Localized Disparities in Climate Finance: The Sub-National Allocation of World Bank Mitigation and Adaptation Aid in Least Developed Countries

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Abstract

Least developed countries (LDCs) contribute minimally to global greenhouse gas emissions yet face disproportionate risks from climate change. To address this inequity, high-income countries have pledged substantial climate finance to support LDCs in both mitigation and adaptation efforts. While existing research provides important insights on climate finance, two important gaps remain: most studies examine adaptation and mitigation finance separately, and few assess allocation patterns below the national level. This limits understanding of whether funds reach the areas where they are most needed or have the biggest impact. This article addresses these gaps by analyzing the sub-national allocation of World Bank–funded climate finance projects in 14 LDCs in Asia and Oceania between 2000 and 2019. We coded 780 projects according to their adaptation and/or mitigation objectives and mapped them to their specific geographic locations. Using two-way fixed effects regression, we test whether adaptation finance is directed toward more climate-vulnerable regions and whether mitigation finance targets areas with higher emission reduction potential. Our results provide a nuanced picture. Consistent with our theoretical expectations, adaptation projects are more likely to be allocated to poorer, more vulnerable sub-national regions. In contrast, the allocation of mitigation projects does not consistently favor more economically developed areas with higher emissions reduction potential. These findings highlight the value of analyzing adaptation and mitigation finance jointly and at the sub-national scale. By doing so, the study advances understanding of how multilateral climate finance is distributed and contributes to broader debates on climate justice and aid allocation.

1 Introduction

Despite contributing minimally to historical global greenhouse gas (GHG) emissions, least developed countries (LDCs) are both disproportionately exposed and vulnerable to climate-related hazards (Formetta and Feyen, 2019). In recognition of this inequity, high-income countries have pledged to provide substantial climate finance to support LDCs in both mitigating and adapting to the impacts of climate change (Michaelowa and Sacherer, 2022). Alongside commitments to increase funding, there is a growing emphasis on ensuring that available resources are allocated, so they achieve their intended goals. For adaptation finance, this means enhancing communities' resilience to environmental change, while mitigation finance aims to reduce carbon emissions effectively.

Whether donors are fulfilling these pledges and meeting these objectives remains an open question of concern to scholars and policymakers. Existing evidence is fragmented and offers several options to advance the current state of knowledge. One notable gap in the literature is that few studies adopt a comprehensive perspective; most research analyzes either adaptation or mitigation finance in isolation (e.g., Betzold and Weiler, 2017; Weiler and Klöck, 2021). Yet these two types of finance differ fundamentally in both their purpose and, consequently, in the logic that should guide their allocation. Adaptation finance should reach the most climate-vulnerable areas, whereas mitigation finance should target regions with the highest potential for emission reductions. Examining them jointly thus allows for a more complete assessment of donor allocation patterns and their overall contribution to climate justice. This research gap is particularly relevant in the case of multilateral donors, such as the World Bank, whose share of total climate finance has steadily increased in recent years. These institutions are often vocal proponents of effective and equitable climate finance distribution. Yet, with few exceptions (Islam, 2022; Michaelowa et al., 2020; Tennant and Gilmore, 2020; Xie et al., 2023), existing research does not examine how multilateral donors allocate adaptation and mitigation finance across different contexts.

A second gap in the current literature is the scarcity of sub-national analyses. To the best of our knowledge, only two studies have examined sub-national adaptation finance allocation, one in Malawi and one in Ecuador (Barrett, 2014; Cisneros and Ilbay-Yupa, 2023). There is virtually no sub-national analysis of mitigation finance, nor any study that systematically compares sub-national allocation patterns across multiple country contexts. This absence is notable given the lessons from the more general development aid literature, which demonstrates that the spatial granularity of analysis can significantly influence and alter the findings on distributive patterns. For climate finance, national-level allocations may align with theoretical goals, but these funds may still fail to reach the most appropriate sub-national regions. This issue is particularly critical for mitigation finance, which comprises the majority of global climate funding. Understanding whether mitigation finance is allocated to areas where emissions can be most effectively reduced is essential for ensuring its impact.

This study addresses these two gaps by examining the sub-national allocation of World Bank-funded climate finance projects in 14 LDCs across Asia and Oceania between 2000 and 2019. By coding each project according to its adaptation and/or mitigation objectives, we assess whether adaptation finance reaches the most vulnerable areas within recipient countries and whether mitigation finance is directed toward regions with the greatest potential for GHG emission reduction.

Drawing on theoretical insights from cross-country studies of climate finance allocation, we hypothesize that within LDCs, mitigation projects are more likely to be located in economically developed sub-national regions, where emission reduction potentials are highest (Halimanjaya, 2015, 2016). In contrast, adaptation finance should be directed toward poorer, more vulnerable areas, those with lower levels of infrastructure and economic development, where climate risks are more acute.

To test these hypotheses, we coded 780 World Bank projects based on their stated objectives and specific geographic locations. This enables a fine-grained analysis of sub-national climate finance allocation. Using quantitative regression analysis with two-way fixed effects, our findings partially support the theoretical expectations. Consistently across all countries studied, adaptation projects are disproportionately allocated to poorer regions. However, contrary to our expectations, mitigation projects are not consistently concentrated in more economically developed regions.

2 Conceptualizing Climate Finance: What It Is and How Does it Work?

Climate change is characterized by profound global injustices. One of the most prominent inequalities, central to discussions of climate justice, is the disproportionate burden borne by low income and more vulnerable populations in the Global South compared to more affluent, resilient populations in the Global North. Industrialized countries have historically contributed the majority of global carbon dioxide (CO_2) emissions over decades of economic development. As a result, these countries today have stronger economies and greater institutional capacities to cope with environmental hazards. In contrast, many countries in the Global South- particularly Least Developed Countries (LDCs) - bear little historical responsibility for climate change yet face its most severe impacts. They also lack the financial, technological, and institutional resources to adapt effectively. Compounding this injustice is the current imperative to reduce emissions globally. Despite their minimal historical contributions to global warming, LDCs now face constrains on how much they can emit along their development pathways. In effect, they are being asked to help address a crisis they did not create, while already experiencing severe climate impacts. This profound imbalance is at the core of calls for climate finance.

To address these inequities, high-income countries, multilateral development banks (MDBs), and dedicated climate funds provide aid for climate change mitigation and adaptation efforts in low-income countries. Climate finance broadly comprises two key components: adaptation finance and mitigation finance. Each serves distinct purposes. Adaptation finance aims to reduce vulnerability to the adverse effects of climate change, including extreme weather events, sea-level rise, and long-term shifts in climatic conditions. In LDCs, this includes financing early-warning systems, the promotion of drought-resistant crops, investments in climate-resilient infrastructure, and improved disaster preparedness. Given their high vulnerability and limited coping capacity, LDCs stand to benefit significantly from well-targeted adaptation finance.

Mitigation finance, by contrast, focuses on reducing or avoiding GHG emissions. This includes support for renewable energy development (e.g., solar, wind, and hydropower), improvements in energy efficiency, low-emissions transportation systems, and cleaner industrial production. Because LDCs are still industrializing, economic growth without climate-sensitive planning could lead to a steep rise in emissions. Mitigation finance helps these countries pursue sustainable development pathways that decouple growth from emissions.

A substantial share of climate finance is provided through bilateral channels—that is, direct financial assistance from one government to another, often through development agencies or specialized climate programs. Examples include Germany's GIZ, the United States' USAID, and Japan's JICA. Bilateral assistance typically accounts for approximately 40–50% of total international climate finance.

