CLIMATE CHANGE AND THE ALLOCATION OF DEVELOPMENT ASSISTANCE

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5/11/2026

I. Abstract

Is aid going to the countries and regions most vulnerable to climate change? This project analyzed aid commitments and disbursements from 2001–2020 with measures of climate vulnerability and poverty at both the national and subnational levels. The results show that aid is more consistently associated with poverty than with climate vulnerability. The Pearson and Spearman correlations are weak in magnitude, but the poverty-aid association remains consistently stronger than the vulnerability-aid association at both levels. Similarly, in the OLS regressions, poverty is a more stable predictor of aid allocation in the main specifications and five-year periods. In brief, aid allocation is more responsive to poverty; aid and climate risk may be associated indirectly through the socioeconomic dimensions embedded in definitions of vulnerability.

II. Introduction

These risks of climate change are concentrated in countries with limited fiscal capacity, making official development assistance (ODA) an instrument for mitigating and adapting to the distributional consequences of climate change. Although aid flows have increased significantly over the past two decades, the literature has been skeptical about their effectiveness; it raises a fundamental question of whether resources are being directed toward the countries and regions most vulnerable to climate shocks? To answer this question, the project links ODA data with popular measures of climate vulnerability and uses Pearson correlations, Spearman rank correlations, and OLS regressions to compare the strength of the association between aid flows, poverty, and climate vulnerability. The empirical analysis is guided by three subquestions.

1. Where has climate-related development finance historically gone?
2. Have those locations coincided with areas likely to be heavily impacted by climate change?
3. Has the location of aid shifted over time in response to changing climate conditions or understanding?

III. Background:

Since 2009, developed countries have increased their commitments to climate finance, nearly doubling over the last decade with cumulative commitments of USD 4.8 trillion between 2011 and 2020, or an annual average of USD 280 billion. However, these increases still fall short of meeting the 1.5 °C global warming target set by the Paris Agreement, with a gap of USD 4.3 trillion in annual financing by 2030 (Climate Policy

Initiative 2022). This gap means that some of the impacts are no longer avoidable, and financing has switched to adaptation in the Global South, which bears the brunt of climate change while having the least resources.

Data from 2011 to 2014 suggests that donors privilege vulnerable countries, but not equally. Small island developing states (SIDS) received the highest per capita; Niue, a small island freely associated with New Zealand, received about 13,000 USD per capita (Betzold et al. 2017). However, Samoa received five times as much adaptation funding as neighboring Fiji, despite having a similar GDP per capita and a population that was five times as large (Donner et al 2016). In terms of total aid, larger (defined by capability) countries still receive more than smaller ones: Vietnam ranked first with 7.52% of all adaptation aid, followed by India and the Philippines. This calculation can be deceiving because a large-scale infrastructure project in the Philippines would be more environmentally valuable than a small, but high-per-capita project in Niue.

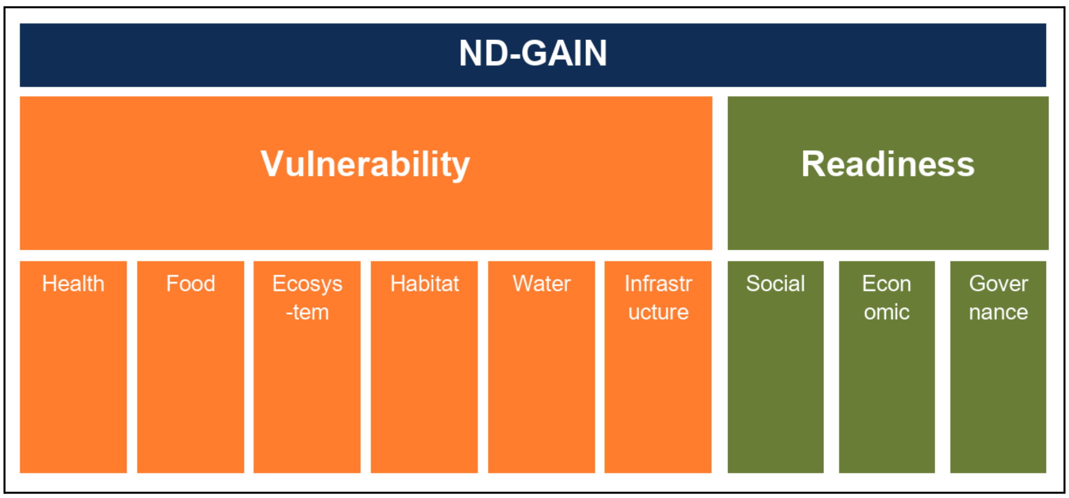
Moreover, most of the climate finance disbursed to developing countries has been for adaptation, which is open to definitional challenges. A project to replace a broken water reticulation in a country threatened by groundwater salinization from sea-level rise would not be seen as an adaptation project by some donors (Donner et al 2016). In contrast,a broad education project might be labeled as an adaptation project. Political incentives on both sides fuel this categorization problem; development institutions and receiving countries might add random climate change objectives to secure additional funding from donors to compete for space in the climate finance market. Based on the Rio Markers for climate change, aid related to Climate Change is twice the explicit total; in other words, the markers are classifying projects as related to adaptation despite their titles and project descriptions not mentioning climate change or adaptation.

