

# Allocation of aid for adaptation to climate change: Do vulnerable countries receive more support?

Carola Betzold<sup>1</sup> · Florian Weiler<sup>2</sup>

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**Abstract** Wealthy countries spend increasing amounts of aid to support adaptation to climate change in developing countries and have committed under the UN Framework Convention on Climate Change to prioritize adaptation aid to those “particularly vulnerable” to climate change. While research has started to track this aid, it has not yet examined its allocation across all donor and recipient countries. We thus do not know to what extent vulnerable countries indeed receive more support for adaptation. We address this research gap and ask: how does this commitment to prioritizing particularly vulnerable countries translate into actual adaptation aid allocation? To what extent do vulnerable countries receive more adaptation aid? We address these questions through a quantitative analysis of data from the Organization for Economic Cooperation and Development on bilateral adaptation aid from 2011 through 2014. In contrast to other studies, we find that vulnerability—or more precisely, vulnerability indicators—matter for adaptation aid allocation. Countries that are more exposed to climate change risks, such as extreme weather events or sea level rise, receive more adaptation aid, both on a per capita basis and as a percentage of all adaptation aid. These results indicate that collectively (even if not at the level of each individual donor) donors align their bilateral adaptation aid allocation with global promises.

**Keywords** Aid allocation · Adaptation · Vulnerability · Climate change · Climate finance

## Abbreviations

CIESIN Center for International Earth Science Information Network  
CRI Global Climate Risk Index

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✉ Carola Betzold  
carola.betzold@uantwerpen.be

Florian Weiler  
f.weiler@kent.ac.uk

<sup>1</sup> Institute for Development Policy and Management (IOB), University of Antwerp, Prinsstraat 13, 2000 Antwerp, Belgium

<sup>2</sup> University of Kent, Rutherford N4.E7, Canterbury CT2 7NX, UK

CRS	Creditor Reporting System
EVI	Environmental Vulnerability Index
GDP	Gross domestic product
LDC	Least Developed Countries
SIDS	Small Island Developing States
SOPAC	Secretariat of the Pacific Community's Applied Geoscience and Technology Division
ODA	Official development assistance
OECD	Organization for Economic Cooperation and Development
UNFCCC	United Nations Framework Convention on Climate Change
WGI	Worldwide Governance Indicators

## 1 Introduction

Climate aid—official development assistance (ODA) relevant for adaptation and mitigation—and as such a subset of public climate finance (see Michaelowa and Michaelowa 2011)—is on the rise. Notably since the Copenhagen climate summit in 2009, where Parties pledged to provide US\$30 billion for mitigation and adaptation in developing countries in the period between 2010 and 2012 and to mobilize \$100 billion per year by 2020 (UNFCCC 2009: Decision 2/CP.15, Article 8), developed countries have scaled up their climate-related aid (see special issue Editorial). Only a small part of overall climate-related aid targets adaptation, but adaptation aid is growing in volume—between 2011 and 2014, bilateral adaptation aid increased from \$6.2 billion to \$9.3 billion. Yet, we still know surprisingly little about international adaptation aid, including how much public adaptation funds are available, who receives how much funding, what the funding is used for, and to what extent it effectively reduces vulnerability and increases resilience among recipients (e.g. Peterson Carvalho and Terpstra 2015: 2).

In this article, we focus on bilateral adaptation aid, and specifically the question of distribution. Parties to the climate change negotiations agree in principle that countries “particularly vulnerable” to the adverse effects of climate change should be prioritized (e.g. UNFCCC 2009: Decision 2/CP.15, Article 3; UNFCCC 2015: Decision 1/CP.21, Article 9). But how does this commitment to prioritizing particularly vulnerable countries translate into actual adaptation aid allocation? To what extent do vulnerable countries receive more adaptation aid?

The institutional architecture for adaptation finance is fragmented (see special issue Editorial), with many different funding sources and channels, both multilateral and bilateral, though bilateral adaptation aid predominates: most adaptation finance is delivered as ODA (Barrett 2014: 131; Khan and Roberts 2013: 183). This may lead to norm fragmentation and a disconnect between multilaterally agreed allocation principles and bilateral allocation practices. Khan and Roberts (2013: 180) lamented “a serious lack of coordination in adaptation finance”, remarking that the “distribution of adaptation finance to highly vulnerable countries and to the most vulnerable people within recipient countries remains uneven, and uncertain”.

Here we examine empirically how donors allocate their bilateral aid for adaptation, and specifically focus on the role of vulnerability in allocation decisions. Our starting point is that even if the system is characterized by institutional fragmentation, this does not necessarily imply norm fragmentation. Specifically, we test the extent to which fragmented

bilateral adaptation aid aligns with the collective goal established by the United Nations Framework Convention on Climate Change (UNFCCC) of prioritising highly vulnerable countries. If bilateral aid allocation follows multilateral goals, we have low norm fragmentation; if we find other allocation logics at play, we have high norm fragmentation.

We address the question of adaptation aid allocation using data from the Organization for Economic Cooperation and Development (OECD) from 2011 through 2014. Our analysis indicates that bilateral aid indeed aligns with the UNFCCC priority to vulnerable countries. Countries classified as vulnerable by different vulnerability indicators tend to receive relatively more adaptation aid. Donors also provide relatively more adaptation aid to middle-income countries, to democracies, and to countries with small populations (at least in absolute terms). Importantly, our findings also point to the inherent difficulties of measuring vulnerability. Identifying countries that are vulnerable to climate change requires fundamentally political and normative decisions that are hard to capture with quantitative indicators (e.g. Klein 2009; Hall, this issue). The analysis here thus primarily serves as a starting point for more detailed analyses of decision-making processes concerning adaptation aid.

The remainder of this paper is structured as follows: Sect. 2 discusses the literature on aid allocation and specifically on the allocation of adaptation aid and derives hypotheses regarding adaptation aid. Section 3 discusses the methods and data used in the paper, and Sect. 4 presents the empirical results of our models. Section 5 concludes.