In addition, multilateral climate funds and multilateral development banks (MDBs) provide roughly 20–30% of international climate finance. Key multilateral funds include the Green Climate Fund, the Global Environment Facility, and the Adaptation Fund. Major MDBs include the World Bank, the Asian Development Bank, the African Development Bank, and the Inter-American Development Bank. Among these, the World Bank remains the largest provider of multilateral climate finance. Private sector investments and philanthropic contributions also represent a growing source of climate finance, though these often complement rather than replace public sector funding.

Since the 2009 Copenhagen Summit (COP15) under the United Nations Framework Convention on Climate Change (UNFCCC) and the adoption of the Paris Agreement in 2015, international climate finance has grown substantially, approximately doubling from the early 2010s to the early 2020s. Although bilateral finance continues to constitute the largest share, multilateral funds and MDBs have seen rapid growth in their climate finance portfolios.

In addition to assessing who provides climate finance, it is also crucial to understand what it is spent on. A notable trend is the historical imbalance between mitigation and adaptation funding. Throughout the 2000s and early 2010s, approximately 75–85% of total climate finance was directed toward mitigation, while adaptation routinely received less than 20%. This disparity is largely due to the nature of the projects themselves. Mitigation initiatives, such as renewable energy installations and energy efficiency upgrades, often generate clear financial returns and are, therefore, more attractive to investors, including private capital. Adaptation projects, by contrast, tend to be highly context-specific, less commercially viable, and more dependent on public grants or concessional financing.

Since 2015, however, adaptation finance has gradually increased its share, reaching approximately 25–30% of total international climate finance in recent years. This shift reflects growing recognition of the escalating climate risks faced by vulnerable countries, as well as commitments under the Paris Agreement, which call for a more balanced distribution between adaptation and mitigation efforts. Nevertheless, this re-balancing is not uniform across donors. The European Union stands out for adopting a relatively balanced approach, channeling approximately 30–40% of its climate aid toward adaptation. In contrast, MDBs continue to allocate a larger proportion of funds to mitigation, typically between 70–80%, with adaptation comprising only 20–30% of their portfolios.

MDBs finance a broad range of projects: These span clean energy, energy efficiency, sustainable transport, and forestry for mitigation aid as well as climate-resilient infrastructure, water resource management, and disaster risk reduction for adaptation aid. Given their global reach and institutional capacity, MDBs are expected to play an increasingly central role in financing responses to climate-related challenges. Some MDBs, such as the World Bank, have already doubled their climate-related lending in recent years. Although mitigation still dominates, MDBs are under increasing pressure to scale up adaptation finance in response to international policy commitments and the demands of recipient countries.

3 Recipients in Focus: Who Should Receive Climate Finance and Who Actually Does?

Beyond the questions of who provides climate finance and how it is spent, the issue of who receives this finance is equally critical. While traditional development aid literature has long explored the geographic and political drivers of aid allocation (Alesina and Dollar, 2000; Berthélemy, 2006; Hoeffler and Outram, 2011; Younas, 2008), a growing body of climate finance research is now beginning to explore similar questions (Bayramoglu et al., 2023; Betzold and Weiler, 2017; Doshi and Garschagen, 2020; Weiler and Klöck, 2021). This emerging “climate finance distribution” literature examines whether climate finance reaches the countries and communities most in need and assesses the extent to which climate finance contributes to equitable and just outcomes on both international and sub-national levels.

Major donors, including the World Bank and various Global North governments, tie the allocation of climate finance to specific assumptions about responsibility, efficiency, vulnerability, and governance. These principles are articulated in funding frameworks, official policy documents, and public statements, often reflecting implicit preferences and ideological positions.

On one hand, there is a widely accepted normative stance that climate finance — particularly adaptation finance —- should be directed toward those most vulnerable to climate change: communities and countries that have contributed least to global emissions yet bear the brunt of climate impacts. This aligns with the UNFCCC principle of “Common But Differentiated Responsibilities” and Respective Capabilities (CBDR-RC). On the other hand, mitigation finance is often justified through an efficiency lens, with the underlying goal of achieving the highest possible emissions reductions per dollar spent. This rationale tends to prioritize regions that already have relatively high levels of emissions, infrastructure, and economic activity.

These two logics, vulnerability-based and efficiency-based, imply that the optimal allocation for adaptation finance may not align with those for mitigation finance. For instance, effective mitigation requires both a substantial baseline level of emissions and the technical and institutional capacity to implement low-carbon technologies. Technologies, such as wind turbines and solar panels, necessitate transport infrastructure and stable regulatory environments, which are often lacking in the least developed and most climate-vulnerable regions. Consequently, LDCs that are most in need of adaptation support may simultaneously be less suited to receive mitigation finance from an efficiency perspective.

However, insights from the much more mature development aid literature underscore a critical caveat: donors do not necessarily follow their stated principles when allocating aid. Numerous studies have documented significant discrepancies between stated goals (e.g., poverty reduction, capacity building) and actual allocation patterns, which are frequently influenced by donors’ political, economic, or strategic interests (Alesina and Dollar, 2000; Berthélemy, 2006; Hoeffler and Outram, 2011; Younas, 2008). These include considerations of geopolitical alliances, trade relations, or governance indicators such as merit or absorptive capacity. Similar distortions may affect the distribution of climate finance.

Despite the growing policy relevance of climate finance, empirical evidence on how this type of aid is allocated remains limited and uneven. One notable pattern is the relative abundance of studies on bilateral climate finance compared to multilateral finance (Bayramoglu et al., 2023; Betzold and Weiler, 2017; Doshi and Garschagen, 2020; Weiler and Klöck, 2021). This is partially understandable given the still-dominant share of bilateral flows in total climate finance. However, it does not reflect the increasing role of multilateral sources, including MDBs and multilateral climate funds, which now account for a significant and growing portion of climate finance flows (Michaelowa et al., 2020).

A second imbalance in the literature exists between studies investigating adaptation versus studies investigating mitigation finance. While the actual financial flows are heavily skewed toward mitigation—with 70–80% of global climate finance historically directed to mitigation efforts, the academic literature is disproportionately focused on adaptation (Betzold and Weiler, 2017; Doshi and Garschagen, 2020; Weiler and Klöck, 2021). Most empirical studies in this area ask whether adaptation finance is allocated according to need: i.e., whether it reaches those most vulnerable to climate impacts.

Findings on this question are mixed. Some studies show that adaptation finance does indeed follow a vulnerability-based logic, going primarily to countries or regions with high climate risk and low adaptive capacity (e.g., Bagchi et al., 2016; Betzold and Weiler, 2017; Cisneros and Ilbay-Yupa, 2023; Islam, 2022; Liu et al., 2024). However, other studies challenge this notion, showing that adaptation finance is not systematically targeted toward the most vulnerable, and may instead reflect strategic or donor-centric considerations (e.g., Barrett, 2015; Doshi and Garschagen, 2020; Lee and Lim, 2025; Robertsen et al., 2015; Robinson and Dornan, 2017).