Past definitional concerns, the critical problem with adaptation aid is that it assumes the country can adapt. For example, SIDs will be affected by an increase in the number of cyclones at sea. Two of the largest economic pains will be a retraction in the fishing industry and a decrease in tourism. One of the projects is to relocate villages to higher terraces to avoid damage from cyclones. That idea will save the population from the risks of climate change, but also means increasing the cost of living (Barnett 2008). If the cost of living increases, while their economy contracts, then people will still be forced to leave the island. The problem is being repackaged, and adaptation without mitigation is climate injustice.

III. Data Description:

Geocoded Official Development Assistance Dataset (GODAD). GODAD provides project-level data on the distribution of development aid, including information on funding amounts, donors, sectors, and locations of aid activities. The data are geocoded, enabling clean national and subnational analysis of aid allocation. GODAD is used to measure the distribution of development assistance.

Notre Dame Global Adaptation Initiative (ND-GAIN). The ND-GAIN dataset provides country-level indicators of climate vulnerability and adaptive capacity through composite indices built from sector-specific measures. Please refer to the figure below.



Source: ND-GAIN Technical Document

Index scores range from 0 to 1. For vulnerability, lower values indicate lower susceptibility to climate change, while higher values reflect greater vulnerability. For readiness, lower values indicate weaker adaptive capacity, while higher values reflect greater readiness to respond. The figure below names a range of countries from high to low vulnerability. In this project, ND-GAIN is used to capture cross-country differences in climate vulnerability to determine the relationship between country vulnerability and aid.

Country	Year	Vulnerability Score	Vulnerability Ranking	Readiness Score	Readiness Ranking
Chad	2023	0.64	187	0.187	186
Pakistan	2023	0.52	147	0.299	154
Indonesia	2023	0.43	98	0.398	101
Brazil	2023	0.37	54	0.350	128
Australia	2023	0.32	20	0.693	8
Switzerland	2023	0.25	1	0.691	9

Source: ND-GAIN

GDL Vulnerability Index (GVI). The Global Data Lab's GVI provides subnational estimates of multidimensional vulnerability, capturing aspects of socioeconomic deprivation, inequality, and exposure to risk across regions within countries. Because the calculations are theoretically similar to NDGAIN, the GVI is used to measure within-country variation in vulnerability at the subnational level.

Poverty and Inequality Platform (PIP). The World Bank's PIP provides country-level estimates of poverty and income distribution based on household survey data. This project uses the imputed poverty headcount at $3.00 per day (2021 PPP). PIP is used to capture cross-country differences in poverty levels, and national-level estimates are proxied to subnational units.

Controls:

Worldwide Governance Indicators (WGI). The World Bank's WGI provides country-level measures of governance quality across dimensions such as government effectiveness, rule of law, control of corruption, and political stability. Governance indicators are used to account for differences in institutional quality that affect aid distribution.