## 2 The political economy of adaptation aid

A growing body of the literature focuses on adaptation and on adaptation aid, including on its allocation. Several authors provide normative arguments for how adaptation aid *should* be allocated, with most emphasizing the need for prioritizing vulnerable countries: adaptation aid should first and foremost support the vulnerable, and specifically those “particularly vulnerable” to climate change (e.g. Barr et al. 2010; Ciplet et al. 2013; Duus-Otterström 2015; Grasso 2010a, b).

Just like adaptation, vulnerability to climate change is an inherently complex concept with no single definition (Hall, this issue). Nonetheless, most scholars agree that vulnerability has two dimensions: physical exposure and sensitivity to natural hazard on the one hand, and adaptive capacity on the other (e.g. Barnett et al. 2008; Smit and Wandel 2006). Empirically, the literature finds only limited evidence that either dimension determines allocation decisions. Several studies examine funding decisions of the multilateral Adaptation Fund established under the UNFCCC’s Kyoto Protocol; they conclude that the Adaptation Fund does *not* accord priority to vulnerable countries (Persson and Remling 2014; Remling and Persson 2015; Stadelmann et al. 2014). Robertsen et al. (2015) focus on bilateral adaptation aid from seven donors to sub-Saharan Africa. Their results similarly suggest that donors do not take into account vulnerability in their allocation decisions: neither poorer countries nor those more exposed to the impacts of climate change receive more adaptation aid. Barrett (2014) analyses the allocation of adaptation aid at the sub-national level in Malawi. His analysis indicates that districts with high physical vulnerability receive more adaptation aid, but not those with high socio-economic vulnerability. Betzold (2015) investigates Germany’s adaptation aid and finds that political and economic interests matter more than vulnerability.

Although there is so far limited evidence that vulnerability matters for aid allocation, developed countries have agreed to prioritize “particularly vulnerable” countries. As early as 1992, the UNFCCC stipulated that developed countries “assist the developing country Parties that are particularly vulnerable to the adverse effects of climate change” (UNFCCC 1992: Article 4(4)). Later agreements confirmed this focus (e.g. UNFCCC 2009: Decision 2/CP.15, paragraph 3; UNFCCC 2010: Decision 1/CP.16, paragraph 11; UNFCCC 2015: Decision 1/CP.21, Article 9).

In other words, adaptation aid should be disbursed on the basis of need. Need, for development aid in general, has been mainly understood as poverty, often measured by per capita income; accordingly, the poorer a country, the more development aid it should receive (e.g. Berthélemy 2006; Clist 2011). In an adaptation context, need translates as vulnerability to climate change impacts: the more vulnerable a country, the higher its need for support with adaptation, and the more adaptation aid it should therefore receive.

In line with the two dimensions of vulnerability, we expect a positive relationship between adaptation aid and exposure and a negative relationship between adaptation aid and adaptive capacity:

- H1** The more exposed a recipient country to the adverse effects of climate change, the more adaptation aid it will receive.
- H2** The lower the adaptive capacity of a recipient country, the more adaptation aid it will receive.

We know from the literature on adaptation aid, as well as from the wider literature on aid allocation, that factors beyond recipient need play a role in allocation decisions. Donors also use their aid to reward recipient merit—typically understood as good governance and democratic institutions—as well as to promote their own political, economic, and security interests (e.g. Alesina and Dollar 2000; Berthélemy 2006; Clist 2011; Hicks et al. 2008; Hoeffler and Outram 2011). However, here we are mainly interested in the role of recipient need, that is, vulnerability to climate change, and its influence on allocation patterns at the aggregate level across all donors.

### 3 Data and method

We test for the role of vulnerability empirically with a newly compiled data set that covers 144 developing countries for the period 2011 through 2014. The following sections explain the individual variables in our data set as well as our statistical models.

#### 3.1 Dependent variable: adaptation aid

Our dependent variable is the level of adaptation aid flowing to developing countries. We rely on data from the OECD Creditor Reporting System (CRS), hence on donors’ self-reported adaptation aid. Although this may be problematic, as donors tend to over-report the climate relevance of their aid (Junghans and Harmeling 2012; Michaelowa and Michaelowa 2011), the OECD provides comparable data across all donors and contains detailed, project-level information. The Biennial Reports submitted to the UNFCCC in contrast are not based on an agreed definition of climate finance, which makes “it difficult to compare the official climate finance statistics across Biennial Reports” (Francke Lund et al. 2015: 36).

The OECD data for adaptation aid are based on the “Rio marker” system for classifying aid as related to multilateral environmental agreements (see Hall; Roberts and Weikmans, this issue). The adaptation marker was introduced in 2010. Accordingly, donors should classify any activity as related to adaptation if “it intends to reduce the vulnerability of human or natural systems to the impacts of climate change and climate-related risks, by maintaining or increasing adaptive capacity and resilience” (OECD 2011: 4).<sup>1</sup> We use all adaptation aid—where adaptation is either a significant objective or the principal objective—as a dependent variable both on a per capita basis and as a percentage of the total adaptation aid flows to developing countries in a given year. Both dependent variables represent aggregate aid flows across all donor countries. For the per capita variable, all adaptation aid flows per capita to the country in a given year were summed up, i.e. we examine how much bilateral adaptation aid a country receives from all donors combined. For the percentage of total aid variable, we added together all adaptation aid flows to a country in a given year and calculated the fraction that this sum represented of all adaptation aid flows to all countries in the same year. This second dependent variable also helps to counter the problem of over-reporting.

In 2010, the first year the OECD CRS used the adaptation marker, considerably less funds were registered as adaptation aid, possibly because not all projects that targeted adaptation were marked as such. For this reason, we consider this first year to be a learning period, for which a different allocation logic (and thus a different data generating process) could apply, and start our analysis in 2011. For the OECD CRS data, both commitments of adaptation by donors and actual disbursements of funds to recipients are available. As other studies of aid allocation (e.g. Clist 2011; Robertsen et al. 2015), we use commitments rather than disbursements, because they to a larger degree reflect recent donor decisions (Berthélemy 2006: 80; OECD and CPI 2015: 18).<sup>2</sup>

### 3.2 Recipient need

Our main explanatory variable is vulnerability to climate change. To capture vulnerability to different climate change impacts, we use several vulnerability measures.