In contrast, the empirical literature on the allocation of mitigation finance is still in its infancy, despite its dominance in overall funding. The few existing studies that examine mitigation finance provide inconclusive findings. Some cross-sectoral studies that include both mitigation and adaptation aid suggest that mitigation aid is not allocated according to where emission savings could be achieved. Rather it tends to go to countries with lower emissions and lower economic development, contrary to donors' stated goals of maximizing emissions reductions (e.g., Han and Cheng, 2023; Liu et al., 2024; Tennant and Gilmore, 2020; Weiler and Sanubi, 2019). However, other studies, particularly those focused on multilateral donors, find evidence that mitigation finance is indeed concentrated in more economically developed countries and regions with higher emissions, consistent with efficiency-based logic (Halimanjaya, 2015; Michaelowa et al., 2020; Xie et al., 2023).

This fragmented and sometimes contradictory body of evidence raises important questions as to what drives climate finance allocation in practice. The observed inconsistencies may reflect a combination of donor priorities, political economy factors, implementation constraints, and gaps in data and methodology. It is also possible that different donors apply divergent logics, depending on their institutional mandates or geopolitical interests. Moreover, existing studies often operate at the national level, which may obscure important sub-national disparities in allocation. Sub-national analyses, which remain rare, are crucial for assessing whether climate finance reaches the most affected regions within countries. Without this level of granularity, it remains difficult to determine whether climate finance fulfills its stated goals of promoting equity, justice, and emissions reduction efficiency.

4 The geographical Scope and Resolution of climate finance

A key dimension often overlooked in debates on the allocation of climate finance is the geographical scope and resolution of the studies examining these patterns. We argue that discrepancies in empirical findings regarding climate finance allocation patterns are rooted in differences in sample composition and spatial granularity.

Existing studies vary significantly in terms of the regions they cover and the level at which they analyze allocation patterns. Some adopt a global lens, encompassing nearly all climate finance flows to low-income countries across diverse regions. Others restrict their focus to specific world regions, such as sub-Saharan Africa, Oceania, or Small Island Developing States (SIDS). These distinctions are not trivial: Whether climate finance is seen to follow a need-based or efficiency-based logic can be influenced by how homogeneous or heterogeneous the sample under scrutiny is.

For example, several studies that examine large, diverse samples, such as Bagchi et al. (2016), Islam (2022), Mori et al. (2019) and Weiler and Sanubi (2019), tend to find support for the idea that climate finance, particularly adaptation aid, is allocated in ways broadly consistent with stated donor priorities (e.g., vulnerability-based or efficiency-oriented allocation). These analyses span a wide range of countries and climate finance flows, offering a more aggregated picture of allocation trends.

By contrast, studies with a more narrowly defined regional focus often reveal far less alignment between funding flows and indicators of need or emissions. Robinson and Dornan (2017), for instance, find that SIDS receive disproportionately high levels of adaptation financing—levels that cannot be fully explained by their vulnerability relative to other developing countries. Tennant and Gilmore (2020) report a similar pattern, noting that SIDS are systematically privileged in adaptation finance allocation over other similarly vulnerable countries that do not hold SIDS status. Donner et al. (2016), focusing on Oceania, highlight significant inconsistencies in adaptation finance, with communities exhibiting comparable levels of need receiving markedly different levels of support. Likewise, Robertsen et al. (2015) observe no meaningful relationship between vulnerability and adaptation finance distribution across sub-Saharan Africa.

This trend extends to sub-national levels of analysis. Barrett's (2014) study of Malawi demonstrates that once the focus shifts from national to sub-national distributions, the alignment between adaptation needs and financial support further vanishes. Vulnerability-based allocation criteria, which might appear valid at the national level, do not seem to hold up when one examines the specific communities receiving aid within a country.

These findings raise an important question: does the apparent logic of need-based allocation only hold at coarse levels of analysis and begin to collapse when viewed through a finer spatial lens? While this possibility is compelling, it remains largely speculative due to the near-complete absence of sub-national analyses across multiple national contexts. Our study seeks to fill this void by investigating how one of the major multilateral aid provider, the World Bank, allocates sub-national climate adaptation and mitigation aid across 14 least developed countries in Asia and Oceania.

By disaggregating data at the sub-national level, we explore whether adaptation finance is targeted toward the most vulnerable regions within countries, and whether mitigation finance is directed toward areas with the highest emissions reduction potential. We argue that if the World Bank allocates climate finance based on its stated goals, then two distinct patterns should emerge: mitigation finance should concentrate in wealthier, more industrialized sub-national regions with high emissions levels and thus highest reduction potentials, while adaptation finance should be directed toward poorer, more vulnerable regions. Therefore, we formulate the following hypotheses:

H1: Within least-developed countries climate mitigation projects are more likely to be allocated to economically developed sub-national regions.

H2: Within least-developed countries climate adaptation projects are more likely to be allocated to sub-national regions that are more exposed and/or more susceptible to the adverse impacts of climate change.

5 Data and empirical strategy

We investigate these hypotheses using newly coded data on the sub-national allocation of climate-related development projects of the World Bank in 14 LDC countries in Asia and Oceania.[1] We focus on these countries as they are among the countries most exposed to climate change and are faced with threats such as rising sea levels, increasingly threatening tropical cyclones, and climate-related drought periods. Additionally, they are also among the countries most unapt to deal with the adverse effects of climate change as they lack the resources and the adaptive capacity that are need to adapt to climate change.

As sub-national unit, we focus on the second-order administrative division of each country (i.e.

[1]The countries are: Afghanistan, Bangladesh, Bhutan, Cambodia, Laos, Myanmar, Maldives, Nepal, Timor-Leste (East Timor), Kiribati, Solomon Islands, Tuvalu, Samoa, and Vanuatu.

counties or districts) and provide robustness results for first-order divisions (i.e. provinces). We combine data on the purpose and sub-national location of all development projects of the World Bank from 2000-2020[2] with data on various indicators of economic development, climate change exposure and vulnerability. Our goal is to assess in how far the allocation of climate mitigation and adaptation projects aligns with sub-national patterns of development, exposure, and vulnerability.

5.1 Climate-related development projects

Our main dependent variables, the number of World Bank mitigation and adaptation projects respectively, are manually coded. For each World Bank project in the countries under analysis we assessed whether one of its stated objectives was climate change mitigation or climate change adaptation.

We based our coding on the detailed project description and documentation that the World Bank provides for its projects. For each project, we obtained the most recent "Project Information Document" via the World Bank's API. In total, we have information on 780 projects. These documents are typically five to eight pages in length and provide information about the context, development objectives and a description of the content and components of the project. With these information, we are able to determine whether one of the stated objectives of the project consists of climate mitigation or climate adaptation.

Specifically, we coded a project as being intended for climate mitigation when one of its stated objectives was the reduction, avoidance, or sequestering of greenhouse gas emissions. Typically, this is done by promoting negative or low-emission activities (e.g. renewable energy projects), transitional activities (e.g. energy efficiency improvements for technologies that still use fossil fuels), or enabling activities (e.g. the manufacture of low-emission technologies).

In contrast, climate change adaptation is more difficult to define a priori as it is heavily dependent on the precise context. Depending on local exposure and vulnerability, effective adaptation can consist of a diverse set of actions, ranging from promoting drought-tolerant crops, building flood protective infrastructure, to increasing community resilience with disaster-related training and ed-

[2]Coding is still ongoing for the years 2017 and 2019 not yet included in this paper version.

ucation activities. Hence, we coded a project as climate adaptation when the project explicitly articulated an *intent* to address and reduce climate change vulnerability irrespective of the exact activity.

To code the precise administrative unit, in which the project was located, we link our purpose-coded projects with geo-location data from the Geocoded Official Development Assistance Dataset (GODAD) project[3] (Bomprezzi et al., 2024; AidData, 2017). In our main analysis, we rely on the number of projects that are allocated to a given administrative unit in each year. As is standard in the literature, we focus on the year the project was approved by the World Bank board rather than the year of the disbursement as we are interested in drivers behind the allocation of projects and not their implementation.