Land Area. The World Bank provides country-level data on land area, measured in square kilometers and excluding inland water bodies. This variable captures the physical size of countries. Land area is used as a control variable to account for differences in country size that may influence the scaling of other variables.

Population. The World Bank provides country-level estimates of total population, based on census data and demographic modeling. This variable captures the size of the population in each country. Population is used as a control variable to account for differences in country size that influence the allocation of development aid.

Gross Domestic Product (GDP). The World Bank provides country-level data on GDP, measuring the total value of goods and services produced within a country. This variable captures overall economic size and level of development. GDP is used as a control variable to account for differences in economic capacity that may influence both the allocation of development aid and cross-country variation in outcomes.

<u>Limitation:</u> The subnational merges required a crosswalk between GODAD GID codes and GDL regional survey boundary codes. The matching was complete with help from AI to structurally sort and translate: it was strong in finding patterns and matching names. Only names that matched at or above a 85% similarity were kept. This process can possibly be improved by emailing the GDL's steward and requesting the dataset with GID codes.

IV. <u>Methodology:</u>

This study examines whether the allocation of climate-related aid is closely associated with the depth of climate vulnerability more than with poverty. To address this question, we utilize two empirical strategies:

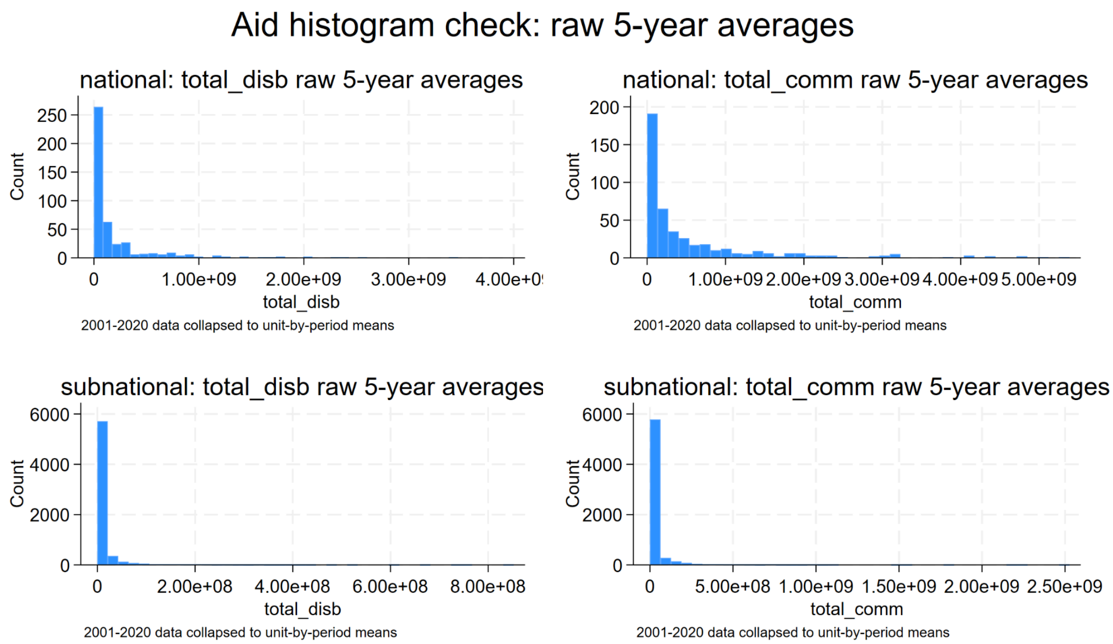
1. Using Pearson and Spearman correlation to examine the bivariate relationship between aid allocation, vulnerability, and poverty at both national and subnational levels.
2. Using linear regression models and the national level data to examine whether aid allocation and vulnerability remain allocated after accounting for poverty, control variables, time periods, and fixed effects.

V. 1 Pearson and Spearman correlation coefficients

This empirical strategy uses Pearson and Spearman correlation coefficients to assess potential bivariate relationships among vulnerability, poverty, and aid allocation.

A major concern of this approach is that aid disbursement and commitment are highly uneven, and that aid may be concentrated in a specific year to cover the aid needs of a few years. Using yearly data may lead to biased results due to many zero-aid readings resulting from concentrated aid allocation.