To test H1, we use multiple indicators because we do not think that any single indicator captures vulnerability to climate change impacts in its entirety, and because some indicators focus more on short-term losses from extreme weather events, while others try to capture long-term effects of climate change. The first proxy is the percentage of the population living below an elevation of five meters above sea level—an indication of exposure to sea level rise, a climate change impact that is also very present in policy and public debate. Data come from the Center for International Earth Science Information Network (CIESIN). Since the last comprehensive data available are for the year 2000, we use those for all years (CIESIN 2012).

Another climate change impact is the increased frequency and intensity of extreme weather events, which we capture with the Global Climate Risk Index (CRI). The index captures the short-term consequences of climate change observable already today and is

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<sup>1</sup> The OECD CRS distinguishes between aid projects with adaptation as their principal objective and aid projects with adaptation as a significant objective. The former projects would not have taken place if it was not for adaptation, while the latter would have taken place even without adaptation, but are still important for adaptation (OECD 2011: 5).

<sup>2</sup> Although research found on average small differences between commitments and disbursements (Hudson 2013), it would be insightful to analyse how committed and disbursed adaptation aid flows differ, especially for specific recipients and donors.

based on losses—human and economic—from climate-related weather extremes such as droughts, floods, and storms and has been computed by the organization Germanwatch since 2006.<sup>3</sup> The CRI scores for the countries in the data set range from 2.5 for Thailand in 2012 (highest vulnerability) to 126.2 for various countries in the same year (lowest vulnerability). In order to facilitate the interpretation of the regression coefficients, we recoded the variable such that the lowest vulnerability is 1, with higher values indicating higher levels of vulnerability.

The Secretariat of the Pacific Community’s Applied Geoscience and Technology Division (SOPAC) provides the more general, long-term Environmental Vulnerability Index (EVI). The EVI “estimat[es] the vulnerability of the environment of a country to future shocks” (SOPAC 2004: 6). Here we use only the EVI’s Climate Change Sub-Index as a third proxy for vulnerability. The Sub-Index, which covers 13 indicators, is time-invariant and ranges from 1 to 7, with higher scores indicating higher vulnerability (for a detailed description, see Kaly et al. 2004). Since the EVI predicts long-term vulnerability, there are no annual data and we use the same value for each country-year.

Vulnerability depends also, and crucially, on adaptive capacity, as H2 reflects. Adaptive capacity depends on many factors, including information, awareness, social cohesion, technology, and resources (see, for example, Barnett 2008). As a somewhat rough proxy, we include financial resources to capture adaptive capacity, measured by gross domestic product (GDP) per capita in constant 2005 US dollars. While poorer countries, which are less able to respond to the challenges of climate change by themselves, should receive more aid, research on development aid has found a nonlinear effect of income: poorer countries receive more aid, but very poor countries receive in fact less aid than their income level would predict (cf. Neumayer 2003b). To capture possible nonlinear effects, per capita income is entered into the regressions in linear as well as quadratic form (Alesina and Dollar 2000; Neumayer 2003a). The data are taken from the World Bank (World Bank 2014).<sup>4</sup>

Decisions reached in UN climate change negotiations specifically recognize Least Developed Countries (LDCs), Small Island Developing States (SIDS) and African countries as particularly vulnerable to climate change (e.g. UNFCCC 2009: Decision 2./CP.15, paragraph 3). Hence, as a final proxy for vulnerability, we use a dummy variable for membership of one (or more) of these groups of countries. Since the three groups partly overlap, we use only one dummy to avoid correlation problems.

### 3.3 Control variables

We control for recipient merit with two measures. First, we use the level of democracy, as democracies tend to receive higher levels of aid, and possibly also higher levels of adaptation aid. We use data from Freedom House because of its wide coverage, both temporally and spatially. Following Neumayer (2003a) and others (e.g. Clist 2011), we use the Freedom Index, the sum of Freedom House’s measures of political rights and civil

<sup>3</sup> See the reports on [www.germanwatch.org/en/cri](http://www.germanwatch.org/en/cri).

<sup>4</sup> There are additional indices that seek to capture vulnerability to climate change impacts, such as the ND-GAIN index and the DARA index. Both indices combine variables capturing the geophysical and the socio-economic dimension of climate change, which is, in our view, not ideal for the purpose of this paper. In addition, the DARA index only divides countries into five categories of vulnerability. For these reasons, we do not use these two indices in this paper.

liberties. The index is recoded such that higher values indicate higher levels of freedom, and data are from Teorell et al. (2015).

As a second measure of recipient merit, we include the Control of Corruption variable from the Worldwide Governance Indicators (WGI; Kaufmann et al. 2011, 2014). This variable is also available for all countries in our data set and is a good indicator for the capacity of countries to make good use of the funds provided by donors. The variable is by design standardized, i.e. it has a mean of zero and a standard deviation of 1. Since donor countries are not part of our data set, the mean in our data (covering only recipient countries) is  $-0.47$  and the standard deviation,  $0.66$ .

We control for two additional variables. First, the level of total development aid a country receives is a good predictor of how adaptation aid is disbursed if donor countries follow similar distribution logics for both types of aid. Aid data are taken from the World Bank (2014). Second, we control for a country's population. The literature on aid allocation has found a "small country bias": while it is unclear why this bias occurs, studies find that countries with small populations receive relatively more aid per capita (e.g. Alesina and Dollar 2000; Neumayer 2003a). Population data are taken from the United Nations (United Nations Statistics Division 2014) and from the Secretariat of the Pacific Community for Niue (SPC 2015).<sup>5</sup>

Ideally, we would control for donor interests. However, this requires a dyadic data set, which we do not develop for three reasons. First, our research question does not ask whether different donors consider vulnerability differently when distributing money, but how, on aggregate, vulnerability affects how much money developing countries receive. From the perspective of the research design, using aggregate data is appropriate for this study. Second, control variables are included to avoid omitted variable bias. Omitted variable bias arises when the variable that is not included both influences the dependent variable and is correlated with the independent variable in question. A country's vulnerability to climate change is unlikely to be correlated with trade data or other measures of donor interest. Thus, the danger of omitted variable bias caused by not including such dyadic variables is, in our opinion, relatively small. Finally, there are serious data availability and reliability problems with many dyadic donor interest variables such as bilateral trade. Not only would we risk losing many of the small island states, for which data generally are rare but which we consider important to answer our research question, but trade and similar data also tend to be inconsistent and suffer from measurement error. For all these reasons, the costs of including this variable into the model outweigh, in our opinion, the benefits of developing a dyadic data set. We therefore rely on aggregate data in the models below to assess our hypotheses.