Figures 1 and 2 display the geographic distribution of the number of mitigation and adaptation projects, respectively, within our countries.

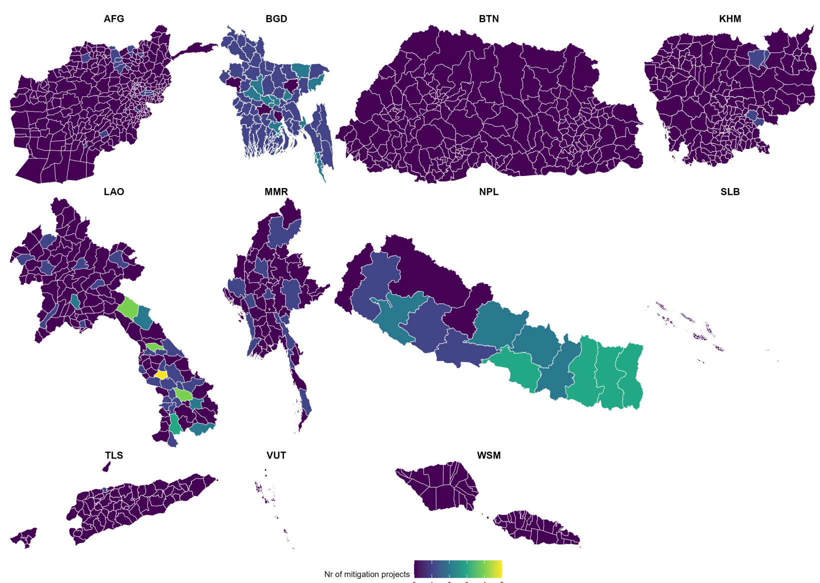

Figure 1: Geographic distribution of climate mitigation projects.

[3]https://godad.uni-goettingen.de/home/.

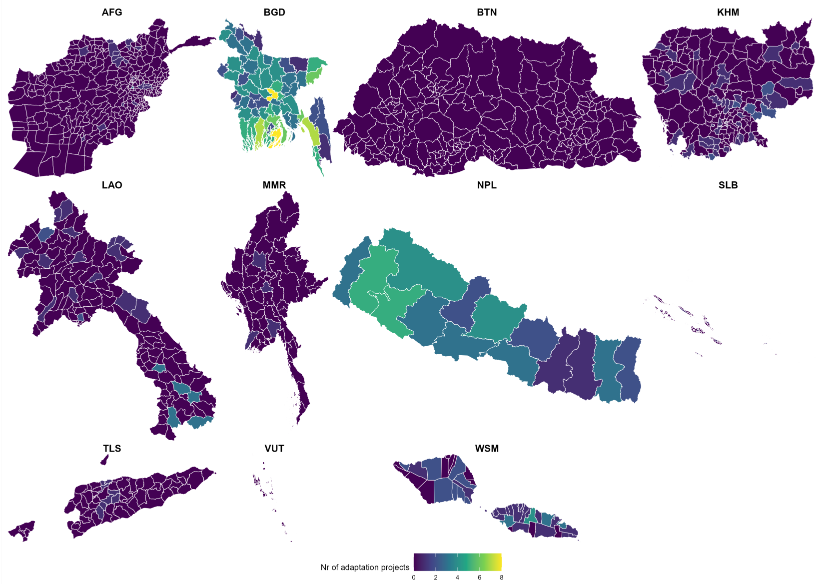

Figure 2: Geographic distribution of climate adaptation projects.

5.2 Climate exposure

We rely on two primary indicators to measure exposure to climate change: the share of the population living below five meter above sea level and abnormal deviations in precipitation and temperature.

To capture the exposure to rising sea levels, we calculate the population share that lives below five meter above sea level. We rely on population data from worldpop.org using the unconstrained data version with a resolution of 1km. We combine this with detailed elevation data using the CGIAR-CSI SRTM Version 4 dataset[4] (Jarvis et al., 2008) to calculate the share of population living below 5 meter above sea level.

We also measure abnormal weather conditions via the Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano et al., 2010). The SPEI is a location-standardized measure of water balance that takes into account both precipitation and the loss of moisture into the atmosphere via evapotranspiration. The index is standardized so that negative values indicate drier, and positive values wetter than average conditions. To match our yearly analyses, we use the 360-day

[4]https://srtm.csi.cgiar.org/

SPEI from Liu et al. (2024), which provides gridded data for the average weather conditions over the preceding 360 days. We aggregate these fine-grained data to the respective administrative unit (first- or second-order) and then create a binary variable for observations that have average SPEI values below -1.5 or above +1.5. These cut-offs are commonly classified as representing, respectively, very dry or very wet conditions.

5.3 Economic development

To assess the economic activity of a geographic unit and thus its potential for emissions reductions, we rely on several proxies of economic development. The most direct measure of economic development—GDP—tends to rather unreliable at the sub-national for LDCs. Hence, we also rely on night time lights emissions, road networks, and a sub-national human development index to proxy economic activity.

First, for GDP per capita, we use data from Kummu et al. (2025), who provide a harmonized global dataset of economic activity. The data are combined, extrapolated, and downscaled from various sources. We use their municipality-level data and aggregate the information up to our units of analysis at the first- and second-order administrative unit.

Second, we use night light emissions as a proxy for economic activity. Data come from Li et al. (2020) in the form of a consistent time series of night lights starting in 1992 by combining and harmonizing data from different sources and satellites.

Third, we use data on road infrastructure from Meijer et al. (2018). These data are time invariant and and represent the average road density per square kilometer in a province.

Fourth, we also employ a sub-national index of human development, which combines measures of GDP, life expectancy, and education. Data come from the Global Data Lab (Smits and Permanyer, 2019).

5.4 Natural disaster

We also include data on natural disasters in our models. Natural disasters are the results of vulnerable populations exposed to natural hazards and can thus be seen as a measure for both exposure and susceptibility to harm. We rely on data from EM-DAT, the International Disaster Database.[5] EM-DAT includes disasters that caused at least ten fatalities, affected 100 people or more, or led to a call of international assistance or an emergency declaration. From EM-DAT, we extract all climatological, hydrological, and meteorological disasters as only those are directly the result of climate-related hazards. EM-DAT has also started to retrospectively geo-code their database from 2000 onward and we use their geo-codes to match disasters to administrative regions. As disaster impact measures are notoriously unreliable (Delforge et al., 2025), we primarily rely on a simple disaster count.

5.5 Controls

As country-level control variable, we include the polyarchy index from the VDEM project (Coppedge et al., 2023). Furthermore, we also control total population in all models.

Descriptive statistics for all variables used can found in Table 1. We present summary statistics on the first-order administrative level in the Appendix in Table A1. We also present descriptive statistics of the project-level data in Table A2 in the Appendix.

[5] https://www.emdat.be

Table 1: Descriptive statistics (admin level 2).