To address this concern, we applied two data treatments prior to the correlation analysis. First, the aid data is aggregated into means of 5-year periods: 2001-2005, 2006-2010, 2011-2015, and 2016-2020, before the correlation analysis to mitigate the influence of uneven allocation. Second, we use the logarithm of the aid allocation in the correlation coefficient to address the aid allocation's right-skewed distribution (see graph x.x below).



The logarithmic treatment has two different approaches to address the large number of observations with zero aid allocations. The first approach is to apply a log transformation, log(x+1), to include all observations in the analysis, including those with zero aid allocation. The second approach is to apply a log transformation, log(x)|x>0, to exclude observations with zero aid allocation. This research will apply both approaches and conduct separate correlation analyses to provide a comprehensive analysis for research purposes.

V. 2 Regression models

This empirical strategy employs linear regression models to further address the comparative research interests and questions. These models compare alternative specifications that include vulnerability, poverty, and control variables, enabling us to assess whether the relationship remains robust when these factors are accounted for and compare the strength and significance of relationships between variables.

Due to the limitation of data completeness, the regression analysis applies only to national-level data. Similar to the correlation strategy, the data used for the regression analysis was aggregated into means of a 5-year period, and treated with a logistic transformation under the log(x+1) approach. In addition, the independent variables' degree of change was standardized with Z-scores for a unified understanding of the regression result's strength.

V. 2. 1 Main Models

Model 1 aims at determining the simple relationship between aid allocations and vulnerability. With the data treatment discussed above, the regression result is assessed as the percentage change in aid allocation when vulnerability increases for β_1 standard deviations. The Z-score is calculated from a pooled distribution of all countries' 5-year vulnerability averages across all time periods.

$$Y_{it}^{C} = \beta_0 + \beta_1 * Vulnerability_{it} + \delta_t + \epsilon_{it}$$
$$Y_{it}^{D} = \beta_0 + \beta_1 * Vulnerability_{it} + \delta_t + \epsilon_{it}$$

Model 2 aims at determining the robustness of the relationship determined in Model 1 when adding poverty into consideration. With the data treatment, the regression result is assessed as the percentage change in aid allocation when vulnerability increases for β_1 standard deviations or poverty increases for β_2 standard deviations.

$$Y_{it}^{C} = \beta_0 + \beta_1 * Vulnerability_{it} + \beta_2 * Poverty_{it} + \delta_t + \epsilon_{it}$$
$$Y_{it}^{D} = \beta_0 + \beta_1 * Vulnerability_{it} + \beta_2 * Poverty_{it} + \delta_t + \epsilon_{it}$$

Model 3 aims to assess the robustness of the relationship identified in Model 1 when control variables are included. The control variable is used to evaluate whether the relationship determined in Model 1 is affected by omitted variable bias from the control variable.

$$Y_{it}^{C} = \beta_0 + \beta_1 * Vulnerability_{it} + \gamma * Control_{it} + \delta_t + \epsilon_{it}$$
$$Y_{it}^{D} = \beta_0 + \beta_1 * Vulnerability_{it} + \gamma * Control_{it} + \delta_t + \epsilon_{it}$$

Model 4 concludes vulnerability, poverty, and control variables into a full regression assessment for a comparative comprehension with Models 1, 2, and 3 to assess the robustness of the relationship determined in these models. The control variable is used to evaluate whether the relationship determined in Model 2 is affected by omitted variable bias from the control variable.

$$Y_{it}^{C} = \beta_0 + \beta_1 * Vulnerability_{it} + \beta_2 * Poverty_{it} + \gamma * Control_{it} + \delta_t + \epsilon_{it}$$
$$Y_{it}^{D} = \beta_0 + \beta_1 * Vulnerability_{it} + \beta_2 * Poverty_{it} + \gamma * Control_{it} + \delta_t + \epsilon_{it}$$

V. 2. 1 (Extension) Period Comparison

Additionally, to assess whether the relationship between variables changes across 5-year periods, we will separately apply Model 4 to observations from each 5-year period, isolated from other time periods, and compare the statistical significance and coefficients.