### 3.4 Model specification

The econometrics of aid allocation is technically debated, notably because dyadic data sets contain a large number of zeroes, as not all donors provide aid to all developing countries. A general response to this problem is to distinguish between a selection stage and an allocation stage (e.g. Berthélemy 2006; Clist 2011). Here, however, we only look at aggregate aid flows, such that almost all countries receive at least some adaptation aid. Accordingly, we exclude the selection stage and only examine the allocation stage. Since the observations are nested within countries, we use hierarchical models with country

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<sup>5</sup> For a full list of variables, descriptive statistics and data sources, and a correlation table, see Tables 4, 5, and 6.



random effects and robust standard errors.<sup>6</sup> With only a few observations per country, random effects are more stable than fixed effects, since the shrinkage back to the mean stabilizes them and makes them less susceptible to the influence of outliers (Clark and Linzer 2014).

Given the high variance and skewed distribution of adaptation aid, income, and population, these variables enter the regressions as their natural logarithm. To avoid potential reverse causalities, the variables for income, democracy, control of corruption, foreign direct investment, and deaths and losses from extreme weather events are lagged by one year. Additionally, to account for time effects, year-fixed effects are included as additional predictors (but not reported).

## 4 Results

### 4.1 Descriptive results

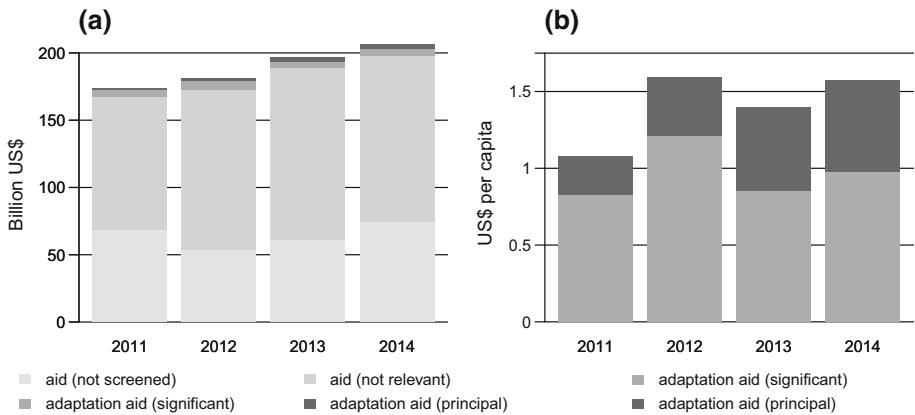
Although (bilateral) adaptation aid is still just a very small proportion of overall development aid (see Fig. 1a), it has increased since the Rio marker for adaptation was introduced (see Fig. 1b). In 2011, OECD bilateral aid to individual developing countries that targeted adaptation totalled \$6.2 billion. For projects worth \$4.7 billion (75% of total adaptation aid), adaptation was a significant objective; for projects worth \$1.6 billion (25% of total adaptation aid), it was the principal objective.<sup>7</sup> In 2014, the year with the highest aid flows on record so far, total adaptation aid had increased to \$9.3 billion, of which almost \$5.8 billion (62% of total adaptation aid) had adaptation as significant, and \$3.5 billion (38% of total adaptation aid) as principal objective. Translated to per capita aid, this means that on average, each individual in the developing world obtained about \$1.56 in 2014 for adaptation measures, up from just above \$1 in 2011.

When we look at which countries received most adaptation aid over the entire period of analysis, per capita and as a percentage of all adaptation aid (Table 1a, b, respectively), the results seem to confirm that donors privilege vulnerable countries, such as SIDS. The top ten per capita adaptation aid recipients are all SIDS. The recipient with the highest per capita aid, Niue, is freely associated with New Zealand, as is the Cook Islands; both traditionally receive very high levels of support from New Zealand. Given the very small population of Niue of only around 1500 inhabitants, the extremely high level of adaptation aid of just under \$13,000 per capita from 2011 to 2014 is less surprising. The picture is different if we look at how much single countries obtained of the adaptation aid disbursed so far (in percent). Unsurprisingly, larger countries receive more adaptation aid in total than smaller ones. India, having received 7.90% of all adaptation aid committed between 2011 and 2014, ranks first, and Vietnam (7.74%) and the Philippines (4.36%) follow. Other large recipients include Bangladesh (3.83%), China (3.28%) and Ethiopia (2.28%).

<sup>6</sup> Since we use aggregate data, we only have 15 observations with entries of zero. For this reason we do not use a Tobit model, as is often used in the aid allocation literature. Further, because the data reported do not allow us to differentiate between entries that are zero and those that are missing, all empty cells have been coded to represent zero. We believe that in such cases no adaptation aid has been reported to the OECD and that this procedure is justified. We therefore do not apply Heckman selection models either.

<sup>7</sup> Note that these figures differ from official OECD statistics (e.g. OECD 2016) because they exclude aid going to regional or unspecified recipients.