Statistic	N	Mean	St. Dev.	Min	Median	Max
Adaptation statement of intent (nr projects)	24,210	0.019	0.150	0	0	3
Mitigation purpose (nr projects)	24,210	0.008	0.088	0	0	1
World Bank projects (nr projects)	24,210	0.135	0.466	0	0	6
GDP per capita	24,210	44,123.410	98,072.080	713	13,931	2,278,094
Human development index	17,653	0.499	0.087	0.261	0.505	0.813
Population	24,210	196,393.200	650,212.100	1.760	23,825.520	14,937,624.000
Population share below 5m sea level	24,210	0.069	0.166	0.000	0.0002	1.000
SPEI >1.5 or <-1.5	24,210	0.098	0.297	0	0	1
Nightlights emission	24,210	1,644.068	6,813.663	0.000	3.711	244,779.400
Road network density	21,798	415.683	638.550	6.618	201.439	7,612.647
Number of disaster events	24,210	0.041	0.236	0	0	4
Polyarchy index	23,436	0.355	0.187	0.072	0.354	0.763

5.6 Empirical strategy

We use fixed effect regressions to model the allocation of climate finance projects as a function of climate exposure and economic development, and natural disasters. Since the dependent variable in all our models is a count variable, i.e., the number of allocated projects, we rely on Poisson regression models. The main alternative, negative binomial models, are not able to account for all unobserved characteristics via fixed effects (Allison and Waterman, 2002). Furthermore, by clustering the standard errors we are able to deal with overdispersion, which is the main reason one would use negative binomial models in the first place (Wooldridge, 1999).

We start by reporting less-restrictive specifications with fixed effects at either the country level or the first-order administrative division level. These models retain substantially more observations than specifications that identify effects solely from within-unit over-time variation. Our main model, however, is a Poisson model with fixed effects at the level of the administrative divisions (i.e. second-order for the main analysis and first-order in the robustness checks) and year fixed effects. These models focus on within-unit changes while accounting for global shocks that affect all countries simultaneously. Furthermore, in some models, we replace the year fixed effects with more conservative country-year fixed effects to account for country-specific shocks. Finally, as a robustness check, we also cluster the standard error at the first-order division level to allow for potential spatial dependencies between counties/districts.

As an alternative to the fixed effects models, we also report results from mixed-effects models with random intercepts both at the levels of the administrative units and years.

We lag all independent variables by one year to account for a time gap between on-the-ground changes and allocation decision and to reduce simultaneity bias.

6 Results

We start the presentation of our results with the less conservative models that only contain country and year fixed effects. These models exploit the within-country variation in project allocation across sub-national units, but do not account for unobserved district-level heterogeneity. In a second step, we present more conservative specifications with county-level fixed effects that isolate the within-district temporal variation. All models include year fixed effects to control for global shocks affecting all regions simultaneously

Table 2 shows our results of these models with regard to mitigation projects. We present four models that each regress the number of mitigation projects on one indicator of economic development at a time: GDPpc, night time lights emissions, road networks, and the human development index. All models control for the total number of World Bank projects in the previous year in this region, population, the share of population living below 5m above sea level, the indicator of extreme SPEI values, the number of natural disasters, as well as the country-level variable measuring democracy. Furthermore, we include both unit and year fixed effects to focus our analysis on the *within* unit distribution and to control for global shocks in aid distribution.

As can be seen in Table 2, we find conflicting evidence with regard to the effect of economic development on the allocation of mitigation projects. GDPpc has a positive effect (statistically significant at the 10-% level), while higher scores on the human development index are statistically significantly associated with fewer projects. This suggests that, in contrast to our theoretical expectations, mitigation is not strongly tied to economic activity and emission reduction potential.

In a next step, we estimate more restrictive models that replace the country-level fixed effects with unit-level fixed effects (i.e. counties/districts). Results are presented in Table 3. In these models we test whether changes within counties/districts are associated with a change in the number of mitigation projects. Here, the only statistically significant finding with regard to development is the human development index which is still negatively related to the number of projects. GDPpc and night time lights emissions remain statistically insignificant. Note that road density drops out as it is time invariant at the district level.

We now present the same models using the number of adaptation projects as dependent variable. For adaptation finance, we expect a negative association between economic activity and adaptation projects: richer provinces should, on average, be less vulnerable to climate change and thus have lower demand for adaptation. Table 4 shows the results for the country and year fixed effects models. Here, all of our indicators economic development are statistically indistinguishable

Table 2: Mitigation projects: country and year fixed effects

Dependent Variable:	Nr mitigation projects			
Model:	(1)	(2)	(3)	(4)
Variables				
log GDP pc	0.212*			
	(0.119)			
log Night-lights		0.051		
		(0.049)		
Human dev. index			-3.673**	
			(1.847)	
Road density				0.000
				(0.000)
Nr WB projects	0.009	0.009	0.016	0.012
	(0.104)	(0.101)	(0.103)	(0.103)
log Population	0.527***	0.471***	0.569***	0.591***
	(0.124)	(0.146)	(0.123)	(0.123)
Pop share under 5m	0.042	0.099	0.305	0.303
	(0.446)	(0.437)	(0.423)	(0.449)
SPEI >1.5 or < -1.5	-0.201	-0.218	-0.116	-0.205
	(0.217)	(0.220)	(0.219)	(0.217)
Disaster events	0.110	0.127	0.094	0.117
	(0.095)	(0.092)	(0.093)	(0.093)
Polyarchy index	-2.606**	-2.746**	-3.030**	-2.632**
	(1.226)	(1.246)	(1.307)	(1.226)
Fixed-effects				
Country	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	12,408	12,408	10,150	11,328

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

from zero.

For adaptation finance, we also expected a positive relationship with our measure of exposure and the number of climate-related natural disasters. And, indeed, Table 4 presents evidence for this: project numbers are higher in regions that are more exposed to climate impacts. Both the coefficients for the share of population living below five meters above sea level and for the indicator for extreme SPEI values are consistently and statistically significantly positive.

Table 3: Mitigation projects: unit and year fixed effects

Dependent Variable:	Nr mitigation projects		
Model:	(1)	(2)	(3)
Variables			
log GDP pc	0.015		
	(0.490)		
log Night-lights		-0.116	
		(0.072)	
Human dev. index			-28.770***
			(9.868)
Nr WB projects	-0.199*	-0.213*	-0.211*
	(0.112)	(0.114)	(0.116)
log Population	-3.547**	-3.345**	-3.603**
	(1.506)	(1.513)	(1.584)
Pop share under 5m	-148.959***	-142.682***	-135.437***
	(44.153)	(44.197)	(49.107)
SPEI >1.5 or < -1.5	0.017	-0.002	0.063
	(0.259)	(0.252)	(0.255)
Disaster events	0.153	0.142	0.096
	(0.132)	(0.133)	(0.136)
Polyarchy index	-1.844	-1.570	-0.768
	(1.314)	(1.304)	(1.504)
Fixed-effects			
County	Yes	Yes	Yes
Year	Yes	Yes	Yes
Fit statistics			
Observations	1,764	1,764	1,715

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

In Table 5 we again replace the country-level fixed effects with fixed effects at the second-order administrative division to analyze changes within counties/districts. In these models, we do find evidence for a negative association between economic activity and adaptation projects. Both GDPpc and the human development index are negatively associated with the number of adaptation projects. With regard to our exposure measures, only the indicator of extreme weather conditions remains positive and statistically significant while the share of population living below 5m above sea level ceizes to be statistically significant.