V. 2. 2 Panel Models

Model 5 is a base reference model for the panel regression model (Model 6). Model 5 uses vulnerability, poverty, and control, but with annual data with Z-score standardization, and uses one-year lagged values of these standardized measures. The design is to reflect whether changes in vulnerability and poverty in year x would lead to changes in aid allocation in year x+1.

$$Y_{i,\tau}^{C} = \beta_0 + \beta_1 * Vulnerability_{i,\tau} + \beta_2 * Poverty_{i,\tau} + \gamma * Control_{i,\tau} + \epsilon_{i,\tau}$$
$$Y_{i,\tau}^{D} = \beta_0 + \beta_1 * Vulnerability_{i,\tau} + \beta_2 * Poverty_{i,\tau} + \gamma * Control_{i,\tau} + \epsilon_{i,\tau}$$

Model 6 is built on Model 5's design, but with added country fixed effects to limit the regression to each country. This model is designed to determine whether, for the same country, changes in vulnerability and poverty in year x would lead to changes in aid allocation in year x+1. Model 6 is the main model for the panel regression study to determine how the relationship between variables in the same country develops over time.

$$Y_{i,\tau}^{C} = \beta_0 + \beta_1 * Vulnerability_{i,\tau} + \beta_2 * Poverty_{i,\tau} + \gamma * Control_{i,\tau} + FE_{i,\tau} + \epsilon_{i,\tau}$$
$$Y_{i,\tau}^{D} = \beta_0 + \beta_1 * Vulnerability_{i,\tau} + \beta_2 * Poverty_{i,\tau} + \gamma * Control_{i,\tau} + FE_{i,\tau} + \epsilon_{i,\tau}$$

V. <u>Results:</u>

VI. 1 Pearson and Spearman Correlation

The following results are produced with StataBE 18 (version 18.5), a statistical analysis working environment. Table VI.1 presents the results of Pearson and Spearman correlation on both national and subnational data, after data treatment explained in the Methodology section:

Table VI. 1: Correlation coefficients

Type	Pearson		Spearman	
Indicator	**Disbursement**	**Commitment**	**Disbursement**	**Commitment**
National, all observations, log (x+1)				
Poverty	0.127***	0.088*	0.126***	0.080*
Vulnerability	0.072	0.033	0.061	-0.004
National, positive aid observations, log x | x > 0				
Poverty	0.104**	0.073	0.114**	0.074
Vulnerability	0.029	0.007	0.050	-0.010
Subnational, all observations, log (x+1)				
Poverty	0.155***	0.193***	0.199***	0.221***
Vulnerability	0.079***	0.137***	0.052***	0.115***
Subnational, positive aid observations, log x | x > 0				
Poverty	0.151***	0.155***	0.160***	0.162***
Vulnerability	0.049***	0.110***	0.026*	0.083***

Significance levels: * p<0.10, ** p<0.05, *** p<0.01.
Sample: All observations

In terms of the correlation results, the outcomes derived from Pearson and Spearman correlation analyses successfully validate each other, confirming the robustness of the findings. From the perspective of the statistical significance of correlations, in national-level data, the correlation between the disbursed aid amount and poverty exhibits high statistical significance, while the correlation between the disbursed aid and vulnerability is not statistically significant. As for committed aid, neither the correlation with poverty nor the correlation with vulnerability is statistically significant.

In the subnational data, all correlations among actually disbursed aid, committed aid, poverty, and vulnerability are highly statistically significant. However, when considering the strength of correlations, the correlations between the two types of aid amounts and poverty are significantly stronger than those between the two types of aid amounts and vulnerability, and this gap is even more pronounced for actually disbursed aid amounts.

Moreover, among all correlations, no coefficient exceeds 0.2, indicating that the strength of all coefficients is relatively weak, despite their statistical significance. Figures VI.1 and VI.2 visualize coefficients derived from Pearson correlations with a quadratic fit.

