyses, health vulnerability mirrored overall vulnerability and had a positive association with health-related adaptation funding, but water vulnerability was not a significant predictor of water-related adaptation funding. These findings provide insight on the role of humanitarian aid in international climate finance and offer detail about two key sectors that contribute to countries' overall vulnerability to climate hazards. Though future work is needed to understand these relationships at a finer geographical scale and understand the efficacy of adaptation funding, this study provides a useful framework for future decision making related to international climate finance.

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Appendix I: Table detailing which countries were included in each analysis. Model numbers correspond to those used in Table 2.

Countries	Models 1, 2, 3, & 6	Model 4 (Health)	Model 5 (Water)
Afghanistan	X	X	X
Albania	X	X	X
Algeria	X	X	X
Angola	X	X	X
Antigua and Barbuda	X		X
Argentina	X	X	X
Armenia	X	X	X
Azerbaijan	X		X
Bangladesh	X	X	X
Belarus	X		X
Belize	X	X	X
Benin	X	X	X
Bhutan	X		X
Bolivia	X	X	X
Bosnia and Herzegovina	X	X	X
Botswana	X		X
Brazil	X	X	X
Burkina Faso	X	X	X
Burundi	X	X	X
Cambodia	X	X	X
Cameroon	X	X	X
Cape Verde	X		X
Central African Republic	X	X	X
Chad	X	X	X
Chile	X		X
China	X	X	X
Colombia	X	X	X
Comoros	X	X	
Congo	X	X	X
Costa Rica	X		X
Cuba	X	X	X
Democratic People's Republic of Korea	X		X
Democratic Republic of the Congo	X	X	X
Djibouti	X	X	X
Dominica	X	X	
Dominican Republic	X	X	X

Ecuador	X	X	X
Egypt	X	X	X
El Salvador	X	X	X
Equatorial Guinea	X	X	X
Eswatini	X		X
Ethiopia	X	X	X
Fiji	X	X	X
Gabon	X		X
Gambia	X	X	X
Georgia	X	X	X
Ghana	X	X	X
Grenada	X	X	
Guatemala	X	X	X
Guinea	X	X	X
Guinea-Bissau	X	X	X
Guyana	X	X	X
Haiti	X	X	X
Honduras	X	X	X
India	X	X	X
Indonesia	X	X	X
Iran	X	X	X
Iraq	X	X	X
Ivory Coast	X	X	X
Jamaica	X		X
Jordan	X	X	X
Kazakhstan	X	X	X
Kenya	X	X	X
Kiribati		X	
Kyrgyzstan	X	X	X
Lao People's Democratic Republic	X	X	X
Lebanon	X	X	X
Lesotho	X	X	X
Liberia	X	X	X
Libya	X		X
Madagascar	X	X	X
Malawi	X	X	X
Malaysia	X	X	X
Maldives	X	X	
Mali	X	X	X
Mauritania	X	X	X
Mauritius	X		X
Mexico	X	X	X

Micronesia, Federated States of	X		
Moldova, Republic of	X	X	X
Mongolia	X	X	X
Montenegro	X	X	X
Morocco	X	X	X
Mozambique	X	X	X
Myanmar	X	X	X
Namibia	X	X	X
Nepal	X	X	X
Nicaragua	X	X	X
Niger	X	X	X
Nigeria	X	X	X
Pakistan	X	X	X
Panama	X		X
Papua New Guinea	X	X	X
Paraguay	X	X	X
Peru	X	X	X
Philippines	X	X	X
Rwanda	X	X	X
Saint Kitts and Nevis	X		
Saint Lucia	X	X	
Saint Vincent and the Grenadines		X	
Samoa	X	X	X
Sao Tome and Principe	X		X
Senegal	X	X	X
Serbia	X	X	X
Seychelles	X		
Sierra Leone	X	X	X
Solomon Islands	X	X	
Somalia	X	X	X
South Africa	X	X	X
Sri Lanka	X	X	X
Sudan	X	X	X
Suriname	X	X	X
Syrian Arab Republic	X	X	X
Tajikistan	X	X	X
Tanzania	X	X	X
Thailand	X		X
Timor-Leste	X	X	X
Togo	X	X	X
Tonga	X	X	
Tunisia	X	X	X

Turkey	X	X	X
Turkmenistan	X		X
Tuvalu		X	
Uganda	X	X	X
Ukraine	X	X	X
Uruguay	X		X
Uzbekistan	X		X
Vanuatu	X	X	
Venezuela	X		X
Viet Nam	X	X	X
Yemen	X	X	X
Zambia	X	X	X
Zimbabwe	X	X	X
TOTAL	130	109	119