Table 4: Adaptation projects - country and year fixed effects

Dependent Variable:	Nr adaptation projects			
Model:	(1)	(2)	(3)	(4)
Variables				
log GDP pc	-0.028			
	(0.087)			
log Night-lights		0.031		
		(0.033)		
Human dev. index			-1.515	
			(1.155)	
Road density				0.000
				(0.000)
Nr WB projects	-0.048	-0.045	-0.021	-0.041
	(0.080)	(0.080)	(0.080)	(0.079)
log Population	0.533***	0.480***	0.553***	0.501***
	(0.091)	(0.094)	(0.089)	(0.084)
Pop share under 5m	1.486***	1.476***	1.716***	1.638***
	(0.307)	(0.309)	(0.335)	(0.333)
SPEI >1.5 or < -1.5	0.714***	0.716***	0.664***	0.706***
	(0.146)	(0.145)	(0.146)	(0.147)
Disaster events	-0.044	-0.048	-0.075	-0.056
	(0.062)	(0.062)	(0.062)	(0.061)
Polyarchy index	-3.860***	-3.949***	-5.001***	-4.072***
	(0.629)	(0.639)	(0.786)	(0.645)
Fixed-effects				
Country	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	13,442	13,442	10,939	12,272

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

In the Appendix, we also present models where we vary our fixed effects structure and cluster standard errors more conservatively at the first-order administrative division. Specifically, we run models using fixed effects at the first-order administrative unit (Tables A3 and A4), and models using country-year fixed effects instead of simple year fixed effects (Tables A5 and A6). Additionally, we also present models with standard errors clustered at the first order administrative division (Tables A7 and A8). Taken together, these results broadly mirror the main results presented

Table 5: Adaptation projects - unit and year fixed effects

Dependent Variable:	Nr adaptation projects		
Model:	(1)	(2)	(3)
Variables			
log GDP pc	-1.730***		
	(0.471)		
log Night-lights		-0.075	
		(0.047)	
Human dev. index			-32.243***
			(6.700)
Nr WB projects	-0.210**	-0.207**	-0.156**
	(0.082)	(0.084)	(0.079)
log Population	0.111	0.195	-0.058
	(0.604)	(0.580)	(0.695)
Pop share under 5m	-22.480	-23.675	27.049
	(25.038)	(24.035)	(24.885)
SPEI >1.5 or < -1.5	0.701***	0.725***	0.589***
	(0.157)	(0.161)	(0.149)
Disaster events	-0.040	-0.036	-0.077
	(0.071)	(0.072)	(0.072)
Polyarchy index	-4.035***	-3.501***	-3.656***
	(0.705)	(0.663)	(0.857)
Fixed-effects			
County	Yes	Yes	Yes
Year	Yes	Yes	Yes
Fit statistics			
Observations	2,457	2,457	2,311

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

above.

We also ran our analyses at the first-order administrative division (i.e. states/provinces). Here, we again report models using country and year fixed effects; province and year fixed effects; as well as province and country-year fixed effects. These results can also be found in the Appendix in Tables A9 to A12. The findings from these models are again largely aligned with the previous results: we find limited evidence for the role of economic development with regard to mitigation and more consistent evidence for the role exposure and vulnerability with regard to adaptation.

Finally, we also present results from mixed-effect models. These models account for the nested structure of the data (counties nested in provinces, which are nested in countries) but partially pool the within- and between-variation of these different levels. Thus, they typically use more variation than the fixed effects estimator, but do not account for all unobserved unit-level heterogeneity. In these models, we allow for random intercepts at the administrative unit and year level. The results can be found in the Appendix in Tables A13 to A16. Overall, these results are in line with our fixed effects models.

Taken together, these preliminary findings suggests that mitigation finance is largely unrelated to to economic activity and thus emission reduction potential. This casts doubts on the effectiveness of international mitigation finance. However, we do find evidence that adaptation finance tends to go regions more exposed to climate hazards, which is line with equity concerns.

7 Conclusion

To be concluded...

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A Descriptives

Table A1: Descriptive statistics (admin level 1).

Statistic	N	Mean	St. Dev.	Min	Median	Max
Adaptation statement of intent (nr projects)	3,114	0.075	0.313	0	0	3
Mitigation purpose (nr projects)	3,114	0.040	0.202	0	0	2
World Bank projects (nr projects)	3,114	0.635	1.078	0	0	9
GDP per capita	3,096	337,068.500	532,365.900	1,737	143,882.5	7,090,072
Human development index	2,318	0.506	0.085	0.261	0.511	0.813
Population	3,114	1,526,899.000	4,742,164.000	7.827	222,453.000	54,904,628.000
Population share below 5m sea level	3,114	0.089	0.207	0.000	0.002	1.000
SPEI >1.5 or <-1.5	3,114	0.091	0.287	0	0	1
Nightlights emission	3,114	12,782.020	41,724.530	0.000	700.932	898,719.700
Road network density	2,826	421.941	577.790	12.635	207.320	5,010.585
Number of disaster events	3,114	0.226	0.485	0	0	3
Polyarchy index	2,754	0.339	0.187	0.072	0.324	0.763

Table A2: Project-level statistics.

Statistic	N	Mean	St. Dev.	Min	Median	Max
Adaptation statement of intent	509	0.191	0.393	0	0	1
Context of vulnerability	510	0.239	0.427	0	0	1
Clear and direct link	508	0.276	0.447	0	0	1
Scope of adaptation	151	2.126	0.733	1	2	3
Mitigation purpose	505	0.137	0.344	0	0	1
Scope of mitigation	73	2.329	0.746	1	2	3
Year	511	2,009.256	4.744	2,000	2,010	2,018

B Further results on the Admin 2 level (counties/districts)

Table A3: Mitigation projects - province (admin 1) and year fixed effects

Dependent Variable:	Nr mitigation projects		
Model:	(1)	(2)	(3)
Variables			
log GDP pc	0.251*		
	(0.139)		
log Night-lights		0.041	
		(0.062)	
Human dev. index			-7.202**
			(3.269)
Nr WB projects	-0.027	-0.029	-0.013
	(0.109)	(0.107)	(0.108)
log Population	0.468***	0.464***	0.581***
	(0.131)	(0.140)	(0.127)
Pop share under 5m	-0.138	0.064	-0.119
	(0.614)	(0.562)	(0.492)
SPEI >1.5 or < -1.5	-0.015	-0.002	0.015
	(0.239)	(0.238)	(0.236)
Disaster events	0.107	0.129	0.079
	(0.106)	(0.103)	(0.105)
Polyarchy index	-2.388*	-2.486**	-2.575*
	(1.236)	(1.260)	(1.360)
Fixed-effects			
Province	Yes	Yes	Yes
Year	Yes	Yes	Yes
Fit statistics			
Observations	5,928	5,928	5,324

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A4: Adaptation projects - province (admin 1) and year fixed effects

Dependent Variable:	Nr adaptation projects		
Model:	(1)	(2)	(3)
Variables			
log GDP pc	0.065		
	(0.098)		
log Night-lights		0.065^{**}	
		(0.033)	
Human dev. index			-3.867^{**}
			(1.680)
Nr WB projects	-0.085	-0.079	-0.037
	(0.079)	(0.077)	(0.080)
log Population	0.586^{***}	0.516^{***}	0.639^{***}
	(0.085)	(0.089)	(0.086)
Pop share under 5m	0.945^{***}	0.934^{***}	1.232^{***}
	(0.277)	(0.266)	(0.288)
SPEI >1.5 or < -1.5	0.677^{***}	0.682^{***}	0.600^{***}
	(0.151)	(0.150)	(0.149)
Disaster events	-0.059	-0.058	-0.095
	(0.064)	(0.065)	(0.067)
Polyarchy index	-3.785^{***}	-4.017^{***}	-4.796^{***}
	(0.647)	(0.665)	(0.804)
Fixed-effects			
Province	Yes	Yes	Yes
Year	Yes	Yes	Yes
Fit statistics			
Observations	9,750	9,750	7,339