**Fig. 1** Adaptation aid trends: **a** adaptation aid compared to overall (bilateral) development aid; **b** total (bilateral) adaptation aid per capita

**Table 1** Top recipients of adaptation aid (a) per capita, and (b) as a percentage of all adaptation aid

Country		Adaptation aid (per capita)	Country		Adaptation aid (percent of total adaptation aid)
(a)			(b)		
1	Niue	12,707	1	India	7.90
2	Tuvalu	3018	2	Vietnam	7.74
3	Cook Islands	879	3	Philippines	4.36
4	Nauru	721	4	Bangladesh	3.83
5	Vanuatu	679	5	China	3.28
6	Kiribati	622	6	Ethiopia	2.28
7	Dominica	576	7	Kenya	2.21
8	Cape Verde	438	8	Cambodia	2.09
9	Palau	397	9	Tanzania	2.09
10	Tonga	365	10	Peru	2.07
	Average*	183		Of total of \$32 billion	

\* Average without Niue: \$94. Numbers are aggregates over the period 2011–2014

## 4.2 Regression results

Let us turn to a more rigorous test of who receives adaptation aid. Table 2 reports the results from the hierarchical regression models for per capita adaptation aid; Table 3 reports adaptation aid as a percentage of all adaptation aid committed that year. The models use the various indicators for vulnerability introduced earlier: Model 1 measures vulnerability using the CRI and the EVI Climate Sub-Index. The former indicator estimates how strongly countries were affected by weather-related events in a given year. In contrast, the EVI Climate Sub-Index assesses how vulnerable countries are to potential future changes in weather, floods, etc. In other words, the first index captures highly

**Table 2** Allocation of per capita adaptation aid

	Dependent variable: Adaptation aid per capita (logged)		
	(1)	(2)	(3)
Climate risk index+	0.004*** (0.002)		0.005*** (0.002)
EVI climate sub-Index	0.145* (0.088)		0.085 (0.092)
Population below 5 m		0.012** (0.005)	0.010** (0.005)
Vulnerable country (dummy)		-0.014 (0.139)	0.048 (0.135)
GDP/capita (logged)+	3.754*** (0.737)	3.422*** (0.768)	3.602*** (0.747)
GDP/capita, squared+	-0.274*** (0.050)	-0.250*** (0.052)	-0.262*** (0.050)
WGI: corruption+	0.280** (0.135)	0.228* (0.134)	0.305** (0.134)
Freedom index+	0.011 (0.024)	0.032 (0.024)	0.011 (0.023)
Population (logged)+	-0.352*** (0.036)	-0.324*** (0.037)	-0.328*** (0.038)
Total dev. aid (logged)+	0.025* (0.015)	0.025* (0.015)	0.029** (0.015)
Constant	-6.691** (2.663)	-5.587** (2.845)	-6.573** (2.774)
Observations	462	478	462
Log Likelihood	-614.296	-651.933	-612.204
Akaike information criterion	1256.592	1331.866	1256.408
Bayesian information criterion	1314.490	1390.241	1322.577

The models are hierarchical models with country random effects and robust standard errors in parentheses. Yearly data lagged (marked +) by 1 year; year dummies included (not shown)

\*  $p < 0.1$ ; \*\*  $p < 0.05$ ; \*\*\*  $p < 0.01$

visible phenomena that seem to influence donors at the time when they decide how to allocate funds, while the second index operationalizes vulnerability as a long-term concept. Thus, these two indices are highly complementary, and we combine them in the first model. Model 2 combines the percentage of population living below an elevation of five meters with the vulnerability dummy combining African countries, SIDS, and LDCs. We put these variables into the same model because they are not composite indices (in contrast to the EVI and the CRI) and are therefore easier to understand for policy-makers as indicators of vulnerability. Model 3 is a full model including all variables contained in the previous two models. All three models include GDP per capita and GDP per capita squared as measures of adaptive capacity, and the control variables (see Sect. 3.3).

**Table 3** Allocation of adaptation aid, percent of yearly total

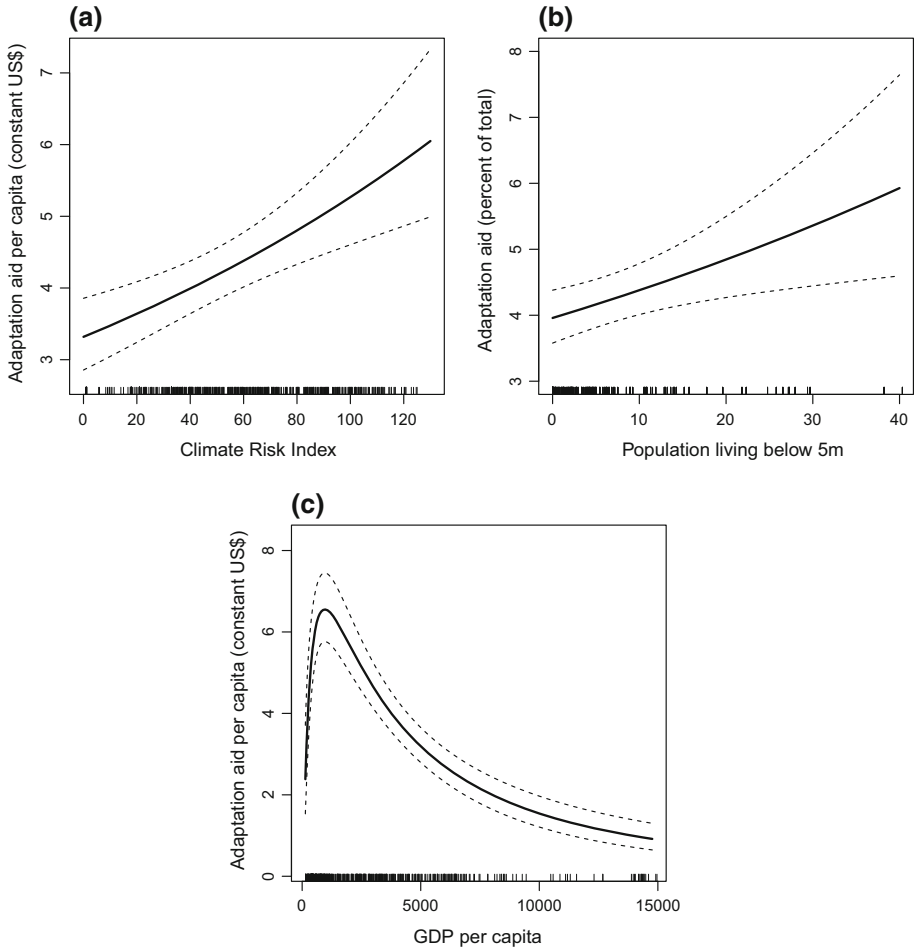
	Dependent variable: adaptation aid (% of total, logged)		
	(1)	(2)	(3)
Climate risk index+	0.002** (0.001)		0.002** (0.001)
EVI climate sub-index	0.108*** (0.039)		0.085** (0.041)
Population below 5 m		0.006*** (0.002)	0.004** (0.002)
Vulnerable country (dummy)		0.078 (0.051)	0.094* (0.051)
GDP/capita (logged)+	0.627* (0.321)	0.590* (0.327)	0.651** (0.321)
GDP/capita, squared+	-0.049** (0.022)	-0.044** (0.022)	-0.049** (0.022)
WGI: corruption+	0.128** (0.058)	0.116** (0.056)	0.132** (0.057)
Freedom index+	-0.0001 (0.010)	0.006 (0.010)	0.004 (0.010)
Population (logged) +	0.130*** (0.016)	0.146*** (0.016)	0.145*** (0.016)
Total dev. aid (logged)+	0.004 (0.006)	0.005 (0.006)	0.006 (0.006)
Constant	-3.942*** (1.160)	-3.919*** (1.203)	-4.399*** (1.183)
Observations	462	478	462
Log likelihood	-155.298	-156.665	-151.700
Akaike information criterion	338.595	341.329	335.399
Bayesian information criterion	396.493	399.704	401.568