Figure VI.1: Pearson Correlation at National Level, All Observations

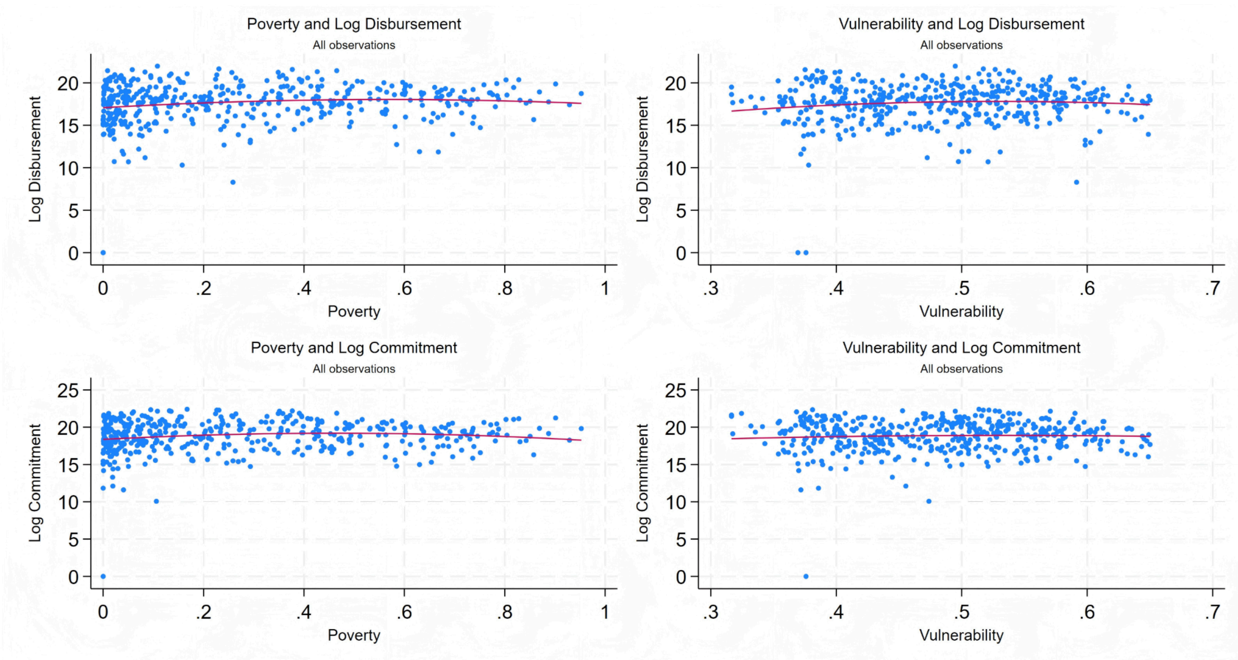
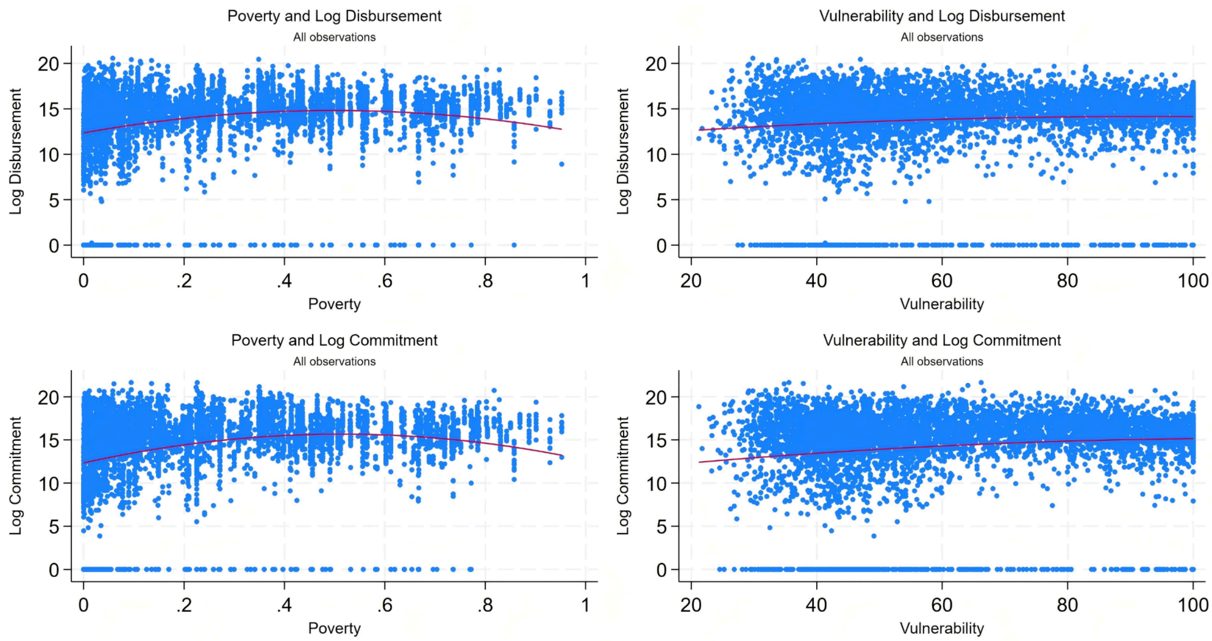