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A5: Mitigation projects - unit (admin 2) and country-year fixed effects

Dependent Variable:	Nr mitigation projects		
Model:	(1)	(2)	(3)
Variables			
log GDP pc	0.412		
	(0.913)		
log Night-lights		0.156	
		(0.104)	
Human dev. index			20.990
			(16.505)
Nr WB projects	0.202	0.205	0.214
	(0.258)	(0.253)	(0.260)
log Population	-1.964*	-1.678	-2.096*
	(1.190)	(1.222)	(1.185)
Pop share under 5m	-12.795	-17.230	-32.754
	(60.825)	(62.170)	(59.479)
SPEI >1.5 or < -1.5	-0.444	-0.446	-0.431
	(0.377)	(0.379)	(0.375)
Disaster events	-0.124	-0.118	-0.072
	(0.171)	(0.172)	(0.160)
Fixed-effects			
County	Yes	Yes	Yes
Country-Year	Yes	Yes	Yes
Fit statistics			
Observations	641	641	637

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A6: Admin 2: Adaptation projects - unit (admin 2) and country-year fixed effects

Dependent Variable:	Nr adaptation projects		
Model:	(1)	(2)	(3)
Variables			
log GDP pc	0.078		
	(0.524)		
log Night-lights		-0.052	
		(0.061)	
Human dev. index			-7.322
			(6.333)
Nr WB projects	0.039	0.040	0.049
	(0.082)	(0.081)	(0.082)
log Population	1.312*	1.367*	1.390*
	(0.740)	(0.751)	(0.753)
Pop share under 5m	14.983	15.789	15.337
	(18.645)	(18.661)	(19.032)
SPEI >1.5 or < -1.5	0.050	0.044	0.042
	(0.154)	(0.154)	(0.155)
Disaster events	0.001	0.002	-0.009
	(0.066)	(0.066)	(0.066)
Fixed-effects			
County	Yes	Yes	Yes
Country-Year	Yes	Yes	Yes
Fit statistics			
Observations	863	863	853

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A7: Mitigation projects - unit (admin 2) and year fixed effects with standard errors clustered at admin 1

Dependent Variable:	Nr mitigation projects			
Model:	(1)	(2)	(3)	(4)
Variables				
log GDP pc	0.015			
	(0.596)			
log Night-lights		-0.116		
		(0.082)		
Human dev. index			-28.770**	
			(12.343)	
Nr WB projects	-0.199*	-0.213**	-0.211*	-0.199*
	(0.106)	(0.108)	(0.113)	(0.104)
log Population	-3.547**	-3.345**	-3.603**	-3.548**
	(1.569)	(1.584)	(1.639)	(1.569)
Pop share under 5m	-148.959***	-142.682***	-135.437***	-148.907***
	(44.263)	(43.626)	(48.823)	(43.627)
SPEI >1.5 or < -1.5	0.017	-0.002	0.063	0.018
	(0.330)	(0.317)	(0.306)	(0.329)
Disaster events	0.153	0.142	0.096	0.153
	(0.160)	(0.163)	(0.172)	(0.160)
Polyarchy index	-1.844	-1.570	-0.768	-1.844
	(1.685)	(1.664)	(2.000)	(1.688)
Fixed-effects				
County	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,764	1,764	1,715	1,764

Clustered (Province) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A8: Adaptation projects - unit (admin 2) and year fixed effects with standard errors clustered at admin 1

Dependent Variable:	Nr adaptation projects			
Model:	(1)	(2)	(3)	(4)
Variables				
log GDP pc	-1.730**			
	(0.727)			
log Night-lights		-0.075		
		(0.053)		
Human dev. index			-32.243***	
			(9.212)	
Nr WB projects	-0.210**	-0.207**	-0.156*	-0.183**
	(0.095)	(0.096)	(0.091)	(0.092)
log Population	0.111	0.195	-0.058	0.155
	(0.627)	(0.608)	(0.695)	(0.599)
Pop share under 5m	-22.480	-23.675	27.049	-4.177
	(30.862)	(29.886)	(26.852)	(29.284)
SPEI >1.5 or <-1.5	0.701***	0.725***	0.589***	0.716***
	(0.211)	(0.217)	(0.187)	(0.219)
Disaster events	-0.040	-0.036	-0.077	-0.048
	(0.068)	(0.068)	(0.061)	(0.067)
Polyarchy index	-4.035***	-3.501***	-3.656***	-4.046***
	(0.901)	(0.832)	(1.083)	(0.912)
Fixed-effects				
County	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	2,457	2,457	2,311	2,392

Clustered (Province) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

C Results on the Admin 1 level (provinces/states)

Table A9: Mitigation projects - country and year fixed effects (admin 1 level)

Dependent Variable:	Nr mitigation projects			
Model:	(1)	(2)	(3)	(4)
Variables				
log GDP pc	0.128			
	(0.138)			
log Night-lights		0.033		
		(0.073)		
Human dev. index			-1.548	
			(1.811)	
Road density				0.000
				(0.000)
Nr WB projects	0.160**	0.163**	0.143*	0.164**
	(0.073)	(0.074)	(0.075)	(0.074)
log Population	0.292**	0.284	0.337**	0.369***
	(0.148)	(0.174)	(0.136)	(0.138)
Pop share under 5m	-0.681	-0.671	-0.110	-0.208
	(1.021)	(1.041)	(0.753)	(0.803)
SPEI >1.5 or < -1.5	0.772***	0.789***	0.783***	0.777***
	(0.230)	(0.236)	(0.230)	(0.233)
Disaster events	-0.157	-0.157	-0.159	-0.154
	(0.178)	(0.177)	(0.179)	(0.179)
Polyarchy index	0.872	0.810	0.578	0.867
	(1.280)	(1.267)	(1.326)	(1.290)
Fixed-effects				
Country	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,524	1,524	1,391	1,476

Clustered (Province (admin 1)) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A10: Adaptation projects - country and year fixed effects (admin 1 level)

Dependent Variable:	Nr adaptation projects			
Model:	(1)	(2)	(3)	(4)
Variables				
log GDP pc	-0.216***			
	(0.075)			
log Night-lights		-0.076*		
		(0.039)		
Human dev. index			-1.943	
			(1.410)	
Road density				0.000
				(0.000)
Nr WB projects	-0.009	-0.019	-0.017	-0.014
	(0.070)	(0.070)	(0.066)	(0.069)
log Population	0.351***	0.385***	0.312***	0.284***
	(0.077)	(0.098)	(0.087)	(0.087)
Pop share under 5m	0.577	0.729	0.831	0.704
	(0.526)	(0.527)	(0.630)	(0.584)
SPEI >1.5 or < -1.5	0.964***	0.920***	0.876***	0.972***
	(0.214)	(0.215)	(0.229)	(0.220)
Disaster events	0.291***	0.302***	0.305***	0.286***
	(0.096)	(0.099)	(0.103)	(0.097)
Polyarchy index	-1.889**	-1.649**	-2.649***	-2.025**
	(0.815)	(0.804)	(0.837)	(0.817)
Fixed-effects				
Country	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,651	1,651	1,495	1,599

Clustered (Province (admin 1)) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A11: Mitigation projects - province and country-year fixed effects (admin 1 level)