The models are hierarchical models with country random effects and robust standard errors in parentheses. Yearly data (marked +) lagged by 1 year; year dummies included (not shown)

\*  $p < 0.1$ ; \*\*  $p < 0.05$ ; \*\*\*  $p < 0.01$

Figures 2 and 3 graphically depict the effects of the statistically significant variables related to recipient need.

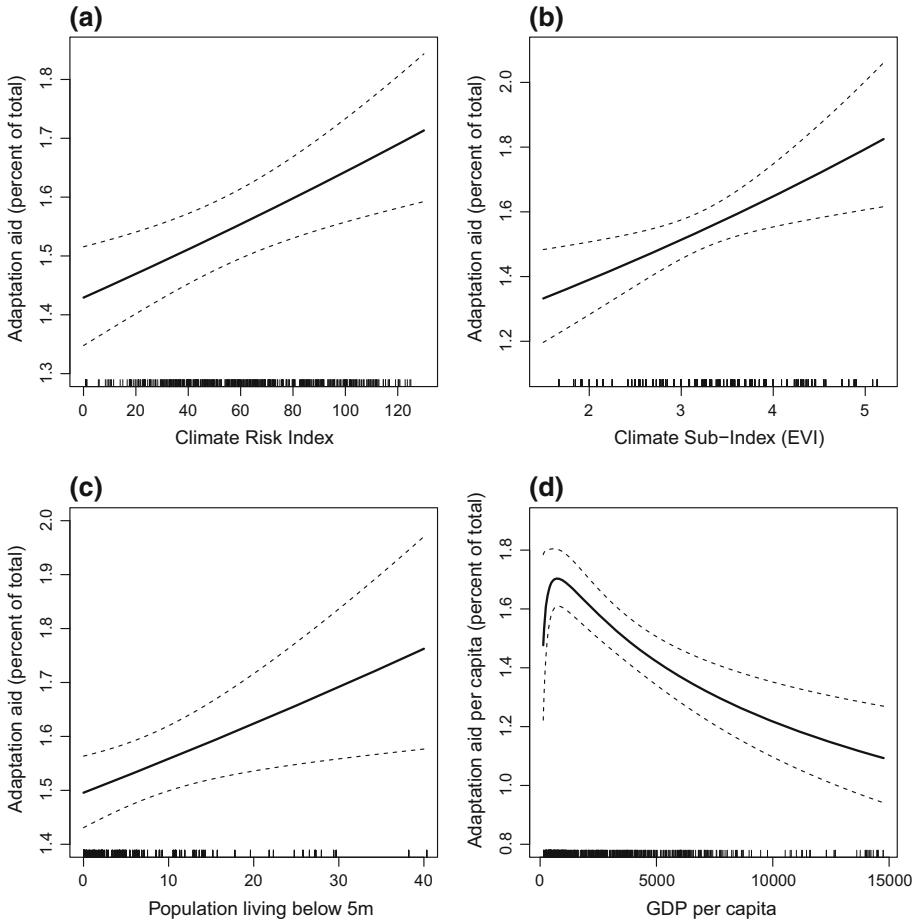
Do countries more exposed to climate change impacts receive more adaptation aid, as proposed by H1? The results indicate that donors indeed take into account physical vulnerability when allocating adaptation aid. Overall, the regression models suggest that countries that are more vulnerable to extreme weather events, as measured by the CRI, receive significantly more adaptation aid, both per capita and as a percentage of all adaptation aid. The CRI coefficient is highly significant in all models for both dependent variables. Panels (a) of Figs. 2 and 3 depict graphically the effect of the CRI for the two full models (Model 3 in Tables 2, 3). As can be seen in Fig. 2, predicted adaptation aid per capita increases, all else being equal, by almost \$3 from the lowest to the highest levels of



**Fig. 2** Substantiated effects ( $p < 0.05$ ) for per capita adaptation aid

vulnerability. In percentage terms, the most vulnerable countries can expect about 0.3% more of totally committed adaptation aid each year than the least vulnerable countries.

The EVI Climate Sub-Index is significant in most models, although in the per capita models, the coefficients are only significant at the 10% level (the partial Model 1 of Table 2) or insignificant (the full Model 3 of Table 2). Still, donors also seem to consider the long-term consequences of climate change when deciding how to allocate adaptation funds. Panel (b) of Fig. 3 shows the EVI Climate Sub-Index effect for the percentage model. As can be seen, the most vulnerable countries can expect about 0.5% more adaptation aid than the least vulnerable countries. In the per capita model (not graphically illustrated as the significance level is too low), this would translate into an increase of over \$3 per capita for particularly vulnerable countries. Thus, our models predict that countries exhibiting both short-term (CRI) and long-term (EVI) vulnerability will obtain substantially more adaptation funds than their less vulnerable peers.



**Fig. 3** Substantiated effects ( $p < 0.05$ ) for adaptation aid as percentage of annual total

Adaptation aid is also strongly related to the percentage of the population living in low-lying areas (the coefficient is highly significant across all models). The effects of the percentage of the population living below five meters altitude are depicted in panel (b) of Fig. 2 for per capita adaptation aid and in panel (c) of Fig. 3 for the percentage of total adaptation aid. The figures were clipped for values larger than 40% because very few countries have such large percentages of people living close to sea level, and as a consequence, the confidence intervals become very wide and are not very meaningful. Yet, the figures show that countries with around 40% of the population living in very low-lying areas are predicted to receive about \$2 more per capita than countries where only very few people live in such areas, and about 0.25% more of the annually disbursed adaptation funds.