Figure VI.2: Pearson Correlation at Subnational Level, All Observations



VI. 2 Regressions

The following results are produced with StataBE 18 (version 18.5), a statistical analysis working environment. Table VI. 3 presents the regression results for aid disbursements at the national level, and Table VI. 4 presents the regression results for aid commitments at the national level.

Table VI. 3: Regression Results, Disbursement

	All Observations				Panel	
Model	1	2	3	4	5	6
Vulnerability	0.215	-0.138	0.899***	0.608**	0.173	0.183
	(0.209)	(0.276)	(0.254)	(0.272)	(0.112)	(0.114)
Poverty		0.523**		0.496***	0.058	-0.007
		(0.222)		(0.164)	(0.122)	(0.100)
Controls	No	No	Yes	Yes	Yes	Yes
Country FE	No	No	No	No	No	Yes
Observations	444	444	441	441	2066	2066
R-sq.	0.040	0.063	0.387	0.407	0.273	0.680

Significance levels: * p<0.10, ** p<0.05, *** p<0.01.
Standard errors are clustered at the country level.

Table VI. 4: Regression Results, Commitment

	All Observations				Panel	
Model	1	2	3	4	5	6

Vulnerability	0.121	-0.196	0.577***	0.321	0.242**	0.234*
	(0.178)	(0.219)	(0.213)	(0.204)	(0.115)	(0.125)
Poverty		0.471**		0.438***	-0.030	-0.060
		(0.187)		(0.132)	(0.109)	(0.106)
Controls	No	No	Yes	Yes	Yes	Yes
Country FE	No	No	No	No	No	Yes
Observations	444	444	441	441	2070	2070
R-sq.	0.073	0.098	0.445	0.465	0.285	0.546

Significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.
Standard errors are clustered at the country level.

From the perspective of the statistical significance of Models 1 to 4, the relationship between vulnerability and the two types of aid is not statistically significant without control variables. After incorporating control variables, the statistical significance of the relationship between vulnerability and the two types of aid rapidly increases to significance at 0.1% level. However, after adding poverty to the model, the statistical significance drops sharply, suggesting that this relationship may be affected by the spillover effect of the poverty variable. In contrast, the statistical significance of the relationship between poverty and the two types of aid is relatively stable, and it further increases from 1% to 0.1% level after adding control variables to the model.

From the perspective of the coefficient strength of Models 1 to 4, the coefficient should be interpreted as follows: when vulnerability or poverty increases by 1 standard deviation, aid disbursement or commitment is expected to increase by what percentage. In general, the coefficient of poverty is relatively higher than vulnerability, except for Model 4 for aid disbursement, where vulnerability has a higher coefficient but lower statistical significance.

Model 6 uses a fixed-effects model to assess whether changes in vulnerability and poverty over time within a country affect aid disbursed to or committed to it. The result shows no statistical significance between vulnerability, poverty, and aid commitment or disbursement, indicating that the model does not expect the two types of aid to change when vulnerability and poverty change within a country.