Dependent Variable:	Nr mitigation projects			
Model:	(1)	(2)	(3)	(4)
Variables				
log GDP pc	2.410			
	(2.253)			
log Night-lights		0.150		
		(0.166)		
Human dev. index			43.735**	
			(17.938)	
Nr WB projects	-0.088	-0.082	-0.095	-0.090
	(0.127)	(0.124)	(0.134)	(0.127)
log Population	0.183	-0.193	-0.348	-0.145
	(1.745)	(1.827)	(1.481)	(1.780)
Pop share under 5m	-80.686	-99.209	-163.567	-96.575
	(114.128)	(123.359)	(117.905)	(125.106)
SPEI >1.5 or < -1.5	0.282	0.245	0.181	0.251
	(0.419)	(0.420)	(0.400)	(0.420)
Disaster events	-0.040	-0.066	0.030	-0.065
	(0.336)	(0.340)	(0.368)	(0.338)
Fixed-effects				
Province (admin 1)	Yes	Yes	Yes	Yes
Country-Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	224	224	221	224

Clustered (Province (admin 1)) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A12: Adaptation projects - province and country-year fixed effects (admin 1 level)

Dependent Variable:	Nr adaptation projects			
Model:	(1)	(2)	(3)	(4)
Variables				
log GDP pc	-1.388			
	(2.104)			
log Night-lights		0.021		
		(0.088)		
Human dev. index			-10.675	
			(7.099)	
Nr WB projects	-0.096	-0.095	-0.089	-0.097
	(0.100)	(0.101)	(0.101)	(0.100)
log Population	3.330***	3.106***	3.251***	3.123***
	(1.222)	(1.183)	(1.191)	(1.164)
Pop share under 5m	-18.200	-17.390	-17.752	-16.876
	(21.419)	(20.388)	(19.949)	(20.640)
SPEI >1.5 or < -1.5	0.132	0.144	0.085	0.140
	(0.210)	(0.209)	(0.222)	(0.207)
Disaster events	-0.012	0.000	-0.014	0.000
	(0.172)	(0.170)	(0.167)	(0.169)
Fixed-effects				
Province (admin 1)	Yes	Yes	Yes	Yes
Country-Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	343	343	333	339

Clustered (Province (admin 1)) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

D Random effect models

Table A13: Random Effects Models: Mitigation Projects (Admin 2)

	GDP pc	Night-lights	HDI	Road density
log GDP pc	0.306**			
	(0.154)			
log Night-lights		0.156		
		(0.143)		
Human dev. index			−0.292*	
			(0.156)	
Road density				−0.090
				(0.109)
Nr WB projects	0.001	0.000	0.006	0.003
	(0.046)	(0.046)	(0.047)	(0.046)
log Population	1.192***	1.190***	1.375***	1.353***
	(0.217)	(0.247)	(0.229)	(0.222)
Pop share under 5m	−0.008	0.001	0.014	0.032
	(0.135)	(0.135)	(0.140)	(0.135)
SPEI > 1.5 or < -1.5	−0.044	−0.046	−0.029	−0.047
	(0.071)	(0.071)	(0.071)	(0.071)
Disaster events	0.029	0.034	0.029	0.031
	(0.031)	(0.030)	(0.031)	(0.030)
Polyarchy index	−0.449***	−0.489***	−0.569***	−0.459***
	(0.169)	(0.169)	(0.179)	(0.170)
Observations	22 134	22 134	16 534	19 856

* p <0.1, ** p <0.05, *** p <0.01
Poisson random effects models with nested structure (admin2 within admin1 within country) and cross-classified year effects. Standard errors in parentheses.

Table A14: Random Effects Models: Adaptation Projects (Admin 2)

	GDP pc	Night-lights	HDI	Road density
log GDP pc	−0.037			
	(0.117)			
log Night-lights		0.117		
		(0.112)		
Human dev. index			−0.156	
			(0.124)	
Road density				0.054
				(0.052)
Nr WB projects	−0.024	−0.024	−0.012	−0.020
	(0.031)	(0.031)	(0.031)	(0.031)
log Population	1.271***	1.156***	1.339***	1.204***
	(0.177)	(0.194)	(0.190)	(0.184)
Pop share under 5m	0.226***	0.219***	0.253***	0.253***
	(0.069)	(0.070)	(0.073)	(0.072)
SPEI > 1.5 or < -1.5	0.213***	0.213***	0.197***	0.210***
	(0.044)	(0.044)	(0.046)	(0.045)
Disaster events	−0.010	−0.011	−0.018	−0.013
	(0.020)	(0.020)	(0.020)	(0.020)
Polyarchy index	−0.691***	−0.709***	−0.893***	−0.724***
	(0.131)	(0.132)	(0.148)	(0.133)
Observations	22 134	22 134	16 534	19 856

* p <0.1, ** p <0.05, *** p <0.01
Poisson random effects models with nested structure (admin2 within admin1 within country) and cross-classified year effects. Standard errors in parentheses.

Table A15: Random Effects Models: Mitigation Projects (Admin 1)

	GDP pc	Night-lights	HDI	Road density
log GDP pc	0.306**			
	(0.154)			
log Night-lights		0.156		
		(0.143)		
Human dev. index			−0.292*	
			(0.156)	
Road density				−0.090
				(0.109)
Nr WB projects	0.001	0.000	0.006	0.003
	(0.046)	(0.046)	(0.047)	(0.046)
log Population	1.192***	1.190***	1.375***	1.353***
	(0.217)	(0.247)	(0.229)	(0.222)
Pop share under 5m	−0.008	0.001	0.014	0.032
	(0.135)	(0.135)	(0.140)	(0.135)
SPEI > 1.5 or < -1.5	−0.044	−0.046	−0.029	−0.047
	(0.071)	(0.071)	(0.071)	(0.071)
Disaster events	0.029	0.034	0.029	0.031
	(0.031)	(0.030)	(0.031)	(0.030)
Polyarchy index	−0.449***	−0.489***	−0.569***	−0.459***
	(0.169)	(0.169)	(0.179)	(0.170)
Observations	22 134	22 134	16 534	19 856

* p <0.1, ** p <0.05, *** p <0.01
Poisson random effects models with nested structure (admin1 within country) and cross-classified year effects. Standard errors in parentheses.

Table A16: Random Effects Models: Adaptation Projects (Admin 1)

	GDP pc	Night-lights	HDI	Road density
log GDP pc	−0.037			
	(0.117)			
log Night-lights		0.117		
		(0.112)		
Human dev. index			−0.156	
			(0.124)	
Road density				0.054
				(0.052)
Nr WB projects	−0.024	−0.024	−0.012	−0.020
	(0.031)	(0.031)	(0.031)	(0.031)
log Population	1.271***	1.156***	1.339***	1.204***
	(0.177)	(0.194)	(0.190)	(0.184)
Pop share under 5m	0.226***	0.219***	0.253***	0.253***
	(0.069)	(0.070)	(0.073)	(0.072)
SPEI > 1.5 or < -1.5	0.213***	0.213***	0.197***	0.210***
	(0.044)	(0.044)	(0.046)	(0.045)
Disaster events	−0.010	−0.011	−0.018	−0.013
	(0.020)	(0.020)	(0.020)	(0.020)
Polyarchy index	−0.691***	−0.709***	−0.893***	−0.724***
	(0.131)	(0.132)	(0.148)	(0.133)
Observations	22 134	22 134	16 534	19 856

* p <0.1, ** p <0.05, *** p <0.01
Poisson random effects models with nested structure (admin1 within country) and cross-classified year effects. Standard errors in parentheses.