In contrast, African countries, SIDS, and LDCs (the vulnerability dummy) do *not* receive more adaptation aid on a per capita basis, despite being singled out as particularly vulnerable in UN climate change negotiations. On a percentage basis, the effect is significant in both models, yet only at the 10% level for the full model. One should, however,

not rush to the conclusion that these highly vulnerable countries, particularly SIDS, do not receive more funds than other countries. As Table 1 shows, SIDS are among the countries receiving most adaptation aid on a per capita basis (over the entire 4-year period), yet only when we enter the vulnerability dummy into the regression are they predicted to receive about \$2 more per capita each year than other countries. When we control for their mostly small population size and their high vulnerability levels, the significance of this effect disappears. These countries still obtain more funds, but the extra aid is explained by the covariates, and being an African country, a LDC, or a SIDS does not contribute to receiving aid in addition to the already high sums that smaller and more vulnerable countries obtain.

Regarding adaptive capacity (H1), the poorest countries do not appear to receive more adaptation aid. Instead, the analysis suggests a bias towards middle-income countries: rather than giving more aid to the poorest countries, donors prefer to allocate funds to middle-income countries. More per capita income is associated with more adaptation aid, both in per capita terms and as a percentage of annually committed funds. Yet, the bias is reversed at some point, as the negative and very significant relationship between the quadratic term and adaptation aid suggests. Thus, middle-income countries benefit most from adaptation aid, possibly because these countries are (perceived to be) better able to absorb incoming aid flows. This relationship is depicted graphically in panel (c) of Fig. 2 for per capita adaptation aid, and in panel (d) of Fig. 3 for the percentage of total annual funds. Both figures show that the lowest income countries receive relatively little adaptation aid, yet this changes quickly as GDP increases. For per capita aid, the maximum is reached at a per capita GDP of almost exactly \$1000, at which point countries are expected to receive slightly over \$6.5 per capita, about \$4.5 more than the poorest countries. Thereafter, aid per capita drops again (yet more slowly than it rises at the beginning), and the richest countries in the data set are predicted to receive less than \$1 per capita in adaptation aid. The situation is similar when we consider the percentage of annual adaptation aid that countries obtain (panel (d) of Fig. 3). Yet this second model predicts the maximum aid countries receive to be earlier at a per capita GDP of around \$890. At this level, countries are predicted, all else being equal, to receive about 1.7% of annually disbursed adaptation funds, while the poorest countries receive around 1.4%, and the richest around 1.1%.

Overall, then, our evidence indicates that vulnerability matters for the allocation of adaptation aid, in terms of both exposure to climate change impacts and adaptive capacity. Thus, we consider H1 and, to a lesser extent, H2 to be substantiated.

Let us now turn briefly to some of the control variables in the model. First, countries with less corruption receive significantly more funds. Such countries are not only seen as better able to absorb funds, as middle-income countries are compared to the poorest countries, but also more likely to utilize funds as intended, rather than divert them for private gains. The effect of corruption control is significant across all models for both dependent variables. The least corrupt countries are expected to receive almost 0.65% more of the annually committed adaptation aid than the most corrupt states, or in dollar terms, about \$4.5 extra per capita each year.

The effect of the Freedom Index, on the other hand, is not significant in the models. However, this is likely a result of the high correlation between the Freedom Index and the WGI control of corruption variable. When the latter is removed, the Freedom Index becomes highly significant and has the expected sign. In other words, it then explains the variance previously taken up by the corruption control variable. When using another WGI variable such as government effectiveness, or another measure for democratic quality, e.g.

the Polity IV scores, we obtain very similar results, i.e. the coefficients are significant and have the expected sign. The other variables in the models are not greatly affected when the variable capturing recipient merit is changed.

The analysis also finds that donors take into account population size: as with general development aid, small countries receive relatively more adaptation aid per capita, while large countries (unsurprisingly) receive a higher share of the total adaptation aid committed. The relationship is significant in all models. The other variables in the models are either insignificant, or show only low levels of significance, and are therefore not further discussed here.

## 5 Conclusion

Adaptation aid, along with adaptation overall, has gained increasing prominence on the international climate change agenda. Despite this growing attention, adaptation aid allocation across developing countries has not been studied extensively so far. The present article is a first step towards filling this research gap. We explored the question of how donors allocate their bilateral adaptation aid to developing countries. We particularly focused on the question whether particularly vulnerable countries—measured by exposure to climate change impacts and by adaptive capacity—receive more adaptation aid, as promised repeatedly by donor countries during international negotiations, and as we would expect from a justice or equity perspective.

In contrast to several other studies that examine the allocation of adaptation aid at the multilateral or individual contributor country level (e.g. Persson and Remling 2014; Robertsen et al. 2015; Stadelmann et al. 2014; Betzold 2015), we find that vulnerability is an important predictor for the allocation of adaptation aid at the aggregate level. Countries that are more vulnerable to climate change—as measured by different vulnerability indicators—receive more adaptation aid. In particular, exposure to extreme weather events, as measured by the CRI, is a good predictor for how much aid developing countries receive each year. We were able to demonstrate that the most vulnerable countries receive about \$3 per year for each citizen more than the least vulnerable countries, or about 0.3% more of annually committed adaptation funds. Similarly, longer-term assessments of vulnerability to climate change impacts, such as the EVI, which captures how strongly climate change will be felt in a given country in the future, seem to influence how policy-makers distribute funds earmarked as adaptation aid. For this indicator, our models predict that the most vulnerable countries obtain, all else equal, about 0.5% more of annually distributed aid than the least vulnerable countries. Furthermore, our models predict that states where many citizens live in high-risk, low-lying areas receive at least \$2 more than countries at higher elevations.