Tables VI. 5 and VI. 6 present the results of the Model 4 extension to compare coefficients between different 5-year periods.

Table VI. 5: Model 4 on Disbursement By 5-Year Periods

	2001-2005	2006-2010	2011-2015	2016-2020

Vulnerability	0.494**	0.476	0.583	0.763*
	(0.231)	(0.316)	(0.370)	(0.391)
Poverty	0.328	0.556**	0.736***	0.509***
	(0.209)	(0.238)	(0.229)	(0.140)
Controls	Yes	Yes	Yes	Yes
Observations	110	110	111	110
R-squared	0.476	0.497	0.347	0.337

Significance levels: * p<0.10, ** p<0.05, *** p<0.01.
Standard errors are clustered at the country level.

Table VI. 6 Model 4 on Commitment By 5-Year Periods

	2001-2005	2006-2010	2011-2015	2016-2020
Vulnerability	0.275	0.406*	0.405	0.214
	(0.168)	(0.239)	(0.362)	(0.224)
Poverty	0.459**	0.323*	0.462**	0.499***
	(0.180)	(0.171)	(0.192)	(0.152)
Controls	Yes	Yes	Yes	Yes
Observations	110	110	111	110
R-squared	0.512	0.512	0.298	0.502

Significance levels: * p<0.10, ** p<0.05, *** p<0.01.
Standard errors are clustered at the country level.

From the results, we can see that, except for the 2001-2005 disbursements, the relationship between vulnerability and the two types of aid is not statistically significant. In contrast, poverty has a relatively higher significance with the two types of aid, except for the 2001-2005 disbursements and the 2006-2010 commitment. From the perspective of coefficient strength, the coefficient between poverty and the disbursement remained consistently above 0.5 (except for 2001-2005) and peaked at 0.736 during 2010-2015. The coefficient strength of the relationship between poverty and the commitment amount has remained conservative and stable, fluctuating around 0.45 (except for 2006-2010).

VI. <u>Conclusion:</u>

Poverty is a better historical predictor of aid flows than vulnerability. At the national level, poverty is significantly associated with aid disbursements, while climate vulnerability is not consistently associated with either disbursements or commitments. Therefore, the locations receiving aid only partially coincide with areas likely to be heavily affected by climate change. At the subnational level, vulnerability is statistically associated with aid, but still weaker than the poverty-aid relationship. In other words, there is no clear evidence that aid allocation has shifted ex post in response to changing climate risks.

Future research could extend this analysis in three ways. First, because GODAD provides project-level information by sector, subsequent work could distinguish climate-related ODA from broader development assistance rather than analyzing aggregate aid flows. Isolating whether the commitment or disbursement was explicitly climate-related provides a stronger test of its responsiveness to vulnerability. Second, adding predicted measures of climate damage, such as CMIP-based climate scenarios, to the current dataset would enable assessment of whether aid allocations were aligned with anticipated climate risks. Third, incorporating those projected damages over successive time periods provides a window into whether donor allocation decisions became more climate-informed over time. In other words, whether the international aid system has adapted to improvements in climate science and risk awareness.

VII. References:

Alesina, A., & Dollar, D. (2000). Who gives foreign aid to whom and why?. *Journal of economic growth*, *5*(1), 33-63.

Barnett, J. (2008). The effect of aid on capacity to adapt to climate change: Insights from Niue. *Political Science*, *60*(1), 31-45.

Betzold, C., & Weiler, F. (2017). Allocation of aid for adaptation to climate change: Do vulnerable countries receive more support?. *International Environmental Agreements: Politics, Law and Economics*, 17(1), 17-36.

Climate Policy Initiative. (2023). State and trends in climate adaptation finance 2023. *Climate Policy Initiative, Global Center on Adaptation. https://www.climatepolicyinitiative.org/wp-content/uploads/2023/12/State-and-Trends-in-Climate-Adaptation-Finance-2023_. Pdf.*

Donner, S. D., Kandlikar, M., & Webber, S. (2016). Measuring and tracking the flow of climate change adaptation aid to the developing world. *Environmental Research Letters*, *11*(5), 054006.