In addition to exposure to climate change impacts, we also tested whether adaptive capacity, measured by a country's GDP per capita, plays a role for donors' disbursement decisions. We find that very poor countries receive relatively little aid, but also that aid flows increase relatively quickly as income increases, presumably because these countries are more capable of absorbing funds and to use them as intended. Lower middle-income countries obtain over \$4 more than the poorest states; then, the level of adaptation aid starts declining again, and the richest countries in our data set are also those receiving least.

The finding that donors do consider the vulnerability of countries when they earmark funds for adaptation aid projects is good news for recipient countries, but also for the



fragmentation of the overall climate finance system. Despite considerable institutional fragmentation in the allocation of adaptation finance, on aggregate there seems to be little norm fragmentation in that donors together provide more adaptation aid to vulnerable countries. However, because we look at allocation aid at the aggregate level, we cannot draw conclusions about the behaviour of individual donors, who may well consider vulnerability to different degrees. Our research design thus limits how much we can say about norm fragmentation.

On the other hand, even if vulnerable countries receive significantly more adaptation aid than less vulnerable countries, the difference is small in absolute terms, at about \$3 per capita or 0.3%. Whether this is fair or adequate (in the sense of being commensurate with their adaptation funding needs) is of course a different question. Further, our analysis is only a first step and has several limitations: we use aggregate data, consider only the period 2011 through 2014, and rely on donors' own classification of adaptation aid. Additionally, we only consider allocation among different developing countries, but not distribution within recipient countries; we therefore cannot be sure that adaptation aid reaches those most vulnerable communities and individuals *within* a country (cf. Barrett 2014; Duus-Otterström 2015). It is also worth mentioning that although we find that donors do consider recipient countries' vulnerabilities to climate change impact, this does not shed light on the question whether such a classification is actually desirable from a normative point of view. Finally, vulnerability is itself a contested concept that is difficult to measure at the national as well as at the sub-national level. Vulnerability is about the potential for loss, and hence about values: it is about identifying what is at risk of loss and whether that would be an acceptable or unacceptable loss and is therefore an inherently subjective process (Barnett et al. 2008).

Analyses that seek to relate adaptation aid to vulnerability are clearly fraught with ambiguity (see Hall, this issue). Nonetheless, research as well as policy should seek to track as well as evaluate climate finance flows, including for adaptation, at international, national, and also sub-national levels. Such a monitoring and evaluation exercise would be made easier if parties agreed on specific vulnerability criteria, yet given the inherently contested nature of vulnerability, such an agreement is unlikely and it lacks evidence of strategic ambiguity (Hall, this issue). There is a need to understand better where adaptation aid is flowing to, and—equally if not more important—when and how this aid effectively supports adaptation and reduces vulnerability for the recipients. Future research should therefore go into more detail to capture donor interests as well. This could be done either by developing dyadic data sets, or via the use of network models. Such a research design should also be able to shed more light on the question of norm fragmentation. Developed countries have an obligation to assist developing countries in their efforts to respond to climate change, not only out of justice considerations but also according to provisions of the UNFCCC and later agreements. That this assistance reaches the vulnerable and really helps and reduces vulnerability to climate change impacts should be a prime concern for donors and recipients alike.

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## Appendix

See Tables 4, 5, and 6.

**Table 4** Data sources

Variable	Data source
Dependent variable	
Adaptation aid, per capita*	OECD (2016)
Adaptation aid, percent of global total*	OECD (2016)
Recipient needs	
Climate risk index+	Germanwatch
EVI climate sub-index	Kaly et al. (2004)
Population below 5 m	CIESIN (2012)
GDP per capita*+	World Bank (2014)
Vulnerable country group (dummy for country belonging to LDCs, SIDS, or Africa)	UN-OHRLLS (2015a, b)
Control variables	
Population*+	World Bank (2014)
Control of corruption (WGI)+	Kaufmann et al. (2014)
Freedom index+	Teorell et al. (2015)
Total development aid*+	World Bank (2014)

\* Natural logarithm used in regression analysis; + lagged variable used in regression analysis

**Table 5** Summary statistics for all dependent and independent variables

Variable	Min	Max	Median	Mean	Std. dev.	<i>N</i>
Adaptation aid per capita*	0	408.47	2.61	12.30	36.32	462
Adaptation aid (percent)*	0	16.47	0.27	0.81	1.47	462
Climate risk index+	2.17	126.20	78.85	72.85	32.30	462
EVI climate sub-index	1.67	5.13	3.17	3.21	0.73	462
Population below 5 m	0	100	2.86	7.38	13.63	462
Vulnerability dummy	0	1	0	0.44	0.49	462
GDP per capita*+	141	15,450	1980	3037	3063	462
Control of corruption (WGI)+	-1.62	1.56	-0.57	-0.47	0.66	462
Freedom index+	2	14	9	8.31	3.35	462
Population (million)*+	0.053	1364.27	10.04	48.06	164.69	462
Total aid (million \$)*+	0	6832	383.0	730.6	1023.19	462

\* Natural logarithm used in regression analysis; + lagged variable used in regression analysis

Table 6 Correlation Table

	Adapt. aid (per capita)	Adapt. aid (% of total)	Climate risk index	EVI climate sub-index	Population below 5 m	Vulnerability dummy	GDP/capita	Population	WGI: corruption	Freedom index	Total development aid
Adaptation aid (per capita)	1.00										
Adaptation aid (% of total)	0.23	1.00									
Climate Risk Index	-0.07	0.36	1.00								
EVI Climate Sub-Index	0.19	0.00	-0.08	1.00							
Population below 5 m	0.29	-0.03	-0.14	0.37	1.00						
Vulnerability dummy	0.14	-0.06	-0.15	-0.05	0.13	1.00					
GDP/capita	-0.02	-0.26	-0.11	0.29	0.10	-0.26	1.00				
Population	-0.50	0.54	0.40	-0.25	-0.32	-0.27	-0.29	1.00			
WGI: corruption	0.25	-0.15	-0.10	0.26	0.07	0.04	0.51	-0.44	1.00		
Freedom Index	0.26	-0.08	0.04	0.23	0.10	-0.02	0.38	-0.34	0.66	1.00	
Total development aid	0.09	0.14	-0.04	-0.07	-0.15	0.13	-0.34	0.09	-0.21	-0.05	1.00

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